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An Improved Real-Time Path Planning Method Based on Dragonfly Algorithm for Heterogeneous Multi-Robot System

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ABSTRACT Heterogeneous multi-robot system is one of the most important research directions in the robotic field. Real-time path planning for heterogeneous multi-robot system under unknown 3D environment is a new challenging research and a hot spot in this field. In this paper, an improved real-time path planning method is proposed for a heterogeneous multi-robot system, which is composed of many unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs). In the proposed method, the 3D environment is modelled as a neuron topology map, based on the grid method combined with the bio-inspired neural network. Then a new 3D dynamic movement model for multi-robots is established based on an improved Dragonfly Algorithm (DA). Thus, the movements of the robots are optimized according to the activities of the neurons in the bio-inspired neural network to realize the real-time path planning. Furthermore, some simulations have been carried out. The results show that the proposed method can effectively guide the heterogeneous UAV/UGV system to the target, and has better performance than traditional methods in the real-time path planning tasks.

INDEX TERMS Heterogeneous multi-robot system, path planning, dragonfly algorithm, bio-inspired neural network.

I. INTRODUCTION

Heterogeneous multi-robot system is a new research hot spot in the robotic field [1]–[4]. Heterogeneous multi-robot system means that the types or the capabilities of the robots in a multi-robot system are different. With the development of multi-robot system, more and more heterogeneous multi-robot systems have been proposed to deal with some complex tasks, which require different robotics to finish, such as the space exploration, urban search and rescue, and so on. The main research topics of heterogeneous multi-robot systems include path planning, task assignment, fault self-healing, and so on [5]–[7].

Among these heterogeneous multi-robot systems, the hybrid UGV/UAV system is the most used type of system. With the continuous improvement of technologies, the unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) have been widely used in military, security, agriculture, disaster relief and other aspects [8]–[10]. But only one type of UGVs or UAVs can not finish the complex job very well sometimes, the hybrid UGV/UAV system is a good solution that can combine the advantages of UAVs and UGVs [11], [12]. However, the hybrid UGV/UAV system has also met some challenges, which are different from those of the homogeneous multi-robot system. In this paper, the real-time path planning is focused, which is the basic task of the hybrid UGV/UAV system [13], [14].

The objective of the real-time path planning is to plan a passable path for the robots, from the starting position to the target position according to certain performance indexes (such as distance, time, etc.) under the dynamic environments with obstacles. The real-time path planning is a challenging

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task for the hybrid UGV/UAV system, because the UGVs walk on the ground and UAVs fly in the air, and the obstacles are unequally spread over the 3D environment.

There are many research results in the path planning for the hybrid UGV/UAV system. For example, Li *et al.* [15] presented a path planning method in unmanned aerial/ground vehicle cooperative systems, which is based on a hybrid genetic algorithm and local rolling optimization algorithm. Seyedi *et al.* [16] proposed a scalable planning strategy for simultaneously finding the trajectories of UAVs and UGVs. Asadi *et al.* [17] implemented the Rapidly-exploring Random Tree (RRT) algorithm for a integrated UGV-UAV system. Although these methods can realize the path planning problem, there are some problems need to be further studied. For example, some methods above just solved the path planning problem of the UGV in a 2D environment. Few of them can deal with the path planning problem as a whole, which are not suitable for real-time path planning for the hybrid UGV/UAV system.

With the development of technologies and the increased demands of applications, more and more researchers have focused on the problem of path planning in real 3D environment [18]. For example, Han [19] proposed a method based on critical obstacles and surrounding point set, which can lower the complexity for efficient 3D path planning. Ni, *et al.* [20] presented an improved dolphin swarm algorithm based navigation method for the autonomous underwater vehicle in 3D underwater environment. Yang *et al.* [21] presented an appropriate spatial representation of the environment for the path planning of ground robots in 3D environment. However, due to the variability and complexity of 3D unknown environment, the real-time path planning of hybrid UAV/UGV system is still a hot spot.

Recently, the bio-inspired intelligent methods have been a hot spot in the real-time path planning [22]. For example, Ni and Yang have studied the bio-inspired neural network (BINN) in the real-time path planning task for different robots and the results show the efficiency of the bio-inspired neural network [23], [24]. Cai *et al.* [25] proposed a 3D real-time path planning method based on cognitive behavior optimization algorithm. Yan *et al.* [26] presented a real-time path planning algorithm for AUV using PSO combining the waypoint guidance. Zhu *et al.* [27] proposed an integrated biologically inspired self-organizing map algorithm for the task assignment and path planning of an AUV system. These bio-inspired methods have achieved some good results. However, most of them are used for the homogeneous robotic system, which can't be used for the hybrid UAV/UGV system directly. And there are still some problems need to be further studied, such as the low accuracy and slow convergence speed problems.

To deal with the problems in the real-time path planning for the hybrid UAV/UGV system, an improved bio-inspired methods is proposed, which is combined with the Dragonfly Algorithm (DA) [28], [29] and the bio-inspired neural network (BINN) [23], [30]. In the proposed method, the motion space of the hybrid UGV/UAV system is converted into a topological state space composed of multiple neurons. The activity of each neuron is updated based on a 3D dynamic movement model in the dragonfly individual local search. Then the path can be generated based on the activities of all the surrounding neurons of the robots.

The main contributions of this paper are summarized as follows: (1) The 3D environment of the hybrid UGV/UAV system is modeled based on the combination of the grid method and an improved bio-inspired neural network model. (2) An improved Dragonfly Algorithm is proposed for the real time path planning of the hybrid UGV/UAV system in unknown dynamic 3D environments. (3) The search space of the proposed method is reduced obviously, which can work for the real-time path planning in complex 3D environments. Furthermore, various simulations are carried out for the real time path planning of the hybrid UGV/UAV system.

This paper is organized as follows. Section II presents the real-time path planning problem of the heterogeneous multi-robot system under 3D environment. The 3D real-time path planning method based on improved dragonfly algorithm is proposed in Section III. The simulations are given in Section IV. Section V discusses the performance of the proposed approach by some comparison experiments. Finally, the conclusions are given in Section VI.

