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Research Article

Routing Optimization of Intelligent Vehicle in Automated Warehouse

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Routing optimization is a key technology in the intelligent warehouse logistics. In order to get an optimal route for warehouse intelligent vehicle, routing optimization in complex global dynamic environment is studied. A new evolutionary ant colony algorithm based on RFID and knowledge-refinement is proposed. The new algorithm gets environmental information timely through the RFID technology and updates the environment map at the same time. It adopts elite ant kept, fallback, and pheromones limitation adjustment strategy. The current optimal route in population space is optimized based on experiential knowledge. The experimental results show that the new algorithm has higher convergence speed and can jump out the U-type or V-type obstacle traps easily. It can also find the global optimal route or approximate optimal one with higher probability in the complex dynamic environment. The new algorithm is proved feasible and effective by simulation results.

1. Introduction

With the development of factory automation and logistics automation, traditional production and material handling are more automated and intelligent, and a lot of large-scale storage centers come into being. However, due to the complexity of goods classification, frequent turnover, large number of houses, complex road conditions, and so on, finding target shelves location in the large-scale storage center is a very difficult task. When working people always need the help of memories or carrying signs for tendency guidelines, the result is inefficient and error-prone, and human, material, and financial resources are wasted on a certain degree. Intelligent vehicle is a cargo automatically handling car in intelligent transport systems that can meet the requirements of warehouse and flexible manufacturing systems, and it is one of the most crucial parts of the whole logistics automation and production automation.

Generally intelligent vehicle also called automated guided vehicle is a mobile robot. Intelligent vehicle is an integrated system which involves computer systems, sensors, automatic control, mechanical, communications, and other technologies. It has been widely applied in many areas such as industry, agriculture, military, and other fields and is one of the hot research issues in the field of robotic applications. Intelligent vehicle system is controlled by computer, with the characters of autonomous navigation, automatically path planning and executing tasks, independently avoiding obstacle, and has the advantages of high degree of automation, easy scheduling and management, safety and reliability, and so forth. Its goal is to achieve the automatically handling of goods. The key technology of intelligent vehicle is similar to the mobile robot and the difficult and critical points include navigation, routing optimization, task scheduling, coordination of multi-AGV control, and information fusion technology. Routing optimization is the focus of this study.

The routing optimization of intelligent vehicle is searching one optimal or approximate optimal route with a specific performance (such as shortest distance, less time, etc.) from starting point to target point in theenvironment with obstacles. The route searching is the prerequisite for intelligent vehicle performing various complex tasks, so the research for effective route planning in a complex environment is necessary and significant in the field of intelligent warehouse. Depending on the degree that environmental information is known, route searching can be divided into two categories: (1) global route searching with environmental information known; (2) local route searching with environmental information unknown or partially unknown. Global route searching is to find the optimal or approximate optimal route to meet certain performance from the starting point to the target point according to the priori model. The key problem is the environment model building and the route searching strategy. Local route searching means in the unknown or partially unknown environment, the intelligent vehicle according to the sensor's information, including the location, size, and shape information of the obstacle, gives a satisfied route with no collision.

For path planning problem of mobile robot, many scholars have had extensive research and also gotten some achievement. The traditional robot path planning methods such as artificial potential [1], visibility graph [2], graph searching, and grid decoupling method each have the advantages and disadvantages. With the development of intelligent algorithms, many scholars introduce them into the field of robot path planning. The intelligent algorithms improve the performance of the robot path planning to some extent, but they also have their own defects. For example, genetic algorithm is easy to fall into local optimum and has premature, slower convergence and other issues. With the increasing of obstacles or encountering complex terrain especially, the complexity of the intelligent algorithms will greatly increase, and we even cannot find the optimal solution [3].

Tuncer and Yildirim [4] in order to solve the problem of genetic algorithm of premature and slow convergence proposed a dynamic path planning of mobile robot based on with improved genetic algorithm. Yang and Fu [5] in order to improve the searching efficiency of genetic algorithm proposed a new mobile robot path planning algorithm combined with grid method and chaos genetic algorithm. There are some problems in the neural network system, such as networks large-scale, common performance, and easy to make a robot into an infinite loop. Glasius et al. [6] proposed a neural network model based on Hopfield network with dynamically avoiding obstacles. The model can avoid local minimum point, but it is difficult to adapt to the dynamic and high speed environment. Ant colony algorithm is easy to fall into local optimal solution and the U-shaped or V-shaped trap. Cai et al. [7] proposed a new method combined with the ant colony algorithm and fuzzy control technology. Although this method can solve the robot path planning problem, it is more complex and difficult. In order to improve execution speed and search efficiency, Liu [8] proposed an improved algorithm based on ant colony algorithm and genetic algorithm. Liu and Cheng [9] presented vision detection colony algorithm with elitist strategy to improve the efficiency. Zhou and Hua [10] presented an improved ant colony algorithm using simulated annealing algorithm to improve the pheromone evaporation coefficient.

About the routing optimization in logistics and warehouse, scholars also do a lot of work, and some do the research based on intelligent algorithms.

Sun [11] researched the path planning of automated guided vehicle system. He built the map model with graph theory in the process of AGV path planning and searched the shortest path by Dijkstra algorithm. Wang and Feng [12] researched the picking path plan for carousel based on ant colony optimization algorithm. They gave a mathematical model for hierarchical leveled carousel system with single picking station of automatic stereoscopic warehouse and proposed an improved ant colony optimization (ACO) algorithm. Zeng and Zong [13] researched routing optimization of AS/RS based on simulated annealing genetic algorithm. The simulated annealing algorithm and genetic algorithm are combined to solve the AS/RS. Pang and Lu [14] researched the path picking optimization of automated warehouses based on the ant colony generic algorithm. They gave an initial population by the ant colony algorithm and then solved the model with the genetic algorithms. Liu et al. [15] researched dynamic material handling route planning based on real-time operation conditions. They considered the complex and changeable material demand environment of the production system and set up a dynamic material transporting routing optimization model, which considered several demanders and multifarious convey angles. References [16, 17] introduced the RFID technology into the path planning. Chen et al. [16] researched the indoor path planning for seeing robot eyes based on RFID. Guo [17] researched the intelligent navigation and scheduling of vehicles in warehouses. For the requirements of saving time and energy, he used bridging RFID module to take charge of the navigation function. Optimal route was generated by a combinative strategy of topological-index and A^* algorithm.

This paper will introduce RFID technology into large-scale warehousing center, and the use of RFID will make the environment map updated automatically and timely, so the routing optimization problem from starting point to target shelf will be solved more effectively. In the process of route searching, for the ant colony algorithm easy to fall into local optimum, and hard to jump out the U-type or V-type trap, the paper proposes an evolutionary ant colony algorithm based on the prior knowledge, to effectively find the optimal route.

The rest of this paper is organized as follows. Our work environment model is formulated in Section 2. In Section 3, we provide the goal of routing optimization problem and present the definitions of ant colony algorithm's parameters. The detailed steps and flow charts are given in Section 3. In Section 4 the simulation results and analysis of four different algorithms are provided. Finally, we conclude our paper in Section 5.

2. Modeling the Working Environment for Intelligent Vehicle

Modeling the working environment is the first step for the path optimization. A reasonable description of the working environment can decrease the searching steps in the process of searching the optimal path and reduce the complexity on time and space. In this section, we will model the working environment, which is mainly the presentations of obstacles, destination, and action space. Shelves and goods in large-scale storage center may not only be the action destination, but also obstacles, which make the working environment complicated. So to facilitate the following analysis, we use grid method to model the working environment. And some assumptions are given as follows.

(1) Assume the storage to be rectangular, and there are some static obstacles, such as shelves and goods. The reason for the static assumption is that, first, all shelves and immobile goods are static; second, although the goods can be moved, corresponding to the moving vehicle, the moving goods are also static. Therefore, all obstacles are considered to be static. However, the working environment can be changed dynamically after each transport.

