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Multi-Agent Coalition Formation Based on Quantum-behaved Particle Swarm Optimization

Bo Xu [a,*], Qing Guan [b], Ke Chen [a]

[a] *Department of Computer Science and Technology, Guangdong University of Petrochemical Technology, Maoming, Guangdong 525000, China*

[b] *Scholl of Information Technology, Jiangnan University, Wuxi, Jiangsu 214122, China*

Abstract

Coalition formation has become a key topic in multi-agent research. It mainly researches on how to generate the optimal task-oriented coalition in dynamic manner. In this paper, the quantum-behaved particle swarm optimization (QPSO) is proposed for this problem. And the multi particle swarms based on public history researching parallel is presented for improving QPSO. On the base of using the better recording locations of all particles and the mutation of the best behaved particle, the particle swarm is filtrated, accelerating the convergence speed. Multi particle swarms are used to research parallel to avoid running into local optima at the same time. The result of experiments shows that the proposed algorithm can reduce the searching time and computing works effectively, and is valid and superior to other related methods as far as the stability and speed of convergence.

Keywords: Coalition Formation; Quantum-Behaved Particle Swarm Optimization; Optimizing Combination Problem

1 Introduction

Coalition is an important way of cooperation through which multi-agent systems accomplish their assignments [1]. However, even different coalitions are assigned with the same task; the system will get different benefit which will be represented by the value of the coalitions. When the system is required to accomplish several tasks, it is necessary to divide the Agent set. Different ways of division will lead to different coalition structures and different total benefits which may vary much. This is the coalition formation problem [2]. Finding optimal solution for multi-agent coalition formation problems has attracted many researchers due to its NP-hardness [3].

Coalition formation is one of the popular domains in multi-agent system. There are many popular topics in this area. The issues are how to decompose a task, how to form a coalition, how to search for suitable agents to join this coalition, and so on. At present, typical algorithms of coalition formation in multi-agent system can be classified into two kinds: the first is many researchers

*Corresponding author.
Email address: xubo807127940@163.com (Bo Xu).

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have studied on how to reduce the complexity of exhaustive method. We identify some of the limitations of deterministic search algorithms reported in literature. These include assumption of independence of coalition values and the exponential growth in computational requirements. For example, Shehory [4] introduced a constant K to confine the number of agents in a coalition, Billionnet and Gerkey introduced low estimation method, reducing search space via cutting down search tree with given restriction requirements. The second is based on Evolutionary algorithms. Hui-Yi Liu [5] introduced coalition formation based on genetic algorithm, Xia Na and Zhang Guofu[6] introduced particle swarm optimization to solve this problem. Yan Shen [7] introduced particle swarm optimization algorithm to solve this Coalition Structure problem. This kind of algorithms have good performances due to the high exploration capacity of evolutionary algorithms, however, they still can be improved [8]. So, a novel method named quantum-behaved particle swarm optimization is developed for multi-agent coalition formation problem in this paper.

2 Background

A. Quantum-behaved Particle Swarm Optimization

PSO was originally developed by Kennedy and Eberhart. In PSO, a swarm consists of a set of particles, where each particle represents a potential solution. Currently, Jun sun [9] etc proposed quantum-behaved particle swarm optimization (QPSO) based on quantum delta potential well. The basic idea is that all particles moving in quantum field will converge to a minimal area where potential power is infinite. QPSO is a new optimum method that combines quantum computation with particle swarm optimization (PSO). It appears strong life-force and be valuable for research. Quantum computation absorbed many essential characters of quantum mechanics, which improved the computation efficiency, and become a brand new model of computation. Hence, QPSO has greatly enhanced the efficiency of search and can compensate for the lack of PSO and it has a wide research foreground.