II. PROBLEM STATEMENT

The real-time path planning problem in unknown 3D environment for a hybrid UGV/UAV system is studied in this paper. In this path planning task, UGVs and UAVs know their own position information and the target position information, but the current 3D environment space information is completely unknown. The UGVs and UAVs in the process of movement can detect the surrounding environment, identify and locate the surrounding obstacles and other robots, by using the onboard sensors. Furthermore, the robots in the same system can communicate to obtain the positions of each other by wireless communication technology. The schematic of the real-time path planning process for the hybrid UGV/UAV system is shown as Fig. 1.

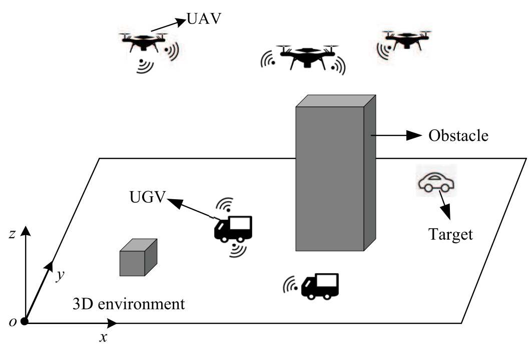

FIGURE 1. The schematic of the real-time path planning process for the hybrid UGV/UAV system.

The problem studied in this paper is described as follows:

(1) A hybrid UGV/UAV system is used to carried out the real-time path planning task. The task τ is denoted by

$\tau=\{P_{\text{target}}, H\}$, where P_{target} is the position of the target and H is the hybrid UGV/UAV system. The target is on the ground and its position is known to all the UGVs and UAVs in the system.

(2) In the hybrid UGV/UAV system, there are N UGVs and M UAVs. The UGV is marked as $U_{gi}, i = 1, 2, \ldots, N$ and the UAV is marked as $U_{aj}, j = 1, 2, \ldots, M$.

(3) The UGVs and UAVs can automatically locate themselves based on some positioning technologies. Because the communication range is big enough, the positions of the UGVs and UAVs in the system are known to each other.

(4) The UGVs and UAVs can obtain the positions of the obstacles based on the onboard sensors. For the sake of analysis, the detection ranges of the UGVs and UAVs are set as equal, which are denoted as R.

As described above, the real-time path planning task studied in this paper is near the real-world applications of the UGV/UAV system, such as the urban rescue task, target searching and field hunting problem [31]–[33].

III. PROPOSED SOLUTIONS

There are two main problems in the real-time path planning task, namely the environment modeling problem and motion planning problem. In this paper, the grid-based method and the bio-inspired method are combined to model the 3D environment. Then an improved dragonfly algorithm (IDA) is proposed to deal with the motion planning problem for the UGVs and UAVs. The work flow of the proposed solutions for the real-time path planning task is shown in Fig. 2.

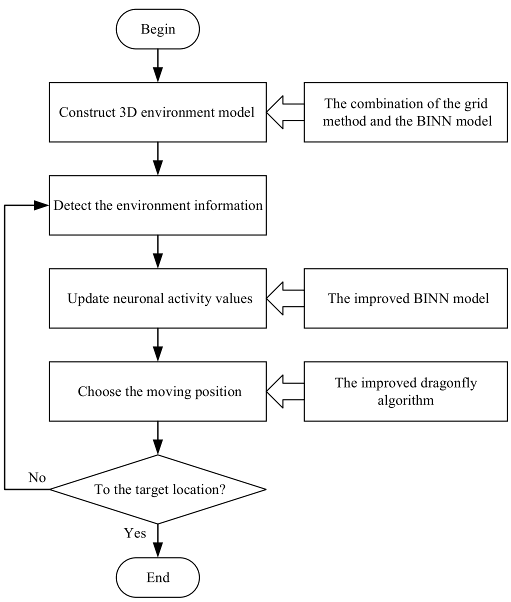

FIGURE 2. The work flow of the proposed solutions for the real-time path planning task.

A. 3D ENVIRONMENT MODELING

The environment of the path planning task studied in this paper is a 3D environment, which is set to a 3D bounded cuboid space Ω. Grid modelling method is used to divide the moving space Ω into a 3D grid map. Each node of this grid map is then taken as a neuron. Thus, the whole grid map is transformed into a topological state space composed of neural networks. The modelling process is shown in Fig. 3.

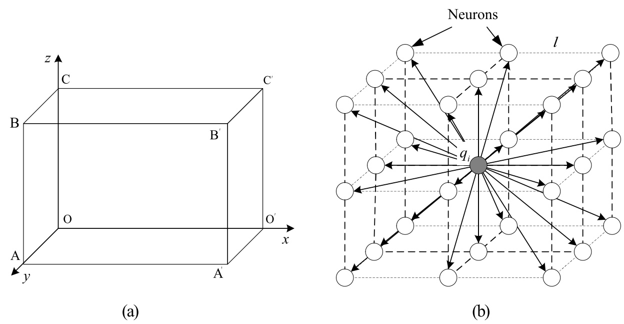

FIGURE 3. The modelling process of the proposed method for the 3D environment: (a) The 3D environment; (b) The grid map based on the BINN model.

