Summer 6-19-2015

Swarm Intelligence Optimization Algorithms and Their Application

Ting Yu
School of Management Science and Information Engineering, Jilin University of Finance and Economics, Changchun 130117, China

Limin Wang
School of Management Science and Information Engineering, Jilin University of Finance and Economics, Changchun 130117, China, wlm_new@163.com

Xuming Han
Institute of Software, Changchun University of Technology, Changchun 130117, China

Ying Liu
School of Management Science and Information Engineering, Jilin University of Finance and Economics, Changchun 130117, China

Li Zhang
School of Management Science and Information Engineering, Jilin University of Finance and Economics, Changchun 130117, China

Swarm Intelligence Optimization Algorithms and Their Application

Ting Yu[1], *LiminWang* [1*],*XumingHan*[2], *Ying Liu* [1], *Li Zhang* [1]
1 School of Management Science and Information Engineering, Jilin University of Finance and Economics, Changchun 130117, China
[2]Institute of Software, Changchun University of Technology, Changchun 130117, China

Abstract: Swarm intelligence optimization algorithm is an emerging technology tosimulate the evolution of the law of nature and acts of biological communities, it has simple and robust characteristics. The algorithm has been successfully applied in many fields. This paper summarizes the research status of swarm intelligence optimization algorithm and application progress. Elaborate the basic principle of ant colony algorithm and particle swarm algorithm. Carry out a detailed analysis of drosophila algorithm and firefly algorithm developed in recent years, and put forward deficiencies of each algorithm and direction for improvement.

Keywords: Swarm intelligence algorithm, Ant Colony Algorithm, Particle swarm optimization, Drosophila algorithm, Firefly algorithm

1. INTRODUCTION

As an emerging field of swarm intelligence[1][2], it has gradually received more and more attentions of research scholars. The concept is inspired by swarm intelligence of ants, geese and other social behaviors produced by groups of organisms. Swarm Intelligence is a group may communicate directly or indirectly with each other. That "the main body of simple intelligent can show the complex characteristics of intelligent behavior through cooperation". Swarm intelligence algorithm use these features to solve certain types of problems, particularly provide the basis for distributed problems and can get satisfactoryresults**.**

Characteristics of swarm intelligence algorithm have practical significance, which aim to improve the deficiencies of the algorithm and to improve the performance of the algorithm. Characteristics of swarm intelligence algorithm are as follows:

(1) Strong robustness[3]

Swarm intelligence algorithm crowd control are distributed, there is no central control. Thus their work environment is in a wide range, one or some individual problems can not have an impact on the group, strong robustness.

(2)Simple

Execution of each individual operation is simple and easy to implement.

(3) Better scalability

The amount of information of each individual sensing is limited.

(4)Self- organization is strong

The complex behaviors exhibited by group are the result of individual interactions.

(5)Potentially parallelism and distributed features.

[*]Corresponding author.Email:wlm_new@163.com (Limin Wang)

2. SWARM INTELLIGENCE ALGORITHM CATEGORY

2.1Particle swarm optimization algorithm

2.1.1Summary to particle swarm optimization algorithm

Particle swarm optimization (PSO) is a swarm intelligence method based on the ability of groups. Particle swarm optimization was found for the first time by Kennedy in 1995. Particle swarm algorithm simulates the behavior of law birds foraging and courtship process. In real life, we often see flocks of birds flying in the sky, and notice that birds' flying will follow certain rules. They constantly change the position and direction of flight. According to their overall information and by adjusting the speed and position, they achieve the best position of the individual and ensure that all the teams maintain the optimum state.

In the Particle swarm optimization, each particle is equivalent to the bird, they constantly update their position and speed. They achieve the optimal solution through continuous iteration. Determining its own position and the quality of velocity by two "extremes" values in each iteration. The first extreme value is the optimal solution found by the particle itself, called personal best[4] , and the other extreme is the optimal solution found by the entire population currently, called the global maximum[5]. Sothat their optimal position and velocity can beensured.

