IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received March 17, 2020, accepted March 26, 2020, date of publication March 31, 2020, date of current version April 14, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2984695

Dynamic Path Planning for Unmanned Vehicles Based on Fuzzy Logic and Improved Ant Colony Optimization

QI SONG[1], QINGLEI ZHAO[2], SHUXIN WANG[2], QIANG LIU[2], AND XIAOHE CHEN[1]
[1]Suzhou Institute of Biomedical Engineering and Technology, Chinese Academy of Sciences, Suzhou 215163, China
[2]Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun 130033, China

Corresponding author: Qinglei Zhao (zhaoql_ciomp@163.com)

This work was supported by the National Natural Science Foundation of China under Grant 11873046.

ABSTRACT Technical advancement has propelled the proliferation of unmanned vehicles. Out of the multiple paths between origin (O) and destination (D), the optimal O-D path should be selected in the light of travel distance, travel time, fuel cost and pollutant emissions. This paper proposes a dynamic path planning strategy based on fuzzy logic (FL) and improved ant colony optimization (ACO). Firstly, the classic ACO was improved into the rank-based ant system. The rank-based ant system works well in static environments, but cannot adapt well to dynamic environments. Considering the difficulty in accurate digitization of dynamic factors, the improved ACO was integrated with the FL into the fuzzy logic ant colony optimization (FLACO) to find the optimal path for unmanned vehicles. Finally, the FLACO, the classic ACO and the improved ACO were separately applied to find the optimal path in a road network, with a novel concept called virtual path length. The results show that the FLACO output the shortest virtual path among the three algorithms, i.e. identified the most cost-effective path. This mean the FLACO can find the most efficient and safe path for unmanned vehicles in a dynamic manner.

INDEX TERMS Path planning, unmanned vehicles, fuzzy logic (FL), ant colony optimization (ACO).

I. INTRODUCTION

Technical advancement has propelled the proliferation of unmanned vehicles [1]. These vehicles can travel safety from origin (O) to destination (D), with the aid of onboard high-precision sensors and intelligent control algorithms. Out of the multiple O-D paths, the optimal path should be selected in the light of travel distance, travel time, fuel cost and pollutant emissions. However, it is difficult to find the optimal O-D path, without considering the dynamic changes of traffic parameters (e.g. vehicle speed and traffic flow).

The search for the best collision-free O-D path is called path planning. In recent decades, path planning has been a research hotspot in the field of unmanned vehicles [2]. Many strategies have been developed for path planning, including the dynamic window approach, potential field method [3], fuzzy logic [4], particle swarm optimization (PSO) [5], simulated annealing (SA) algorithm [6], genetic algorithm (GA) and neural network (NN) [7].

Extended from the capacitated vehicle routing problem (CVRP), the vehicle routing problem with time window (VRPTW) aims to find the optimal paths for 100 or more vehicles, which is obviously difficult to achieve. Ombuki *et al*. [8] described the VRPTW as a multi-objective problem, and solved the problem with non-dominated sorting genetic algorithm (NSGA). But the NSGA is no match for tabu search (TS) in dealing with the VRPTW. To solve the defect, Prins [9] proposed a simple yet effective hybrid GA, and created a new heuristic rule for vehicle routing based on expert knowledge and human experience. Chemouil *et al*. [10] developed a fuzzy routing system for the long-distance telephone network of France. For the safety of unmanned vehicles, Yin and Fu [11] designed a hybrid path planning algorithm based on SA algorithm and the PSO. Nevertheless, the above methods are poor in robustness and adaptability, and prone to the local minimum trap.

In the early 1990s, Dorigo *et al*. [12] proposed the ant colony optimization (ACO), a meta-heuristic evolutionary algorithm inspired by the foraging behavior of ants [13]–[18].

The associate editor coordinating the review of this manuscript and approving it for publication was Dalin Zhang.

The ACO is the most successful swarm intelligence (SI) method for combinatorial optimization problems. With advantages like parallel and distributed processing, the ACO can effectively solve problems like secondary distribution, network routing and vehicle routing.

Drawing on the heuristic features of the ACO, Purian and Sadeghian [19] presented a novel navigation method for mobile robots in a dynamic environment. In the existing SI-based routing protocols, the optimal path is searched for based on only one or two indices (e.g. hop count or delay), without considering the correlation between multiple indices. This search strategy cannot work in applications with multiple paths or multiple indices to be optimized. Therefore, Goswami *et al.* [20] put forward a new routing protocol based on fuzzy ant colony optimization (FACO), in which the optimal path is identified through multi-objective optimization by fuzzy logic (FL) and the SI. The advantages of the ACO as an SI algorithm were fully utilized in the proposed protocol.

Thanks to its strong computing power and robustness, the ACO has been increasingly applied in the field of unmanned vehicles. For today's users, the shortest length is not the sole attribute of the optimal O-D path. The other attributes include the minimum number of intersections, a small traffic flow, a beautiful scenery, and safety. There is not yet a feasible path planning system that can rapidly and easily plan such a path in a dynamic manner.

In light of the above, this paper proposes the fuzzy logic ant colony optimization (FLACO), which can find the optimal paths for unmanned vehicles dynamically based on multiple indices. As its name suggests, the FLACO combines the merits of the FL and the improved ACO to find the O-D path with multiple optimal variables. The optimal path refers to the path whose variables all live up to user expectation, including distance, traffic flow and incident risk. The variable set can be expanded by adding terms like width (number of lanes), quality (e.g. medical and entertainment facilities) and traffic lights. The main contributions of this research are summarized as follows:

1. An improved ant colony algorithm is proposed to tackle the fact that traditional ant colony algorithm is easy to fall into local optimization.
2. Most of previous literatures only considered static factors (such as road distance), but this paper considered the dynamic factors (traffic flow (F), incident risk (R) and speed limit (S)) together to plan the optimal path.
3. The proposed method can provide the most cost-effective path.

