Improved Quantum Genetic Algorithm and Its Application in Nutritional Diet Optimization

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Abstract

An improved quantum genetic algorithm (IQGA) is proposed to avoid declining of the searching ability for multi-peak function optimization and multi-genes chromosome encoding problem. Improvements include adjusting initialization way of chromosome's genes, changing elitist strategy and introducing partial population disaster strategy. Experimental results on continuous multi-peak function optimization and actual nutritional diet optimization show that IQGA is superior to traditional quantum genetic algorithm on convergence speed and global optimization ability. Even for multi-genes encoding problem, this improved quantum genetic algorithm still has higher searching capability, usability and robustness than traditional quantum genetic algorithm.

1. Introduction

With society development and increasing of people living standard, nutrition and health issue has gradually been turned into the major concern in society and living. Appling computer technology to realize nutritional diet optimization has gradually and widely become the most attractive topic in nutrition and computer science.

Quantum genetic algorithm (QGA) is a new probabilistic optimization algorithm combines quantum computing principle and evolutionary algorithm theory. A lot of literature materials indicated that QGA has the advantages of smaller population scale, better population diversity, stronger adaptability and higher convergence efficiency over the conventional genetic algorithm (GA). However, conventional QGA also has the defect of premature convergence when it is used to solve multi-peak function optimization and complex combinatorial optimization problem. Some experts putted forward some improvements of QGA, for example, the multi-universe parallel quantum genetic algorithm[1], the quantum genetic algorithm based on chaotic optimization[2], the quantum genetic algorithm based on particle swarm optimization method[3], the hybrid quantum genetic algorithm[4], etc. The performances of these improved quantum genetic algorithms are often superior to unimproved QGA, however the validities of these improvements were commonly validated with multi-peak function optimization experiments or simple combinatorial optimization problems such that the 0/1 knapsack problem or the traveling salesman problem[5]. It is necessary to further study improved methods of conventional QGA in order to put QGA in better use. In this paper, a study is made to some novel improvements of QGA, and an actual application of quantum genetic algorithm is made on computer aided optimization of nutritional diet. In the simulation of actual work of dietitians, IQGA can effectively meet the requirements of speed and precision in diet optimization.

2. Basic principle and defects of QGA

2.1 Basic principle of QGA

In QGA, the quantum bit (qubit) is the elementary information unit. The qubit according to principles of quantum mechanics does not represent only the value 0 or 1 but a superposition of the two at the same time. Its state can be given by:

$$|\phi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{1}$$

(α, β) is a pair of complex numbers (named as probability amplitude) such that

$$|\alpha|^2 + |\beta|^2 = 1 \tag{2}$$

The probability to have the value 0 is $|\alpha|^2$ and the probability to have the value 1 is $|\beta|^2$ .This superposition mechanism makes it possible to represent

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an exponential set of states with a small number of qubits. This mechanism makes QGA has better population diversity and higher computing parallelism than traditional GA. The random observation simulating quantum collapse could bring diverse individuals, and the evolution of quantum chromosome can also pilot the evolution. QGA normally take quantum gates as updating methods, replaces transitional GA's complex crossover and mutation operators. In QGA, new offspring is obtained according to the best individual in its parent generation and its probability amplitude, not the whole individuals in parent generation. By the successive evolutions of population, QGA can obtain global optimization solution or satisfactory solution.

2.2 Defects of conventional QGA

QGA has the advantages of small population size, excellent population diversity and high searching efficiency due to its characteristics of Q-bit Coding, evolutionary mechanism, and randomicity of possibility. However, with the limitation of probabilistic optimization and quantum representation, conventional QGA also has the defect of premature convergence to some extent.