2.1.2 Analysis of the advantages and disadvantages

Particle swarm optimization is easy to implement. The principle of particle swarm optimization is simple, its parameters are less and its application effect is obvious. It mainly used to handle non-linear optimization problems, non-differentiable and complex multi- peak function. It's solving process starting from random solutions, through iterative calculation to find the optimal solution, and then to evaluate the quality of the solution through fitness. This algorithm can be flexible to meet the needs of practical applications through improved, showing its strong practicability.

2.2 Ant colony algorithm

2.2.1Summary to ant colony algorithm

Ant colony algorithm (ACO) was proposed in 1991 by Marco Dorigo inspired by the behavior of ants in searching for food in the process. Ant is a typical gregarious creature. Individual ant is with a clear division of labor, it can efficiently complete the assigned tasks through collaboration with each other. The study found that the transmission of information between individual ants is by means of a special substance called pheromone, the behavior of ants completed under the guidance of pheromone. Pheromone concentration is higher, the more ants gather,the more pheromone left by then, showing a positive feedback mechanism of information. The higher concentration of pheromone path often means the shortest path, so the path attracts more ants, the end result is that all the ants have chosen this path .It can be seen that ant colony algorithm is without any prior knowledge, it initially selected randomly search path, with the understanding of the solution space, searching gradually become a regular until the approximate global optimal solution is found.

2.2.2 Analysis of the advantages and disadvantages

Ant colony algorithm has strong robustness and the ability to search for a better solution in solving performance. Ant colony algorithm is a population-based evolutionary algorithm easy to parallel implementation. It is very easy to combine with a variety of heuristic algorithms to improve the performance of the algorithm. Ant colony algorithm converges slowly and easy to fall into local optimum. Ant colony algorithm initial pheromone is deficient and generally require a longer search times, and this method is prone to stagnation, namely search proceeds to a certain extent. The solution is almost identical for all individuals found. Lacking further search process in solution space is not conducive to find a better solution.

2.3 Drosophila optimization algorithm

2.3. 1Summary to drosophila optimization algorithm

Drosophila optimization algorithm (FOA) is a new method inspired by global drosophila foraging behavior and evolution of optimization. Drosophila has a powerful sense of smell and vision. They can search for food within 25 miles, and then rely on keen sight and smell of food flying, once the location of an individual is discovered, all the drosophila will fly in this direction. Drosophila optimization algorithm first initializes the initial position coordinates of drosophila populations, initializing an initial position according to the individual variation range, then give the random direction and distance according to the behavior of the fruit fly in searching for food and introduced flavor concentration determination value. This value is the reciprocal of drosophila origin position to a distance to represent, then taken the taste concentration decision value to the density determination function and find the taste of the individual concentration of drosophila, identifying the best flavor concentration of groups of drosophila and finding the optimal value. The last saved is optimum concentration of drosophila value and its position coordinates. At this time the population of flies will fly to this location.

2.3. 2 Analysis of the advantages and disadvantage

Drosophila algorithm is simple and easy to implement, and other algorithms do not have the advantage. It is more easily applied to solve practical problems. Drosophila algorithm also has its own drawbacks, for example, drosophila algorithm is not suitable for solving the problem of the argument which is negative, because the taste density determination function can only process the argument which is positive. In addition, the algorithm is lack of stability when dealing with complex issues of the algorithm.

Drosophila algorithm is easy to implement. It has strong global optimization capability and high precision, and at the same time it is of great useful in solving the optimization parameters of the nonnegative real issue.

2.4 Firefly optimization algorithm

2.4.1 Summary to firefly optimization algorithm

Through careful observation of nature courtship and foraging behavior of fireflies, researchers propose a new intelligent optimization algorithm. The main idea of firefly optimization algorithm is to regard the solution in the space as firefly individual, judging the quality of solutions by two indicators radius named the fluorescein value and the radius of perception. The size of fluorescein value is used to judge the merits of the individual positions, that the solution of the pros and cons. The size of the radius of perception is used to measure individual search. Individuals are looking for outstanding individuals within the search range and move to it. The algorithm involves two key factors, namely the relative fluorescence intensity and the relative attractiveness. The brightness of the fluorescent is affected by itself fireflies emit of target location, the higher brightness better illustrate the location, that is the better target. Attractiveness and brightness are concerned. The brighter the fireflies have, the higher attraction will be. Brighter fireflies can attract weakness of the brightness of the fireflies than it to move in this direction within the sight of the brightness. If the luminescence brightness is the same, their movement of fireflies is random. Inversely proportional to the distance between the degree of brightness and attraction, both decrease with increasing distance.