In the grid map shown in Fig. 3(b), the nodes (namely the neurons) are interconnected, and the distance between two adjacent neurons is set as the length of the robot moving step l:

$$l = V_i * S_{\text{step}} \tag{1}$$

where V_i is the speed of the i-th robot and S_{step} is the simulation step size. The coordinate of each node in the grid map is expressed as (x, y, z), and the environmental information of the node in the grid map is defined as:

$$W(x, y, z) = \begin{cases} 1 & \text{target location} \\ 0 & \text{movable position} \\ -1 & \text{obstacle position} \\ k & \text{robot position} \end{cases} \tag{2}$$

where k means the serial number of the robots in the multi-robot system. With the robot movement, the activities of the neurons (nodes in the grid map) will be updated based on the dynamic function of the bio-inspired neural networks (BINN) [23]:

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)([I_i]^+ + \sum_{j=1}^{h} \omega_{ij}[x_j]^+) - (D + x_i)[I_i]^- \tag{3}$$

where, x_i is the activity value of the i-th neuron; A, B, D are the parameters of the BINN, which are all nonnegative constants; h represents the number of adjacent neurons in the i-th neuron; ω_{ij} is the connection weight between the i-th neuron and the i-th neuron; Function $[I]^+$ and $[I]^-$ are nonlinear functions defined as $[I]^+ = \max\{I, 0\}$, and $[I]^- = \max\{-I, 0\}$, respectively. Here, I_i is the external input of the i-th neuron, which is defined as:

$$I_i = \begin{cases} E & \text{target area} \\ -E & \text{obstacle area} \\ 0 & \text{movable area} \end{cases} \tag{4}$$

where $E \gg B$ is a larger normal number.

Based on the proposed environment modeling method, with the movement of the robots in the 3D environment, each robot will construct a local grid map within its detection range. And the environment information will be updated with the activities of the neurons simultaneously. Thus, the environment information can be presented by the activities of the neurons and the calculation can be reduced obviously.

Remark1: In the proposed 3D environment modelling method, the advantages of the grid method and the BINN method are both utilized. Meanwhile, the shortcomings of the two methods are overcome, such as the insufficient information presentation of the general grid method and the great deal of calculation of the basic BINN method.

B. REAL-TIME PATH PLANNING METHOD BASED ON IMPROVED DA

To deal with the real-time path planning problem for the hybrid UGV/UAV system, an improved dragonfly algorithm (DA) is presented. The fundamentals of DA are based on the foraging principle of dragonflies in groups, which have some advantages in the path planning, such as the real-time performance, robustness, and so on [34], [35]. However, there are still some shortcomings of the general DA, including the locally optimal problem and the stability problem. To deal with these problems, the dragonfly algorithm is improved combined with the BINN method, which will be introduced in details as follows.

1) UPDATE THE POSITIONS OF THE DRAGONFLIES

There are five main behaviors in the process of the dragonfly foraging, namely separation, formation, aggregation, obstacle avoidance and target predation. Based on these behaviors, if there are some dragonflies around the i-th dragonfly, its position P_t^i is updated by:

$$\begin{aligned} P_{t+1}^i &= P_t^i + dP_t^i \\ dP_{t+1}^i &= (sS_i + aF_i + cA_i + eO_i + fT_i) + wdP_t^i \end{aligned} \tag{5}$$

where dP_{t+1}^i denotes the step vector of the dragonfly; s denotes separation coefficient; a denotes the formation coefficient; c denotes the aggregation coefficient; e denotes obstacle influence factor; f denotes target influence factor; w is inertial coefficient; S_i, F_i, A_i, O_i, and T_i represent the position of the i-th dragonfly after the five behaviors above respectively.

The position S_i after the separation behavior is defined as:

$$S_i = -\sum_{j=1}^{Q} P_i - P_j \tag{6}$$

where Q denotes the number of dragonflies around the i-th dragonfly, and P_j denotes the position of the j-th dragonfly.

The position F_i after the formation behavior is defined as:

$$F_i = \frac{\sum_{j=1}^{Q} V_j}{Q} \tag{7}$$

where V_j denotes the velocity of the j-th dragonfly.

The position A_i after the aggregation behavior is defined as:

$$A_i = \frac{\sum_{j=1}^{Q} P_j}{Q} - P_i \tag{8}$$

The position O_i after the obstacle avoidance behavior is defined as:

$$O_i = P_{\text{obstacle}} + P_i \tag{9}$$

where P_{obstacle} denotes the position of the obstacle.

The position T_i after the target predation behavior is defined as:

$$T_i = P_{\text{target}} - P_i \tag{10}$$

where P_{target} denotes the position of the target.

When there no other dragonflies around the i-th dragonfly, its position is updated by Levy flight in the general Dragonfly Algorithm, namely

$$P_{t+1}^i = P_t^i + Levy(3) * P_t^i \tag{11}$$

where $Levy(3)$ is the Levy flight in 3D environment. Because the Levy flight is based on a levy distribution to provide a random walk for robots, this process is slower and less efficient [20], [36].

To deal with the problems existed in the general DA, the Levy flight search is replaced by the 3D dynamic moving model based on the bio-inspired neural network (see Fig. 3(b)). Based on the proposed search method, the search range of the dragonfly individual is reduced to 26 directions in the 3D grid map, corresponding to the topological neuron cyberspace in the environment. In this BINN-based grid map, the active value of the target is maintained at a higher positive level, and the active values of the neurons corresponding to the obstacles are maintained at lower negative level. The activities of the neurons corresponding to the free locations are set as 0. By solving the shunting equation (3), obstacles only partially affect the movements of UAVs and UGVs, and the target can attract the UAVs and UGVs globally.

2) FITNESS FUNCTION OF THE DRAGONFLY ALGORITHM

The fitness function is used to determine which position is the next position for the current robot. In this study, the fitness function Fitness(·) is defined as follows:

$$\text{Fitness}(q_i) = \zeta_1 x_i + \zeta_2 \left(\frac{1}{\text{Dist}(q_i, q_T)} - \zeta_3 \text{SafeCheck}(q_i) \right) \tag{12}$$

where ζ_1, ζ_2, and ζ_3 are the weight coefficients, which are all non-negative numbers; x_i and q_i represent the activity value and position of the i-th candidate neuron, respectively; q_T is the position of the target; Dist(·) is the distance function;

SafeCheck($\cdot$) is the function to check whether the position of i-th neuron is safe, which is defined by

$$\mathrm{SafeCheck}(q_i) = \begin{cases} 1, & \text{If } \mathrm{Dis}(q_{ij}, R_k) < D_{\text{safe}} \\ 0, & \text{Otherwise} \end{cases} \tag{13}$$

where q_{ij} is the position of the j-th robot at the location of the i-th neuron; $k = 1, 2, \ldots, (N + M), k \neq j$; R_k means the position of the k-th robot in the hybrid UGV/UAV system; and D_{safe} is the safe distance between two robots.