The remainder of this paper is organized as follows: Section 2 introduces the ACO and the FL; Section 3 describes the route guidance system of unmanned vehicles; Section 4 develops the FLACO for path planning of unmanned vehicles; Section 5 verifies the FLACO through simulation; Section 6 puts forward the conclusions and looks forward to future research.

II. PRELIMINARIES

A. ANT COLONY OPTIMIZATION

The ACO is an intelligent evolutionary heuristic search algorithm for optimization problems. The algorithm mimics the ant behavior in the search for the shortcuts from the nest to food sources [12]–[18]. To find and record food sources in a random search space, each ant releases a certain amount of pheromone on its path; once a food source is found, the ant, capable of sensing the pheromone intensity, will move to a place with a higher pheromone concentration. As the ant moves towards the place, the pheromone concentration will increase on its path. As a result, more ants will be attracted to the path, further increasing the pheromone concentration. This is how the ants choose the optimal O-D path.

Let i be the current node of ant k. At time t, ant k will move from node i to an unvisited node j, according to the distance between nodes i and j and the pheromone concentration on edge ij. If there are multiple unvisited nodes, the probability for ant k to choose node j can be expressed as:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}{\sum\limits_{s \in allowed_k} [\tau_{is}(t)]^{\alpha} \cdot [\eta_{is}(t)]^{\beta}} & j \in allowed_k \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where, α is the weight (importance) of pheromone concentration in path selection; β is the weight (importance) of heuristic information (visibility) in path selection; $allowed_k$ is the set of candidate nodes for ant k to choose from; τ_{ij} is the pheromone concentration of edge ij; η_{ij} is the visibility of edge ij:

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

where, d_{ij} is the distance between two adjacent nodes i and j, i.e. the length of edge ij:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{3}$$

Once all the ants have completed their searches, the pheromone concentration on each edge will be updated according to the volatilization of existing pheromone and the pheromone released by each ant:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{4}$$

where, ρ is the evaporation rate of pheromone; m is the number of ants; $\Delta\tau_{ij}^{k}$ is the amount of pheromone left by ant k in the current iterations:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k} & \text{edge}(i,j)\text{is selected by ant } k \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where, L_k is the length of the path selected by ant k; Q is a constant.

B. FUZZY LOGIC

In 1965, Lotfi A. Zadeh proposed the concept of fuzzy set, a derivation of common set. The fuzzy set is defined by the membership function, rather than the characteristic function, whose value is either zero or one [21]. The membership refers to the probability of each object to be an element of a set. The membership value falls in the interval of [0, 1]. If the membership is zero, the object does not belong to the set; if the membership is one, the object must belong to the set.

In the late 1970s, Assilian and Mamdani suggested controlling complex processes with the FL especially in the absence of strict models [10], [22]. The FL control can be described as a control method using conditional sentences (if-then rules) instead of equations. The derivation of a rule is called inference, which needs to be characterized by a membership function. Through interference, it is possible to evaluate the truthfulness of each proposition. Figure 1 explains the procedure of a simple FL control system.

As shown in Figure 1, the FL control can be realized in three steps: fuzzification, rule evaluation and defuzzification.

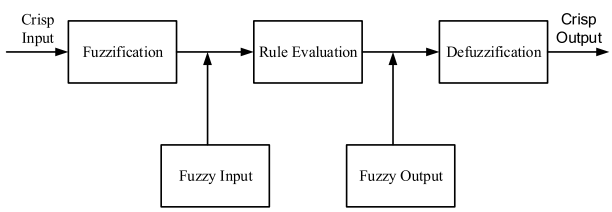

FIGURE 1. The procedure of a simple FL control system.

1) FUZZIFICATION

Each FL control system can be implemented in the form of fuzzy rules, such as:

Rule I: If M is p_1 & N is q_1, then R is g_1;

Rule II: If M is p_2 & N is q_2, then R is g_2.

where, M and N are conditional variables; R is the response variable; p_i, q_i and g_i are fuzzy parameters characterized by membership functions.

Since the conditional variables are often measured as 1, Mamdani provided the fuzzy inference process for the two rules and any membership function: Taking D_1 and D_2 as intervals, the memberships of the conditional variables were determined as $\mu_{p1}(m)$ and $\mu_{q1}(n)$ for Rule I, and $\mu_{p2}(m)$ and $\mu_{q2}(n)$ for rule II. Then, the measured values were matched with the corresponding fuzzy variables.

2) RULE EVALUATION

From the rule base, the control rules satisfying $M = m$ and $N = n$ can be connected into the following rules:

$$\text{Rule I}: \mu_1 = \mu_{p_1}(m) \wedge \mu_{q_1}(n);$$
$$\text{Rule II}: \mu_2 = \mu_{p2}(m) \wedge \mu_{q_2}(n)$$

where, ^ is an operation of Mamdani-type rule evaluation, namely, the min function; μ_1 and μ_2 are the truth degrees of Rules I and II, respectively.

The Mamdani-type rule evaluation is illustrated in Figure 2, where $\mu_{g1}(R)$ and $\mu_{g2}(R)$ are the memberships of m and n to fuzzy subsets $g_1(R)$ and $g_2(R)$, respectively.

