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A Hybrid Genetic-Ant Colony Optimization Algorithm for the Optimal Path Selection

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ABSTRACT

The shortest path problem lies at the heart of network flows that seeks for the paths with minimum cost from source node to sink node in networks. This paper presents a hybrid genetic-ant colony optimization algorithmic approach to the optimal path selection problem. First, some existing solutions for the optimal path selection problem are analyzed, and some shortages and flaws are pointed out. Second, the data organization method for road network based on the graph theory is proposed. Furthermore, the optimal path selection algorithm integrated of sinusoidal probability transfer rules, pheromone update strategy and dual population is presented. Finally, the experimental results show that the proposed algorithm speeds up the convergence rate and improves the efficiency.

KEYWORDS

The optimal path selection; Genetic algorithm; ACO

1. Introduction

The traditional optimal path is a combinatorial optimization problem and a NP conundrum (Non-deterministic Polynomial Problem) (Ahn & Ramakrishna, 2002; Duque, Lozano, & Medaglia, 2015; Zhou, Yang, & Wang, 2014). There are three main kinds of optimal path problems: One is seeking the shortest path between given spot to another in the graph, the second is seeking the shortest path between given spot to more in the graph, the third is seeking the distance between two passing points, which are the main form of the optimal path application in the emergency geographic information service (Dorigo & Stützle, 2003; Jaillet & Porta, 2013; Siddiqi, Shiraishi, Dahb, & Sait, 2014). At present there are some classical algorithms to solve such problems such as Dijkstar algorithm, A * algorithm and Flyod algorithm, etc. (Blum, 2005; Bolívar, Lozano, & Medaglia, 2014; De Carufel, Grimm, Maheshwari, Owen, & Smid, 2014).

The optimal path problem is always a hot research topic with common attention in subjects such as the computer science, operations research, geographic information science and mobile robot navigation(Devaurs, Siméon, & Cortés, 2015; Tan, He, & Sloman, 2007; Zhang, Lin, Liu, & Shen, 2011). A large number of experts and scholars all over the world have done a great deal of studies on this issue (Donati, Montemanni, Casagrande, Rizzoli, & Gambardella, 2008; Lin, Zhang, & Shen, 2012; Lolla, Lermusiaux, Ueckermann, & Haley, 2014; Xu, Liu, Zhang, Wang, & Sun, 2015). At present, the algorithms using simple spatial geometry theory to planning the path are almost mature. With the effective combination between the classic graph theory and continually developed computer data structures and algorithms, the new optimal path algorithms are constantly emerging, which have different characteristics in space complexity, time complexity, ease of implementation and application scope (Juang & Wang, 2009; Sidek & Quadri, 2012; Zhou et al., 2014).

To analyze the optimal path of road network, the first must abstract the reality of road network entity into the network chart in graph theory, and then realize the road network optimal path analysis through the network analysis theory in graph theory. In practical applications, the manifestation of road network is usually as the digital vector map, but in order to analyze the optimal path efficiently it must be abstracted as the structure of the graph according to the relationships between nodes and arcs at first.

Genetic algorithm (GA) has fast global search capability without making full use of the feedback information in the system leading to redundancy iteration (Ghoseiri & Nadjari, 2010; Lounis, Aissa, Rabia, & Ramoul, 2013; Pham, 2014). Ant colony optimization converged at the optimal path through the accumulation and update of pheromones, but slowly (Azimirad & Shorakaei, 2014; Barb & Shyu, 2012; Mohamed, Bassem, & Taicir, 2010; Sun, Duan, Sun, & Yang, 2014). This paper inspired by ACO and GA algorithms puts forward a new kind of optimal path method with fusing GA algorithm and ACO algorithm. This algorithm introduced the ant genetic operator in the ant colony optimization algorithm to get better quality solution.

