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# Research on Sensor Networks Perception and Routing Optimization Based on Quantum Genetic Algorithm

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Abstract. In light of the delay and performance degradation of wireless sensor networks, this paper combines quantum computing and genetic computing to improve the overall performance of the network while optimizing the load of nodes. All parts of wireless sensor networks are analyzed and designed in detail, including node perception, gene state measurement, optimal child generation, quantum rotation system iteration, etc. A dynamic quantum gate rotation strategy is proposed to improve the routing algorithm of wireless sensor networks, optimize the search process and accuracy of the algorithm, reduce the energy consumption of network nodes, to ensure global optimality of the network and fast convergence.

Keywords: perceptual evolution, quantum genetics, routing optimization, wireless sensor networks

## 1 Introduction

The dense distribution of a large number of nodes in wireless sensor networks serve as a wireless network of numerous static or mobile sensors in a self-organizing and multi-hop manner, which can be randomly self-organized into sub-networks and enable the perceived information transmitted to the user terminal in the way of multi-hop relay. On the other hand, the transmission mode of short-distance multi-hop routing will increase the network delay and degrade the real-time performance of the network. Messages between nodes often go through multi-hop relay to reach the destination node, where each node is a potential route. Without fixed infrastructure, nodes assume friendliness but lack the necessary trust mechanism, making them vulnerable to attacks such as fake nodes.

The question of meeting business application requirements, seeking data transmission route with the lowest energy consumption and the shortest transmission path in the shortest time becomes critical. A review of current research progress in this field at home and abroad shows that the current path planning strategy has strong pertinence and poor adaptability, not able to adapt to the realistic complex environment. Scholars at home and abroad have made some progress. For example, Sun Jun et al. Proposed quantum delta-potential-well-based particle swarm optimization (QDPSO). Targeting characteristic length of wave function, the searching ability and convergence speed are improved by the wave function parameter control method based on global level; Shi and Eberhart introduced inertia weight m into the evolution equation to balance the globality and convergence rate; R.A.Krohling changes the acceleration factor in the evolution equation to (0, 1) normal distribution to improve the convergence performance of the algorithm.

Quantum genetic algorithm (QGA) is formed by combining quantum computing and genetic algorithm. QGA uses multi-state gene qubit coding and general quantum revolving door operation, dynamically adjusts rotation angle mechanism to evolve individuals, and uses multi-state gene qubit coding to express individuals in the network. Quantum crossover and quantum mutation operations are used to exchange

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information. At present, the improvement of QGA is mainly focused on the improvement of quantum coding and quantum rotation strategy, as well as the introduction of new operators, etc. In this paper, we use the efficient searching ability of quantum genetic algorithm to improve and optimize the existing algorithms to make wireless sensor networks equipped with improved global optimization and faster convergence. It enables to identify the best path between source node and destination node, thus reducing the network delay, minimizing the overall energy consumption of the network, and prolonging the lifetime of wireless sensor networks.

## 2 Perceptual Evolutionary Computational Model and Algorithm Design

### 2.1 Perceptual Evolutionary Computing Model

Each node in wireless sensor networks is a potential route. Quantum wireless sensor networks use the efficient searching ability of quantum genetic algorithm to select multiple paths for transmitting data information and finding the optimal path among multiple paths. Through multiple individuals to search at the same time, the search performance of the algorithm is enhanced. This paper addresses the low sensing and positioning accuracy of ranging nodes in wireless sensor networks, to construct an evolutionary computing model of network node perception, as shown in Fig. 1.