(2) The intelligent vehicle is viewed as a particle without size.

(3) Expand each obstacle into a circumscribed rectangle. If the expansion cannot fill a complete grid, then it will be considered as a grid.

(4) Assume the starting point to be fixed, and the destination may be different as the changing of the goods. However, the environment will be updated after goods is moved to the destination, so the destination of the new path optimization problem is still static.

In the following, we will model the working space. Let C denote the whole storage space including all action space and finite obstacles. Define a rectangular coordinate system where the left upper corner is the origin of the coordinate and the upper border of C is x-axis, and the left border of C is y-axis. Let $x_{\max}$ denote the maximum value of the horizontal axis of the point in C, and $y_{\max}$ denote the maximum value of the longitudinal axis of the point in C, so the work space is

$$A = \{(x, y) \mid x \in [0, x_{\max}], y \in [0, y_{\max}]\}. \tag{1}$$

Let R_c denote the maximum length of each action step and divide the domain C into the grids with equality segmentation, and let both lengths of each step in x-axis and y-axis be R_c. The column number of the grid domain is denoted by N_x, and the row number is denoted by N_y. In this paper, we consider the rectangular C to be a square. Let $N_x = N_y$. So, the continuous domain A can give a discrete space A_d defined by

$$A_d = \{(i, j)\, i, j = 0, 1, 2, \ldots, N_x\}. \tag{2}$$

We set the sequence number for each grid, so A_d also can be denoted by

$$A_d = \left\{(x_k, y_k) \mid x_k = \text{fix}\left(\frac{k}{N_x}\right) + 1,\ y_k = k \bmod N_x + 1,\right.$$
$$\left. k = 0, 1, \ldots, N_x^2 - 1\right\}. \tag{3}$$

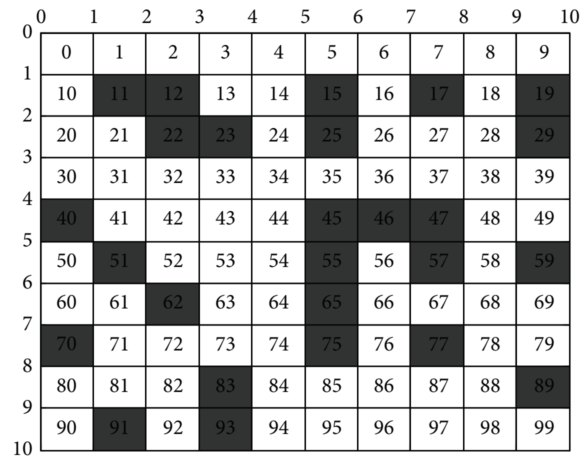

Figure 1: Environment map.

In Figure 1, we give a grid description of a working space with 100 grids. In the grid domain, a black grid denotes an obstacle and a white grid denotes an action space.

3. Modeling for Routing Optimization of Intelligence Vehicle

3.1. Objective Function. We consider a working environment in Figure 1, where the start point is (x_s, y_s), the destination is (x_d, y_d). The routing optimization is to find an optimal route from all feasible paths. The feasible path is a path from (x_s, y_s) to (x_d, y_d) and can avoid possible obstacles. Generally we set the start point to be (x_1, y_1).

We define the path length by Euclidean distance, so the length of an edge with the points $p_i(x_i, y_i)$ and $p_{i+1}(x_{i+1}, y_{i+1})$ is given as follows:

$$d = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}. \tag{4}$$

The path with L grids can be denoted as follows:

$$p_{i_1}(x_{i_1}, y_{i_1}) \longrightarrow \cdots \longrightarrow p_{i_k}(x_{i_k}, y_{i_k}) \longrightarrow \cdots \longrightarrow p_{i_L}(x_{i_L}, y_{i_L}),$$
$$i_1 = 1, \quad i_L = n. \tag{5}$$

Therefore, the total length $D(L)$ of the path is

$$D(L) = \sum_{k=1}^{L-1} \sqrt{\left(x_{i_{k+1}} - x_{i_k}\right)^2 + \left(y_{i_{k+1}} - y_{i_k}\right)^2}. \tag{6}$$

In practical operations, when making a turn the vehicle needs to judge the obstacle, calculate its size and space extent, and relocate the direction, which cost a lot of time and energy, so we should reduce the number of turns as possible as we can. Therefore, the routing optimization problem has two objectives: the least number of turns and the shortest path length. We consider a weighted sum objective function as follows:

$$F1 = \left(1 + \frac{1}{\sqrt{1+L}}\right) \times D \times w_d + \text{curve} \times w_c, \quad (7)$$

where L is the total number of all grids in a path, $D/\sqrt{1+L}$ is a correction item, and curve is the total number of turns. w_d and w_c are the weight, and $w_d + w_c = 1$.

To facilitate the observation and the show of experiment results, we use the following new objective function:

$$F = \frac{100}{\left(1 + \left(1/\sqrt{1+L}\right)\right) \times D \times w_d + \text{curve} \times w_c}. \quad (8)$$

In summary, the path optimization problem can be summarized as the following model:

$$\max \{G(L), L = 1, 2, \dots, I\}$$
$$\text{s.t.} \begin{cases} G(L) = \max\limits_{P} F \\ \text{s.t.} \begin{cases} \left(\theta x_{i_k} + (1-\theta) x_{i_{k+1}}, \theta y_{i_k} + (1-\theta) y_{i_{k+1}}\right) \notin A_O, \\ \qquad \text{for any } \theta \in [0,1], \ i_k, i_{k+1} \in S_a, \\ p = (p_1, p_2, \dots, p_m), p_k = \left(x_{i_k}, y_{i_k}\right), \\ \left(x_{i_1}, y_{i_1}\right) = (x_1, y_1), \\ \left(x_{i_L}, y_{i_L}\right) = (x_d, y_d), \end{cases} \end{cases} \quad (9)$$

where I denotes the total number of feasible grids in the working environment; that is, $I = N_x^2 - s$. Here we set the upper-bound of L to be I, which is just the reason that the path including withdraw steps is not optimal.

3.2. Parameters of Ant Colony Algorithm. When looking for food, ants release special secretions called pheromones on their paths, which will evaporate with time. The later ants will select one path with the probability that is proportional to the intensity of pheromones on the path. When more ants pass through one path, there will be more pheromones released on the path, and then this path will be selected by ants with higher probability. Thus, a kind of positive feedback mechanism is formed by which ants can eventually find the optimal route. The parameters and strategies of basic model of ant colony algorithm are as follows.

Let m be the number of ant colony algorithm.

Definition 1. Tabu table is an array of two dimensions, which records the traversed nodes of each ant. tabu_k records currently traversed nodes of ant k in each generation. When ant k reaches the target point, the route of ant k is just given by the tabu table tabu_k.

Definition 2. $\tau_{ij}(t)$ is the pheromones factor. t represents time and (i, j) represents the path from node i to node j, $(i, j = 1, 2, \dots, n)$. $\tau_{ij}(t)$ represents the retained pheromones of edge (i, j) at time t.

Definition 3. Heuristic factor η_{ij} denotes expectation degree that the ants move from node i to node j and usually is defined as follows:

$$\eta_{ij} = \frac{1}{d_{ij}}, \quad (10)$$

where d_{ij} is the distance between node i and node j.

Definition 4. Let P_{ij}^k be the transition probability with which ant transfers from node i to node j. The definition is as follows:

$$P_{ij}^k = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum_{s \in \text{allowed}_k}\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}, & \text{if } j \in \text{allowed}_k, \\ 0, & \text{else}, \end{cases} \quad (11)$$

where allowed_k (where $k = \{1, 2, \dots, n\}$) represents the set of allowed next nodes which can be selected by ant k on the current environment. α and β denote the degree of importance of pheromones on the path and heuristic factor η_{ij}.

