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An Improved Quantum-behaved Particle Swarm Optimization Algorithm for the Knapsack Problem

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Abstract: An improved Quantum-behaved particle swarm optimization algorithm is proposed for 0-1 knapsack problem.In the new algorithm, the inertia weight is expressed as functions of particle evolution velocity and particle aggregation by defining particle evolution velocity and particle aggregation so that the inertia weight has adaptability. At the same time, slowly varying function is introduced to the traditional location updating formula so that the local optimal solution can be effectively overcome. The simulation experiments show that improved Quantum-behaved particle swarm optimization algorithm has better convergence and stability in solving knapsack problem.

Introduction

Knapsack problem is a famous NP problem, is also a typical combinatorial optimization problem, in many fields have a wide range of application. Currently used in the algorithm of solving knapsack problem mainly genetic algorithm [1], particle swarm optimization algorithm [2], ant colony optimization algorithm [3], etc. But the particle swarm optimization algorithm and other evolutionary algorithm, there are inevitably the premature convergence phenomenon.

Therefore, this paper proposes a solution for 0-1 knapsack problem with the improvement of quantum behavior of the particle swarm optimization algorithm. Through the simulation test and analysis show that the method can be more effective to solve knapsack problem.

Mathematical model of knapsack problem

Knapsack problem assumed a backpack and n items , In the backpack volume v limit premise, How to reasonably will n volume for a_i, value for c_i items into the bag, backpack that load of the total value of the largest item? The mathematical model expression is as follows:

$$\text{target} \quad \max \sum_{i=1}^{n} c_i x_i \tag{1}$$

$$\text{s.t} \quad \max \sum_{i=1}^{n} a_i x_i \le v$$

Quantum behavior particle swarm optimization algorithm

SunJun of Jiangnan university has put forward some quantum behavior particle swarm optimization (QPSO) in 2004 [4]. The particle's velocity and position in quantum space can’t be determined at the same time, so the state of the particle is described with the aid of wave function, and probability density function of particle's appearence in a certain point of the space by solving schrodinger equation. The particle's position equation got by using Monte Carlo stochastic simulation method is as follows:

$X(t) = P \pm \frac{L}{2}\ln\left[\frac{1}{u}\right]$. In the formula: u is random number in evenly distributed [0,1]; L value is determined by formula $L(t+1) = 2\, b\, |\, mbest - X(t)\, |$. Finally the QPSO algorithm's evolution equation is get[5]:

$$P = \alpha * Pbest(i) + (1-\alpha) * Gbest \tag{2}$$

$$mbest = \frac{1}{M}\sum_{i=1}^{M} Pbest(i) \tag{3}$$

$$b = 1.0 - generation/maxgeneration * 0.5 \tag{4}$$

$$position = P \pm b * |mbest - position| * \ln(1/\mu) \tag{5}$$

Improvement strategy of quantum behavior particle swarm algorithm

A Dynamically adjusting inertia weights according to the particle evolution speed and crowding level

1) The definition of particle evolution speed

Set *f (Gbest (t))* and *f (Gbest (t-1))* t time and t-1 time iteration's fitness value of global optimum position value respectively, then the definition of evolutionary rate is

$$Es = f(Gbest(t-1)) / f(Gbest(t)) \tag{6}$$

2) The definition of particle aggregation level

Set *f (Gbest (t))* is the global optimum position fitness value of particle swarms' t iteration. *f (Gbest (t))* is better than the best position fitness value *f (Pbest (t))* of each particle's t iteration. The average of the best position fitness value f *(Pbest (t))* of all particles' t iterations is defined as:

$$\mathrm{Fa} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{f(Pbest(t))} \tag{7}$$

In the optimization process of the great value, f(*Gbest*(t))≥Fa, and then particle aggregation level is defined as:

$$\mathrm{gd} = \mathrm{Fa} / \mathrm{f}(Gbest(\mathrm{t})) \tag{8}$$

3) The definition of dynamic adjustment inertia weight

Inertia weight b is dynamically adjusted based on the particle evolution speed es and particle aggregation level gd value, namely

$$b = \beta_0 - es\beta_1 + gd\beta_2 \tag{9}$$

B Adopting slowly varying function to overcome premature convergence

Slowly varying function's disturbance is introduced in position updating formula, which enhances the local search ability and helps to improve the accuracy of solution. It is suitable to keep population diversity for middle-to-late-stage particles.

$$position = P \pm b * |mbest - position| * \ln(1/\mu) \quad + L(x) \tag{10}$$

Because there is no increase (or decrease) of the fastest slowly varying function, nor swing (or oscillation) of the fastest slowly varying function [6], this paper adopts $L(x)=(lgx)^{\alpha}$ form slowly varying function, including $\alpha \in R$.