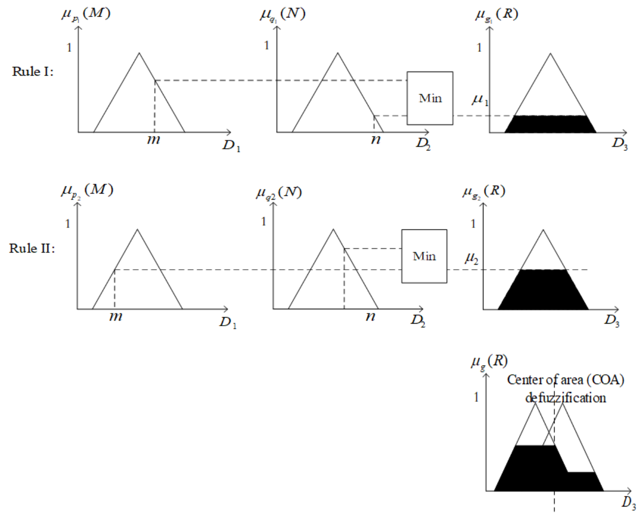

FIGURE 2. Mamdani-type evaluation of Rules I and II.

Taking D_3 as the interval of the output variable, the output $g(R)$ of FL control system can be expressed as the set of all fuzzy subsets $g_i(R)$. The membership $\mu_{gi}(R)$ of the output is the sum of all memberships:

$$\mu_g(R) = \mu_{c_1}(R)^* \mu_{c_2}(R), \tag{6}$$

where, * is the max function for Mamdani-type rule evaluation.

3) DEFUZZIFICATION

The fuzzy result, i.e. the inference result, can be converted into a real value to serve as the input of the FL control system. Since the desired output is a non-fuzzy result, the quantitative value of the output of the FL control system can be derived from $\mu_{gi}(R)$. The area of gravity (COA) method is often adopted for defuzzification:

$$Z_{COA} = \frac{\int_z \mu_A(Z)Zdz}{\int_z \mu_A(Z)Zd} \tag{7}$$

where, $\int_Z$ is the algebraic integral of the memberships of all elements in the output fuzzy subset on the continuous domain Z. The areas on the two sides of Z_{COA} are equal.

III. ROUTE GUIDANCE SYSTEM OF UNMANNED VEHICLES

A. BACKGROUND KNOWLEDGE

Route guidance is essential to the positioning and navigation of unmanned vehicles. The route guidance system aims to plan a path with the least cost (e.g. travel time and travel distance) from the inputted positions of origins and destinations. The constraints of path planning are provided in Figure 3.

Onboard positioning and navigation system are an indispensable data source for route guidance. In intelligent transportation, a powerful transportation network can be built

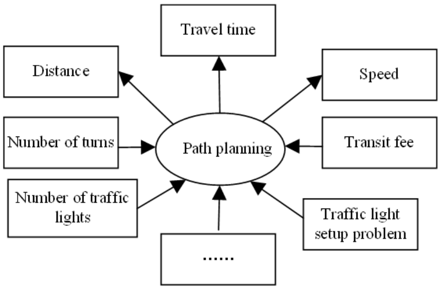

FIGURE 3. Constraints of path planning.

upon the positioning and navigation information, providing vehicles with the information of road and surroundings in real time.

Therefore, the path planning module of our route guidance system was established based on the onboard positioning and navigation system. Path planning can be realized through global search and local search. Global search aims to find the optimal collision-free O-D path on the digital map, under several constraints. Based on global search, local search adjusts the optimal path to avoid collision in local environment, according to the real-time data from onboard sensors. The two search methods complement each other. In general, path planning is implemented in four steps: abstracting the road network, assigning weight to each road section, solving the optimal path, and restoring the actual roads.

After path planning, the unmanned vehicle(s) will be guided to the destination by audio or images, completing the route guidance. The route guidance system can serve only one vehicle or multiple vehicles in the same system. The route guidance is affected by various factors. If these factors are time-invariant, the route guidance is static; otherwise, the route guidance is dynamic. Static guidance applies to global search, while dynamic guidance suits local search.

To sum up, our route guidance system for unmanned vehicles mainly plans the optimal path based on the onboard positioning and navigation system and digital map, and then guides the vehicle(s) to reach the destination rapidly and safely.

B. TOPOLOGY OF ROAD NETWORK

The path of unmanned vehicle(s) was planned based on the road network. Before path planning, the actual roads were abstracted into a model. Drawing on the graph theory, the intersections were defined as nodes, and the road sections between two intersections were defined as edges. In this way, the road network was modelled as a network of nodes and edges in the geographic information system (GIS).

Next, the influencing factors of path planning were considered as resistances faced by vehicles on roads, and thus described by the road resistance function. The function is influenced by various factors, including but not limited to edge length, travel time and transit fee. The road resistance function could be static or dynamic. In static road resistance function, the influencing factors (e.g. edge length and road grade) do not change with time; in dynamic road resistance function, the influencing factors (e.g. vehicle speed, travel time and traffic flow) vary with the elapse of time.

Considering the application requirements and computing load, the main influencing factors were selected, such as travel distance, travel time, transit fee and road quality. After the road network was abstracted, the relevant information was stored into a computer in the form of adjacency matrix or adjacency list. The two storage structures were selected to control the data size and remove redundant data.

To identify the optimal path, the above information was sorted out to plot the topology of the road network. As shown in Figure 4, the topology map was plotted by mapping the relationship between intersections to that between nodes, the relationship between intersection and road section to that between node and edge, and the relationship between road sections to that between edges.

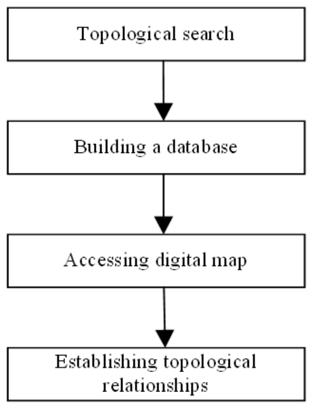

FIGURE 4. Preparation of the topology map.