Then, the j-th robot in the system will select the neuron with the biggest fitness value as the next position to move from the surrounding neurons, namely

$$q_n \Leftarrow \mathrm{Fitness}(q_n) = \max_{j=1,\ldots,k} \left\{\mathrm{Fitness}(q_{ij})\right\} \tag{14}$$

where $q_{ij}, i = 1, 2, \cdots, k$, is the location of the i neuron in the detection region of the j-th robot (see Fig. 3(b)); q_n is the location of the neuron, with the maximum fitness value in these neurons.

In summary, the pseudo code of the proposed dragonfly algorithm in this paper is shown in **Algorithm1** (see Fig. 4).

```
Algorithm1: Improved dragonfly algorithm for real-time path planning

Initialization;
%Initialize the  population size , the  maximum number of
  iterations, the weight coefficient, and so on.
For each robot in the hybrid UAV/UGV system
  {
  Calculate the neuronal activities in the detection range;
  If (the target isn't reached by this robot)
    Do
      {
      Calculate the fitness for all dragonfly individuals;
      Update the step size;
      Update the five behavior factors;
      Update the inertia weights;
      }
    While (the maximum iterations are reached)
    Choose the next position of the robot;
  Endif
 Endfor
```

FIGURE 4. The pseudo code of the proposed dragonfly algorithm.

The whole work flow of the proposed approach for the real-time path planning task of the hybrid UAV/UGV system are summarized as follows:

Step1: Construct the 3D environment model based on the proposed grid map and the BINN model;

Step2: Detect the environment with onboard sensors;

Step3: Update the neuron activities of all the neurons in the detection range according to (3);

Step4: Calculate the fitness values of all the candidate locations according to (12);

Step5: Choose the next location based on the improved DA algorithm according to (14), and move to this location;

Step6: If the target position is not reached, return Step2, otherwise the task is completed.

Remark2: Based on the proposed path planning method, the robots in the hybrid UAV/UGV system can deal with the obstacle avoidance in real time. The robots can finish the path planning task cooperatively without too much communications. Furthermore, the robots in the system can deal with the heterogeneous problem (such as the different movement speed) efficiently based on the proposed environment model and movement model.

IV. EXPERIMENTS AND ANALYSIS

To verify the effectiveness of the improved dragonfly algorithm in real-time path planning in unknown 3D environment, some simulation experiments are carried out in the Matlab platform, by a computer with i5-3230M CPU and 8G memory. There are some assumptions about the UGV and UAV in the system: (1) The UAVs and UGVs are all regarded as particles without shapes, and the effects of the shapes can be dealt with by enlarging the safe distance D_{safe}. (2) Because the time of turning is very small in the total process of the real-time path planning task, the turning radius and the time of turning of the robots are ignored in the simulations. (3) In the task τ, the hybrid UGV/UAV system H is composed of two UAVs in the air and one UGV on the ground, namely $H = \{U_{a1}, U_{a2}, U_{g1}\}$. To remove the effects of the randomness, all the experiments in this study are conducted 20 times and the mean values are given out. The parameters of the proposed method and the simulation parameters in this study are listed in Table 1.

TABLE 1. Parameters of the proposed method.

Parameters	Values	Remarks
R	10 (m)	Detection range of robots
V_{UAV}	15 (m/s)	Velocity of UAV
V_{UGV}	5 (m/s)	Velocity of UGV
N_p	40	Population size of DA
Max_t	500	Maximum iterations of DA
S_{step}	1 (s)	The step size of the simulation in (1)
A	500	Decay rate of neuron activity in (3)
B	500	Upper limit of neuron activity in (3)
D	500	Lower limit of neuron activity in (3)
E	500	Target incentive weights in (4)

A. STATIC ENVIRONMENT EXPERIMENT

To test the performance of the proposed algorithm, a static experiment is carried out firstly. In this experiment, the environment is static, and the position of the target is fixed. The initial state of the environment is shown in Fig. 5(a). The initial positions of the two UAVs are $(87, 87, 65)$ and $(89, 55, 60)$ respectively. The initial position of the UGV is $(40, 80, 0)$ and the position of the target is