B. Model for Multi-Agent Coalition Formation

Currently multi-agent coalition formation algorithms assume that $A = \{A_1, A_2, \ldots A_n\}$ is for n agents and that each has r-dimension capability vector $B_i =< b_i^1, b_i^2, \cdots b_i^r >, b_i^j \geq 0, (1 \leq i \leq n, 1 \leq j \leq r)$, where each capability is a property that quantifies the ability to perform an action. $T = \{t_1, t_2, \ldots t_m\}$ is for m tasks, and that a set of corresponding capability vector $B_{t_I} =< b_{t_I}^1, b_{t_I}^2, \cdots, b_{t_I}^r >$ is required to complete each task t_i in T.

Suppose that $CS = \{C_1, C_2, \cdots C_m\}$, A coalition C_i is a group of agents that decide to cooperate to perform a common task and each coalition performs a single task t_j. A coalition C_i has r-dimensional capability vector B_{c_i} representing the sum of the capabilities that the coalition members contribute to this specific coalition. A coalition C_i can perform a task t_j only if the capability requirement vector satisfies $B_{t_j}^k \leq B_{C_i}^k$. For each C_i, there exist coalition cost $Cost_{c_i}$ and coalition value $Value_{c_i}$. $Cost_{c_i}$ is the total cost for members to complete t_j in C_i. And the coalition $Value_{c_i}$ is determined by $Cost_{c_i}$ and $\Pr ofit_{t_j}$ upon the completeness of t_j, After t_j is completed, Benefit $\Pr ofit_{t_j}$ is acquired. The multi-agent coalition is an optimization problem and can be depicted as follows:

$$\text{Object function Max}Value_{CS} = \sum_{i=1}^{m} Value(C_i) \quad (1)$$

Restriction $B_{t_j}^k \leq B_{C_i}^k (1 \leq i, j \leq m, 1 \leq k \leq r)$

3 Multi-Agent Coalition Formation Based on QPSO

This section provides an algorithmic description along with necessary modifications required for application to the multi-agent domain.

A. Algorithm Design of Coalition Formation

(1) Fitness Function Design

Suppose $Cost_{C_i}$ for the cost of coalition C_i, t represents task, and $\Pr ofit_t$ represents benefit for t. If C cannot complete t, $\Pr ofit_t = 0$, and the coalition $Value_{C_i} = 0$, otherwise it is positive. The fitness function is defined as

$$F(C) = Value_{C_i} = \Pr ofit_t / Cost_{C_i} \tag{2}$$

To put the problem simple, for coalition structure CS and task $T = \{t_1, t_2, \dots t_m\}$, CS can be formed by m coalitions, each coalition C_i is in correspondence with t_i, and C_i includes several agents or none. If C_i does not include agent, t_i is not chosen. Therefore, the fitness function is defined as

$$F(CS) = Value_{CS} = \sum_{i=1}^{m} Value(C_i) = \sum_{i=0}^{m} \Pr ofit_{t_i} / \sum_{i=0}^{m} Cost_{t_i} \tag{3}$$

(2) Public history researching

From QPSO formula we know, *mbest* is the particle swarm best position itself in the historical dimension of the average, P is a random value between the optimal location of themselves s and the history of and optimal location of groups (each particle its own history optimal location of the best value). The convergence rate of PSO particles dues to the best means of the end of history determines the location. In iterative process of particle swarm optimization, P_i with the particle does not exist between X_i the operation of the location of a direct link, but only a few records in the search process there have been a better location. Therefore, in this algorithm, P_i as well as X_i to sort through, P_i come to value for all particles that arise in the location of the first i historical optimal position, so that the fitness of the particle X_i number i based on iteration, and *mbest* continues to take P_i in all dimensions of the mean. This history of the best alternative to the public the history of the optimal particle itself, and present the history of the best particle to the direction of the optimal location of a search algorithm will be faster the speed of convergence.