IV. FLACO

A. VECHILE ROUTING PROBLEM (VRP)

The VRP is an important problem in logistics distribution, for the optimal path can greatly reduce transport cost and improve distribution efficiency. The VRP asks what is the optimal set of routes from one or several origins to one or more destinations? The optimality means the minimum of all kinds of costs, namely, transport cost and time cost.

In real-world scenarios, the VRP is subjected to multiple constraints: each vehicle only visits one destination; every vehicle must leave from and return to the origin; the loading capacity of every vehicle must be equal to or greater than the demand of destination i; the travel time or travel distance cannot surpass the corresponding limits; each destination must be visited in a specified time window.

B. IMPROVED ACO

In the classic ACO, each ant moves from the nest to search for the optimal path to food sources, according to the concentration of pheromone left by the other ants on each path. At the beginning, all paths are of the probabilities to be selected by the ant, i.e. have the same amount of pheromone. Hence, it is difficult to identify the optimal path solely based on the pheromone left by the other ants. With the elapse of time, the classic ACO is very likely to fall into the local optimum trap. To solve the problem, this paper modifies the classic ACO in two steps.

1) ELITIST ANT SYSTEM

The elitist ant system is an early improved version of the ACO. Under this system, the ant that first finds the optimal path is considered an elite ant. At the end of each iteration, an additional amount of pheromone is released onto the optimal path, making the latter more competitive in the next iteration. The optimal path thus obtained is called the global optimal path. In the elitist ant system, the pheromone on each path can be updated by:

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Delta\tau_{ij} + \Delta\tau_{ij}^{*} \tag{8}$$

where, $\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}$:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k} & \text{If antkpasses edge ij in the current iteration} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$\Delta\tau^{*} = \begin{cases} \sigma \cdot \dfrac{Q}{L^{*}} & \text{If edge ij is part of the optimal path} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

where, $\Delta\tau^{*}$ is the additional amount of pheromone released by elite ants on edge *ij*; σ is the number of elite ants; L^{*} is the length of the optimal path.

2) RANK-BASED ANT SYSTEM

There is a major defect with the elitist ant system: it is almost impossible to converge to the optimal path, because of the small difference between the candidate paths. To resolve the defect, the ants were ranked by fitness. The higher the ranking of an ant, the more likely it is for its path to be selected. Let *w* be the number of elite ants, and σ is the number of elite ants. Suppose the ranking of an ant is positively correlated with the amount of pheromone released by the ant. In the rank-based ant system, the pheromone on each path can be updated by:

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Delta\tau_{ij} + \Delta\tau_{ij}^{*} \tag{11}$$

where, $\Delta\tau_{ij} = \sum_{\mu-1}^{\sigma-1} \Delta\tau_{ij}^{\mu}$ is the amount of pheromone on edge *ij* updated by σ-*1* ants in the order of their rankings;

$$\Delta\tau_{ij}^{\mu} = \begin{cases} (\sigma-\mu) \cdot \dfrac{Q}{L^{\mu}} & \text{If elite ant } \mu \text{ pass edge ij} \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

$$\Delta\tau_{ij}^{*} = \begin{cases} \sigma \cdot \dfrac{Q}{L^{*}} & \text{If edge ij is part of the optimal pat}h \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

where, $\Delta\tau_{ij}^{\mu}$ is the additional amount of pheromone released by elite ant μ on edge ij; L^{μ} is the length of the path covered by elite ant μ; $\Delta\tau_{ij}^{*}$ is the additional amount of pheromone released by elite ants on edge *ij*; σ is the total number of elite ants; L^{*} is the length of the optimal path.

C. FLACO FOR PATH PLANNING OF UNMANNED VEHICLES

The FL and the improved ACO were combined for the path planning of unmanned vehicles. Several time-varying factors that are often ignored were taken into account, namely, traffic flow and incident risk. The pseudocode of the FLACO is given in Figure 5.

```
Initialize
    For each loop
        Locate ants
        For each iteration
            For each ant
                If ant is active
                    Construct probability
                    Select route
                    Update tabu list
                End
            Next ant
        Next iteration
        Update pheromone
    Next loop
    Select the optimal path
End FLACO
```

FIGURE 5. The pseudocode of the FLACO.

As shown in Figure 5, the basic steps of the FLACO are as follows:

Step 1. Initialization

The FLACO parameters were initialized, including the number of ants, the evaporation coefficient and the mean vehicle speed.

Step 2. Ant positioning

All the ants were placed at the origin. The ants are either active or inactive. An active ant is not blocked at any node before reaching the destination. In each iteration, every ant could traverse all the nodes. Hence, an ant will be blocked at a node if it has no chance to get closer to the destination and no chance to move back.

Step 3. Probability construction

The probability for an active ant to choose an edge can be computed by the cost function. For ant k, the probability to move from node i to node j can be calculated by:

$$p_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \prod_{l\in\text{parameters}} \xi_{ijl}^{-\alpha_1}}{\sum_{h\notin\text{tabu}_k} \tau_{ih} \prod_{l\in\text{parameters}} \xi_{ihl}^{-\alpha_1}} & j \notin \text{tabu}_k, \\ 0 & \text{otherwise,} \end{cases} \tag{14}$$

where, τ_{ij} is the pheromone concentration on edge *ij*; $\alpha = 2$ controls the importance of τ_{ij} [12], [23], [24]; *tabu* is a list of blocked edges (the visited nodes); *parameters* is the set of key parameters that affect the vehicle motions in large cities; *l* is the serial number of each parameter; α_l adjusts the importance of parameter *l*; $1 \leq \xi_{ijl} \leq 10$ is the cost function of parameter l. Here, the set of key parameters covers travel distance, traffic flow and incident risk. Other parameters could also be included, such as road width (number of lanes), the number of traffic lights and road quality (e.g. medical and entertainment facilities). The key parameters are introduced below:

(1) Travel distance

$$\xi_{ij\text{distance}} = D(i, j, t) \tag{15}$$

where, $D(i, j, t)$ is the travel distance on edge ij at time t. The value of this parameter varies with time, because a road section could be bidirectional at a time and unidirectional at another. If the travel distance is long, the total cost will be pushed up, and the long path in (14) will be less likely to be selected.