2. The data organization of road network

Road network is an important part of the intelligent transportation system and the data base of all kinds of network analysis functions, such as optimal path searching, map matching, etc. The graph researched in the Graph theory is a binary relation defined in the vertex set. The definition is:

$$G = (V, E) \tag{1}$$

Where V stands for Node set, $V = \{V_1, V_2, \ldots, V_n\}$, n is the number of nodes in the graph. E is the set of all edges in the graph $E = \{e_1, e_2, \ldots, e_m\}$ and m stands for the number of the

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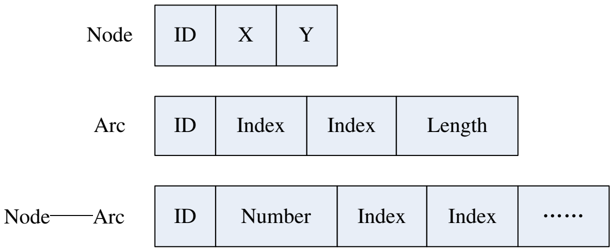

Figure 1. Data Structure of the Road Network.

edges in the graph. Edge e_i is a kind of point team, which is essentially made up of all the points in V that is $e_i = (V_{i1}, V_{i2})$. Every edge is the direct path between every adjacent node.

In the road network model, it also needs to figure the edges assignment; the value may represent all sorts of different meanings of the edge, or the length of the edge, or the time spent passing through edge. Let's define the value of edge e_i as a_i, then

$$E = \{(e_1, a_1), (e_2, a_2), \ldots, (e_m, a_m)\} \quad (2)$$

Provide

$$A = \{a_1, a_2, \ldots, a_m\} \quad (3)$$

Then the road network model is a three-element group

$$G = (V, E, A) \quad (4)$$

As shown in Figure 1, the data structure of road network basically consists of node, three-arc-sect and node-three-arc-sect. The information of the road is stored in the node, including the Node ID and the information of spatial location (x, y) of the node. Three-arc-sect consisting of Three-arc-sect ID, Three-arc-sect Two-node index, and Three-arc-sect Length describes the topological relations of the edge and the node. The node-three-arc-sect which consists of the node-three-arc-sect ID, the number of the adjacent edges of the node and the Three-arc-sect ID, describes the topological relations of the node and the edge, reflecting the connected relation of the graphs. According to the node-three-arc-sec graph, it is very easy to find the arc adjacent to the node, so it improves the efficiency of the Algorithm for the best path.

3. Ant colony optimization

In the 1990s, inspired by the mechanism of biological evolution, the Italian scholars Dorigo, Maniezzo and Colomi etc., put forward a new simulation algorithm, which is called the ant colony algorithm after simulating ants searching for the diameter (Dorigo, Maniezzo, & Colorni, 1996). And the new algorithm is presented to solve the Traveling Salesman Problem (Traveling Salesman Problem, TSP), distribution, homework scheduling Problem, network routing Problem and so on, which has made a series of good experimental results.

3.1. The principle of ant routing

After a long time of researching and observing, bionomists observed that although having no vision, the ant colony will pass on the path by releasing a special secretion (pheromones) to look for the path. Ant colony algorithm has two key strategies; the ants' procedural rules and pheromone update strategies. This paper improves the efficiency of the algorithm by improving the transfer rules and pheromone update strategies, and by using the double-population ant colony.

3.2. Transfer rules

Standard ant colony algorithm is calculated through the state transition probability to choose a node. Ants in the search process, calculate the state transition probability according to the amount of information on various paths and the inspiration of information. The expression $p_{ij}^k(t)$ indicates the state transition probability that the ant k transferred from the node i to the node j at the moment t, and its expression is:

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \times [\eta_{ij}(t)]^\beta}{\sum_{s \in allowed_k} [\tau_{is}(t)]^\alpha \times [\eta_{is}(t)]^\beta} & j \in allowed_k \\ 0 & \text{Otherwise} \end{cases} \quad (5)$$

In this formula, $allowed_k = \{0, 1, \cdots, n-1\} - tabu_k$ shows the node that the ant $k(k = 1, 2, \cdots, m)$ is allowed to choose in the next step; $tabu_k$ shows the taboo table of the ant k, to record the current node that the ants have passed through; n means the number of nodes; τ_{ij} expresses the residual pheromone strength on the path between node i and node j at the moment t, in order to simulate the real ants secretions; η_{ij} calculating through some kind of heuristic algorithm stands for the said visibility of the edge (i, j), using the expression $\eta_{ij} = \frac{1}{d_{ij}}$ generally, in which d_{ij} expresses the distance from node to node j; α, the information heuristic factor, means the relative importance of track, reflecting that the information accumulated by ants plays an important role in its athletic process; β, the desirable heuristic factor, means the relative importance of visibility, reflecting the great value that heuristic information has in choosing the path while ants are moving.