(3) Initialization strategy

Quantum particle swarm optimization algorithm although has the state of random in the searching process. But when a particle found a local optimum location in the process of other particles moving closer to it. And not find the local optimum than better position location, the algorithm will also be a local optimum. In resolving the issue, many scholars have put forth a strategy for a variety of variations; the state of particle swarm in various re-distributions can search for a better position than the current best results. This variation in the strategy to solve some of the issues have played a better effect, but when the local optimal solution to a similar global optimum distance away from the situation, only a certain redistribution of the probability of finding a better local optimum than the current location in order to get out of their present local optimum, the effect is not satisfactory. Although the group into a local optimum is the inherent drawbacks of intelligent algorithm, it should be possible to avoid the situation. Out the best in the local context, the search strategy for a variety of groups is far superior to a single population, as long as there is no two populations into the same location, the probability of a local population will be smaller than the individual $\frac{1}{n^2}$.

B. Description of Proposed Algorithm

According to the analysis above, we propose the general flow of our algorithm as follows.

a) If $\forall 1 \leq i \leq r, b_t^i > b_C^i$, that is, the system capacity of the Agent can not complete the task, then return to f); Otherwise, all the particles must initialize and meet the constraints, initialize M of the population in the location of vector particles, the particles randomly generated speed; based mathematical model of the coalition of type (5) evaluate the fitness of each particle, the particle is set to the current individual maximum position, the overall maximum set for the initial population in the best position of particles.

b) Particle swarm of M group fitness to carry out in accordance with descending order, and give initial value to $P_i(1 \leq i \leq M)$. Each particle update local best position p_{ii} and related variables; update the global optimum location $pBest$ and other relevant variables; the N previous month P_i(total M) calculation.

c) Calculated for each particle inertia weight, update the speed and location of particles based on type (2) (3), thereby creating a new generation of population, updating the population of individual particles and global extremum.

d) Based on the probability of p_c re-initialization of the particles to maintain the diversity of populations of particles.

e) After the evolution of the particle swarm of particles carried out in accordance with descending order of fitness, check before entering the next generation of particles N. Repeat step a to step e, the number of iterations until the meet.

f) If stopping condition is satisfied, then stop.

4 Model Experimental Results and Analysis

In this paper, in order to demonstrate the effectiveness of the developed method and improved operator for coalition formation problem, we designed two experiments of GA [5]; PSO [7] and QPSO are compared with. The parameters of algorithms are set as follow and we run them 100 times respectively. Firstly, produce some parameters what are needed in the experiment: The numbers of available agents $n = 30$, the capability value of agents produces rand, The parameters of the GA are set as: the cross probability $P_c = 0.90$, the aberrance probability $P_m = 0.8$, the colony size $P = 100$.

A. Experiment I: Coalition Formation

Given that Task t requires the capability value $B_t =< 185, 145, 186, 244 >$. The experiment results of the three methods are given in Fig. 1, Fig. 2 and Table 1.

B. Experiment II: Coalition Structure Formation

Given that $T = \{t_1, t_2, t_3\}$; t_1 requires the capability value $B_{t_1} =< 181, 144, 231, 177 >$, t_1 requires the capability value $B_{t_2} =< 298, 176, 121, 521 >$, t_2 requires the capability value $B_{t_3} =< 685, 135, 121, 876 >$, the experiment results of the three methods are given in Fig. 3, Fig. 4 and Table 2.

Fig. 1 and Fig. 2 show the process of the best value of coalition found by GA, PSO and improved QPSO. Fig. 3 and Fig. 4 show the process of the best value of coalition Structure found by GA, PSO and improved QPSO. The statistical comparisons are showed in Table 1 and Table 2.

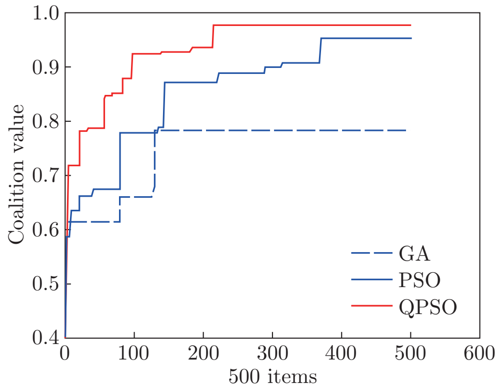

Fig. 1: the optimal solution evolving curve (500 items)