(2) Traffic flow

$$\xi_{ij\text{traffic}} = F(i, j, t) \tag{16}$$

where, $F(i, j, t)$ is the traffic low on edge ij at time t. This parameter was selected in our path planning system to minimize air pollution, time waste and gas consumption. If the traffic flow is high, the total cost will be pushed up, and the path with heavy traffic in (14) will be less likely to be selected.

(3) Incident risk

$$\xi_{ij\text{risk}} = R(i, j, t) \tag{17}$$

where, $R(i, j, t)$ is the incident risk on edge ij at time t. This parameter measures the risk of incidents on each edge based on statistics. If the incident risk is high, the total cost will be pushed up, and the highly risky path in (14) will be less likely to be selected.

Step 4. Path selection

The parameter q, which is randomly distributed in [0, 1], was compared with parameter $0 \leq Q \leq 1$, which is usually fixed at 0.9:

$$j = \begin{cases} \arg\max\left(p_{ih}^{k}\right) & q > Q, \\ \text{roulette strategy}\left(p_{ih}^{k}\right) & \text{otherwise.} \end{cases} \tag{18}$$

If q is greater than Q, each active ant will select the edge with the highest probability; otherwise, each active ant will select the next node by the roulette strategy.

Step 5. Tabu list update

The path (nodes) covered by ant k was added to the tabu list, such that it will not be selected again. The probability of the path will not be calculated any more.

If ant k has arrived at the destination or been blocked, it will be removed from the list of active ants. In other words, the ants that have arrived at the destination or been blocked were disabled in the current iteration.

Step 6. Pheromone update

The pheromone was updated by two rules: the local update rule and the global update rule. The former was adopted during path planning, while the latter was employed after a path had been planned. For ant k, the pheromone concentration on edge ij can be updated by:

$$\tau_{ij}^{\text{new}} = \tau_{ij}^{\text{old}} + (10 \times \Delta\tau), \tag{19}$$

where, $\Delta\tau$ is the additional amount of local pheromone outputted by the FL control system.

Considering the FL and Mamdani-type rule evaluation in subsection 2.2, the FL control system for the FLACO was constructed as shown in Figure 6.

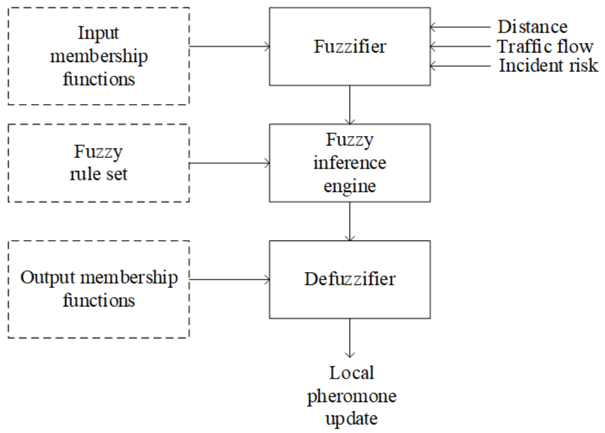

FIGURE 6. FL control system of the FLACO.

The inputs of the FL control system include the travel distance, traffic flow and incident risk of the path selected by ant k. For each input, only two fuzzy subsets were defined: low and high. The trapezoidal membership functions of the three inputs are presented in Figures 7–9, respectively.

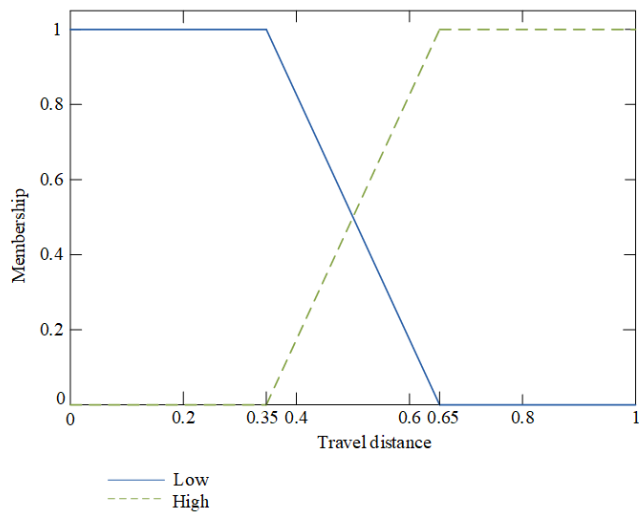

FIGURE 7. Membership function of travel distance.

Take travel distance for example. If the total travel distance along the path selected by an ant is greater than 65% of the maximum total travel distance selected by all ants in the same iteration, the membership function will follow the high curve; If the total travel distance along the path selected by an ant is smaller than 35% of the maximum total travel distance selected by all ants in the same iteration, the membership function will follow the low curve. The same applies to the membership functions of traffic flow and incident risk.