Definition 5. $\Delta\tau_{ij}(t)$ is the pheromone increment. It represents the pheromone increment on edge (i, j) after time Δt. The definition is as formula (12). Generally when initialized, $\Delta\tau_{ij}(0)$ is always set to zero:

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}(t), \quad (12)$$

where $\Delta\tau_{ij}^k(t)$ represents the pheromones increment of ant k on edge (i, j) after time Δt. The definition is as follows:

$$\Delta\tau_{ij}^k(t) = \begin{cases} \dfrac{Q}{L_k}, & \text{ant } k \text{ pass edge } (i, j), \\ 0, & \text{others}, \end{cases} \quad (13)$$

where Q is the enhancing coefficient of pheromones, which affects the speed of convergence to a certain extent; L_k represents the distance of the route which is created by ant k in the current iteration.

Therefore, after the time Δt, the pheromones on each edges can be updated by the following:

$$\tau_{ij}(t + \Delta t) = (1 - \rho)\,\tau_{ij}(t) + \Delta\tau_{ij}(t), \quad (14)$$

where ρ is the evaporating coefficient of pheromones, $1 - \rho$ represents the retain factor. In order to prevent the unlimited accumulation of pheromones, set $\rho \in [0, 1]$.

For the first goal of shortest distance, the basic idea of ant colony algorithm is to place m ants at the starting point at the same time, and each ant selects one feasible node with a certain probability and meanwhile updates the local pheromones. The ants select the next available node with the same strategy until they reach the target point. Thus, the path passed by each ant is a feasible solution and then in accordance with their contribution to the problem they update global pheromones. If the conditions of termination are met, the current optimal solution is output, otherwise the next iteration continues.

About the second goal of reducing the turns of route, the modeling and related strategies will be described in detail in Section 4.

4. Routing Optimization for Intelligent Vehicle Based on Evolutionary Ant Colony Algorithm

4.1. Steps of Ant Colony Algorithm. The general steps for solving the routing optimization problem by ant colony algorithm are as follows.

Step 1 (*initialization*). The ants are placed at the starting point S, and S is added to the tabu list tabu_k. Let the initial pheromones of each side be a constant; $\tau_{ij}(0) = \tau_0/d$ (τ_0 is a constant, d is the distance to the next grid, $d = 1$ or $\sqrt{2}$). Here, we redefine the initial pheromones with the distance factor considered, so it is different from the traditional ant colony algorithm $\tau_{ij}(0) = \tau$. The new definition helps to improve the convergence. Set the current experiment iterations NG = 1; the maximum iterations are NGMAX.

Step 2 (*select the next available node*). In the algorithm we select the next available node j with roulette strategy. At any time t, transfer probability P_{ij}^k from node i to j is as shown in formula (11).

Step 3 (*pheromones update*). After time Δt, the pheromones are updated according to formula (14), and the pheromones evaporating coefficient is adaptive. The pheromones evaporating coefficient is very important when the environment map is complex. If ρ is too small, it is very easy to fall into local optimum solution. If ρ is too large, it will reduce the convergence speed of the algorithm. So in this paper the pheromones evaporating coefficient is dynamically adjusted according to the situation of path length. As formula (15), if the path length of the path set has distinct difference, it will slow convergence speed or, otherwise, accelerate convergence speed:

$$\rho(t) = \frac{D_{\text{ave}} - D_{\min}}{D_{\max} - D_{\min}}, \tag{15}$$

where $D_{\max}$ is the length of the longest path, D_{ave} represents the average length of all paths, and $D_{\min}$ is the length of the shortest path.

Here we also set a limitation for the pheromones evaporating coefficient. The limitation is just to prevent the algorithm falling into local optimum due to the coefficient being too big or too small. Here the maximum and minimum values are given.

Step 4. Set iteration NG = NG + 1. If NG > NGMAX, then go to Step 5; otherwise, adopt elite ant strategy. The ant with best fitness value in this iteration is chosen as the elite ant, which is automatically selected into the next iteration, and thus can increase the impact of the optimal route of the previous iteration and improve the convergence of the algorithm. Go to Step 2.

Step 5. Output the optimal route and the algorithm end.

In order to prevent the ants falling into a U-shaped or V-shaped trap, fallback strategy is adopted in the algorithm. When ants fall into the trap, if there is no good method to deal with the situation, the ants will be in "dead" state that the current feasible node set is empty, so the entire algorithm will be influenced. In the paper when ant k falls into U-shaped or V-shaped trap, we let it back to the previous node, and then the previous node is added to tabu table tabu_k. If now the feasible nodes set is still empty, do backing until the feasible set of ant is not empty.

The whole algorithm flow chart is as shown in Figure 2.

4.2. Strategy of Routing Optimization. As referred to in Section 3.1, routing optimization of intelligent vehicle has two goals: one is the shorter distance, and the second is the fewer number of turns. Inspired by the cultural algorithm, we propose the reducing turns strategy based on the prior knowledge.

The main idea of the cultural algorithm is that in the population space individuals have individual experience during the evolutionary process, and the individual experience will be passed to the belief space through the function Accept(). Individual experience received in belief space will be compared and optimized according to certain rules, thus forming groups experience, and then update the group experience with update() function according to the existing group and individual experience. In belief space, after the formation of the group experience the behavior of individuals in the population space will be modified by Influence() function, in order to enable individuals to achieve higher evolutionary efficiency. The basic framework of cultural algorithm [18] is as shown in Figure 3.

Considering the second goal, we should minimize the turns of the route. This goal can be achieved by the optimization operation based on the a priori knowledge on the route which is obtained during iterations of ant colony algorithm. The optimization operation is the experience update in belief space of cultural colony algorithm. In the belief space the two optimizing operations are based on the a priori knowledge. One operation is abandoning the roundabout and the other is reducing turns by parallelogram strategy.

(1) Strategy of Abandoning the Roundabout. Roundabout will emerge when ants are looking for food, and it will influence the pheromones of the path, which is not conducive for routing optimization, and thus will mislead other ants, so the roundabout makes the algorithm have poor convergence. In order to improve the convergence of the algorithm, the operation of abandoning roundabout must be applied to the current route. Set the grid number of one path to be Ln; calculate the allowed nodes set for the current node. If the next nodes (except the first next node of the current node)

