Traffic Path Planning Method Based on VANET and Ant Colony Algorithm

Changlin Yang¹, Zhenglin Li², Yang Peng³ and Guangsong Yang¹,*

¹School of Aerospace Engineering, Xiamen University, Xiamen, Fujian 361005, China
²School of Electrical and Information Engineering, Dalian Jiaotong University, Dalian, Liaoning 116028, China
³School of Information Engineering, Jimei University, Xiamen, Fujian 361021, China

*Corresponding author. Email: gsyang@jmu.edu.cn

Abstract. Intelligent Transport System (ITS) has been widely used in our life. A traffic path planning method based on VANET (Vehicular Ad Hoc Network) is proposed, which considers the path length and congestion comprehensively, uses ant colony algorithm to find an optimal path with the shortest delay, redesigns the pheromone update and heuristic function, dynamic adjusts evaporation rate to avoid the old information and reduce the re-exploration of the visited path, in order to speed up the convergence speed and expand the search space. Simulation results show that this method can avoid congestion path, shorten path search time, and ensure the effectiveness of the path.

Keywords: path planning, VANET, ant colony algorithm, intelligent transportation system.

1. Introduction

With the development of computer technology and the improvement of people's living standards, Intelligent Transportation System (ITS) [1][2] has become an indispensable part of the city. ITS aims to achieve traffic efficiency and improve traffic safety and comfort by minimizing traffic problems. In the intelligent transportation system, cars can exchange information via wireless communication technology with other cars or Fixed Stations (FS) by the methods of V2V (Vehicle to Vehicle communication) or V2I (Vehicle to Infrastructure), to build a VANET (Vehicular Ad Hoc Network) [3]. The application of ITS includes not only traffic congestion control and information exchange, but also road safety and highly efficient infrastructure use.

With the increasing number of vehicles, traffic management and congestion controls related problems are inevitable. Vehicles equipped with vehicle navigation system can find an optimal path and reduce road congestion by using VANET. The path search problem can be regarded as a graph problem with weight. But when the number of vertexes increases, the computation is very large by using classic algorithm such as Warshall-Floyd [4]. Therefore, in practical application, some methods are adopted by using the approximate solution to reduce the problem space. Ant Colony Optimization (ACO) [5] is a kind of optimization method based on ant colony's efficient foraging behavior. In the process of finding the path from nest to food, ants form an optimal path according to the pheromones left by different ants.
An Ant Colony algorithm was proposed to solve the problem of robot path planning in [6]. Ants choose the path probability from the starting point to the destination according to the pheromone, and then update the pheromone according to the evaluation of the completed path. The results show that the larger the size of the graph, the more efficient the search time. Reference [7] presented a Ant Colony Heuristic Method in Long-term transportation planning for larger regions, and first applied it to a realistically sized network. Reference [8] proposed a bio-inspired meta-heuristic and mathematically probabilistic technique of the Ant Colony Optimization where efficient path establishment and information transfer can be achieved. ACO was used to solve the benefit problem of large-scale transportation network under limited cost in [9]. In Reference [10], ACO was used to generate the comprehensive traffic corridor layout structure of urban agglomerations. Reference [11] focuses on the use of ant colony algorithm in all routes to allocate traffic flow reasonably. An ant colony algorithm was improved [12], which has a broader application prospect in the transmission network of high-dimensional and dynamic functional parameters.

In this paper, we propose an ant colony algorithm for path planning in the weighted graph of cost variation. The rest of the paper is organized as follows. The system model is given in section 2. In section 3, we describe the proposed path planning method based on ant colony algorithm. The simulation research and performance evaluation of the proposed method is presented in section 4. Finally, the concluding remarks and future work are presented in Section 5.

2. System model

The ITS system based on VANET is shown in Figure 1. Fixed stations (FSs) are set at the intersection or roadside. A vehicle can communicate with other vehicles or fixed station in the form of V2V or V2I. The fixed station is connected to the Internet by wired or wireless. Each fixed station can collect the information of road between adjacent FSs, such as the number of vehicles, and these information are gathered to the data processing center in the cloud through the Internet.

