The Comparative Analysis and Prospect of Two Heuristic Algorithms -------- The Firefly Algorithm and the Basic Ant Colony Algorithm

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Abstract

This paper introduces two heuristic algorithms and illustrates the similarities and differences between the two algorithms; in the end, through the empirical analysis to find their respective advantages. This paper mainly focuses on the firefly algorithm, which is a new type of algorithm, inspired by the fluorescence information exchange between the fireflies in the nature. By comparative analysis with the basic ant colony algorithm, this text gives a final assessment of the firefly algorithm, and makes a prospect for its development.

Keywords: Swarm intelligence, Fireflies algorithm simulation, Ant colony algorithm

1. Introduction to Algorithms

1.1 Introduction Firefly Algorithm

Approximately 2,000 kinds of fireflies live in nature, most them emits a short, rhythmic fluorescence, different types of fireflies glow different purposes, their real reasons are still negotiating. Generally, adult fireflies glowing biological significance is the use of species-specific flash signals to locate and attract the opposite sex, thereby completing the mission courtship mating and breeding; minority firefly flash signals utilize prey; There is also a role as a warning signal, that is, when stimulated firefly emits light. Firefly luminescence behavior simulation optimization algorithm is constructed out of fireflies in nature stochastic optimization algorithm, but the algorithm discards some biological significance fireflies glow, emitting only use its features to look for partners based on their search area, and to the neighborhood structure fireflies in the optimum position to move in order to achieve the position of evolution.

1.2. Algorithm Bionic Principle

In this algorithm, the reason fireflies attracted to each other depends on two factors, body brightness and attractiveness. Wherein the brightness of the fluorescence emitted firefly their location depends on the target, the higher the luminance represented better location, i.e. the target value, the better. Attract and brightness related, the more bright fireflies have higher appeal, within sight of the brightness can attract mobile than its weak fireflies go in this direction. If the emission brightness is the same, they will take a random movement of fireflies. Inversely proportional to the brightness and the distance between firefly and attractiveness are reduced with increasing distance, which corresponds to the mold space propagation characteristics of the phosphors in the media is absorbed and attenuated gradually. Fireflies go through simulation algorithm is constructed out of a group behavior stochastic optimization algorithms.

Its bionic principle is: The point of the search space simulation fireflies individual in nature, will simulate a search and optimization process and the process of moving fireflies attract individuals will solve the problem of the objective function to measure the location of the individual merits of the survival of the fittest individual analog process optimization for the search and replace using a good feasible solution iterative process less feasible solution.

1.3 Mathematical Description and Analysis of Algorithms

As mentioned above, the firefly algorithm consists of two elements, namely the degree of brightness and attractive.

Brightness embodies the merits of fireflies to determine their location and direction of movement of the degree of attraction determines the distance traveled fireflies, attracted by the degree of brightness and constantly updated, in order to achieve objective optimization. From the mathematical point of view of the mechanism of firefly algorithm to optimize the following description:

The definition of a relative fluorescence intensity of firefly:

$$I = I_0 \times e^{-\gamma r_{ij}} \qquad (1)$$

Where: I0 is the maximum fluorescence intensity of firefly, i.e. itself (r = 0 Office) fluorescence intensity, the value of the objective function associated with the target value, the more excellent function of their higher brightness; γ is the absorption coefficient of light intensity as the fluorescence with distance absorption increases gradually weakened and the media, so the absorption coefficient of light intensity settings to reflect this feature can be set to a constant; rij as fireflies i and j spatial distance between.

Definition 2 fireflies attract degrees

$$\beta = \beta_0 \times e^{-\gamma r2_{ij}} \qquad (2)$$

Where: $\beta 0$ is the maximum degree of attraction, that the light source (r = 0 Office) of attractiveness; γ, rij meaning as above.

Definition 3 is attracted to the firefly i j is updated by moving the position of the formula (3) determines:

$$X_i = X_i + \beta \times (x_j - x_i) + \alpha \times (rand - 1/2) \qquad (3)]$$

Where, xi, xj is the spatial location in which fireflies i and j; α is the step size factor, is a constant [0, 1]; rand random factor to obey uniform distribution [0, 1].