2.4.2 Analysis of the advantages and disadvantages

The populations of firefly optimization algorithm is consisted of multiple individual fireflies randomly distributed in space, each individual has their own perception of the radius, the perception of the individual can determine the radius of the search outstanding individuals within a certain range, and then moved to outstanding individuals, gradually close the outstanding individuals. When the firefly population reaches a specified evolution algebra, all individuals were gathered at some point within a certain range, these points is local optima in multimode function , and all local optimal solution is the global optimal solution. Therefore, firefly algorithm can not only optimize unimodal function and find the global optimal solution, but also can optimize multimode function and find various local optima. In the evolutionary process, each individual optimization fireflies is independent, these factors are useful of concurrent execution algorithm procedures.

Firefly optimization algorithm is also easy to operate, to implement and it has less impact parameters, less parameters of the algorithm advantages and so on. But the shortcomings of the low peak detection, slow convergence, solution inaccurate remains.

3. APPLICATION RESEARCH

Swarm intelligence optimization algorithm has passed continuous development and maturity in decades. It has been successfully applied in many fields with its simple, efficient and many other advantages, so it has achieved many good results. The study shows that swarm intelligence optimization algorithm could get good search results in solving the discrete and continuous problems. It also had an outstanding performance in combinatorial optimization problems.

Particle swarm optimization has been widely used in various areas with its advantages of concept simple, less parameters and easy to implement, etc. These areas include neural networks, power systems, robotics, imaging processing and so on. Particle swarm optimization algorithm also have a good effect in solving complex nonlinear constrained programming, job scheduling optimization, distribution and data mining on the economy and other issues.

Ant colony algorithm has great advantages on dynamic optimization problems, stochastic optimization, multi-objective optimization problem and so on. It can solve the traveling salesman problem, quadratic assignment problem and vehicle routing problems. And in terms of power system fault diagnosis, fuzzy systems, data mining, clustering analysis, it is widely used. Although ant colony algorithm has been widely used in various fields, the current theoretical and applied research on ant colony algorithm is continually going to develop, a lot of issues excavated and need to be resolved.

Drosophila optimization algorithm is a new optimization algorithm that has broad application field without any restrictions. It covered various fields such as military, engineering, medicine, management and financial. In addition, it can also combine with other technologies. It is very flexible in use, so the user can use it flexibly according to their ideas.

For the firefly optimization algorithm, many scholars are conducting some studies in depth. They propose some effective strategies and methods for improvement. Firefly optimization algorithm performances good effects in the multi-mode global optimization function, power systems, engineering design, image processing, data mining, communication field, neural network training and other aspects. In addition, firefly optimization algorithm can also be applied in the field of parameter identification, fault diagnosis and path planning.

4. CONCLUSIONS

Research shows that swarm intelligence optimization algorithm can solve some optimization problems and provide technical support for handling large data, but compared to other sophisticated optimization algorithms, its study is in the early stages. There are many issues needed further study. Firstly, the theory of swarm intelligence optimization algorithm is relatively weak, and theoretical analysis of universal significance is inadequate. The setting of various parameters is basically determined by experience. There is no exact theory to supportswarm intelligence optimization algorithm. There is higher dependence on the application environment and specific issues. Secondly, there is a lack of adequate comparative study between other relatively sophisticated algorithms and swarm intelligence optimization algorithm. It is not sufficient that its techniques integration analyzes with other intelligent methods. Finally, the analysis of a variety of swarm intelligence optimization algorithm results can be summarized that the scope of each algorithms is relatively narrow and there is no generally applicable optimization algorithms. Therefore, depth analysis scope of each swarm intelligence optimization algorithm and developing appropriate field of different algorithms will be imperative.

