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# Research on Path Planning and Location Optimization of Quantum Wireless Sensor Networks

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Abstract. An iterative process search algorithm that enables "generation + monitoring" can be formed by combining quantum computing and evolutionary computation; This paper researches on how to apply quantum genetic algorithm to path planning and location optimization of wireless sensor networks and builds a path planning optimization model. It also adopts an adaptive adjustment strategy to improve the search for the optimal path, reduce network delay and energy consumption on wireless sensor nodes. In this paper, an optimization algorithm for reducing positioning error and correction is proposed to compensate the error and address local positioning optimization.

Keywords: Wireless sensor networks, quantum genetic, path planning, perceptual evolution, localization

## 1 Introduction

Wireless sensor network (WSN) is an emerging frontier field of research that are highly inter-disciplinary, and is considered to be the second largest network after the Internet worldwide. With the cooperation of all kinds of integrated micro sensors, and by real-time monitoring, sensing and collecting information from different environments or objects, which is processed by the embedded system, WSN is able to integrate a variety of technologies such as sensors, embedded system, modern network and wireless communication, distributed information processing, etc [1]. Quantum genetic algorithm (QGA) was first proposed by Narayanan and Moore in 1996. On the basis of the traditional genetic algorithm (GA) [2], a probabilistic evolutionary algorithm was formed by adding the concept of quantum computing (QC) [3]. Its parallelism by nature would enable QGA to handle and solve complex problems and massive information [4-5]; Shi and Eberhart introduce inertia weight m into the evolution equation to balance the globality and convergence rate [6]; R.A.Krohling changes the acceleration factor in the evolution equation to (0, 1) normal distribution, which improves the convergence performance of the algorithm; By introducing divergence behavior, Riget et al maintain the diversity of the population and effectively improve the global search ability of the algorithm [7]. According to the basic convergence property of particle swarm [8]; Sun proposed the QPSO algorithm based on quantum mechanics [9]. However, there are few cases of applying the algorithm to wireless sensor networks.

Quantum genetic algorithm optimizes the data by quantum bit coding, quantum superposition and quantum chromosome mutation. Based on the representation of quantum state vector, quantum bit coding is used to represent chromosomes, quantum revolving gate and quantum non-gate used to update the chromosome, so as to realize the optimal solution of the target problem. Based on the traditional genetic algorithm (GA) and the probabilistic evolutionary algorithm by adding quantum computing (QC) [10], this paper creatively applies quantum genetic algorithm to path planning and location optimization of

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wireless sensor networks. As the evolution speed of traditional genetic algorithm is limited, the information provided by immature subpopulations in evolution is used, as well as a better guidance mechanism to enhance the intelligence of the algorithm, improve the search efficiency, and resolve the problems of prematurity and improve convergence speed in GA [11]. The research results address how to build a path planning optimization model, apply a self-adaptive adjustment strategy to improve the search for the optimal path, reduce network delay and wireless sensor node energy consumption, reduce positioning errors and compensate for errors, to achieve local location optimization.

## 2 Application of Quantum Genetic Algorithm in Wireless Sensor Networks

Quantum computing combined with genetic algorithm is applied to wireless sensor networks. Quantum genetic algorithm is used to select the optimal or sub-optimal individuals, and a double fitness evaluation function is introduced to evaluate the evolutionary individuals. It provides a guarantee for the optimal or suboptimal individuals to enter the next generation. Quantum genetic algorithm (QGA) has the characteristics of fast convergence and short computing time, so it can be widely used in many aspects, such as energy saving, routing protocol, Q0s guarantee, etc. At the same time, the quantum ion swarm optimization algorithm also solves the local optimization problem of the particle swarm optimization algorithm, so as to better improve the positioning performance. Low in cost and in power consumption, it fits perfectly into the requirement of wireless sensor networks and constitutes a practical optimal location [12].

Based on the concept and theory of quantum computing, QGA uses qubits to encode chromosomes, which results in two states of 0 or 1 for any given qubit. The formula is stated as follows:

$$|\varphi>=\alpha|0>+\beta|1>. \quad \textbf{(1)}$$

$\alpha$ and $\beta$ are the two complex numbers representing different probabilities of occurrence in different states. As $|\alpha|^2+|\beta|^2=1$, in which $|\alpha|^2$ and $|\beta|^2$ represent probability of qubits in state 0 and state 1 respectively, such probability amplitude representation would allow quantum chromosome to represent the information of multiple states at the same time, bringing a rich population. The information of the current optimal individual can be easily used to guide mutation, making the population evolve towards a robust model with a higher probability and speed up the convergence of the algorithm [13].