Process optimization algorithm is: first firefly populations randomly scattered in the solution space, every firefly fluorescence intensity emitted because of the different location is different, by comparing (according to equation (1)), high brightness, brightness attract fireflies Firefly to their low moving distance moved depends on the size of attractiveness (according to formula (2)). In order to increase the search area, to avoid premature local optimum, increasing the disturbance $\alpha \times$ (rand -1 / 2) at the location update process, the position (3) to calculate the updated according to the formula. By moving so many times, all individuals will gather the brightest firefly in a position to achieve optimization.

1.4 Algorithm Flow

In summary, the firefly optimization process is as follows:

a) Basic initialization algorithm parameters. Firefly set number m, the maximum attractiveness $\beta 0$, light intensity absorption coefficient γ, step factor α, or a maximum number of iterations maxT search accuracy ε.

b) Random initialization fireflies' position, the objective function value is calculated as the respective maximum fluorescence fireflies' brightness I0.

c) by the formula (1) (2) to calculate the relative brightness of the firefly population I and attractiveness β, according to the relative brightness of the decision to move the direction of fireflies.

d) According to equation (3) updating the spatial location of the firefly, fireflies in the best position to be in random perturbations.

e) According to the updated position of fireflies, firefly recalculated brightness.

f) When the search accuracy or satisfy the maximum number of searches you turn g); Otherwise, the number of searches increased by 1 turn c), for the next search.

g) Output of the global extreme point and the best individual values.

The time complexity of the algorithm is O (m2), m is the number of fireflies.

2. Introduction to the Basic ant Colony Algorithm

Ant colony algorithm (ant colony algorithm) by the Italian scholar Colorni et al [1] A in the early 1990s through the analog nature of the behavior of ants collective routing proposed heuristic algorithm based on bionic evolution population from public published papers, China's first ant colony algorithm is Dr. Zhang Jikuai and Professor Xu Xinhe Northeastern University.

Ant colony algorithm was first successfully applied to solve the famous traveling salesman problem (T SP). It uses a distributed parallel computer system, easy to combine with other methods, is robust, but the long search time limit and easily into the local optimal solution is its prominent shortcomings.

Currently, the ant colony algorithm has become a hot topic in the international forefront of intelligent computing and areas of concern. 1998 in Brussels held a special session of the ant colony optimization first international seminar held once every two years later, despite a strict theoretical basis of ant colony algorithm yet lay, but this new bionic intelligent evolutionary algorithm has shown great vitality.

Given an n-city TSP, the number of artificial ants is m, each artificial ant behavior conform to the following rules:

(1) According to the pheromone on the path to the corresponding probabilities to select the next path.
(2) No longer select their own has gone through this cycle path for the next path , using a data structure (tabu list) to control this.
(3) Upon completion of the first cycle, the entire path length according to the respective concentrations of pheromone released and updates the information on the concentration of the path traversed. T represents the cycle of generation t search, arcs (i, j pheromone size) on.

3.The Comparison of the Two Algorithms

3.1basic Ant Colony Algorithm

3.1.1 Basic Ant Colony Algorithm Advantages

(1) the robustness of the algorithm model is slightly modified, they can be applied to other problems; ant algorithm is less demanding on the initial route, that the results of the ant algorithm for solving depends on the initial route selection, but also in search process does not require manual adjustment.
(2) Distributed Computing. The algorithm is an algorithm based on the proposed ecosystem population, with the nature of parallelism, easy parallel implementation.
(3) Easy to combine with other methods. The algorithm is easy to combine with a variety of heuristics to improve the performance of the algorithm.
(4) Ant colony algorithm is an inherently parallel algorithms. Process independently of one another each ant searches only communicate through pheromones. It also started an independent multi-point solution of the problem space search, not only increases the reliability of the algorithm, but also makes the algorithm has strong global search capability.