Standard ant colony algorithm rules are well-applied to the transfer of TSP. This transfer rules apply to complete charts, while the number of nodes' adjacent edges in the road network is no more than five, and the length of each adjacent edge is quite different. If we use the probability transfer rules to identify a node, it will be easy to get into local optimal solution.

It is one of the key points for the research of the ant colony algorithm that the ant moves along different nodes according to the transfer rules, and establishes a balanced point between "discovery" and "use". To define two intelligent agents, namely the positive ants and the reverse ant, the positive ants $F_{s \to d}$ move from the source node towards the purpose node, and the reverse ants $F_{d \to s}$ move from the purpose node to the source node. The positive ants mainly use the path "explored" by the information element on the road network to collect information of road network; the reverse ant mainly "use" positive ants' information to update road network. Therefore, positive ants take a different transfer rules from the reverse ant.

When the positive ant $F_{s \to d}$ reaches its destination node, the positive ant $F_{s \to d}$ will create another reverse ant $F_{d \to s}$, and make all its memory transferred to the reverse ant, but its own will be deleted. When the reverse ant $F_{d \to s}$ returns to the destination node, the reverse ant $F_{d \to s}$ will generate another positive ant $F_{s \to d}$. At this time, the positive ant $F_{s \to d}$ doesn't have any memory, and the reverse ant $F_{d \to s}$ will be deleted.(1)

(1) The forward ants

The positive ants $F_{s \to d}$ transfer rules are determined according to Benzatti's formula:

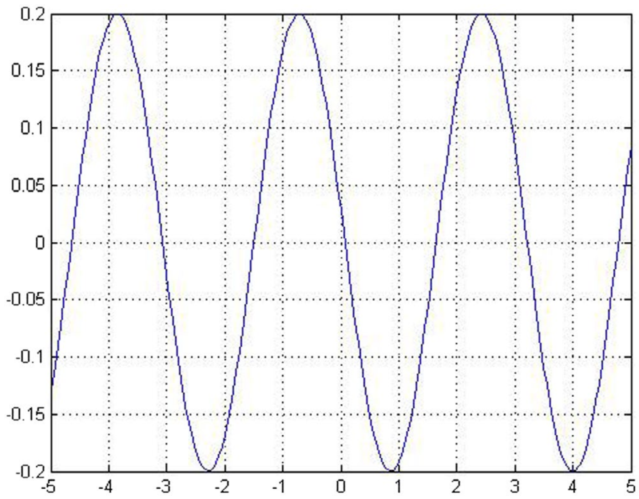

Figure 2. Positive Ants Transition Probability Curve.

$$T(\tau_{ij}) = \alpha_k \times \sin(\beta_k \times \tau_{ij} + \gamma_k) \tag{6}$$

In this formula, $\alpha_k, \beta_k, \gamma_k$ are correlation coefficients, generating at random. Their values are real numbers between −5 and 5. When $\alpha_k = 0.2$, $\beta_k = 2$, $\gamma_k = 3$,$T(\tau_{ij})$ changing with the curve τ_{ij} as shown in Figure 2, in which horizontal axis means τ_{ij} and vertical axis means $T(\tau_{ij})$, is the Sinusoidal whose cycle is $\frac{2\pi}{\beta_k}$. As it can be seen above, it isn't the greater the residual strength of pheromone τ_{ij} is, the bigger $T(\tau_{ij})$ is, and this kind of transfer rule not only maintains the randomness of the ants' selecting the next node, but also guarantees the determination of the next node based on residual strength of the pheromone intensity within a certain residual pheromone range.

(2) The backward ants

The path of the reverse ant $F_{d\to s}$ is the same as the one of its corresponding positive ant $F_{s\to d}$, just marching in opposite directions, along the same path in the opposite direction to return to the source node.

3.3. Pheromone update strategy

After the ant takes a step, the pheromone on the path will update and change. The change of the pheromone is divided into two parts; one is that the pheromone will volatilize with the time changing, and the other is that ants will release some pheromone on the path they passed through.

In standard ant colony algorithm, after the moment Δt when the ant completes a cycle, pheromone on each path will be adjusted according to the following formula:

$$\tau_{ij}(t + \Delta t) = (1 - \rho) \times \tau_{ij}(t) + \rho \times \Delta\tau_{ij}(t) \tag{7}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^k \tag{8}$$

In this formula, ρ is the pheromone evaporation coefficient. In order to prevent the unlimited accumulation of pheromone, ρ values the real number between 0 and 1, $\Delta\tau_{ij}^k$ means the amount of information that ant k left on the path ij in this principal and interest cycle, $\Delta\tau_{ij}(t)$ means the amount of information increment during the cycles.