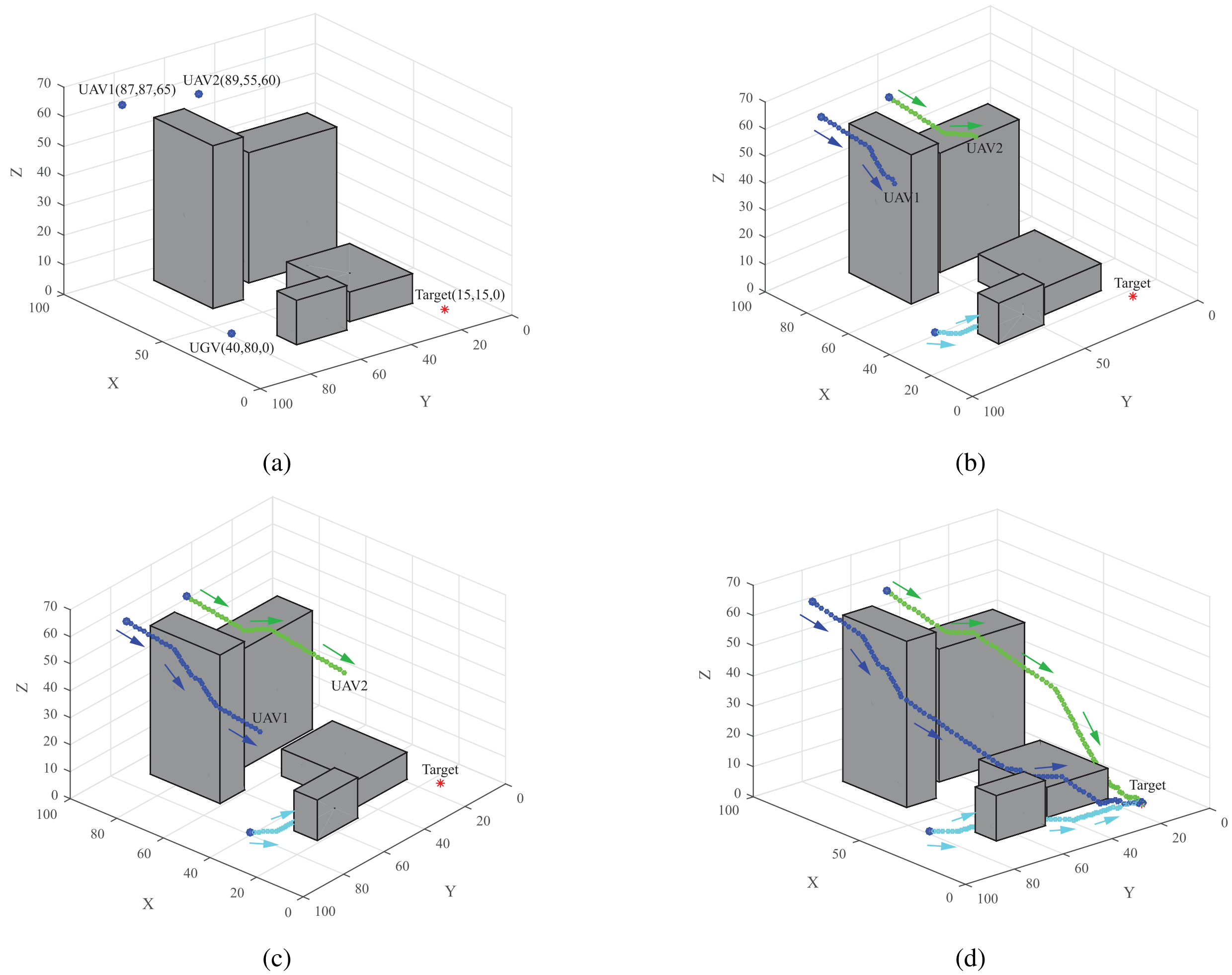

FIGURE 5. **The real-time path planning in the static environment for the hybrid UAV/UGV system: (a) Initial positions of the robots and target, view=(−128°, 22°); (b) At the 20th step, view=(−133°, 32°); (c) At the 38th step, view=(−139°, 29°); (d) Final trajectories, view=(−131°, 21°).**

$P_{\text{target}} = (15, 15, 0)$. The path planning results of the hybrid UAV/UGV system are shown in Fig. 5 and Table 2.

TABLE 2. **The path planning results of the hybrid UAV/UGV system in the static environment.**

	The length of the path (m)	The time of the robots (s)
UAV1	158.75	10.58
UAV2	133.25	8.88
UGV	79.46	15.89

The results in Fig. 5 show that the UAVs and the UGV can effectively avoid obstacles and reach the target position based on the proposed method. The generated paths based on the proposed method are smooth. In addition, the trajectories of the robots are optimized. For example, the two UAVs can fly as close to the buildings as possible and the UGV can go between the two buildings (see Fig. 5(d) and Table 2).

B. DYNAMIC ENVIRONMENT EXPERIMENT

To further test the performance of the proposed algorithm, a dynamic experiment is carried out, where the environment is the same as that of experiment in Section IV-A, except there are some dynamic obstacles. The initial positions of the two UAVs, the UGV, and the target are also the same as those of Section IV-A. And the initial positions of the three dynamic obstacles are (45, 90, 25), (60, 45, 32), (50, 35, 20), respectively (see Fig. 6(a)). The results of this dynamic experiments are shown in Fig. 6 and Table 3.

TABLE 3. **The path planning results of the hybrid UAV/UGV system in the dynamic environment.**

	The length of the path (m)	The time of the robots (s)
UAV1	164.4	10.96
UAV2	139.25	9.28
UGV	79.46	15.89

The results show that the proposed approach can deal with the dynamic environment efficiently. For example, when the UAV2 detects the dynamic obstacle $O2$, it will change its direction and move toward the target at once (see Fig. 6(b) and Fig. 6(c)). The final results of the path