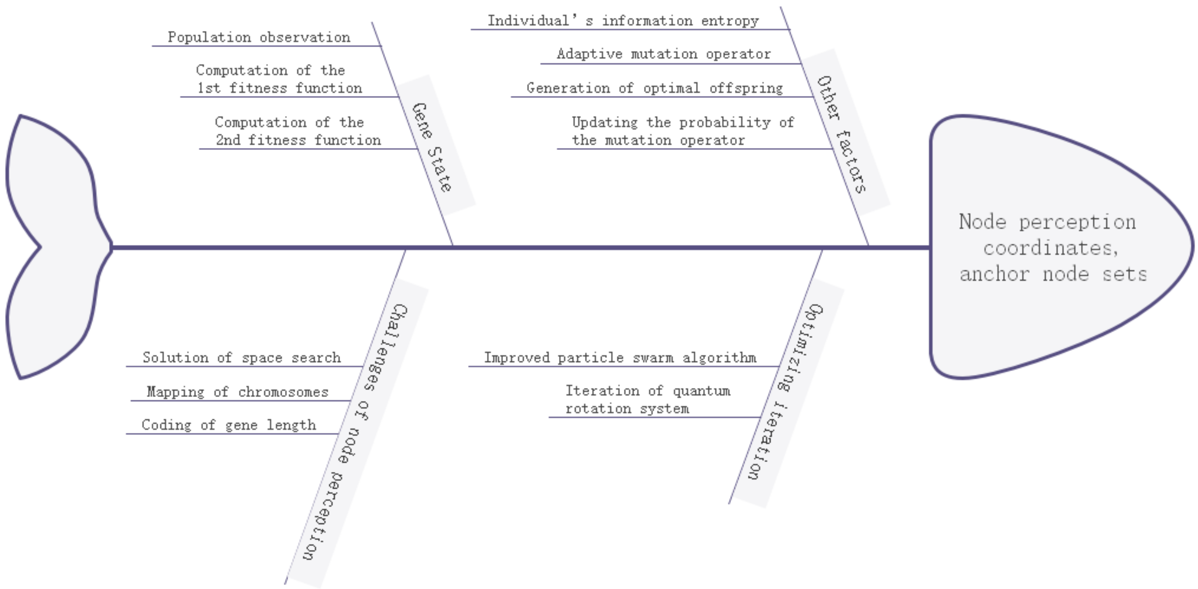


**Fig. 1.** Perceptual evolution model of wireless sensor networks

The node perception challenge is transformed into finding a solution for search space optimization with constraint conditions, according to the model. The improved quantum genetic algorithm is used to map node perception together with adaptive gene length coding. After outputting the optimal node of the wireless sensor network, a certain proportion of individuals in the population are mutated according to the mutation operator. The optimal operator is selected and updated after iterative reproduction, after which the maximum incentive mutation rate is applied to the global optimal individual neighbor particle to generate the maximum value. Offspring is reproduced with the comparatively optimal. The probability of the mutation operator is updated after each iterative reproduction. Each computation would add 1 to the total number of anchor nodes. If the total number of anchor nodes is N, the algorithm would end and iteratively output the node perception coordinates of anchor node sets.

### 2.2 Proposal and Algorithm Design

According to the improved computational model of quantum genetic algorithm for wireless sensor networks, the flow of perceptual evolutionary algorithm is shown in Fig. 2, and the key technologies of its application are as follows.