Quantum chromosome variation can make the best use of information from the current generation, and deduce the probability distribution of a quantum chromosome from the current optimal solution. After the optimal individual obtained from the current evolutionary operation deduces a guiding quantum chromosome, the latter would be randomly scattered around as the next generation of quantum population, which is described by the formula as:

$$Q_{guide}(t)=\alpha\times p_{curbest}(t)+(1-\alpha)\times(1-p_{curbest}(t)) \quad \textbf{(2)}$$

$$Q(t+1)=Q_{guide(t)}+b\times norm(0,1) \quad \textbf{(3)}$$

A novel coding method based on qubits is used in QGA, that is, a pair of complex numbers is used to define a qubit. A system with m qubits can be described as:

$$\begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_m \\ \beta_1 & \beta_2 & \cdots & \beta_m \end{bmatrix} \quad \textbf{(4)}$$

In the equation, $|\alpha_i|^2+|\beta_i|^2=1(i=1,2,\ldots,m)$, and it can represent any linear superposition state.

The chromosome population of the t generation is $\boldsymbol{Q}(t)=\{q_1^t,q_2^t,\ldots,q_n^t\}$, where n is the population size and t is the evolutionary algebra, $q_j^t$ is the chromosome defined as follows.

$$q_j^t=\begin{bmatrix} \alpha_1^t & \alpha_2^t & \cdots & \alpha_m^t \\ \beta_1^t & \beta_2^t & \cdots & \beta_m^t \end{bmatrix}(j=1,2,...,n) \quad \textbf{(5)}$$

In the initial population Q (t), $\alpha_i^t, \beta_i^t = 1(i = 1, 2, \ldots, m)$ and all $q_j^t$ are initialized to $\frac{1}{\sqrt{2}}$, in which case all possible linear superposition states would appear with the same probability. P (t) is generated from Q (t), thus a set of ordinary solution P (t) would be generated by observing the state of Q (t), where in the t generation $\boldsymbol{P}(t) = \{x_1^t, x_2^t, \ldots, x_n^t\}$, each $x_j^t (j = 1, 2, \ldots, m)$ is a string of $(x_1, x_2, \ldots, x_m)$ with a length of m. This is obtained by the amplitude of qubits $|\alpha_i^t|^2$ or $|\beta_i^t|^2$ $(i = 1, 2, \ldots, m)$. The corresponding binary process is as follows: first to randomly generate a number of [0, 1], if it is greater than $|\alpha_i^t|^2$, take 1, otherwise take 0; In the updated Q (t), not only crossover and mutation in the traditional sense can be used, but also some suitable quantum gate transformations to generate Q (t) according to the superposition characteristics of quantum and the theory of quantum transition.

# 3 Path Planning for Wireless Sensor Networks

## 3.1 Path Planning Optimization Model

At present, the commonly used path planning strategies are highly specific, but relatively poor in adaptability, making it difficult to adapt to the real complex environment. This paper proposes an optimization by identifying and establishing an energy-saving and efficient reliable path for data transmission from the sensor node to the receiver node. It not only focuses on path length, but to a larger extent, the energy saving and the balanced consumption of the whole network energy, so as to maximize the life span of the wireless sensor network [14].

As shown in Fig. 1, this paper proposes to use the highly efficient search by quantum genetic algorithm, and run routing computing and genetic evolution computing simultaneously until the approximate optimal path is found. Practical factors such as node energy consumption and routing recovery time are taken as the constraints of the optimized path, which are prioritized together with various objectives according to their importance.