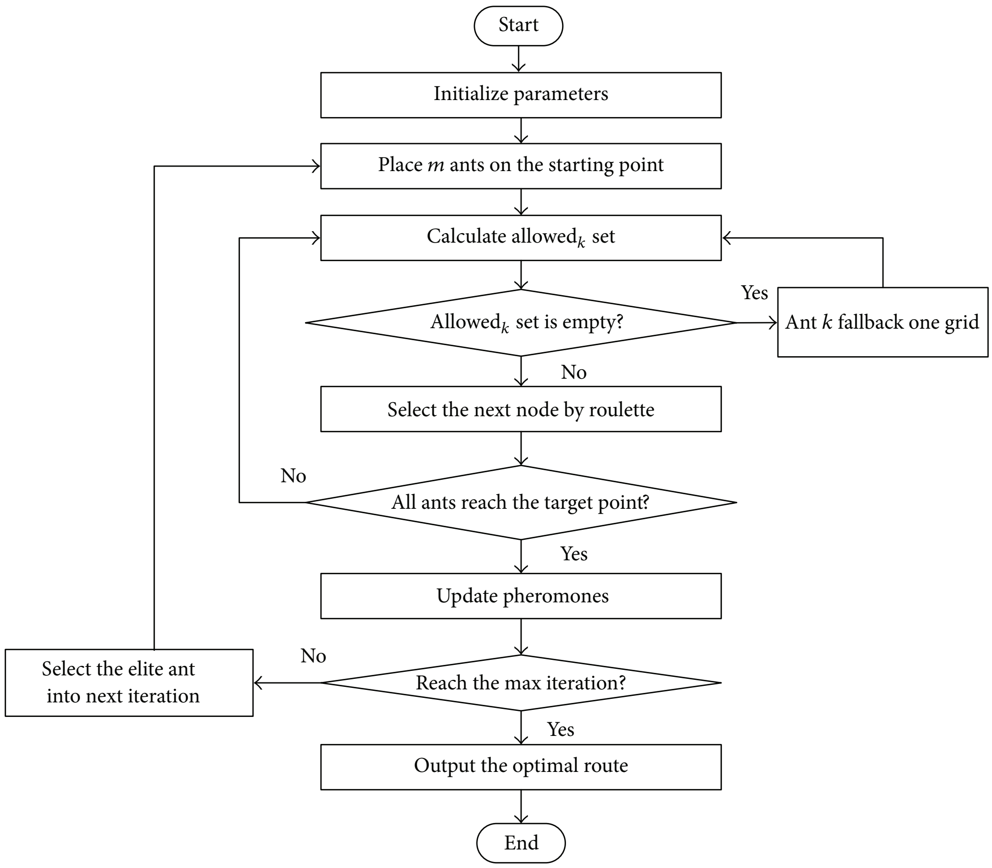

Figure 2: Flow chart of ant colony algorithm.

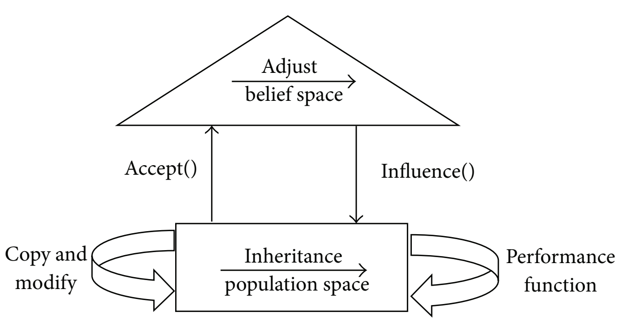

Figure 3: Basic framework of cultural algorithm.

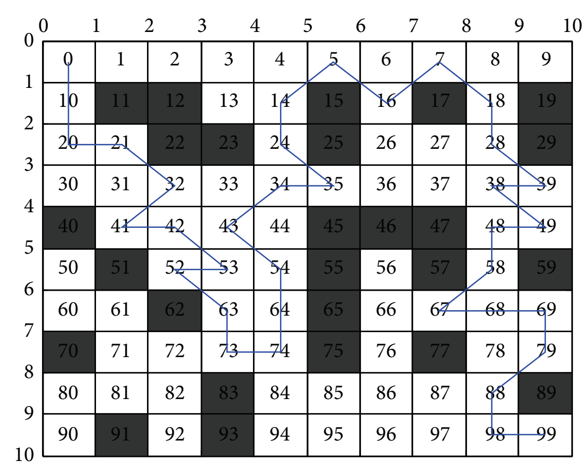

Figure 4: Route before abandoning roundabout.

after current node are in the allowed nodes set, you can delete the nodes between the current node and the next node directly from the circuitous path, and then the quality of the path will be improved. Figure 4 shows the original circuitous path. For node 32, its allowed node set is (31, 33, 41, 42, 43). Except the next node 41, we find node 43 in the next nodes set and also in the allowed nodes set, so the path between node 43 and node 32 can be deleted. The new route after the optimization is shown in Figure 5. From Figure 4 and Figure 5 we can see the quality of the route is significantly improved after the operation of abandoning roundabout and the number of turns is effectively reduced also. The flow chart of optimization operation for abandoning the roundabout is shown in Figure 6.

(2) Strategy of Reducing Turns by Parallelogram. The strategy is to reduce the number of vehicle turns and thus can reduce

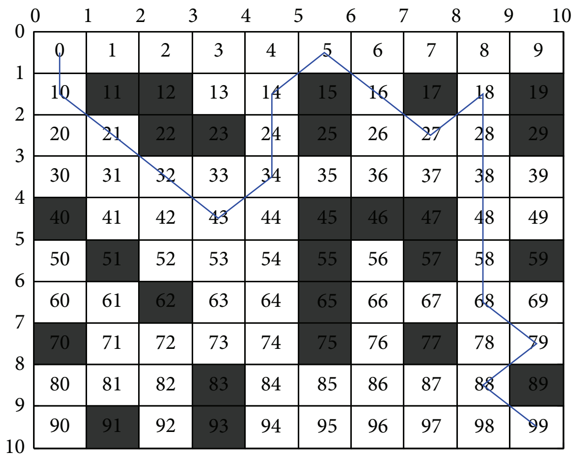

FIGURE 5: Route after operation of abandoning roundabout.

the vehicle's walking energy consumption and improve the fitness value of route. Select three consecutive nodes: the connection between the first node and the previous node on the route forming segment 1 and the connection between second and third node forming segment 2. When segment 1 and segment 2 are parallel, draw a parallelogram with the three nodes as the three vertices of the parallelogram, and then we will get two new segments which are not on the original route. If the grids passing by the new segments are all free grid, then the two original segments on the route will be deleted, the two new segments replace the original, and a new route then comes up. Obviously, the new route has less turns than the old one. The map and the original route are shown in Figure 7. We explain the strategy in detail taking nodes 10, 43, and 63, for example. Segment 1 between nodes 0 and 10 parallels segment 2 between nodes 43 and 63, so draw up a parallelogram with nodes 10, 43, and 63 as the three vertices of the parallelogram. Then, two new segments come up. One is segment between nodes 10 and 30, the other is the one between nodes 30 and 63. The grids passing by the two new segments are all free grid, so the two old segments are substituted by the two new ones. Then the new route comes up and is as shown in Figure 8. From Figure 7 and Figure 8 we can see after the optimization of reducing turns by parallelogram that the new route has less turns and higher fitness value than the old one. The flow chart of optimization operation for reducing turns by parallelogram is shown in Figure 9.

4.3. Steps of Evolutionary Ant Colony Algorithm. The integration of Sections 4.1 and 4.2 is the whole evolutionary ant colony algorithm. The algorithm takes the ant colony as the population space and the optimization for the route with operation of abandoning roundabout and reducing the turns by parallelogram based on the a priori knowledge as the group experience updating of belief space. The main steps of the evolutionary ant colony algorithm for routing optimization are as follows.

(1) In the population space the route set is generated by ant colony algorithm, and each route with individual experience is delivered to the belief space.

(2) In the belief space all the routes are optimized by strategies of abandoning roundabout and reducing turns by parallelogram based on the a priori knowledge and thus form the groups experience.

(3) The optimized routes are delivered back to the population space to update the pheromones. Repeat steps (1)–(3) until the end condition of the algorithm is satisfied.

The flow chart of evolutionary ant colony algorithm is as shown in Figure 10. Specific operation is as follows.

(1) Population Space. Detailed operation steps in population space are as follows.

(1) Build model for working environment of intelligent vehicle by grid method. Obtain information of the current environment through RFID technology and then build the current environment map. Determine the starting point and the destination point.

(2) Parameter initialization for ant colony algorithm. Set the initial value of iteration, initial time, initial pheromones, tabu list, and so forth.

(3) According to the ant colony algorithm mentioned in Section 4.1, select nodes and update pheromones, and generate corresponding route set for m ants.

(4) Deliver the route set to the belief space by Accept() function.

(5) Receive the updated route set from the belief space by Influence() function.

(6) Global pheromones are updated.

(7) Judging the termination conditions. If the condition is not satisfied, go to step (8). If satisfied, output the optimal route and the intelligent vehicle advances according to the route through the assistance of RFID. During the process of returning starting point from target point the environment map is updated through RFID technology timely and intelligent vehicle preparing for the next goods handling.