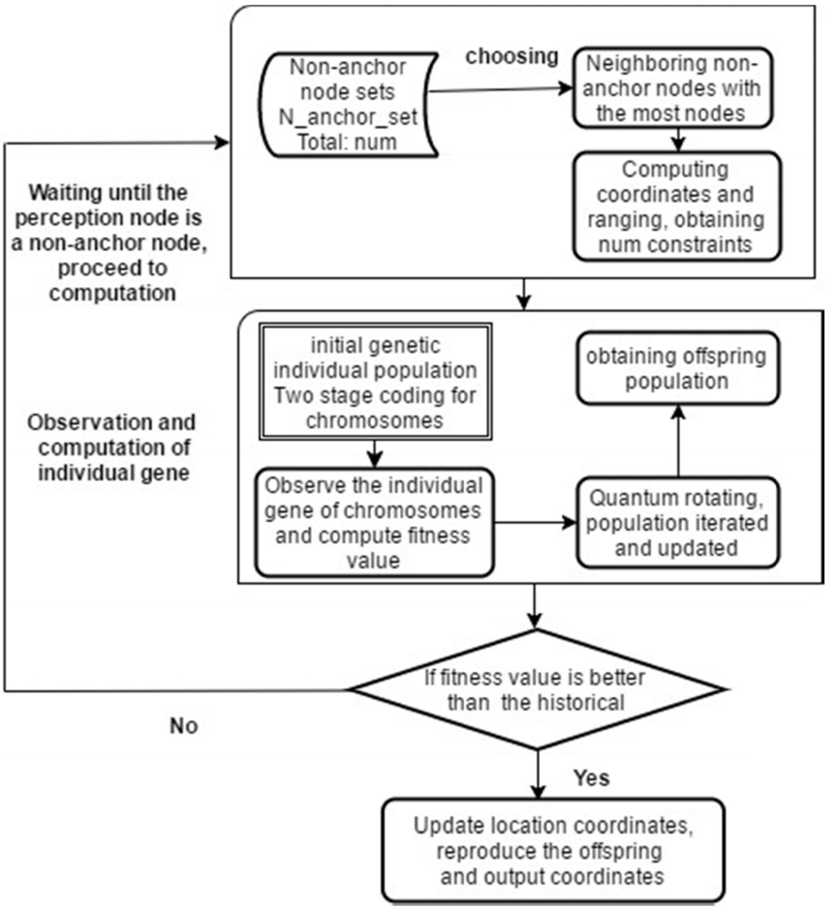


**Fig. 2.** Improved quantum genetic algorithm node perception algorithm for wireless sensor networks

According to the improved computing model of quantum genetic algorithm for wireless sensor networks, the process of perceptual evolutionary algorithm is designed as shown in Fig. 2. First, construct non anchor set (N_anchor_set) by selecting the non-anchor nodes with the largest number of neighboring anchor nodes (N_anchor). Calculating the coordinates and ranging to obtain (num) constraints; Second, initialize the genetic individual population, encode the chromosomes with the two-stage system, observe the individual genes of chromosomes and calculate the fitness values. Update and iterate the quantum rotation and population to obtain the offspring population. Finally, decide whether the fitness value is better than the history. If not, continue iterative calculation and observation; if yes, update the location coordinates, breed the offspring, and output the coordinates. The key technologies for the application of the algorithm are as follows.

(1) Quantum bit coding

Traditional coding can only represent a specific state. QGA adopts the qubits coding mode, i.e. one qubit represents the smallest unit of information. The chromosomes encoded by the qubits method are called quantum chromosomes, where one chromosome can express the superposition of multiple states at the same time, making it easier to maintain the diversity of the population. The quantum population of the t generation is expressed as:

$$Q(t)=\{q_1^t, q_2^t, \ldots, q_n^t\},\ q_j^t=\left[\begin{array}{c|c|c|c}\alpha_{j1}^t & \alpha_{j2}^t & \cdots & \alpha_{jm}^t \\ \beta_{j1}^t & \beta_{j2}^t & \vdots & \beta_{jm}^t\end{array}\right] \quad \textbf{(1)}$$

Where n is the population size, $q_j^t$ is the No. j quantum chromosome of the t-generation population, m represents the number of qubits, j=1, 2, …, n. With $|\alpha|^2$ or $|\beta|^2$ gradually approaching 1 or 0, the quantum chromosome would gradually converge to a single state, while the population diversity decreases, and the algorithm converges.

(2) Modification of anchor node function

Suppose that the distance between nodes on the wireless sensor network are all within the sensor ranging. There are N nodes and M anchor points in the system, and there are 3 neighboring nodes around the anchor node. The non-anchor node becomes a new anchor node after computation and iteration. The function to modify and compute the anchor node is defined as formula 2.

$$f(x,y)=\sum_{i=1}^{n}\sqrt{(x_i-x)^2+(y_i-y)^2-d_1^2}*\phi_i \tag{2}$$

(3) Design of fitness function

Fitness function is a measure used by the evolutionary algorithm to indicate the quality of the individual. Observe the population to determine the gene state, followed by computing the first fitness function and the second fitness function. In the algorithm, the smaller the path cost is, the higher the fitness. The link cost shall be counted only once in the case of same link being passed through, to avoid repeated computation. The individual fitness evaluation operator of the population is used to evaluate the quality of the first individual in the current population, which is defined in formula (3), where $f_{\max}$ and $f_{\min}$ represent the optimal fitness value and the worst fitness value in the current population, respectively. The higher the value of $y_{fit}^i$ is, the closer the individual's fitness value is to the worst value, and vice versa to the optimal solution.

$$y_{fit}^i=\begin{cases}\dfrac{f_{\max}-f_i}{f_{\max}-f_{min}}, & f_{\max}\neq f_{\min}\\ 0, & f_{\max}=f_{\min}\end{cases} \tag{3}$$

## 3 Routing Optimization of Wireless Sensor Networks Based on the Strategy of Dynamic Quantum Gate Rotation

### 3.1 State Transfer of Quantum Swapping Gate

Each node of wireless sensor has limited energy and storage capacity, but it can also serve as a route. Therefore when optimizing the routing protocol, it is important to comprehensively reduce the energy consumption and loss of sensor nodes on wireless sensor networks, which is to prevent some nodes from consuming energy substantially due to heavy load.

The quantum gate would realize the corresponding logic function through a series of qubits swapping. Thus the general quantum gate can be converted into any quantum gate, and the basic general quantum gate is composed of a phase shift gate and two controlled non-gates.