With QGA, one chromosome is defined as:

$$q_j^t = \begin{bmatrix} \alpha_1^t & \alpha_2^t & \alpha_3^t & \cdots \alpha_m^t \\ \beta_1^t & \beta_2^t & \beta_3^t & \cdots \alpha_m^t \end{bmatrix} \tag{3}$$

In initialization stage, every chromosome's gene (α_i, β_i) in conventional QGA is initialized as $1/\sqrt{2}$ identically [6]. This equal probability initialization mode is not always available and efficient, for instance, if the number of genes in a chromosome is very large, equal probability initialization mode may cause a lot of low quality individuals in original population, and therefore restraints convergence speed correspondingly. To quicken the convergence speed, raising the value of the rotation angle (θ) is an available and simple means to obtain satisfactory solution. Raising the value of θ would inevitably affect the accuracy of solution. If algorithm falls into local extreme, the equal probability initialization mode may lead to difficulty in global convergence. Blindly adopting this initialization method without analyzing the characteristics of the optimization problem may be results in optimization defection.

Conventional QGA takes such elitist strategy that only reserves the best individual in every generation and uses the best individual's probability amplitudes to update other individual's genes. If the quality of the best individual is very poor, other individuals may accept harmful influence accordingly. This conventional elitist strategy is not favorable to the global convergence, and affects the convergence speed.

Conventional QGA is easy to cause a lot of invalid individuals in solution space, and therefore population will not evolve sufficiently. It is easy to find a certain low quality individual usurps the optimum status for a long time in actual execution stage of algorithm. It is necessary to take some techniques to help algorithm to break away from this stagnation of evolution.

When the quantity of chromosome's genes is small and the optimization problem is relatively simple, QGA can commonly obtain the optimal solution or satisfactory approximate solution. With rising of problem scale or rising of problem complexity, conventional QGA may not equal to its ambition, and is easy to converge prematurely.

3. Improvements of QGA

3.1 Essence of improved methods

According to the defects of QGA, this paper presents three improved methods of conventional QGA:

(1) Adjusting initialization way of chromosome's genes

By adjusting initialization way of chromosome's genes is meant reasonably initializing the values of (α, β) according to the characteristics of optimization problems. This improved method facilitates enhancing the quality of initial population, and therefore raises the convergence speed, and reduces the probability of premature convergence. This adjusting strategy helps population avoid staying on "primitive society" for ages.

(2) Changing elitist strategy

This improved method adopts the global optimum retention strategy to replace the current optimum retention strategy. When program obtains the current optimum individual in current evolution generation, algorithm will firstly compare it with the optimum individual which is obtained from initialization to former generation. If the current optimum individual's fitness is better than the former optimum individual, algorithm updates the quantum rotation gate with the current optimum individual's genes, else takes the former optimum individual as the global optimum individual to update θ . This elitist strategy raises the convergence speed, and effectively reduces the likelihood on getting into local optimization.

(3) Introducing partial population disaster strategy

If the global optimum individual is not substituted for continuous many generations, algorithm may probably be suffering from local convergence. In this case, analogous to the catastrophe of population in biology, algorithm introduces the partial population disaster strategy to get rid of local convergence. Partial population disaster strategy only remains the current optimum individual and small number of excellent and valid individuals, and regenerates other individuals in the population. Partial population disaster strategy is efficient in eliminating invalid individuals, and simultaneously retains some excellent and valid individuals to let them evolve continuously. This partial population disaster strategy can raise the stability and global search ability of conventional QGA.

3.2 Algorithm realization of the improved QGA

(1) Initialization: produce the initial population $P(t)=\{ p_1^t, p_2^t, p_3^t, \cdots, p_n^t \}$, n is the scale of the population， p_j^t $(j=1,2,3,\cdots n)$ is an individual in the generation t .

$$p_j^t = \left[\alpha_1^t, \alpha_2^t, \alpha_3^t, \cdots, \alpha_m^t ; \beta_1^t, \beta_2^t, \beta_3^t, \cdots, \beta_m^t \right] \quad (4)$$

m is the number of quantum genes, namely the length of a chromosome, multi-genes means the value of m is very large. The first improvement method is adopted in initialization stage.