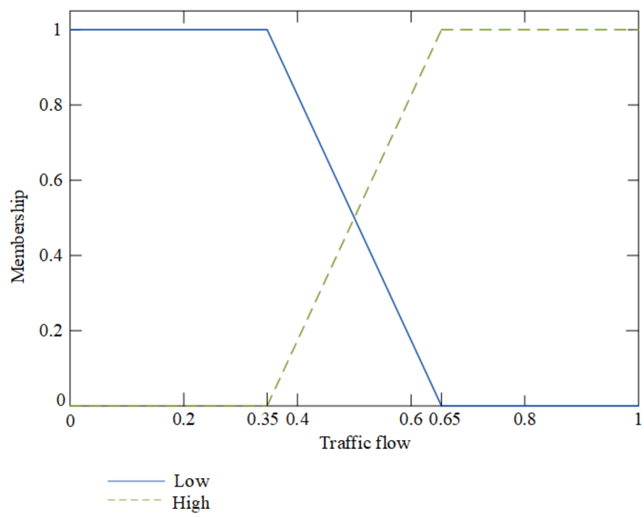

FIGURE 8. **Membership function of traffic flow.**

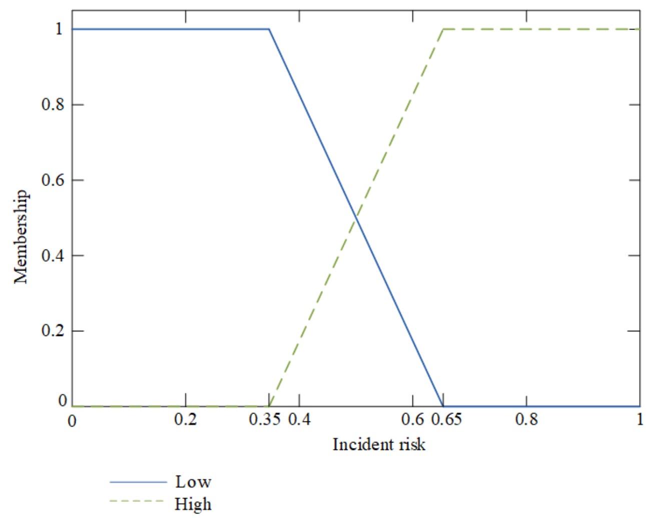

FIGURE 9. **Membership function of incident risk.**

For the output of the FL control system, four fuzzy subsets were designed for pheromone concentration (Figure 10): very weak, weak, strong and very strong. Finally, the COA method was adopted to identify a single output from the fuzzy subsets.

Multiple fuzzy rules were predefined in the FLACO system. The user could load his/her desired fuzzy rules into the FL control system. Table 1 lists the if-then rules for the three parameters, which correspond to their importance. In our case, the preferred importance for travel distance, traffic flow and incident risk were high, low and low, respectively. As a result, the workload of local pheromone update is minimized on the path with high travel distance, low traffic flow and low incident risk.

At the end of each iteration, the global pheromone was updated:

$$\tau_{ij}^{\text{new}} = \rho \tau_{ij}^{\text{old}}, \tag{20}$$

where $0< \rho <1$ is the volatilization coefficient, which is often set to 0.9.

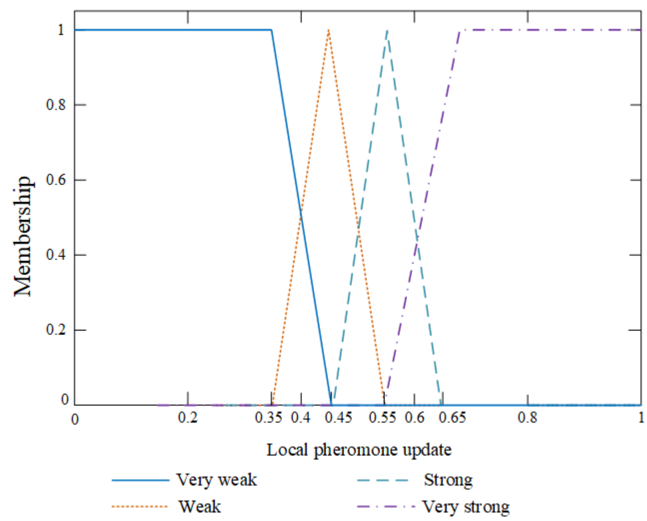

FIGURE 10. **Membership function of local pheromone update.**

TABLE 1. **The if-then rules for the three parameters.**

Rule number	Travel distance	If traffic flow	Incident risk	Then local pheromone update
1	High	Low	Low	Very Strong
2	High	High	Low	Strong
3	High	Low	High	Strong
4	Low	Low	Low	Strong
5	Low	Low	High	Weak
6	Low	High	Low	Weak
7	High	High	High	Weak
8	Low	High	High	Very weak

Step 7. Optimal path selection

After m iterations, the FLACO system recommends the O-D path with the lowest cost.

V. SIMULATION VERIFICATION

The clarity and readability of the road network are critical to path planning. The information from the road network is either dynamic or static. The dynamic information cannot be digitized, and thus rarely considered in path evaluation, which often relies on path length L.

This paper proposes a new concept called the virtual path length. For an actual path with the length L_k, the virtual path length L_k^* integrates four dynamic parameters: travel distance (D), traffic flow (F), incident risk (R) and speed limit (S):

$$L_k^* = \sum_{i=1,j=1}^{n} D_{ij}[1 + F_{ij} + R_{ij}(1 + S_{ij})] \tag{21}$$

To verify the proposed FLACO, two nodes in the road network were abstracted as nodes A and B in Figure 11, where white grids are road sections and black grids are obstacles.