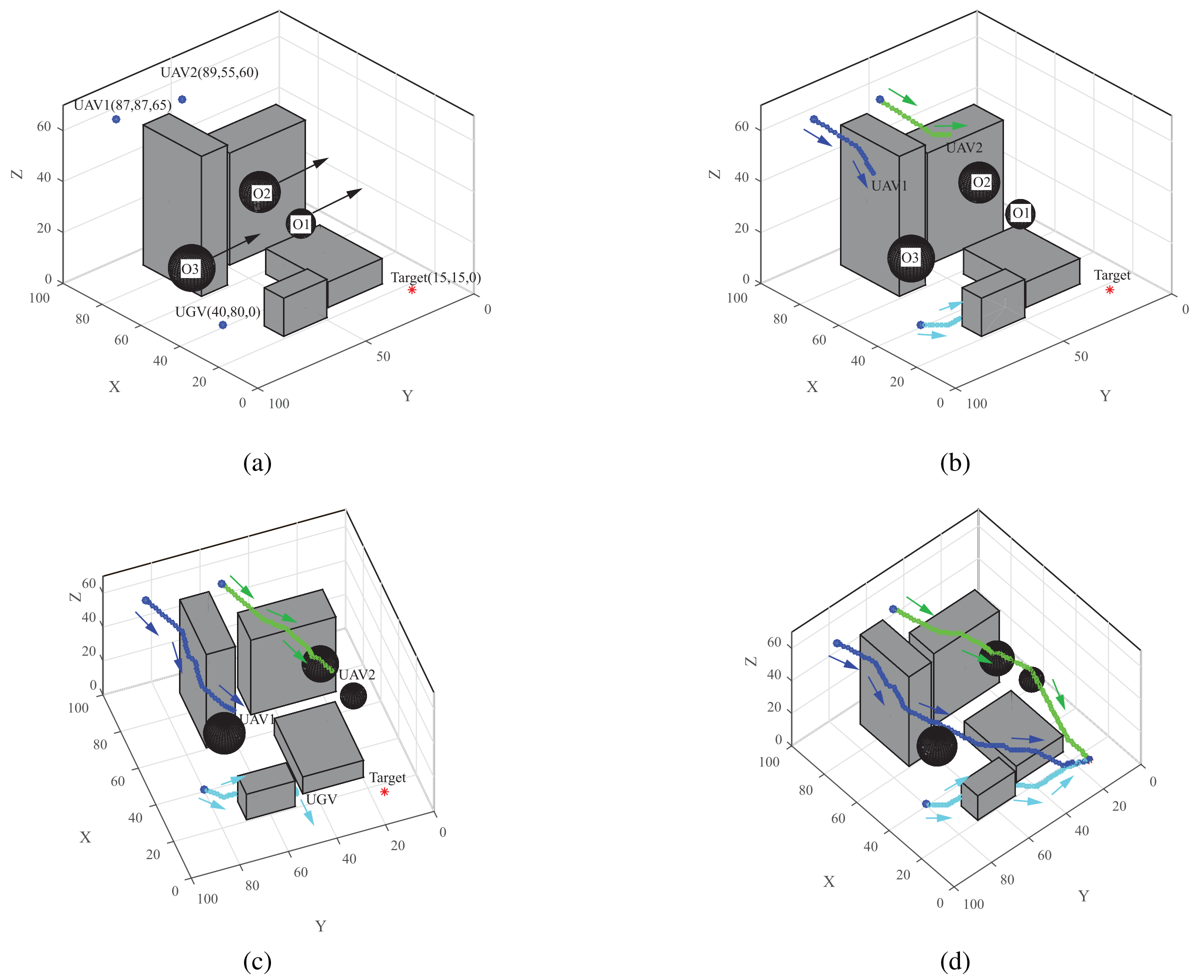

FIGURE 6. The real-time path planning in the dynamic environment for the hybrid UAV/UGV system: (a) Initial positions of the robots and target, view=(−132°, 29°); (b) At the 18th step, view=(−132°, 29°); (c) At the 38th step, view=(−110°, 49°); (d) Final trajectories, view=(−131°, 49°).

planning in Fig. 6(d) and Table 3 show that the path is longer than that of the static experiment, the results are optimized too. In addition, as the starting positions of the UGV, UAVs, target in the experiment and the starting positions, size and number of obstacles can be set arbitrarily, the results of this experiment show that the proposed method has strong robustness and universality.

C. DYNAMIC TARGET EXPERIMENT

To test the performance of the proposed algorithm in the real-time state, a dynamic target experiment is carried out, where the position of the target is changing randomly. In this study, when all the robots arrive at the position of the target, the task will be end. To make the task executable, the movement speed of the target is set as 2.5 m/s, which is lower than those of the UAVs and the UGV. In this experiment, the environment is complex, which is similar as a mountainous environment and the ground is rugged. The initial environment is shown in Fig. 7(a). The initial positions of three robots (two UAVs and one UGV) are (10, 50, 50), (10, 70, 60), (40, 95, 3), respectively. The initial position of the target is $P_{\text{target}} = (90, 90, 3)$. The final results of this task are shown in Fig. 7 and Table 4.

TABLE 4. The path planning results of the hybrid UAV/UGV system in the dynamic target experiment.

	The length of the path (m)	The time of the robots (s)
UAV1	202.26	13.48
UAV2	181.8	12.12
UGV	63.42	11.88

The simulation results show that all the robots can reach to the position of the target quickly, and the paths generated by the proposed approach is optimized. For example, the UAVs and UGV will change their movement directions and move toward the target quickly, when they detect the changing of the target position (see Fig. 7(b) and Fig. 7(c)). The results of this experiment show that the proposed method can deal the path planning task efficiently when the target is dynamic,