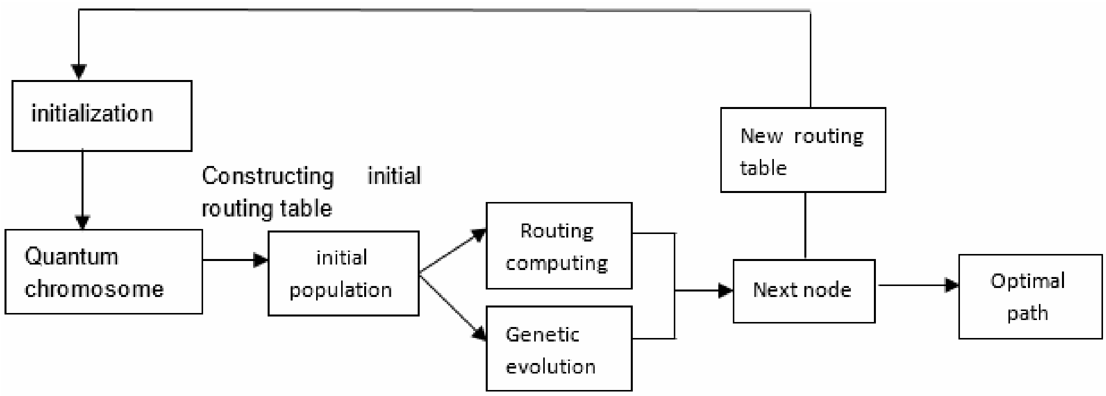


**Fig. 1.** Path Planning Model for the Wireless Sensor

(1) After constructing the path optimization model of wireless sensor network, initialization is carried out. Quantum genetic algorithm is simple, universal, robust, and enables parallel search, group optimization, which are helpful to improve the search efficiency of the algorithm.

(2) Initial routing table, i.e., quantum chromosome, is constructed. The initial population is constructed according to the routing table. Routing computing and genetic evolution are carried out at the same time.

(3) After the current node is optimized by quantum genetic algorithm, the next node to hop on is determined according to the link set, and a new routing table is formed, followed by the chromosome being extended and evolved until the optimal path is identified.

Safety and path cost are the two main factors to be considered when evaluating the path. The research proposes to use two different fitness functions for evaluation.

$$f(X_i)=\sum_{j=1}^{m} f_i^{(j)},\quad f_i^{(j)}=\beta\mu+\gamma\upsilon \tag{6}$$

Among them, $\beta$ and $\gamma$ are weighted adjustment coefficients.

### 3.2 Adaptive Adjustment Strategy

The transfer of the quantum state is realized by the quantum gate through the transformation matrix. The rotation angle of the quantum rotation gate is used to express the accelerated convergence speed of the quantum chromosome [15]. The adjustment operation of the quantum rotation gate is as follows:

$$U(\theta)=\begin{bmatrix}\cos(\theta) & -\sin(\theta)\\ \sin(\theta) & \cos(\theta)\end{bmatrix} \tag{7}$$

$$\begin{bmatrix}\alpha' \\ \beta_i'\end{bmatrix}=U(\theta)\cdot\begin{bmatrix}\alpha \\ \beta_i\end{bmatrix}=\begin{bmatrix}\cos(\theta) & -\sin(\theta)\\ \sin(\theta) & \cos(\theta)\end{bmatrix}\cdot\begin{bmatrix}\alpha \\ \beta_i\end{bmatrix} \tag{8}$$

Among them, $\begin{vmatrix}\alpha_i' \\ \beta_i'\end{vmatrix}$ is the No.i qubit in the chromosome, and the rotation angle is $\theta_i=s(\alpha_i,\beta_i)\Delta\theta_i$, $\theta_i=s(\alpha_i,\beta_i)$ and $\Delta\theta_i$ represent the direction and angle of the rotation respectively, which is adjusted by self-adaptation. Focusing on two factors, i.e., the fitness of the individual's current measured value $f(x_i)$ and the fitness of the individual's current targeted value $f(b_i)$, if $(f(x_i)-f(b_i))/f(b_i)<$ the threshold (depending the actual optimization problem), when the individual closest to the optimal solution appears, the value of $\Delta\theta_i$ will be reduced, while the convergence speed will be accelerated; If $(f(x_i)-f(b_i))/f(b_i)$ exceeds the threshold, the individual in the solution group will have poor fitness, leading to the value of $\Delta\theta_i$ to be increased, which will make the solution group deviate from the local optimal solution or increase the chance of generating the optimal solution.

## 4 Location Optimization Algorithm based on Quantum Particle Swarm Optimization

### 4.1 Algorithm Model and the Process

Location is an important supporting technology for wireless sensor networks, providing important information for monitoring. It is not feasible to go through the global positioning system due to its high cost, large energy consumption and large volume of user nodes. In comparison, wireless sensor networks are self-organized and cost less.