The calculation method of $\Delta\tau_{ij}^k$ can be depended on the calculation model. Dorigo once gave three different calculation models (Dorigo et al., 1996), and they were an ant-cycle system, ant-quantity system and ant-density system.

In ant-cycle system $\Delta\tau_{ij}^k$ is:

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L_k} & \text{if the kth ant uses edge}(i, j) \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

In ant-quantity system $\Delta\tau_{ij}^k$ is:

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{d_{ij}} & \text{if the kth ant uses edge}(i, j) \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

In ant-density system $\Delta\tau_{ij}^k$ is:

$$\Delta\tau_{ij}^k = \begin{cases} Q & \text{if the kth ant uses edge(i,j)} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

Their difference is that the latter two models use the local information, while the first one uses the whole information, which performs better in solving problems about TSP, and which is often chosen as a basic model.

The optimal path of the road network related closely with the network topology relation. The structure of the road network is very complex, and number of the road network node and the three-arc-sects is very large. Using the pheromone update strategy above is easy to make the ant converge to the same path prematurely.

Di Caro designed the algorithm of Ant Net, inspired by the ant colony algorithm, in order to solve the problem of routing in the communication network (Di Caro, 2004), it's the expansion of ant colony algorithm. The optimal path selection problems of road network is very similar to the problems of communication network routing, both are incomplete figures. The number of the adjacency three-arc-sect of each node is small. The latter one chooses the road with link bandwidth regarded as the core, while the former one chooses the path with the path cost regarded as core way. Here we apply the pheromone update strategy of the Ant Net algorithm into the optimal path algorithm of road network.

Define data structure $M_k(\mu_d, \sigma_d^2, W_d)$ at node $k$in the road network, and update it according to the following formula:

$$\begin{cases} \mu_d \leftarrow \mu_d + \eta(O_{k\to d} - \mu_d) \\ \sigma_d^2 \leftarrow \sigma_d^2 + \eta((O_{k\to d} - \mu_d)^2 - \sigma_d^2) \end{cases} \tag{12}$$

Among them, μ_d and σ_d^2 are the mean value and variance of the distance that positive ants move from node $k$to d; $O_{k\to d}$ is the distance that positive ants move from node k to destination node d; η which is a weighted constant, is used to estimate the weight of the sample μ_d and its values are the real numbers between 0.2 and 0.4; W_d is the window of the best value for the distance from node k to d, and only when the distance from node k to d is satisfactory (namely the distance is less than $\mu_d + I(\mu_d, \sigma_d^2)$, $I(\mu_d, \sigma_d^2)$ to μ_d is confidence interval estimate), W_d will be updated.

When reverse ants $F_{d\to s}$ return from the destination node, if f is the next marching node, and the current node is k, then the pheromone strength of the side kf can be updated according to the following formula:

$$\tau_{kf} \leftarrow (1 - r)\tau_{kf} + r \tag{13}$$

If i is not the next node, and the current node is k, then the pheromone strength of side can be updated according to the following formula:

$$\tau_{kf} \leftarrow (1-r)\tau_{kf} \tag{14}$$

Among them, r is a positive strengthen of the side kf that the ants passed by, it is a factor of quality of travel distance $T_{k\to d}$ that positive ants moved from node k to node d.

r is given according to the experience of the formula:

$$r = c_1 \times \frac{W_{best}}{T_{k\to d}} + c_2 \times \frac{I_{\sup} - I_{\inf}}{(I_{\sup} - I_{\inf}) + (T_{k\to d} - I_{\inf})} \tag{15}$$

Among them, $c_1 = 0.7$, $c_2 = 0.3$; $I_{\sup}$ and $I_{\sup}$ are upper and lower limits of estimated confidence interval for μ_d, calculated according to the following formula:

$$\begin{cases} I_{\sup} = \mu_d + \frac{1}{\sqrt{1-\gamma}} \times \frac{\sigma_d}{\sqrt{w}} \\ I_{\inf} = W_{best} \end{cases} \tag{16}$$

Among them, the scope for γ is from 0.7 to 0.9, w is calculated according to the following formula:

$$w = \frac{5 \times c}{\eta} \tag{17}$$

Among them, the scope for c is (0, 1].