ACKNOWLEDGEMENT

The authors are grateful to the support of the National Science Foundation of China under Grant No. 61202306, 61472049 and 61402193, Science-Technology Research Foundation of Jilin Province under Grant No. 2012185, 2012189 and 2014159, the Social Science Research Foundation of Jilin Province under Grant No. 2014B166. The Application Basis Foundation of Jilin Provincial Science & Technology Department under Grant No. 20100507, 201215119, 20130522177JH and 20130101072JC, the Young Talent Funds of Jilin University of Finance and Economics, and the Education Science Programming Funds of Jilin Province under Grant No. GH14216 and GH13444.

REFERENCES

[1]Brambilla M, Ferrante E, Birattari M, et al.Swarm robotics:areview from the swarmengineering perspective[J]. Swarm Intelligence, 2013, 7(1): 1-41.

[2]Derrac J, García S, Molina D, et al. A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms[J]. Swarm and Evolutionary Computation, 2011, 1(1): 3-18.

[3]Fritsche - Guenther R, Witzel F, Sieber A, et al. Strong negative feedback from Erkto Raf confers robustness toMAPK signaling[J]. Molecular systems biology, 2011, 7(1).

[4]Gawande A. Personal best[J]. The New Yorker, 2011, 3.

[5]Nguyen T L, Low K S.A global maximum power point tracking scheme employing DIRECT search algorithm for photovoltaic systems[J]. Industrial Electronics, IEEE Transactions on, 2010, 57(10): 3456-3467.

[6]Wang L, Han X M, Li M, Zhang C J, Zhang Y T. Atmospheric Quality Assessment Model Based on Immune Clonal Selection Algorithm. Advanced Material Research, Volumes 255-260, 2011:3013-3017.

[7]Elhamifar E, Vidal R. Sparse subspace clustering: Algorithm, theory, and applications[J]. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 2013, 35(11): 2765-2781.

[8]Lee K, Gray A, Kim H. Dependence maps, a dimensionality reduction with dependence distance for high-dimensional data [J]. Data Mining and Knowledge Discovery, 2013, 26(3): 512-532.

[9]Shang F, Jiao L C, Shi J, et al. Fast density-weighted low-rank approximation spectral clustering[J]. Data Mining and

Knowledge Discovery, 2011, 23(2): 345-378.

[10]Wang L, Rege M, Dong M, et al. Low-rank kernel matrix factorization for large-scale evolutionary clustering[J]. Knowledge and Data Engineering, IEEE Transactions on, 2012, 24(6): 1036-1050.

[11]Liu G, Yan S. Latent low-rank representation for subspace segmentation and feature extraction[C]//Computer Vision (ICCV), 2011 IEEE International Conference on. IEEE, 2011: 1615-1622.

[12]Vidal R, Favaro P. Low rank subspace clustering (LRSC)[J]. Pattern Recognition Letters, 2014, 43: 47-61.

[13]Zhuang L, Gao H, Lin Z, et al. Non-negative low rank and sparse graph for semi-supervised learning[C]//Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on. IEEE, 2012: 2328-2335.

[14]Zhou Shibing, XuZhenyuan, Tang Xuqing. Method for determining optimal number of clusters based on affinity propagation clustering [J]. Control and Decision, 2011, 26(8): 1147-1152.

[15]Lee K, Gray A, Kim H. Dependence maps, a dimensionality reduction with dependence distance for high-dimensional data [J]. Data Mining and Knowledge Discovery, 2013, 26(3): 512-532.

[16]Qi Kang,TianLan,YongYan,LeiWang,Qidi Wu. Group search optimizer based optimal location and capacity of distributed generations[J]. Neurocomputing . 2011 (1).

[17]Saber M. Elsayed, Ruhul A. Sarker, EfrénMezura-Montes. Self-adaptive mix of particle swarm methodologies for constrained optimization[J]. Information Sciences, 2014.

[18]J.F.A. Madeira, A.L. Araújo, C.M. MotaSoares et al.. Multiobjective optimization of viscoelastic laminated sandwich structures using the Direct MultiSearch method[J]. Computersand Structures, 2014.

[19]Karaboga D, Gorkemli B, Ozturk C, et al. A comprehensive survey: artificial bee colony (ABC) algorithm and applications[J]. Artificial Intelligence Review, 2014, 42(1): 21-57.

[20]Akay B, Karaboga D. A modified artificial bee colony algorithm for real-parameter optimization[J]. Information Sciences, 2012, 192: 120-142.