(8) The number of iterations $t = t + 1$; go to step (3).

(2) Belief Space. Detailed operation steps in belief space are as follows.

4.4. Evolutionary Genetic Algorithm. For the problem of routing optimization, coupled with the a priori knowledge is a very effective method. In order to verify this conclusion, apply the a priori knowledge into genetic algorithm. Also based on the framework of cultural algorithm, genetic populations are the population space, and in the belief space group experience is updated based on the a priori knowledge. The algorithm is called evolutionary genetic algorithm. The routing optimization for intelligent vehicle is mainly involved in the following

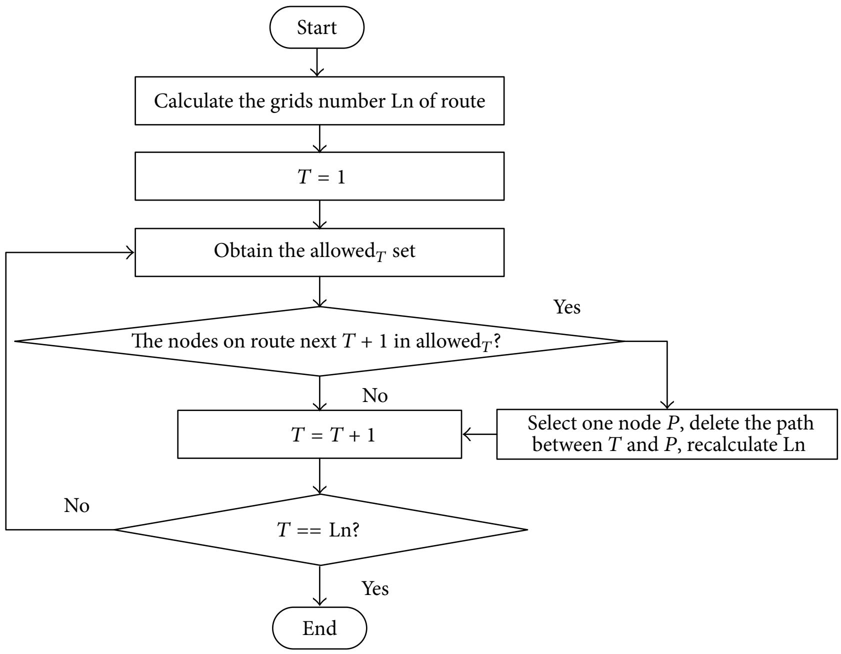

Figure 6: Flow chart of abandoning the roundabout.

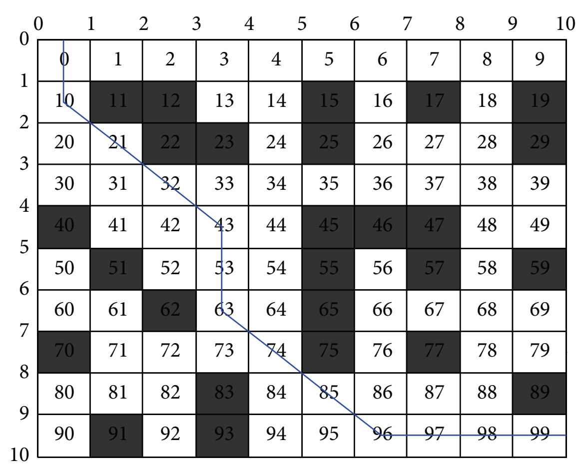

Figure 7: Original route before reducing turns.

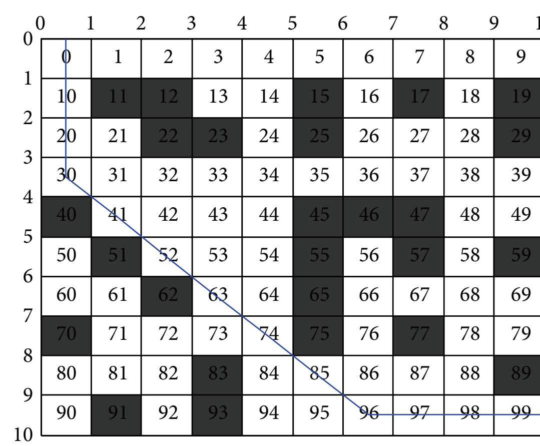

Figure 8: Route after reducing turns by parallelogram.

points: (1) initializing the population, giving the original route set in the feasible region, (2) giving appropriate fitness function combined with the actual working environment of the intelligent vehicle, (3) according to different situations of population adaptive genetic algorithm selecting appropriate crossover and mutation operator, and (4) keeping the diversity of the population in the belief space. Flow chart of evolutionary algorithm is shown in Figure 11. Specific steps of algorithm are as follows.

(1) Population Space

(1) Initializing the genetic algorithm, setting the iteration number $T = 1$.

(2) Modeling for working environment of intelligent vehicle by grid method, obtaining the feasible route set and set it as the initial population of genetic algorithm.

(3) According to the fitness function to calculate each individual's fitness value, do the selection operation for the population with roulette selection, adopt elitist kept strategy, and generate new populations.

(4) Do the single point crossover operation on the adjacent chromosomes to generate new individuals.

(5) Do mutation operation on part of individuals with mutation probability to produce new individuals.

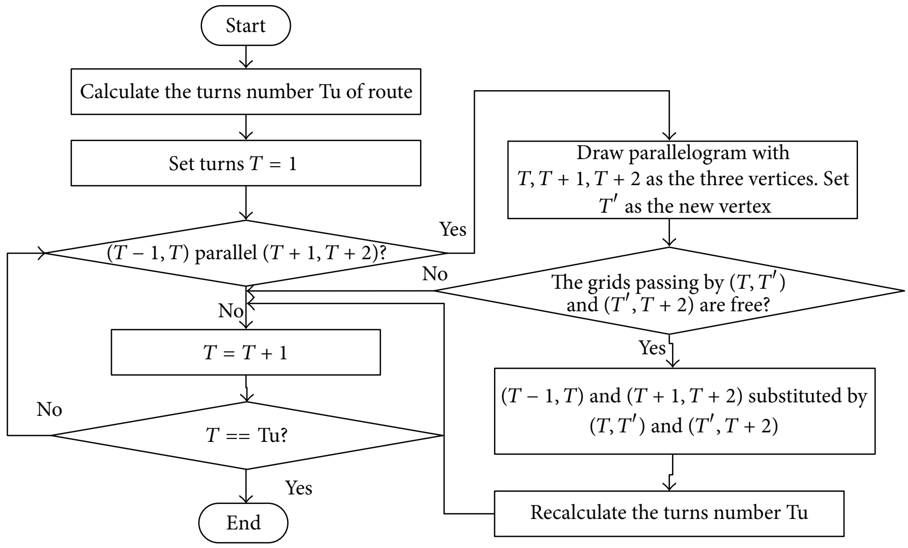

FIGURE 9: Flow chart of reducing turns by parallelogram.