The central task for reverse ants is to handle the pheromone strength of the road network with the experience statistic difference correction formula, which has lagged effect for the ability to estimate. This updated strategy strengthens the current optimal path, and weakens the poorer path, so as to accelerate the convergence speed.

3.4. Double-population ant colony

The basic thought of the double-population ant colony is; create two groups of the population. One is that the positive ants search from source node to destination node, another one is that the positive ants search from destination node to source node. Each group searches independently, with its own transfer rules and pheromone updated strategy. This strategy can make two groups share the search results with each other, breaking the stagnation of a single species in many internal appears after its iteration, improving the efficiency of the algorithm.

4. Genetic algorithm

Genetic algorithm was first proposed by Holland in the University of Michigan in the United States in the 1970s. It was based on Darwin's theory of evolution and Mendelian's genetics principle (Holland, 1973). It simulated the process of natural selection and genetic breeding, cross, biological competition and mutation phenomenon, according to the natural law that the survival is the fittest, and it finally searched with excellent individuals in the way of selecting, crossing and mutating to generate a candidate.

The basic principle of genetic algorithm is; the digital coding produced by random method for solving problems, namely the chromosome, form the initial groups. Give each individual a numerical evaluation according to the fitness function, get rid of the low fitness individual, and choose high fitness in the individual genetic operation. Then there will be a new group of species formed by the genetic individuals coming to the next round of evolution.

4.1. Selection

Selection is an operation that chooses the superior individuals and eliminates the inferior ones in the group. The purpose of selection is to make the better individual genetic directly inherited to the next generation, or inherit the new individual produced by cross matching to the next generation.

The proposed algorithm uses two fitness standards to choose good ant individual; the first one is the times the ant crawls go to and back from the source and destination nodes, and the other one is the distance it takes for one ant to travel for at least one cycle from the source node to the destination node. The more times the ant travels in a cycle, the shorter the distance is for one ant to travel for at least one cycle from the source node

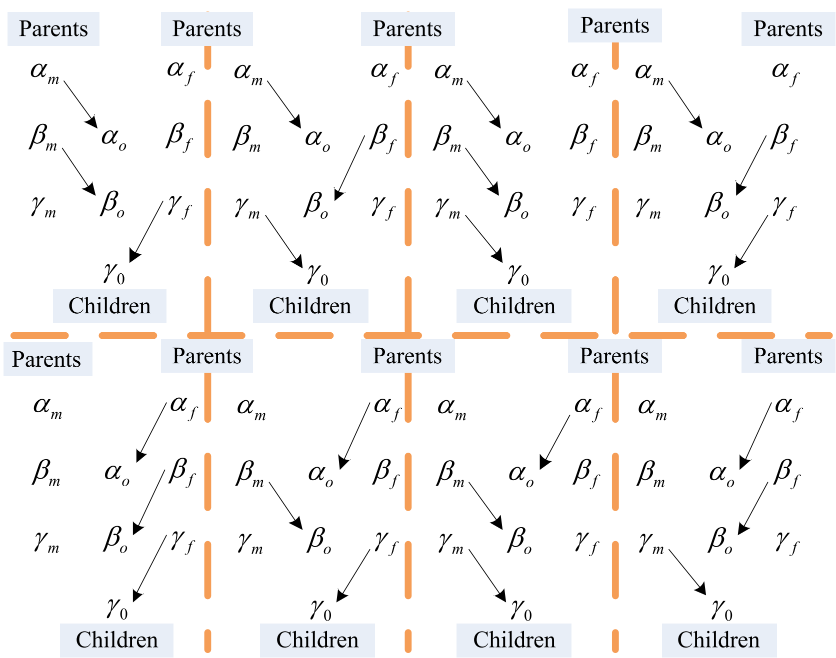

Figure 3. Possible Cross-cases of Ant Chromosomes.

to the destination node, which means the path this ant chose is better than that of other ants', and there are more pheromone left on the path, which can make greater contributions to search path, so this kind of ants belongs to the better groups and will be used as excellent individuals in inheritance operations.

4.2. Crossover

In biological genetic and natural evolutionary process, two homologous chromosomes are restructured into new chromosomes through the crossover, so as to generate new individual or species. The crossover of the genetic algorithm exchange part genes of two paired chromosomes according to some way, forming a new individual.

If we define $\alpha_k, \beta_k, \gamma_k$ of the transfer rules as the chromosomes of ant individuals, choose two ant individuals from the same standard of fitness as a parent generation chromosome, let them cross randomly and new ant generation will be created, all possible cross-cases are shown in Figure 3.