The function of a phase shift gate is to complete the phase shift, which can be defined in formula (4).

$$U(\theta)=\begin{pmatrix}\cos & -\sin\theta\\ \sin\theta & \cos\theta\end{pmatrix} \tag{4}$$

In quantum computing, any quantum gate can be transformed from a quantum gate, and two controlled empty gates $C^{2qubit-NOT}$ can be formed by a quantum non-gate $\sigma^X$, where $I$ is a unit matrix, $O$ is a zero matrix. $C^{2qubit-NOT}$ would come into play when a double qubit passes through the quantum gate, the first qubit is in $|1>$ state, and the second qubit is swapped.

$$C^{2qubit-NOT}=\begin{pmatrix}I_{2\times2} & O_{2\times2}\\ O_{2\times2} & \sigma^X\end{pmatrix}=\begin{pmatrix}1&0&0&0\\0&1&0&0\\0&0&0&1\\0&0&1&0\end{pmatrix} \tag{5}$$

The state transfer of quantum is realized through the quantum swapping gate. In the quantum rotation gate, the rotation direction and angle of the quantum are selected according to the look-up table. The fixed rotation angle in each case would lead to the "precocious" phenomenon or slow convergence of the quantum population. The generation of offspring is not determined by the parent population, but by the optimal individual of the parent and the probability amplitude of the state. The quantum gate acts on the superposition state or entangled state of the chromosome respectively, so that they would interfere with each other and change the phase. Thus the probability amplitude of each ground state is changed.

### 3.2 Improved Routing Optimization Algorithm

In the optimization of routing protocols, it is necessary to consider the energy consumption of hopping nodes to prevent excessive consumption due to heavy load. If k-bit data is sent to a location with a distance of d, the energy consumption formula is (6).

$$E_{T_X}(k,d)=\begin{cases} kE_{elec}+k\varepsilon_{fs}d^2 \\ kE_{elec}+k\varepsilon_{mp}d^4 \end{cases} \tag{6}$$

The energy consumed by the wireless transceiver circuit is $E_{elec}$, $\varepsilon_{fs}$ is the proportional coefficient of the energy consumed by the signal amplifier when $d<d_0$, and the energy loss is proportional to $d^2$; $\varepsilon_{mp}$ is the proportional coefficient of the energy consumed by the signal amplifier when $d>d_0$. In evolution, use probability $\mu$ to rotate towards the global optimal quantum, and if the condition is not satisfied, then rotate towards the historical optimal $p^{gopt}$. Probability $\mu$ is computed in formula (7).

$$\mu=e^{t/T-1} \tag{7}$$

Where t is the current number of iterations and T is the total number of iterations, which means the quantum can maintain diversity at the beginning of evolution, but rotate towards the global optimal in the middle and later stage. The quantum revolving door is used to change the gene location of the quantum chromosome to ensure its convergence. The process is shown in formula (8).

$$\begin{bmatrix}\alpha' \\ \beta'\end{bmatrix}=u(\theta)\begin{bmatrix}\alpha \\ \beta\end{bmatrix}=\begin{pmatrix}\cos(\theta) & -\sin\theta \\ \sin\theta & \cos\theta\end{pmatrix}\begin{bmatrix}\alpha \\ \beta\end{bmatrix} \tag{8}$$

$$\theta_i=S_1S_2\theta_0e^{-(f_x-f_b)} \tag{9}$$

The rotation angle $\theta_i$ is computed by equation (9), $\theta_0$ is the initial rotation angle, $S_1$ and $S_2$ are to control the rotation direction. If the $\alpha$ or $\beta$ of qubits converges prematurely to near 0 or 1, the quantum revolving door operation will further accelerate the convergence of qubits, and modify the gene location of qubits after revolving. A threshold e is set, and when the sum of $|\alpha|^2$ and $|\beta|^2$ is less than e, the formula (10) is used to modify the rotated gene location of the qubits. (10).

$$\begin{aligned} & if\,|\alpha_i^{t+1}|^2\le and\,|\beta_i^{t+1}|^2\ge 1-e \\ & \quad [\alpha_i^{t+1}\beta_i^{t+1}]^T=[\sqrt{e}\sqrt{1-e}]^T \\ & if\,|\beta_i^{t+1}|^2\le e\ and\,|\alpha_i^{t+1}|^2\ge 1-e \\ & \quad [\alpha_i^{t+1}\beta_i^{t+1}]^T=[\sqrt{1-e}\sqrt{e}]^T \\ & otherwise \\ & \quad [\alpha_i^{t+1}\beta_i^{t+1}]^T=[\alpha_i^{t+1}\beta_i^{t+1}]^T \end{aligned} \tag{10}$$

The quantum revolving door operation adaptively computes the appropriate rotation angle according to the current quantum gene location and chromosome fitness value, so as to increase the population diversity when insufficient and avoid the premature convergence of the algorithm.