![Figure 1. Intelligent transport system based on VANET.](image)

In a certain region (such as a city), the road model can be modeled as a weighted graph $G = (V, E, W)$, which composed of the set $V = \{v_1, v_2, \ldots, v_n\}$ of $n$ vertexes $v_i$, the set $E = \{e_{ij}\}, i, j = 1, 2, 3, \ldots, m; i \neq j$ of $m$ edges $e_{ij} = \{v_i, v_j\}, v_i, v_j \in V$, and the set $W = \{w_{ij}(t)\}, i, j = 1, 2, 3, \ldots, m; i \neq j$ of the weight $w_{ij}$ of edge $e_{ij}$. If there is no direct connection between the two points, their weight is less than zero.

Therefore, when a weighted graph $G = (V, E, W)$ is given, the path planning problem can be considered as searching the path $P_{s,d} = (V', E', W')$, which from the starting vertex $v_s$ to the destination vertex $v_d$, and the sum of the weights $w_{ij}$ in $P_{s,d}$ is expressed as $T_{s,d} = \sum_{w_{ij} \in P_{s,d}} w_{ij}$. To find the optimal path is to find the path with the minimum $T_{s,d}$ in the path between two vertexes of a given weighted graph.
3. Path planning method based on ant colony algorithm

3.1. Ant colony algorithm

Based on the system model in Section 2, the detailed process of ant colony algorithm is as follows.

**Step 1:** system initialization
The initial position of each ant and pheromone of each side are set randomly.

**Step 2:** select next hop node
The selection probability of the next vertex is determined based on pheromone. If the total number of ants is set to $A$, the probability $P^k(t)$ of the $k = 1 - N_A$ ant choosing edge $e_{ij}$ from vertex $i$ to vertex $j$ is expressed by the equation (1).

$$P^k(t) = \left\{ \begin{array}{ll} \tau_{ij}(t)^{\alpha} \cdot \eta_{ij}^{\beta} & (i = 1 - N_s, j \in C, n = 1 - N_A) \\ 0 & (i = 1 - N_s, j \notin C, n = 1 - N_A) \end{array} \right. \tag{1}$$

where, $\tau_{ij}$ represents pheromone, $\eta_{ij}$ represents heuristic value, $\alpha$ and $\beta$ are indices of pheromone and heuristic value respectively, $C$ represents the set of neighbor nodes, $N_s$ represents all vertexes, and selects the next hop path according to equation (1).

The pheromone $\tau_{ij}$ of equation (1) is the information that ants attach to the path, the shorter the path, the higher the pheromone; the heuristic value $\eta_{ij}$ is the reciprocal of the path distance, which is given by the equation (2)

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{2}$$

Heuristic information $\eta_{ij}$ is related to distance, when ants select next vertex, the shorter the path distance is, the higher the selection probability is.

In addition, from the current vertex $v_i$, to next vertex $v_j$ should be selected from the vertex set $C$ that has never been visited.

If the more pheromones $\tau_{ij}$ accumulated in a certain path, the shorter the distance $d_{ij}$, the higher the probability of choosing this path.

**Step 3:** Calculation and judgment
In Step 2, calculate the total distance of the path selected by each ant, and select a path with the shortest distance.

**Step 4:** update pheromone and add pheromone to the path. Since the purpose is to minimize the total distance, the pheromone makes the total distance shorter and higher, $\Delta \tau_{ij}$ is the additional pheromone of $k$th ant,

$$\Delta \tau_{ij} = \frac{1}{L_q} \tag{3}$$

where, $L_q$ is the total distance of the path selected by $k$th ant. In addition, pheromones attached to the whole path will be evaporated as in nature. The updated pheromones can be expressed as:

$$\tau_{ij}(t + 1) = (1 - \rho) \cdot \tau_{ij}(t) + \sum_{k=1}^{N_A} \Delta \tau^k_{ij} \tag{4}$$
where, $\rho$ is the evaporation rate, because the information evaporates in the time series, it can avoid repeating the latest action and falling into the local solution, so it can carry out a wider range of exploration.