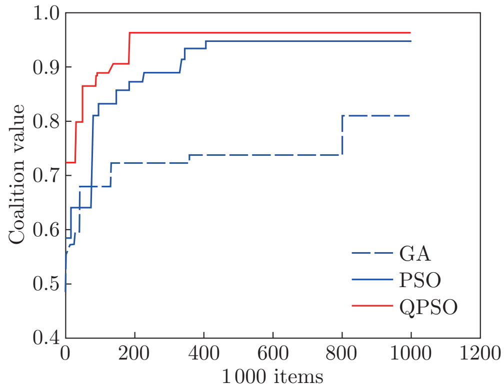

Fig. 2: the optimal solution evolving curve (1000 items)

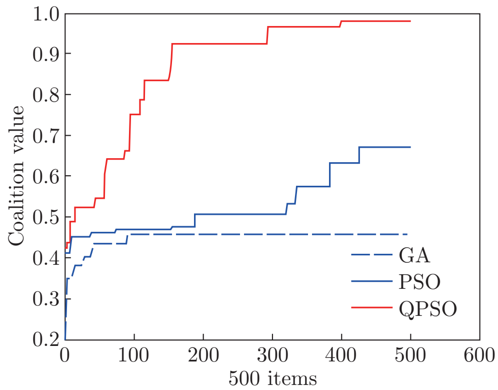

Fig. 3: the optimal solution evolving curve (500 items)

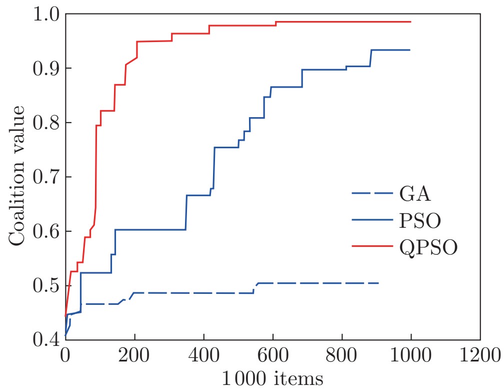

Fig. 4: the optimal solution evolving curve (1000 items)

Table 1: the performance comparison of three algorithms

	500 items			1000 items		
	GA	PSO	QPSO	GA	PSO	QPSO
Maximal Coalition Value	0.8557	0.9654	0.9711	0.9233	0.9622	0.9798
Minimal Coalition Value	0.7324	0.9132	0.9299	0.7987	0.9123	0.9332
Average Coalition Value	0.8012	0.9221	0.9389	0.8044	0.9344	0.9588

Table 2: the performance comparison of three algorithms

	500 items			1000 items		
	GA	QPSO	RQPSO	GA	QPSO	RQPSO
Maximal Coalition Value	0.6769	0.9586	0.9835	0.7442	0.9788	0.9898
Minimal Coalition Value	0.6128	0.8901	0.9227	0.6023	0.9512	0.9476
Average Coalition Value	0.6218	0.9233	0.9701	0.6653	0.9633	0.9787

From above Fig. 1, Fig. 2, Fig. 3 and Fig. 4, we can see that improved QPSO show a faster convergence than PSO and GA and can get better results in a smaller time. Improved methods make the algorithm evolve smoothly. From Table 1 and Table 2, we can find that improved QPSO hardly falls in the local minimum. And the algorithm in this paper is superior to the other two methods on the solution quality. On the other hand, its running time to reach the optimal solution is a little faster than the GA and PSO. The results of contrastive experiment show that the algorithm in this paper not only improves the solution quality but also quickens the constringency. From the above experiment and analysis, we can see that in most of the cases, improved QPSO can converge to get the best solution more speedily. Overall, we can conclude that our approach is very suitable and efficient for the complex multi-agent coalition formation problem.

5 Conclusion

Our approaches have advantage in search performance and quick convergence, greatly reducing the time for finding the optimal or feasible solution of coalition or coalition structure, and the found coalition or coalition structure executes the task with a lower cost.

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