4.3. Mutation

Although selection and crossover, which are the first in the genetic algorithm, are very important, they cannot guarantee any loss of important genetic material that is a value on a specific location. In order to prevent the population in the value of certain individual genes are in the unchangeable state, we have a need for mutation operation. The main purpose of mutation is to change the search direction, to expand the algorithm search space, to avoid the early evolution into a local solution, thereby prevent premature genetic algorithm.

Mutation operation is some variation to some loci of the new individual according to a certain probability. Too large mutation probability can lead to excessive search space, leaving the search becomes blind; too small mutation probability will hinder the formation of new genes. The mutation algorithm in this article aims at $\alpha_k, \beta_k, \gamma_k$ of the transfer rules, taking the mutation probability of 0.05.

5. The proposed method

The algorithm flow chart is shown in Figure 4 and the algorithm steps are as follows:

(1) Load road network data, determine the source node and destination node of the path; initialize the pheromone intensity;
(2) Generate ants' numbers randomly: α_k, β_k, γ_k, set the progress of a long line of ants Δs and assigned the value of the source node and destination node to the ants;
(3) Set the termination conditions: maximum number of cycles *MaxTurns*, the maximum number of ants' round trips *NumFood*;
(4) Determine whether the loop termination condition is satisfied. If so, to enter (14), if any, into (5);
(5) Select according to the probability of selection p_s and use two fitness standards for all the ants, choosing two fine individuals respectively;
(6) According to the crossover probability p_c make cross-operating to produce a new individual ants;
(7) According to the mutation probability p_m make mutation operation on the new-generated individuals;

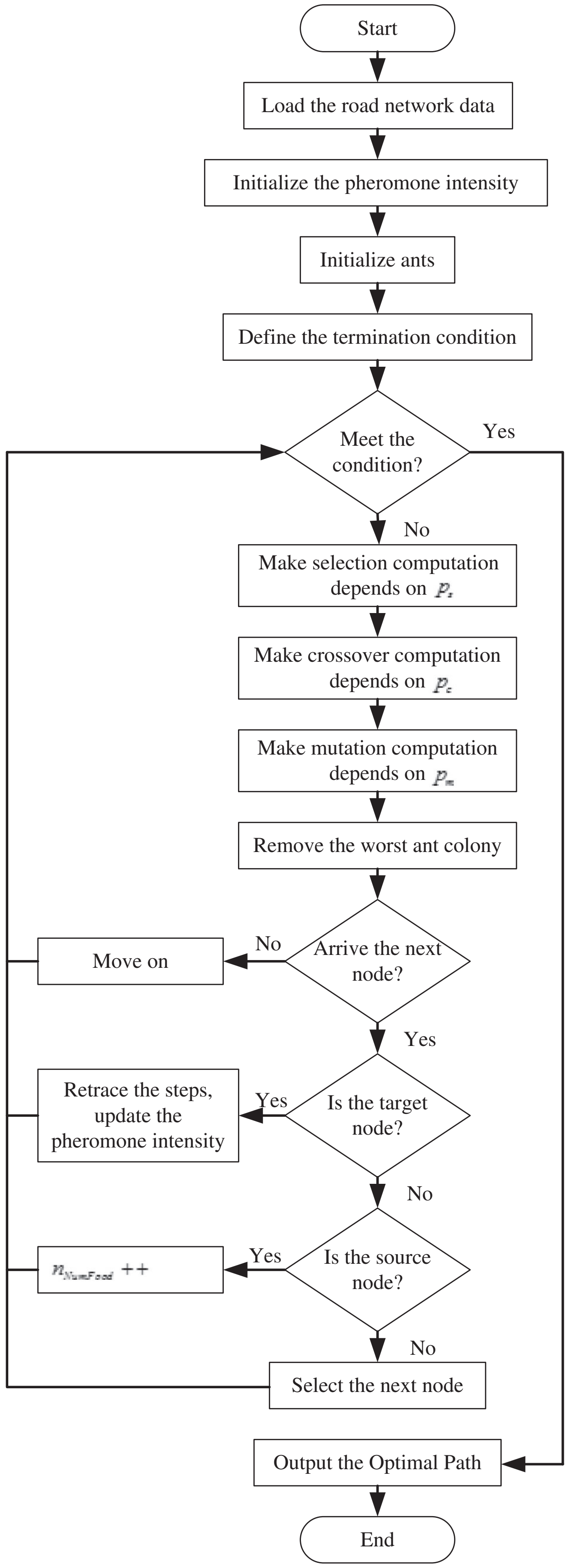

Figure 4. Algorithm Flow Chart.