**Step5:** Determine the end condition

If the number of exploration loops exceeds the maximum number of loops, then go to Step2.

### 3.2. Path planning with weight based on ant colony algorithm

For the network model in Section 2, each fixed station $FS$ corresponds to a vertex, and each road (or street) corresponds to an edge, as shown in Figure 1. First, a vehicle sends an ant agent to the destination node through the nearest fixed station, collects the load information of the roads, constructs the routing table based on pheromone, and finds the shortest path through ant colony algorithm similar to the method in section 2.

1. In the STEP2 of Section 2, the ant agent moves from the starting vertex $FS_s$ to the destination vertex $FS_d$ to search the optimal route based on the pheromone. Because the congestion degree of each road is different, we can allocate different weights $\omega_{ij}$ to each road shown in equation (5),

$$\omega_{ij} = \frac{NR_y}{NMAX_y}$$  \hspace{1cm} (5)

where, $NR_y$ is the actual number of vehicles in the road between $FS_i$ and $FS_j$, $NMAX_y$ is the maximum number of vehicles that the road can accommodate between $FS_i$ and $FS_j$.

Moreover, the heuristic function $\eta_{ij}$ in equation (1) can be modified as

$$\eta_{ij} = \frac{1}{d_{ij}} \times \omega_{ij}$$  \hspace{1cm} (6)

Then select the next fixed station $FS_j$ according to the probability $P^0_y(t)$ of equation (1), and record the weight of it and its surrounding roads in the memory.

If one fixed station has been accessed, the same probability is re-selected from the adjacent fixed station set. If the selected path becomes closed, the data that is part of the closed path is deleted from the memory.

2. For Step4, pheromones can be updated by equation (4), but congestion factors are considered. The pheromones can be defined by the following equation:

$$\Delta \tau_y = \sum_{k=1}^{N} \Delta \tau_{yk}^i = \sum_{k=1}^{N} \frac{Q}{d_{ij}} \times \omega_{ij}$$  \hspace{1cm} (7)

In the process of path search for the cost change weight graph, if the updating period of weight becomes longer, the accuracy of path search based on the over mature pheromone will be reduced. Therefore, to prevent the over mature pheromone and update information of routes, when the vehicle runs for a period of time, or the congestion degree of the selected path changes greatly, it can return to step1 of initialization.

### 4. Simulation and analysis

In order to simulate the scenario described in Section 2, $n$ fixed stations are randomly distributed in the area of 20km×20km, and the weights $\omega_{ij}$ are randomly set between each fixed station $i$ and $j$ to indicate the congestion degree of the road. If the weight is less than zero, then there is no directly

424
connected road between the two stations \( i \) and \( j \). The simulation scene is shown in Figure 2. We use matlab tool to simulate our proposed method, and take the average value after ten times of simulation,

![Simulation scene with 30 fixed station and 50 roads.](image)

**Figure 2.** Simulation scene with 30 fixed station and 50 roads.

### 4.1. Impact of network size

In the scenario of Figure 2, change the size of the network, use our proposed method to find the path from the start FS to destination (Dotted line), and count the iterations of the best path in different network sizes. It can be seen from Figure 3 that the number of iterations increases as the network size increases. Compared with the conventional ant colony algorithm (Solid line), our proposed method has less convergence times. This is because ACO only considers distance when choosing path, while the number of optimal paths based on Euclidean distance is limited. However, our algorithm takes congestion into account, and there will be many alternative paths. Therefore, the probability of obtaining the optimal path is increased.

![Relationship between network size and iterations.](image)

**Figure 3.** Relationship between network size and iterations.
4.2. Impact of Congestion degree

Figure 4. The relationship between iterations and congestion degree.