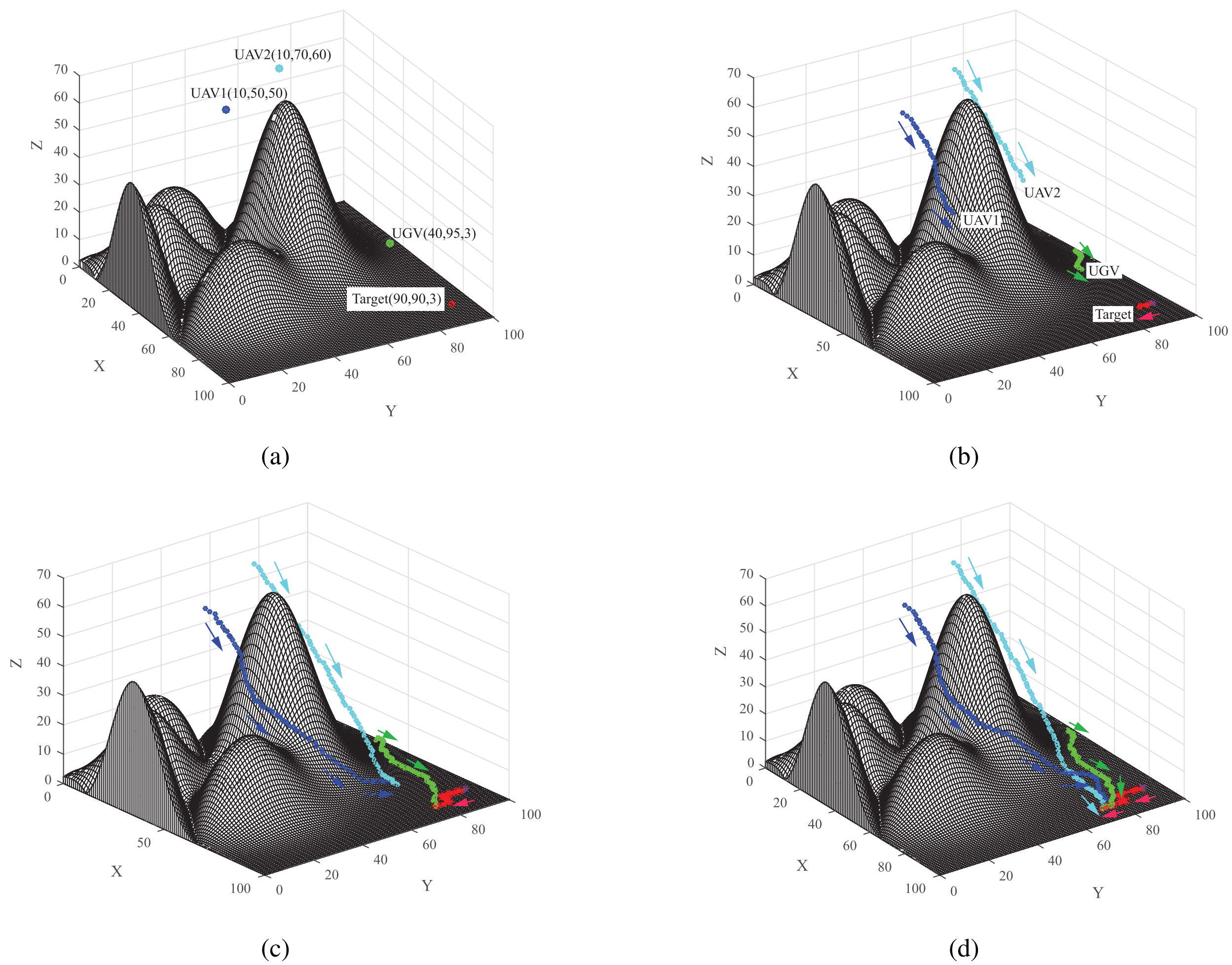

FIGURE 7. The real-time path planning of the dynamic target for the hybrid UAV/UGV system: (a) Initial positions of the robots and target, view=(61°, 26°); (b) At the 18th step, view=(56°, 22°); (c) At the 38th step, view=(51°, 22°); (d) Final trajectories, view=(55°, 26°).

which is very important for the hybrid UAV/UGV system in real world applications, such as criminal hunting, etc.

D. DYNAMIC TARGET EXPERIMENT UNDER DYNAMIC ENVIRONMENT

To test the performance of the proposed algorithm in some complex states, a dynamic target experiment under dynamic environment is carried out. In this experiment, the initial positions of the two UAVs and the UGV are the same as those of the experiment in Section IV-C, except there are two dynamic obstacles in the environment. The initial positions of the two dynamic obstacles are (60, 60, 30) and (35, 80, 20) (see Fig. 8(a)). The two dynamic obstacles will move in the environment and the final positions of them are (60, 60, 20) and (50, 80, 20) (see Fig. 8(d)). The final results of this task are shown in Fig. 8 and Table 5.

The simulation results of this experiment show that the UAVs and UGV can reach to the target quickly and avoid the dynamic obstacles efficiently (see Fig. 8(b) and Fig. 8(c)). The time of the robots in the hybrid system doesn't increase obviously than that of the experiment in Section IV-C (see Table 4 and Table 5). The results of this experiment prove that the proposed method has good performance in the complex real-time path planning task where the target and the environment are both dynamic.

TABLE 5. The path planning results of the hybrid UAV/UGV system in the dynamic target experiment under dynamic environment.

	The length of the path (m)	The time of the robots (s)
UAV1	213.21	14.21
UAV2	190.56	12.75
UGV	63.42	11.88

V. COMPARISON AMONG THE PROPOSED APPROACH, THE BASIC DA AND BINN

To demonstrate the effect of the improved dragonfly algorithm (I-DA), a comparison experiment is carried out. In this experiment, the proposed approach is compared with the approach based on the basic DA (B-DA), and that based on the basic bio-inspired neural network (BINN). The task in this