3.1.2 Shortcomings of Basic ant Colony Algorithm

(1) Take a long calculation time, prone to stagnation. Ant motion is random for each individual, although possible through the exchange of hormone evolution toward the optimal path, but when a large population size, it is difficult in a short times to find a good path from the path of the large clutter. This is because in the early evolution of pheromones little difference in each path, through the positive feedback path is preferably such that the information on the hormone increases, a longer period of time, in order to make a better path pheromones significantly higher than the other path, with the progress of the process, significantly increasing the difference, ultimately converge, this process generally requires a longer period of time.

(2) All candidate solutions through search path corresponding sections of the road will bring incremental pheromone. In fact, the solution is not always the best solution candidate, pheromone increment this calculation will result in erroneous guidance information, resulting in a large number of invalid search, the system freezes.

(3) using a uniform distribution of pheromone strategy, which has been searching for all sections of the path using the same pheromone increment, the importance of road with nothing to do, when you do not consider when converted into continuous space optimization problems directed graph search problem pheromone assigned to scale changes brought feasible solution for the continuous search for efficiency of the solution space.

3.2 Firefly Algorithm

3.2.1 Firefly Algorithm Advantages

(1) It has a strong versatility, robustness relatively strong. Firefly algorithm in the search process does not require manual adjustments. Second, the small number of parameters firefly algorithm, simple to set up, easy to apply this to other combinatorial optimization algorithms to solve the problem.

(2) Capture very fast range, high capture efficiency of the algorithm is a firefly essentially parallel algorithm firefly search process each independently of one another, communicate only via fluorescence. So it is with the ant colony algorithm, the multi-point the problem space and began searching for independent solution not only increases the reliability of the algorithm, but also makes the algorithm has strong global search capability.

3.2.2 Firefly Algorithm Drawbacks

Basic firefly algorithm in solving global optimization problems easy to fall into local minima , slow convergence and solution accuracy is not high defect , the need for debugging and improvement. Researchers have now proposed to improve the dynamic algorithm automatically gathered firefly path planning , mating behavior with the chaotic Human firefly optimization algorithm and the maximum and minimum values of the artificial firefly luciferase algorithm , these improvements are carried out in a certain extent, its disadvantages improvement.

4. Conclusion

Two algorithms are derived from natural biological communities intelligent behavior , and through analysis of swarm intelligence to simplify their behavior patterns , a mathematical model , converted into machine language , the use of swarm intelligence program to simulate its behavior on your computer, so as to find a problem the optimal solution. And take advantage of some media to coordinate behavior between groups .

Numerous studies have demonstrated the ant colony algorithm has strong ability to find a better solution, it is because the algorithm not only takes advantage of the positive feedback principle , to a certain extent, can accelerate the evolutionary process , and is an essentially parallel algorithms, different individuals ongoing exchange of information between and delivery , which can collaborate with each other , help find a better solution , ant colony algorithm can be interpreted as a special kind of reinforcement learning) algorithm. Determined by some heuristic algorithms, and how these two together is the key to improving the efficiency of ant colony algorithm. Although there are many advantages of ant colony algorithm, but this algorithm has some shortcomings, such as: Compared with other methods, the algorithm generally require a longer search time, the complexity of the ant colony algorithm can reflect this ; and the method prone to stagnation (stagnation behavior). After that the search to a certain extent, all the solutions found exactly the same individual, not the solution space for further search, is not conducive to find a better solution.

For Firefly algorithm, which is a new swarm intelligence algorithm bionic firefly courtship or natural foraging behavior and proposed the algorithm in recent years in the field of computational intelligence aroused great attention and has become a new field of Computational Intelligence hotspot. With the deepening of the study, the algorithm has been successfully applied to noise testing and simulation robot sensors and so on. The advantage of this method is that the capture range extremely fast speed, high capture efficiency, with a strong commonality advantages. However, the algorithm is also dependent on the existence of the distribution of the initial solution is high, late slow convergence solutions to capture, not high precision. But this kind of algorithm appears late, many researchers are to improve their shortcomings. I boldly predict that this new algorithm in the improvement in the near future will be like the ant colony algorithm , as in all walks of life to fulfill their potential as a mature intelligent heuristic algorithm to show its mettle .

5. References

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