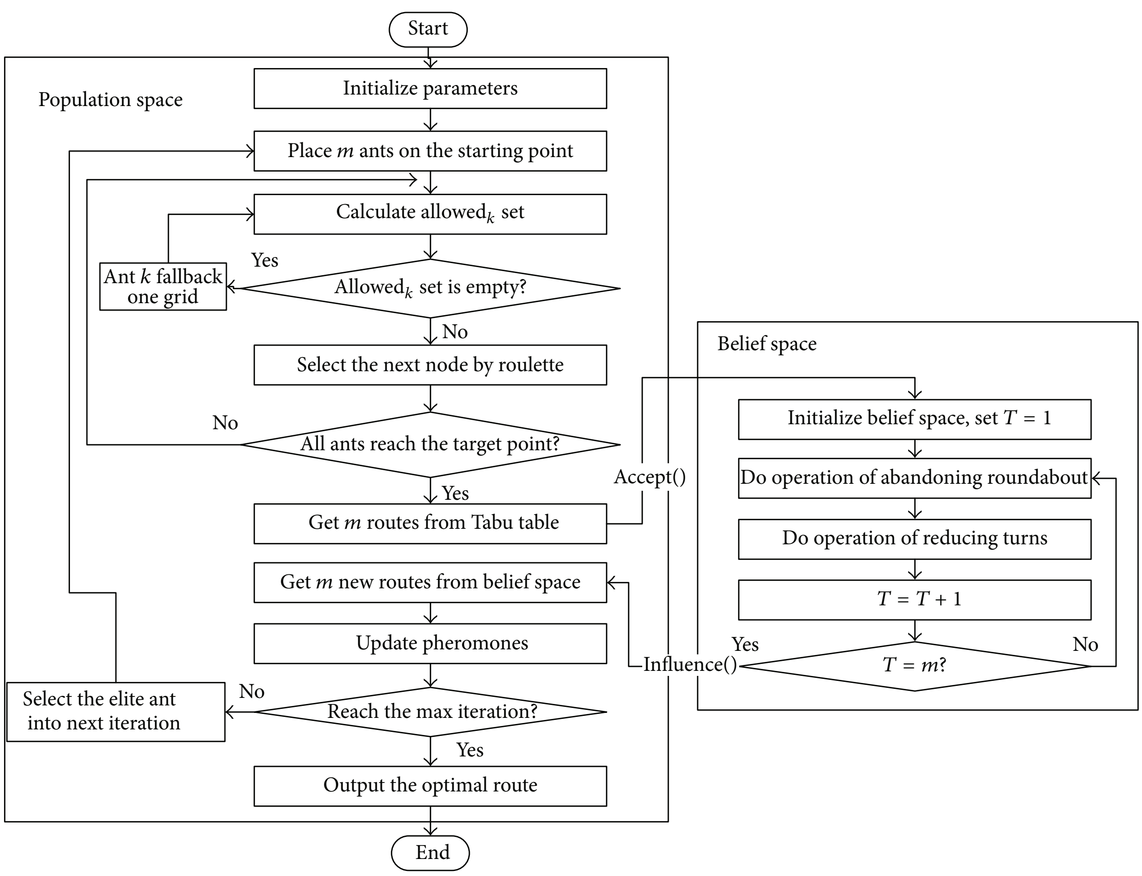

FIGURE 10: Flow chart of evolutionary ant colony algorithm.

(6) The new population is delivered to the belief space by Accept() function.

(7) Receive the new generation of population by Influence() function of belief space.

(8) Judging the conditions for termination $T < t\max$, if the termination condition is satisfied, output the best individual.

(9) $T = T + 1$, go to step (3).

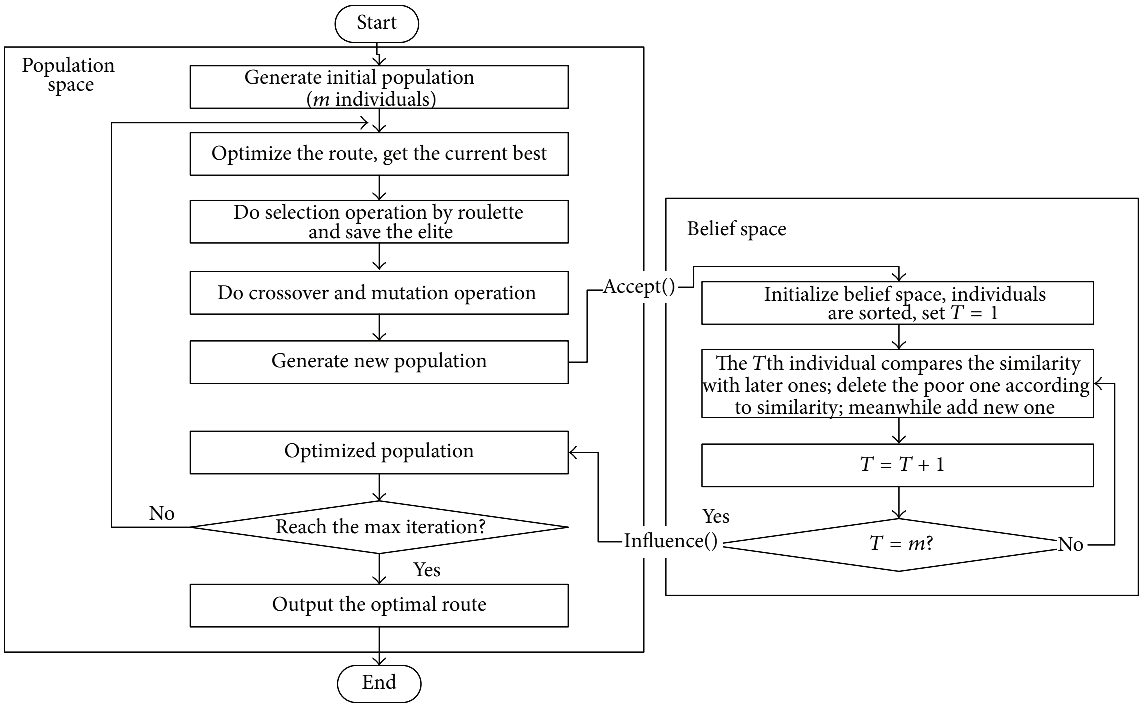

Figure 11: Flow chart of evolutionary genetic algorithm.

(2) Belief Space. The steps in belief space are as follows: the population after selection, crossover, and mutation of population space is delivered to belief space; the individuals with fitness value less than a certain threshold in the population do similarity comparison with each other; if the similarity is greater than a certain threshold, then the individuals with lower fitness value are deleted and randomly generate a new individual to join the populations. When comparison finishes the new populations return to population space.

5. Simulation

5.1. Simulation Environment and Parameter Settings. In order to study the efficiency of evolutionary ant colony algorithm for intelligent vehicle searching optimal route, a lot of simulation experiments are done. The hardware environment of simulation: Processor Core (TM) i3-2120, CUP 3.30 GHz, RAM 6 GB, 64-bit operating system, and hard disk 500 GB. Operating system is Windows 8, and Matlab 7.10.0 is the programming tool. Environment map can be changed as the actual environment change. Here we select three maps with $20*20$ grids, $50*50$ grids, and $100*100$ grids. All parameters are as shown in Table 1, where m represents the number of ants, α and β represent, respectively, the importance of the pheromones and heuristic factor, ρ represents the global pheromones evaporation coefficient, τ_0 represents the initial value of pheromones, and Q represents intensity factor of pheromones.

5.2. Simulation Results. The environment mapI is as shown in Figure 12. The start point is S, and the destination point is G. We make the comparison with four algorithms: the evolutionary ant colony algorithm (EAC), the ant colony genetic algorithm (AC-GA) in [8], the improved ant colony algorithm (SA-AC) in [10], and the evolutionary genetic algorithm (EGA). There are two algorithms (EAC and EGA) based on experiential knowledge. The four algorithms all run 50 times; randomly select one result; the optimal fitness convergence results are as shown in Figure 13. We can see

Table 1: Parameters of evolutionary ant colony algorithm.

m	α	β	ρ	τ_0	Q
20	0.6	0.8	0.3	10	100

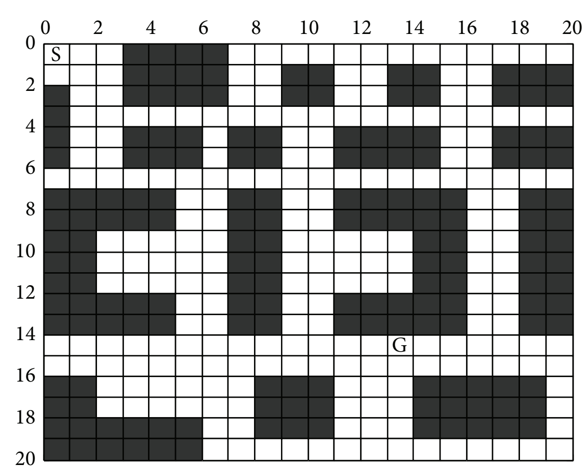

Figure 12: Environment map I.