(2) Make $R(t)=\{ b_1^t, b_2^t, b_3^t, \cdots, b_n^t \}$ by observing the states of $P(t)$: Produce a random number r (value in 0~1) successively, compare r with the ith gene from the left in individual j of $P(t)$, if $\left|\alpha_{ji}\right|^2 < r$ then set $b_{ji}=1$, else set $b_{ji}=0$. After m times comparison, algorithm can obtain all values in b_j , b_j is looked as a definitive solution.

(3) Evaluation: evaluate and store the global optimum individual according with the improved elitist strategy. If algorithm satisfies the termination condition, algorithm is terminated, else continue running.

(4) Update $P(t)$ using quantum gates: use quantum gates act on every $\left(\alpha_i, \beta_i\right)$ to obtain the new $\left(\alpha_i, \beta_i\right)$ in a chromosome, updating process is defined as:

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta_i) & -\sin(\Delta\theta_i) \\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i) \end{bmatrix} \cdot \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \quad (5)$$

$\theta = s\left(\alpha_i, \beta_i\right) \cdot \Delta\theta$， $\Delta\theta$ and $s\left(\alpha_i, \beta_i\right)$ are the value and orientation of rotation angle which can be obtained form querying table. Updating process promotes the genes in non-optimum individuals to be updated towards the global optimum individual's genes, and hence facilitates the evolution of population.

(5) Introduce partial population disaster strategy or not by judgment: if necessary, introduce disaster strategy, else update and store the global optimum individual. Continue running.

(6) Increase generation $t=t+1$, algorithm goes to step (2).

4. Experimental results and analyses

4.1 Experiment 1 Optimization problem of multi-peak function

To validate the improvements, an experimental computation example in reference [7] is firstly adopted as the test function. The multi-peak function in reference [7] is given by:

$$f\left(x\right) = e^{-0.001x} \cos^2(0.8x) \quad x \ge 0 \quad (6)$$

For $x = 0.0000$, the maximum of $f\left(x\right)$ is 1.0000. When $x \in \left[0,18\right]$, except the maximum 1.0000, this successive multi-peak function also has four local peaks, 0.9961， 0.9922， 0.9883， 0.9844. This paper adopts QGA and IQGA respectively to optimize the function. Table 1 illustrates the comparison of algorithm performance between conventional QGA and improved QGA.

Table 1. Comparison on performance of QGA and IQGA

	QGA	IQGA
probability of successful convergence	83%	100%
least generation of obtaining optimal solution	17	12
average generation of obtaining optimal solution	22	14

4.2 Experiment 2 Problem of multi-genes nutritional diet optimization

To validate the improvements’ effects of IQGA when it is used to solve complex combinatorial problem, IQGA is adopted as the core algorithm in an actual multimedia nutritional diet optimization system. The nutritional diet optimization system has a dishes database consists of 116 cooked dishes at present. Every cooked dish has a quantity of heat value calculated by its primary materials, accessorial materials, and cooking characteristics. Quantity of heat of cooked dishes takes kJ as basic dimension, maintaining 7 digits after decimal point. Diet optimization system is needed to generate the optimum or some optional diet menus for service object (a person or a group) mainly according to the service object’s requirement of heat quantity every meal or every day. The smaller discrepancy between the heat quantity of diet menu provided by computer and the requirement of service object, the better algorithm has optimization performance.

In program design stage, a chromosome represents a diet menu, and a chromosome has 116 gene bits which represents the definite 116 cooked dishes. After quantum collapse measurement, if $b_i = 1$ means selecting the ith finished dish as the dish in diet menu provided by computer, else means not selecting the ith finished diet. The diet optimization problem is a typical complex multi-genes encoding problem.