### 3.3 Simulation Experiment and Algorithm Analysis

The simulation experiment of the algorithm compares the QoS routing algorithm with the optimization algorithm based on dynamic quantum gate rotation strategy proposed in this paper. Based on the perceptual evolution model, the experiment outputs the perceptual coordinates of anchor points according to the ranging and positioning accuracy of nodes in wireless sensor networks. The proposed algorithm is compared with QoS (Quantum Behavioral Particle Swarm Optimization) algorithm, as simulation for analytics, in terms of average transmission delay and total consumption performance.

The simulation is carried out by using Matlab software, assuming that in an experimental area of 80m × 80m, the initial 120 nodes are evenly distributed, the maximum transmission distance is 80m, the size of each packet is 100 bytes, with the same initial energy of all nodes. As shown in Fig. 3, when the simulation time is set to 300s, the average delay time of the proposed algorithm is 61.2ms and the average delay time of the QoS routing algorithm is 64.5.

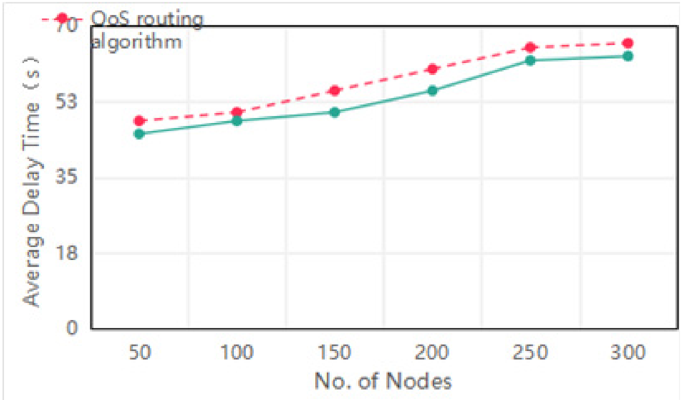


**Fig. 3.** Delay of the Network

Fig. 4 shows the total energy consumption of the network in the process of simulation. When the simulation time is 600s, the energy loss of QoS routing algorithm is about 131J, and that of the proposed algorithm is about 122J. The global optimal link derived from the latter can effectively reduce the energy loss of the network.

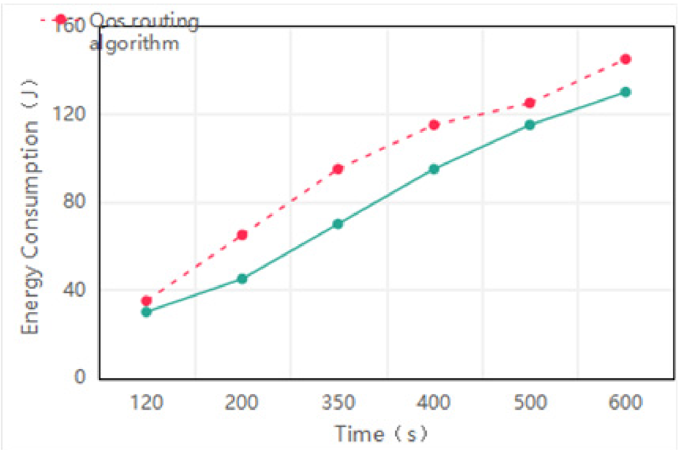


**Fig. 4.** Energy Consumption of the Network

The experimental results show that the dynamic quantum gate optimization algorithm based on the perceptual evolution model has a smaller average transmission delay and a smaller growth range as the number of nodes increases, and the total energy consumption of the network is lower when using the same number of nodes. It can also prolong the lifetime of wireless sensor networks.

## 4 Conclusion

The wireless sensor network cooperatively perceives, collects, processes and transmits the information of the perceived object in the physical area, and eventually sends the information to the owner of the network. The transmission mode of short-distance multi-hop routing will increase the network delay, resulting in a decline in the real-time performance of the network. Route optimization is needed to meet the requirements of business applications, with a goal to seek the data transmission route with the least energy consumption and the shortest transmission path in the shortest time. In this paper, according to the characteristics of wireless sensor networks, the perceptual evolution computing model of network nodes is constructed by using improved quantum genetic algorithm, and the perceptual coordinates of network nodes are output iteratively. Updating the quantum revolving door with the information of the current optimal individual can accelerate the convergence of the algorithm, and the introduction of quantum crossover, mutation and catastrophe can overcome the phenomenon of premature convergence, thus improving the search efficiency and location performance. it is suitable for the requirements of low cost and low power consumption in wireless sensor networks. Simulation results show that the perception model and improved algorithm proposed in this paper can effectively solve the problems of node overload and excessive energy consumption.

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