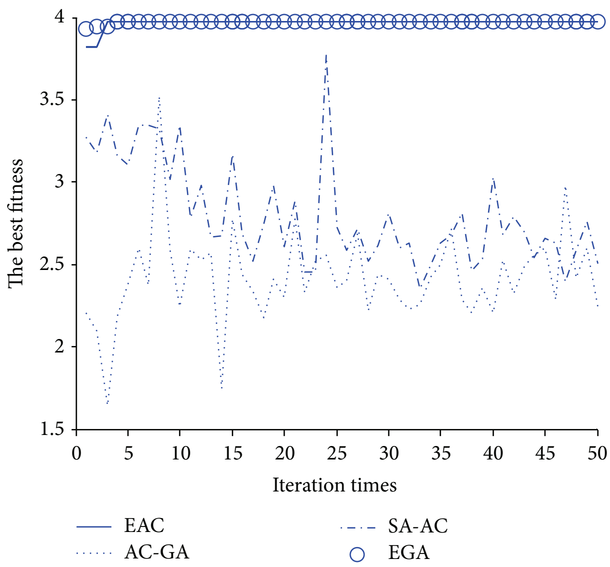

Figure 13: Convergence curves about the optimal fitness on map I.

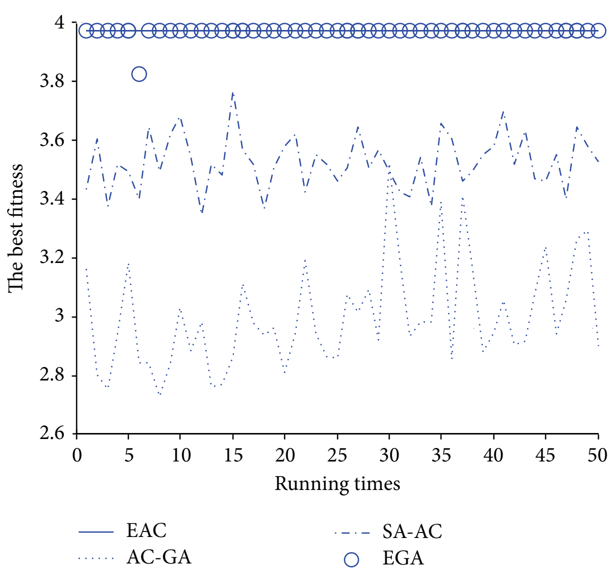

Figure 14: Convergence curves about the optimal fitness running 50 times on map I.

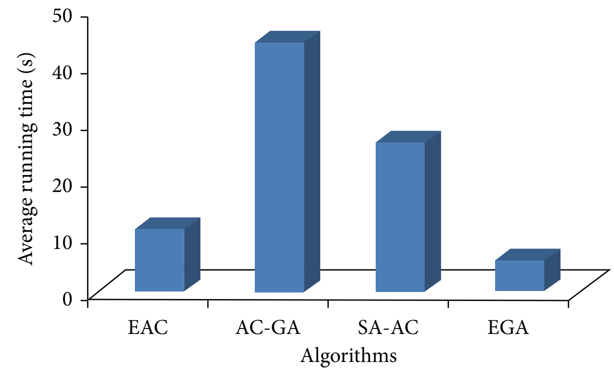

Figure 15: Comparison of average running time on map I.

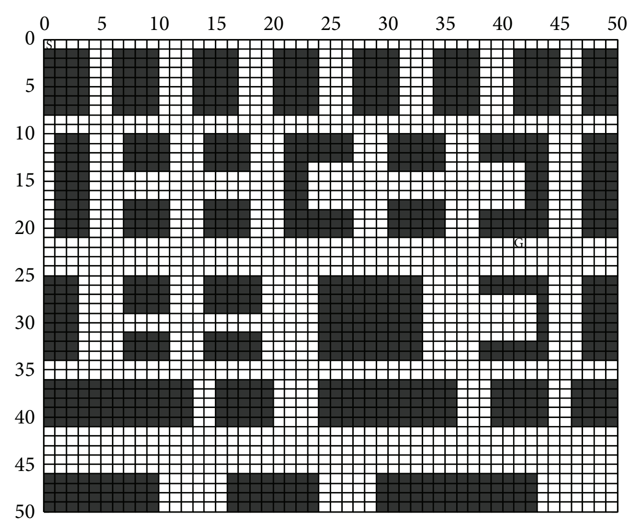

Figure 16: The working environment map II.

from Figure 13 EAC algorithm has the highest efficiency and the best convergence. Although EGA also can find the optimal route, its convergence speed is slower than EAC algorithm. The AC-GA algorithm and the improved SA-AC algorithm can hardly find the optimal route and have poorer convergence than the evolutionary algorithms.

The comparison of four algorithms on fitness value of 50 times is as shown in Figure 14. We can see that the EAC algorithm can find the optimal route every time, and the EGA can find the optimal route with high probability. The AC-GA algorithm and the SA-AC algorithm cannot find the optimal route yet, and their fluctuations are relatively large, but they all can find the approximate optimal route. We also compare the average running time of four algorithms, and the result is as shown in Figure 15. From Figure 15 we can see that EAC and EGA run faster than AC-GA and SA-AC. EGA is the fastest and AC-GA is the lowest. In summary, the EAC algorithm is the most effective one.

We do a lot of simulation experiments with 30 different environment maps and have the same conclusion. Randomly select another two maps as shown in Figure 16 is $50 * 50$ map, and Figure 17 is $100 * 100$ map. The experimental comparison results of map II are as shown in Figures 18, 19, and 20, and the comparison results of map III are as shown in Figures 21, 22, and 23. The experimental results prove that the EAC algorithm has the highest optimal searching efficiency and best convergence. The EGA has the shortest running time. The more complex the working environment maps are, the more superior the EAC is. In summary, EAC algorithm is a feasible and an effective algorithm for routing optimization of automated vehicle.

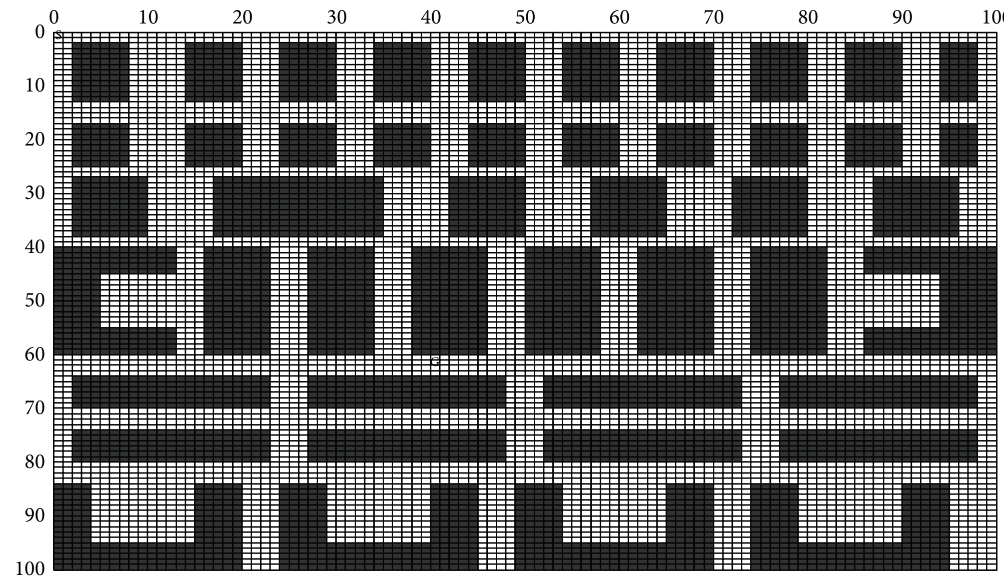

Figure 17: The working environment map III.