(8) Add a new generation of ants, initialize the new ant' source node and destination node, and enter the circulation;
(9) According to two fitness standards eliminate the worst ant individuals;

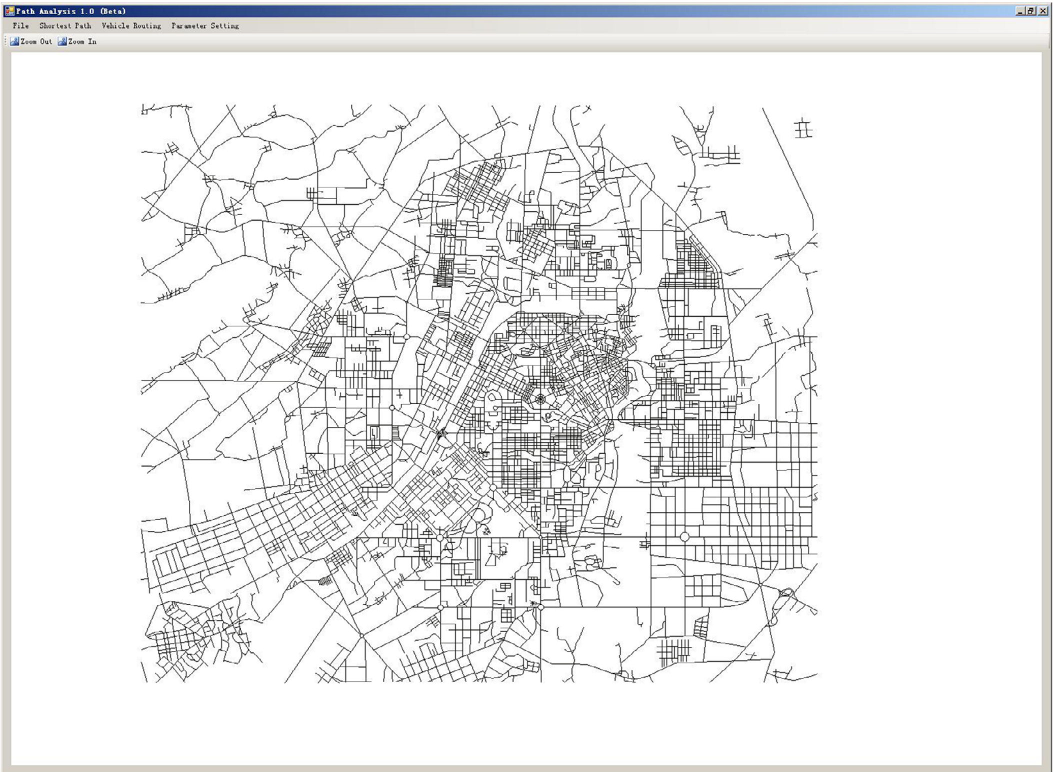

Figure 5. The Road Network Data in Changchun City.

Table 1. Experimental Data.

No.	Nodes	Arcs
1	15,919	19,502
2	12,108	14,803
3	9,509	11,648
4	5,007	6,033
5	3,238	3,867
6	1,202	1,595
7	891	1,227
8	438	537

(10) If the ants have not yet reached the next node, move on as the speed of Δs;

(11) If the ants reach a node, and the next node is the destination node, select the node directly, or select the next node based on the transfer rules;

(12) If the ants are at the destination node, then return along the original path and update the pheromone intensity of road network;

(13) If the ants return to the source node, the value of *NumFood* will increase. Then choose the next node based on the transfer rules;

(14) According to the pheromone intensity of the road network, output the optimal path.

6. Experiment and analysis

6.1. Experiment data

The original data has 15,919 nodes and 19,502 arcs. These nodes and arcs make up the undirected graph road network. In order to verify the efficiency of the algorithm on different numbers of nodes and arcs, a series of sub-graph is generated. The number of sub-graph's nodes and arcs is shown in Table 1.