Solving knapsack problem improvement quantum particle swarm optimization algorithm

Choose vector X = { $x_1,x_2,\ldots,x_n$} said all the particle's position. Whether particle current position in quantum particle swarm optimization algorithm is good or bad is evaluated by the fitness value. The corresponding fitness function is:

$$f(p^*) = \max \sum_{i=1}^{n} c_i x_i \tag{11}$$

In the formula, the vector quantity p* represents a complete coding scheme.

Improved quantum particle swarm optimization algorithm for knapsack problem ：
Step 1 Coding and initializing particle swarm.
Step 2 All particles fitness is calculated according to the objective function expression (11). If meet the convergence, execute step 7; Otherwise, execute step 3.
Step 3 Calculate the rate of evolution and aggregation degree based on formulas (6) ~ (8). The inertia weight value b is determined according to formula (9).
Step 4 With the calculation of the fitness value, update each particle's optimal position *Pbest (i)* and group optimal position *Gbest*. Update each particle's position according to formulas (2) ~ (5), and create a new particle swarm.
Step 5 If the gd value closes to 1 for a long time but do not satisfy the termination criterion, disturb location updating formula through formula (10); Otherwise, turn to step 6.
Step 6 If reach the set termination condition, execute step 7; Otherwise turn to step 2.
Step 7 Output global optimal position *Gbest* and its fitness value.

Solving knapsack problem algorithm testing

In order to validate the proposed improved quantum particle swarm optimization algorithm for solving knapsack problem of performance, The algorithm in Intel Pentium χ 2.0 GHz CPU, 2 G memory, Windows XP platform, MATLAB 7.2 under the environment of simulation.

Example 1 n = 10，v = 269，w = { 95，4，60，32，23，72，80，62，65，46} ，c = { 55，10，47，5，4，50，8，61，85，87}.

Example 2 n =20，v =878，w = { 92，4，43，83，84，68，92，82，6，44，32，18，56，83，25，96，70，48，14，58} ，c = { 44，46，90，72，91，40，75，35，8，54，78，40，77，15，61，17，75，29，75，63} .

Each group of data experiment respectively with particle swarm algorithm, quantum particle swarm optimization algorithm and improved quantum particle swarm optimization test.

Particle swarm optimizationalgorithm parameter set to c_1=c_2=2; w initial 0.9, then linear decline to 0.4. Inertia weight b of quantum behavior particle swarm algorithm in the interval [1.2, 0.4] decreases linearly with the increase of iteration times. This paper's algorithm β_1's value is 0.5 and β_2's value is 0.1. Population size is 50, and the maximum iterative number is 200.Test results as is shown in table 1.

Table 1 The test results

Optimization algorithm	Experiment 1 test results		Experiment 2 test results	
	Get Maxmum value	Get quality（kg）	Get Maxmum value	Get quality（kg）
PSO	246	263	1014	850
QPSO	272	267	1020	861
Algorithm proposed	295	269	1024	873

The experimental results show that algorithm proposed has a particle swarm optimization algorithm and quantum behavior of the particle swarm optimization algorithm is more effective in solving knapsack problem.

Conclusion

Particle evolutionary rate and particle gathered degree formula are defined, and the inertia weight is expressed as particle evolutionary rate and particle gathered degree function. Therefor inertia weight has dynamic adaptability. Slowly varying function is introduced to the traditional position updating formula in order to effectively overcome getting into the local optimal. The improved quantum behavior particle swarm algorithm has higher global search capability. By the improved algorithm presented to solve knapsack problem mathematical model. The simulation results show that this algorithm has higher search performance and faster convergence speed compared with standard particle swarm optimization algorithm and quantum behavior particle swarm algorithm. The feasibility and effectiveness of the algorithm are verified.

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