Supposing that a service object's requirement of heat quantity every meal is 2384.8801kJ, diet optimization program takes $B = 2384.8801$ kJ as the target value of optimization. To validate the performance of IQGA, improvements are divided into two stages. In the first stage, the changing elitist strategy and the partial population disaster strategy are only adopted; the second stage involves all the three improved methods. Experimental results showed that, in the first stage, improved algorithm obtains better optimization effects than conventional QGA, but few optimization results have disparity with B to some certain extent, algorithm also has slight premature convergence problem.

Testing program shows that the rotation angle is commonly necessary to set about 0.025π for obtaining satisfactory solution of combinatorial dishes if (α, β) is initialized as $1/\sqrt{2}$. Considering the diet optimization only for one person or small group with several persons, to raise the quality of initial population, the value of α should be set bigger accordingly β is smaller. Setting $\alpha = \sqrt{0.915}$, $\beta = \sqrt{0.085}$ (setted by program automatically in preliminary analysis), $\Delta\theta = 0.005\pi$, and hence program introduce the third improved method - adjusting initialization way of chromosome's genes in the second stage. With all the three improved methods, program obtains the best optimization effects. Fig.1 shows the variation of heat quantity of best individual with evolution generations in three test conditions.

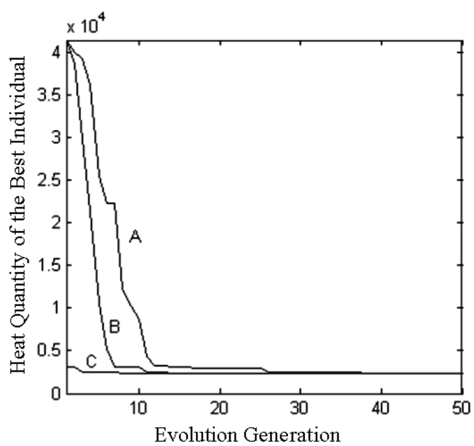

Fig. 1. Population evolution schematic diagram in three conditions

It can be noticed that the quality of the first population generation is raised tremendously with three improvements (corresponding to curve C). The ultimate IQGA's optimization effect is better than conventional QGA (corresponding to curve A) and improved algorithm with two improved methods in the first improvement stage (corresponding to curve B).

For population scale=13, evolution generations =100, diet optimization program based on QGA and program based on IQGA are run 100 times respectively, statistics of experimental results is shown in Table 2.

Table 2. Comparison on algorithms' performance in diet optimization

	QGA	IQGA
probability of obtaining known optimal solution	3%	15%
least generation of obtaining known optimal solution	48	17
average generation of obtaining known optimal solution	68	32
probability of obtaining global satisfactory solution	83%	100%
average generation of obtaining global satisfactory solution	43	12

Because the quantity of genes in a chromosome is excessive and the heat quantity of every cooked dish reaches the seventh place after decimal point, the probability of acquiring the known optimal solution in IQGA is only about 15%. In actual diet optimization condition, slight error within several kJ will not influence the validity and precision of diet optimization result; on the other hand, slight error to some extent enhances the diversity of the combination recipes provided by computer. Considering above reasons, this paper defined the concept - global satisfactory solution. Global satisfactory solution is defined as the satisfactory solutions which their errors less than 0.2% with global optimal solution or target value B . Experimental results show that the probability of obtaining global satisfactory solution in IQGA reaches 100% also with excellent computation speed. Taking IQGA as the core algorithm in nutritional diet optimization problem has evident advantages in speed, searching performance and global optimization. IQGA has excellent proportionality in searching performance and searching speed.

5. Conclusions

This paper puts forward some novel improved method of conventional QGA according to its defects to raise its searching performance in solving multi-peak functions and complex multi-genes encoding combinatorial optimization problems. Simulation experimental results and analyses of actual application show that this improved quantum genetic algorithm is superior to traditional quantum genetic algorithm. IQGA has faster convergence speed and the powerful capability of breaking away from local convergence, and it is fitter for solving continuous function optimization and complex multi-genes encoding combinatorial optimization problems. IQGA has higher searching capability, usability and robustness than traditional quantum genetic algorithm.

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