Table 2. Parameters of the Proposed Method.

p_s	p_c	p_m	Δs
25%	18%	5%	20

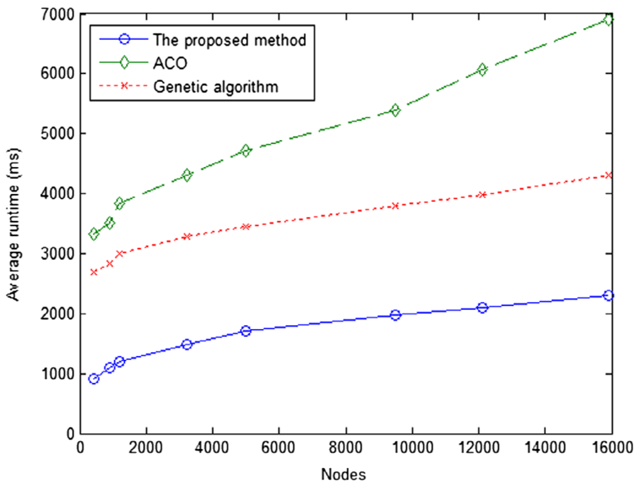

Figure 6. Average Running Time of the Three Algorithms in Case of Different Nodes.

The probability parameters and step length parameters of the algorithm in this article are based on the experience of several tests and priority knowledge. As shown in Table 2, several other parameters are randomly generated by the system.

6.2. The results

Three algorithms all get the average value of the 10 trials' results on the same start and end points. The experimental results, in case of different numbers of nodes, are shown in Figure 6 and Figure 7.

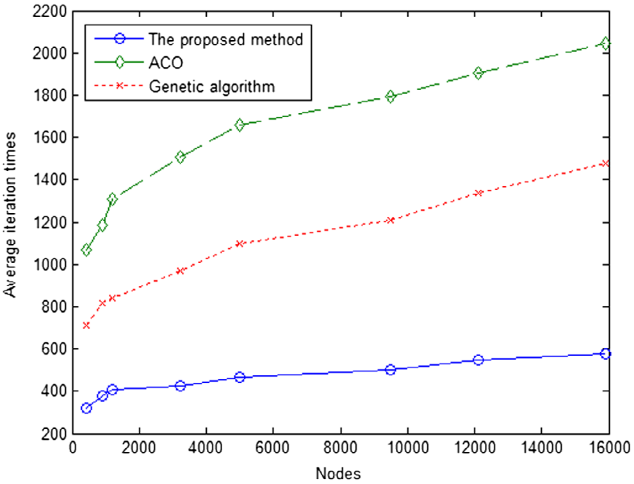

Figure 7. Average Numbers of Iterations of the Three Algorithms in Case of Different Nodes.

As can be seen from Figure 6, in case of the same node number, this algorithm has the shortest average running time, and with the increasing of the number of nodes, the average running time of this algorithm increases the smallest. We can see that the algorithm in this article improves the efficiency of the classical ant colony algorithm and genetic algorithm.

As can be seen from Figure 7, this algorithm has the minimum average numbers of iterations in the case of the number of nodes, showing that this algorithm improves convergence of the classical ant colony algorithm and genetic algorithm.

7. Conclusion

This paper proposes the selection algorithm of the optimal path of vehicle emergency supplies, which integrates genetic algorithms and ant colony optimization algorithm. For the ant colony optimization algorithm is easy to fall into local optimal solution, we take genetic algorithm into consideration to make the ants keep out poor populations to retain good ant populations using the transfer rules of sinusoidal probability not only has maintained the randomness that the ants select the next node, but also has guaranteed to determine the next node based on residual strength of the pheromone intensity in a certain range of residual pheromone intensity, introducing the pheromone update strategy in the AntNet algorithm into the optimal path algorithm has avoided the ants' premature convergence to the same path, has strengthened the current optimal path and weakened the worse path, thereby speeded up the convergence rate, using dual ant populations to bi-directional search the optimal path, has increased the intensity of pheromone on the optimal path, using two fitness standards to select superior ant individuals through crossover and mutation, has ensured the best individual's continuous transmission in the genetic manipulation and the entire population groups continue to evolve well. Experiments show that this algorithm improves the convergence speed and improve the efficiency of the algorithm.

Although the combination of genetic algorithm and ACO for the optimal path selection problem obtains satisfactory achievements, there are still some spaces for improvement, such as how to effectively construct the road network and how to precisely judge the local optimal solution. And some further research for applying the proposed algorithm should be carried out in our future work.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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