Travel distance, traffic flow and speed limit are called state parameters, because they reflect the state of each road section in real time. Three cases were designed for verification:

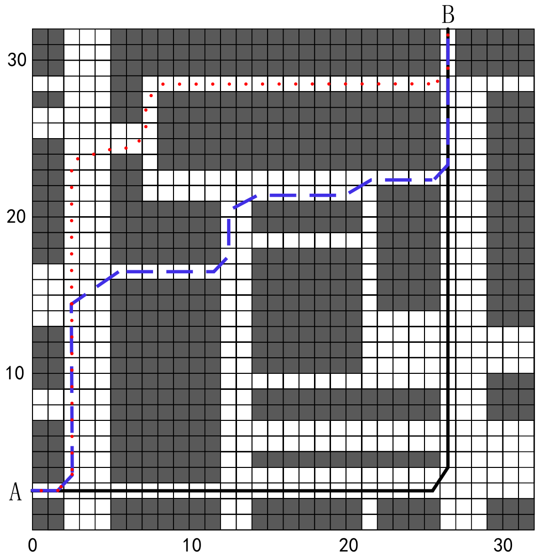

FIGURE 11. Optimal paths of contrastive algorithms.

three white grids (Case 1), two white grids (Case 2), and one white grid (Case 3). The traffic flow is unknown in all three cases. The speed limit (and the traffic flow) is high in Case 1, low in Case 2 and ultra-low in Case 3; the incident risk is low in Case 1, medium in Case 2 and high in Case 3.

The intervals and values of the state parameters are given in Tables 2 and 3, respectively.

TABLE 2. Interval of each state parameter.

State parameter	Incident risk (R)		
	Low	Normal	High
Value	0.1	0.5	1
State parameter	Speed limit (S)		
	Low	Normal	High
Value	0	0.5	1
State parameter	Traffic flow (F)		
	Low	Normal	High
Value	0	0.5	1

TABLE 3. State of each state parameter.

State	State parameter		
	R	S	F
Case 1	1	1	(0, 0.5, 1)
Case 2	0.5	0.5	(0, 0.5, 1)
Case 3	0.1	1	(0, 0.5, 1)

The FLACO, classic ACO and improved ACO were separately introduced to find the optimal path from A to B in Figure 11, where the red dotted line (path 1) is outputted by the classic ACO, the blue broken line (path 2) is outputted by the improved ACO, and the black solid line (path 3) is outputted by the FLACO. Table 4 shows the virtual path lengths of each algorithm in the three cases.

As shown in Table 4, the length of virtual path decreased with the traffic flow. In the actual path, no other factors are considered, only the road distance is considered. The virtual path takes travel distance (D), traffic flow (F), incident risk (R) and speed limit (S) into consideration, so the virtual path is closer to the real situation. Judging by the actual path length, the improved ACO achieved the best result, followed in turn by the FLACO and the classic ACO. However, the actual path only works in static environments. Under the dynamic environments, the virtual path 3 was much shorter than virtual paths 1 and 2, especially in Case 3. The reason is that the speed limit on this path is relaxed, for the risk on the latter part of the path is lower than that on the initial part, and the traffic flow is zero.

TABLE 4. Virtual path lengths under various algorithms and in different situations.

Path name	Actual path length	Virtual path length		
		Case 1	Case 2	Case 3
1	95	159	150	128
2	80	176	165	146
3	83	154	125	106

VI. CONCLUSION

Based on the FL and the improved ACO, this paper puts forward a route guidance system for unmanned vehicles. Firstly, the elite strategy was introduced to prevent the classic ACO from falling into the local optimum trap, creating the elitist ant system. However, the elitist ant system might not converge to the global optimal path, because of the small difference between the candidate paths. To improve solution accuracy, the elitist ant system was further improved into the rank-based ant system. The improved ACO works well in static environments, but cannot adapt well to dynamic environments. Considering the difficulty in accurate digitization of dynamic factors, the improved ACO was integrated with the FL into the FLACO to find the optimal path for unmanned vehicles. To verify its performance, the FLACO was compared with the classic ACO and improved ACO through a simulation on the topology of a road network. In the simulation results, the actual path length of path 3 is not the shortest, but among the virtual paths considering the dynamic environment, the virtual length of path 3 is the shortest. Especially in case3, the lowest of the three path length values is 106. The comparison shows that the FLACO output a more cost-effective path than the contrastive algorithms. The future research will further optimize the FLACO (e.g. reducing the computing time) and extend it to the path planning of a fleet of unmanned vehicles.

REFERENCES

[1] Y. F. Payalan and M. A. Guvensan, "Towards next-generation vehicles featuring the vehicle intelligence," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 1, pp. 30–47, Jan. 2020.

[2] I. Shim, J. Choi, S. Shin, T.-H. Oh, U. Lee, B. Ahn, D.-G. Choi, D. H. Shim, and I. S. Kweon, "An autonomous driving system for unknown environments using a unified map," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 1999–2013, Aug. 2015.

[3] P. Mellodge, *Model Abstraction in Dynamical Systems: Application to Mobile Robot Control*. Charlottesville, VA, USA: Univ. of Virginia Press, 2007.

[4] T. Tuncer and O. Yar, "Fuzzy logic-based smart parking system," *Ingénierie des systèmes d Inf.*, vol. 24, no. 5, pp. 455–461, Nov. 2019.

[5] A. Belkadi, H. Abaunza, L. Ciarletta, P. Castillo, and D. Theilliol, "Design and implementation of distributed path planning algorithm for a fleet of UAVs," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 55, no. 6, pp. 2647–2657, Dec. 2019.

[6] D. Xin, C. Hua-Hua, and G. Wei-Kang, "Neural network and genetic algorithm based global path planning in a static environment," *J. Zhejiang Univ.-Sci. A*, vol. 6, no. 6, pp. 549–554, Jun. 2005.

[7] M. A. Wajeed and V. Sreenivasulu, "Image based tumor cells identification using convolutional neural network and auto encoders," *Traitement du Signal*, vol. 36, no. 5, pp. 445–453, 2019.

[8] B. Ombuki, B. J. Ross, and F. Hanshar, "Multi-objective genetic algorithms for vehicle routing problem with time windows," *Appl. Intell.*, vol. 24, no. 1, pp. 17–30, Feb. 2006.