Fig. 4 shows the relationship between congestion degree and iterations for 400 fixed stations. The vertical coordinate represents the average average congestion degree of the selected path. It can be seen that with the increase of the number of iterations, the two algorithms can gradually find the path with less congestion degree. Compared with ACO, our proposed method can find a better path, accelerate convergence speed and save search time because of considering congestion factors.

5. Conclusion

In the intelligent transportation system, the application of VANET is helpful to the collection and analysis of data. It is very necessary to find a path without congestion in the urban road, but the exited path planning method based on ACO to find the shortest path has some limitations.

In this paper, an improved ACO path planning method is proposed and compared with the classical ant colony algorithm. Firstly, considering the road congestion factor, the path with less congestion is selected to save travel time. Secondly, the heuristic function is modified to reduce the number of iterations and improve the search efficiency. Finally, in order to avoid the obsolete information of pheromones on the path, the pheromone is updated regularly to enhance the pheromone, update the rules and dynamic evaporation strategy to improve the global search ability and convergence speed. Simulation results show that the improved ant colony algorithm is better than the classical ant colony algorithm in path search and fast convergence.

The next research direction will be considered in the actual map and traffic flow environment to verify the effectiveness of this scheme.

Acknowledgement

The work is partially supported by National Key Scientific Research Programmer of China under Grant No. 2018YFC1406600, Science Foundation of Fujian Province under Grant No. 2015J01267, and the Training Program of FuJian Excellent Talents in University.

References

[1] K.N.Qureshi, A. H. Abdullah. A survey on intelligent transportation systems. Middle-East Journal of Scientific Research, 15.5(2013):629-642.
[2] M. L. Mfenjou, A. A. A. Ari, W. Abdou, F. Spies, Methodology and trends for an intelligent transport system in developing countries. Sustainable Computing: Informatics and Systems, 19(2018):96-111.

[3] M.S. Anwer, C. Guy, A survey of VANET technologies. Journal of Emerging Trends in Computing and Information Sciences, 5.9(2014):661-671.

[4] A. Aini, A. Salehipour, Speeding up the Floyd–Warshall algorithm for the cycled shortest path problem. Applied Mathematics Letters, 25.1(2012): 1-5.

[5] G.D. Caro, D.M. Anet, a Mobile Agents Approach to Adaptive Routing. IRIDA, Universite Libre de Brusseles, Brussels, Belgium. Technical Report IRIDA, (1997):97-12.

[6] N. Buniyamin, N. Sariff, W.A.J. Wan Ngah, Z. Mohamad, (2011). Robot global path planning overview and a variation of ant colony system algorithm. International journal of mathematics and computers in simulation, 5.1(2011):9-16.

[7] B.J. Vitins, K.W. Axhausen, Optimization of large transport networks using the ant colony heuristic. Computer-Aided Civil and Infrastructure Engineering, 24.1(2009):1-14.

[8] S. Majumdar, P.R. Prasad, S.S. Kumar, An efficient routing algorithm based on ant colony optimisation for VANETs. In 2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT). IEEE, (2016):436-440.

[9] R. Musa, J.P. Arnaout, H. Jung, Ant colony optimization algorithm to solve for the transportation problem of cross-docking network. Computers & Industrial Engineering, 59.1(2010):85-92.

[10] Q. Xiong, J. Hu, J. Kuai. Comprehensive Transportation Corridor Layout of Urban Agglomeration Based on Improved Ant Colony Algorithm. In ICTE 2019. Reston, VA: American Society of Civil Engineers.(2020): (77-85).

[11] A. Rehman, M. M. Rathore, A. Paul, F. Saeed, R. W. Ahmad, Vehicular traffic optimisation and even distribution using ant colony in smart city environment. IET Intelligent Transport Systems, 12.7(2018): 594-601.

[12] V. Danchuk, O. Bakulich, V. Svatko, An improvement in ant algorithm method for optimizing a transport route with regard to traffic flow. Procedia Engineering, 187(2017):425-434.