Particle Swarm Optimization (PSO) is a random search algorithm based on group cooperation, developed by simulating the foraging behavior of birds. The solution of each optimization task is a bird in the search space, which we call the "particle". Each particle has a fitness determined by the optimized function (fitness value), and a speed that determines the direction and distance they fly. The particles then follow the current optimal ones to search in the solution space.

This paper researches a large number of measured data from the path loss model of wireless sensor networks, and corrects the deviation LQI value with quantum particle swarm optimization algorithm. As a result, a location optimization algorithm based on error correction is proposed to compensate the error and address the challenge of local optimization.

In the M-dimensional sensor particle swarm node, each particle converges to the P point, $P=(p_1,p_2,\ldots,p_N)$, a total of $I$ particles have their J-dimension coordinate at $P_{i,j}(t)=\phi_j(t)\cdot P_{i,j}(t)$ $+[1-\phi_j(t)]\cdot G_j(t)$ . For a total of N particle swarm in the target search space, $X_N(t)\}$ $X, X(t)=$ $\{X_1(t),X_2(t),\ldots,X_n(t)\}$, At certain time t, the position of the i particle is $X_j(t)=$ $\lfloor X_{i,1}(t),X_{i,2}(t),\ldots,X_{i,m}(t)\rfloor$.

After positioning optimization, the optimal position of particles is $G(t)=\lfloor g_1(t), g_2(t), \ldots, g_M(t)\rfloor$. The algorithm model is shown in Fig. 2, and the process of positioning optimization is as follows:

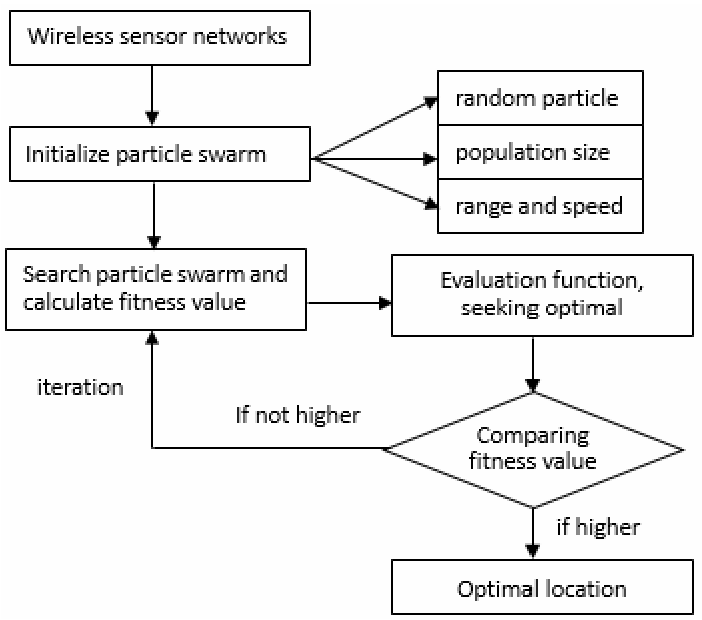


**Fig. 2.** Optimization model of location algorithm for quantum particle swarm

(1) Initialize the particle position t = 0.

(2) Adopt $G_j(t)=\frac{1}{N}\sum_{i=1}^{N}P_{i,j}(t)$ to calculate the average optimal position of the particle swarm.

(3) Update the equation according to the particles.

$$X_{i,j}(t+1)=P_{i,j}(t)\pm\beta\,|\,C_j(t)-X_{i,j}(t)\,|\cdot\ln[1-u_{i,j}(t)] \quad \textbf{(9)}$$

(4) Calculate the current fitness of the particles and make comparisons. If $f\lfloor X_i(t+1)<\rfloor f\lfloor P_i(t+1)\rfloor$, then $P_i(t+1)=X_i(t+1)=X_i(t+1)$.

(5) Compare the fitness value of particle i with that of G (t). If higher, the former will be regarded as the optimal location; if lower, then the previous one shall prevail.

(6) Calculate the new position of the particle with (3) and repeat the iteration, until the pre-set condition is met, which ends the cycle.