[9] C. Prins, "A simple and effective evolutionary algorithm for the vehicle routing problem," *Comput. Oper. Res.*, vol. 31, no. 12, pp. 1985–2002, Oct. 2004.

[10] P. Chemouil, J. Khalfet, and M. Lebourges, "A fuzzy control approach for adaptive traffic routing," *IEEE Commun. Mag.*, vol. 33, no. 7, pp. 70–76, Jul. 1995.

[11] J. Yin and W. Fu, "A hybrid path planning algorithm based on simulated annealing particle swarm for the self-driving car," in *Proc. Int. Comput., Signals Syst. Conf. (ICOMSSC)*, Dalian, China, Sep. 2018, pp. 696–700.

[12] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: Optimization by a colony of cooperating agents," *IEEE Trans. Syst., Man Cybern. B, Cybern.*, vol. 26, no. 1, pp. 29–41, Feb. 1996.

[13] S. Zidi, S. Maouche, and S. Hammadi, "Real-time route planning of the public transportation system," in *Proc. IEEE Intell. Transp. Syst. Conf.*, Toronto, ON, Canada, Sep. 2006, pp. 55–60.

[14] F. Quan, "Design of robot ant colony algorithm to reduce transport risks of dangerous chemicals," *Revue d'Intelligence Artificielle*, vol. 32, no. s1, pp. 57–66, Dec. 2018.

[15] S. Gajjar, M. Sarkar, and K. Dasgupta, "FAMACROW: Fuzzy and ant colony optimization based combined mac, routing, and unequal clustering cross-layer protocol for wireless sensor networks," *Appl. Soft Comput.*, vol. 43, pp. 235–247, Jun. 2016.

[16] B. Cheng, K. Li, and B. Chen, "Scheduling a single batch-processing machine with non-identical job sizes in fuzzy environment using an improved ant colony optimization," *J. Manuf. Syst.*, vol. 29, no. 1, pp. 29–34, Jan. 2010.

[17] P. Kumar, R. Dwivedi, and V. Tyagi, "Fuzzy ant colony optimization based energy efficient routing for mixed wireless sensor network," in *Proc. Int. Conf. Issues Challenges Intell. Comput. Techn. (ICICT)*, Ghaziabad, India, Sep. 2019, pp. 1–7.

[18] K. Akka and F. Khaber, "Mobile robot path planning using an improved ant colony optimization," *Int. J. Adv. Robotic Syst.*, vol. 15, no. 3, May 2018, Art. no. 172988141877467.

[19] F. K. Purian and E. Sadeghian, "Mobile robots path planning using ant colony optimization and fuzzy logic algorithms in unknown dynamic environments," in *Proc. Int. Conf. Control, Autom., Robot. Embedded Syst. (CARE)*, Jabalpur, India, Dec. 2013, pp. 1–6.

[20] M. M. Goswami, R. V. Dharaskar, and V. M. Thakare, "Fuzzy ant colony based routing protocol for mobile ad hoc network," in *Proc. Int. Conf. Comput. Eng. Technol.*, Jan. 2009, pp. 438–444.

[21] Y. Sun, J. Xu, H. Qiang, and G. Lin, "Adaptive neural-fuzzy robust position control scheme for maglev train systems with experimental verification," *IEEE Trans. Ind. Electron.*, vol. 66, no. 11, pp. 8589–8599, Nov. 2019.

[22] E. H. Mamdani, "Application of fuzzy algorithms for control of simple dynamic plant," *Proc. Inst. Electr. Eng.*, vol. 121, no. 12, pp. 1585–1588, 1974.

[23] C. Taylor and D. Meldrum, "Freeway traffic data prediction using neural networks," in *Proc. Pacific Rim TransTech Conf. Vehicle Navigat. Inf. Syst. Conf., 6th Int. Ride Future (VNIS)*, Seattle, WA, USA, 1995, pp. 225–230.

[24] M. Dorigo and L. M. Gambardella, "Ant colony system: A cooperative learning approach to the traveling salesman problem," *IEEE Trans. Evol. Comput.*, vol. 1, no. 1, pp. 53–66, Apr. 1997.

QI SONG was born in Liaoyang, Liaoning, China, in 1980. He received the Ph.D. degree in electrical engineering and computer science from the University of California, Irvine, in 2013. He is currently a Professor with the Suzhou Institute of Biomedical Engineering and Technology, Chinese Academy of Sciences. His research interests include SLAM navigation systems, the intersection of control theory, machine vision and machine learning, and with applications to autonomous vehicles and robot.

QINGLEI ZHAO was born in Daqing, Heilongjiang, China, in 1982. He received the Ph.D. degree from the University of Chinese Academy of Sciences, China. He is currently working with the Changchun Institute of Optics, Fine Mechanics and Physics. He is also mainly involved in the research of embedded system design and automatic control.

SHUXIN WANG was born in Baicheng, Jilin, China, in 1981. He received the Ph.D. degree from the University of Chinese Academy of Sciences, China. He is currently working with the Changchun Institute of Optics, Fine Mechanics and Physics. He is also mainly involved in the research of optomechanical design.

QIANG LIU was born in Chifeng, Inner Mongolia, China, in 1981. He received the bachelor's degree in mechanical design, manufacturing, and automation from the Harbin Institute of Technology, in 2005, and the Ph.D. degree in optical engineering from the University of Chinese Academy of Sciences, in 2013. He has been involving in the research of structural design of space optical remote sensors with the Changchun Institute of Optics, Fine Mechanics, and Physics of the Chinese Academy of Sciences.

XIAOHE CHEN received the Ph.D. degree in EE from the Missouri University of Science of Technology, in 2007. He is currently a Professor with the Suzhou Institute of Biomedical Engineering and Technology, Chinese Academy of Sciences. His main research interests are signal processing and high-speed digital design.