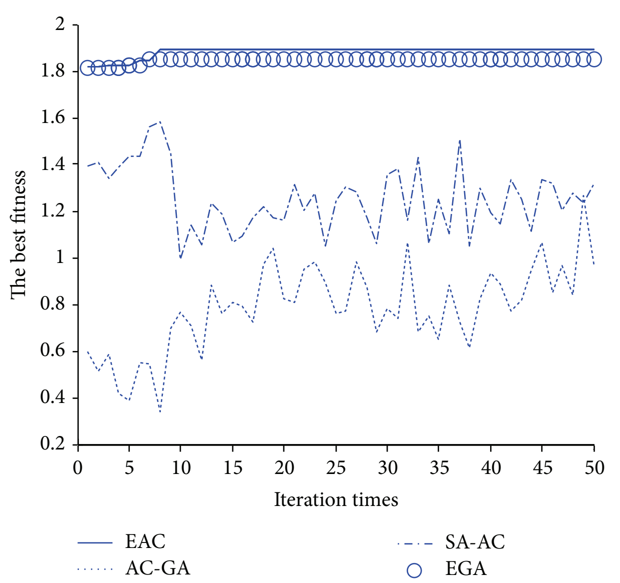

Figure 18: Convergence curves about the optimal fitness on map II.

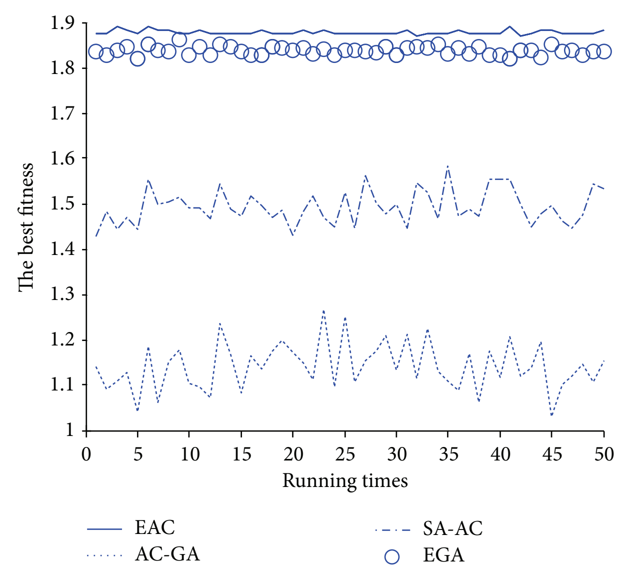

Figure 19: Convergence curves about the optimal fitness running 50 times on map II.

6. Conclusion

Intelligent vehicle is one of the most crucial parts of the whole logistics automation and production automation, in which the routing optimization is one key technology. In the paper we study the route searching problem based on evolutionary ant colony algorithm with RFID technology. We first build the environment map and give the target goal. When searching the optimal route in order to overcome the defect of traditional ant colony algorithm, such as easy falling into local optimum and slow convergence, based on the experiential knowledge, we propose an evolutionary ant colony algorithm.

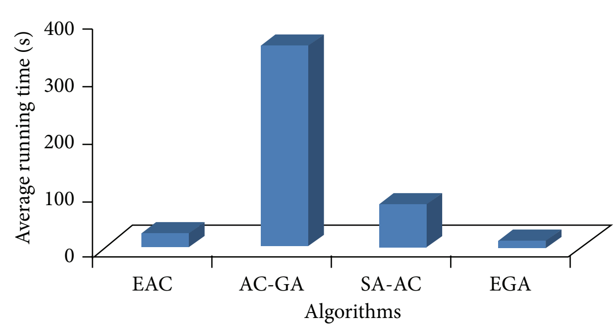

Figure 20: Comparison of average running time on map II.

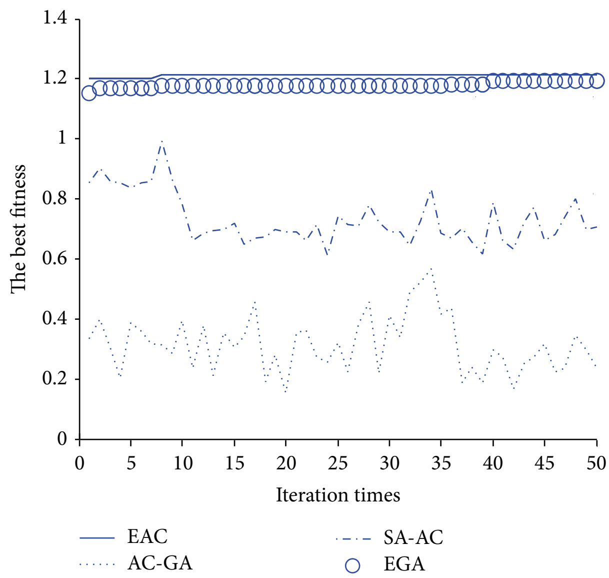

FIGURE 21: Convergence curves about the optimal fitness on map III.

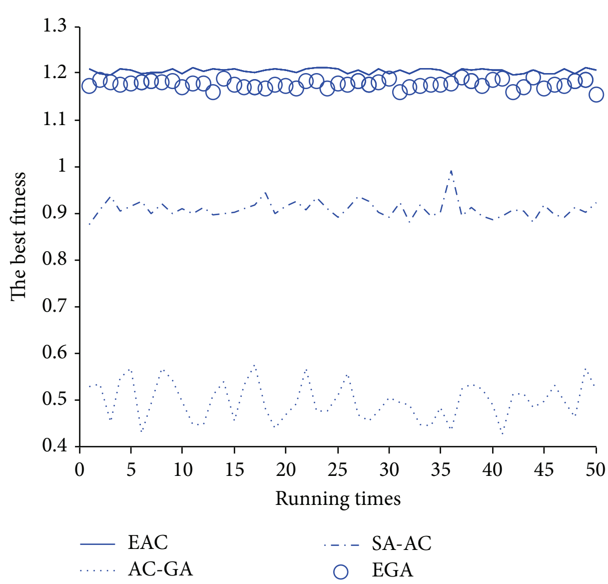

FIGURE 22: Convergence curves about the optimal fitness running 50 times on map III.

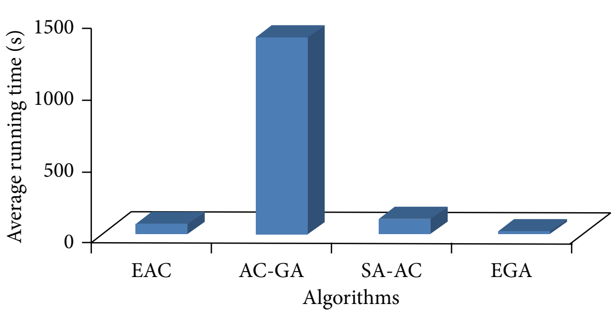

FIGURE 23: Comparison of average running time on map III.

The new algorithm adopts elite ant strategy, ant fallback strategy, and pheromones evaporation coefficient adaptive adjustment strategy which is proved feasible and effective. When the groups experience is updated, the optimizing operations of abandoning roundabout and reducing turns by parallelogram based on experiential knowledge are done. A lot of experimental results show that the new algorithm is practical and efficient. It is also proved that the algorithm has a high convergence speed and can find the optimal route with higher probability. Due to the fact that the actual working is more complex, how to use the advanced technology to help the vehicle obtain more information timely and dynamically avoiding obstacles is still worth researching.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

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