### 4.2 Analytical test

The purpose of the experiment is to randomly generate a wireless sensor network with 30 nodes. The simulation experiments are carried out by genetic algorithm and quantum particle swarm location optimization algorithm, then calculated by Schaffer function and six-peak hunchback function respectively.

Schaffer function:

$$f_1(x_1,x_2)=0.5+\frac{\sin^2\sqrt{x_1^2+x_1^2}-0.5}{[1+0.01(x_1^2,x_2^2)^2]},\ x_i\in[-100,100], i=1,2 \quad \textbf{(10)}$$

Six-peak hunchback function

$$f_2(x_1,x_2)=(4-2.1x_1^2+x_1^4)x_1^2+x_1x_2+(-4+4x_2^2)x_2^2,\ x_i\in[-3,3], i=1,2 \quad \textbf{(11)}$$

The performance of the algorithm is measured in terms of success rate, average optimal value and optimal value; The efficiency of the algorithm is measured in terms of average computing time and average termination algebra.

The algorithm is simulated by Matlab simulation software. The distribution area of point nodes is set at 120m, while the number of individuals of the initial population is 25, and the number of iterations is 100. At first, the coordinates are randomly generated, and a set of node spacing is formed. When the distance error exceeds the ranging radius, it is counted as an unmeasurable point 0. The positioning accuracy is noted at different anchor points, ranging, radius and by total number of nodes for comparison. For example, Fig. 3 shows the average error rate of distance estimation using traditional algorithm and optimized algorithm with different number of nodes, it can be seen that with the increase of the number and connectivity of nodes, the optimized distance matrix of the algorithm is more accurate, and with the increase of the number of nodes, the error of distance estimation is reduced. The experimental results show that the average location error and the maximum and minimum error of the location optimization algorithm based on quantum particle swarm are smaller than those of the traditional algorithm, indicating that the ability of locating the node is stronger and more accurate.

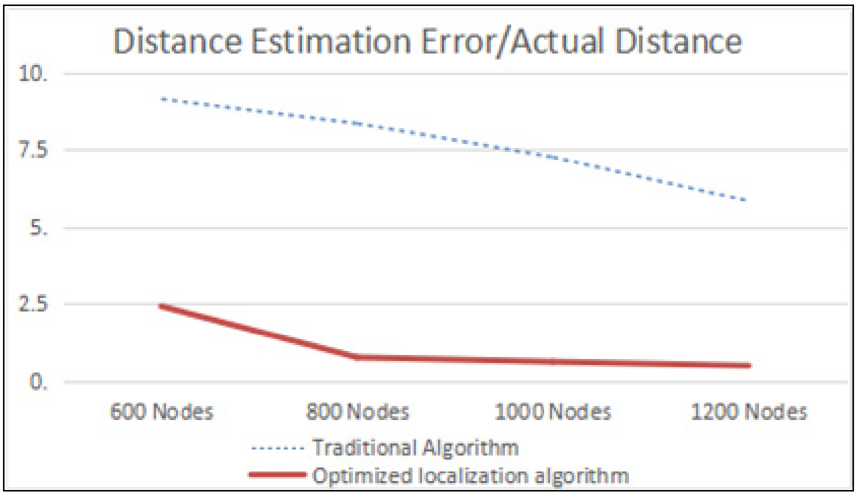


**Fig. 3.** Average Error Rate of Distance Estimation Traditional Algorithm vs. Optimized Algorithm

## 5 Conclusion

In the process of learning from biological intelligence, artificial intelligence combines the idea of “immunity” with existing evolutionary algorithms to form an evolutionary algorithm based on immune strategy. The evolutionary algorithm represented by genetic algorithm is a search algorithm with an iterative process of “generation + detection”. In the iterative process, evolutionary algorithms are basically globally convergent on the premise of retaining the best individuals of the previous generation.

Wireless sensor network is different from traditional computer network, as the former features small storage space, low computing power, large coverage density, etc. Genetic algorithm is an iterative process search algorithm that enables “generation + detection”. The combination of quantum computing and evolutionary algorithm focuses on automatic planning technology, which can be used for path planning and location optimization of wireless sensor networks. The highly efficient search by quantum genetic algorithm would enable routing computing and genetic evolution computing to be run simultaneously, thus iterating the optimal path. The location optimization algorithm using quantum particle swarm has proved by experiments to have better positioning accuracy and performance.

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