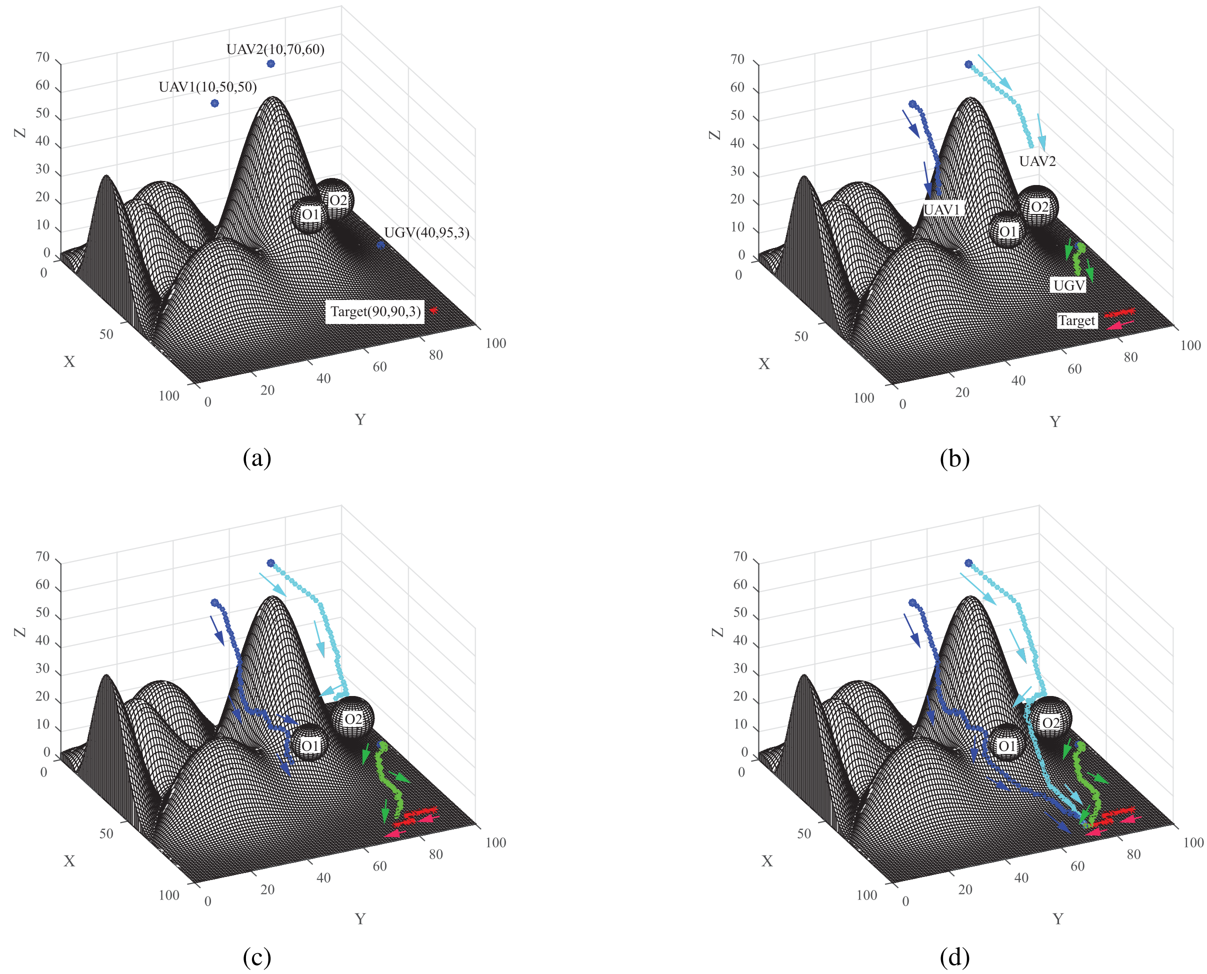

FIGURE 8. The real-time path planning of the dynamic target experiment under dynamic environment, view=(65°, 26°): (a) Initial positions of the robots, dynamic obstacles and target; (b) At the 20th step; (c) At the 40th step; (d) Final trajectories.

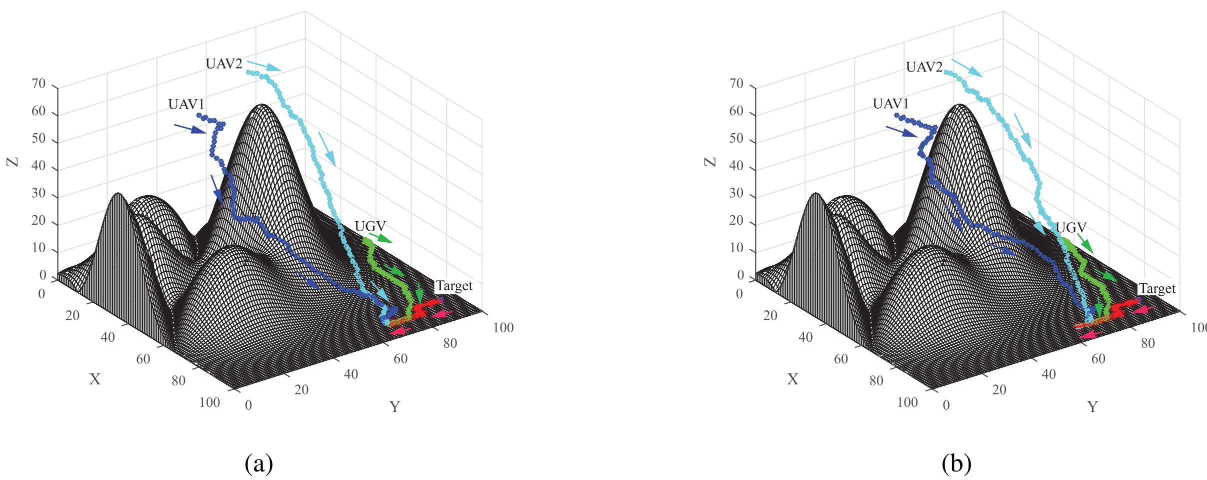

FIGURE 9. The real-time path planning of the dynamic target for the hybrid UAV/UGV system, view=(55°, 26°): (a) Final trajectories of the basic BINN; (b) Final trajectories of the basic DA.

experiment is the same as that of Section IV-C. The results of the basic BINN and the basic DA algorithms are shown in Fig. 9, and the result of the proposed method can be seen in Fig. 7(d). The final length of the trajectories obtained by the three methods and the computational time of the three methods are listed in Table 6.

TABLE 6. The results of the path planning for the hybrid UAV/UGV system in the dynamic target experiment.

Methods	The length of the path (m)			The maximum time of the robots (s)	The computation time of the simulation (s)	The computation time of each step (s)
	UAV1	UAV2	UGV			
G-DA	235.32	191.12	72.97	15.69	155.93	0.82
BINN	222.66	189.23	69.64	14.84	126.2	0.70
I-DA	202.26	181.8	63.42	13.48	82.33	0.52

The results in Table 6 show that the performance of the basic DA is the worst among the three algorithms. The main reason is that the basic DA algorithm waste a lot of time in the early random search stage. The performance of the basic BINN algorithm is better than the basic DA algorithm, but the computational time of it is longer than the proposed algorithm (see Fig. 9(a) and Fig. 7(d)). The main reason is that the basic BINN algorithm need calculate the activities of all the neurons in the environment. However, the proposed method can overcome the shortcomings of both the basic DA and BINN algorithms, which can reduce the computational time and obtain an optimal path for the hybrid UAV/UGV system. For each step of the simulation, the time of the proposed method is just 0.52s, which can satisfy the requirements of the real-time path planning task.

VI. CONCLUSION

The real-time path planning task in unknown 3D environment for the hybrid UAV/UGV system is studied in this paper, and a new path planning method is proposed. This method transforms the 3D environment into a neuron topology model by combining the grid method with the bio-inspired neural network. Then the improved DA is used to realize the path planning, where the initial search process of the DA is optimized by establishing a new 3D dynamic moving model based on the bio-inspired neural network to improve the search efficiency.

To verify the effectiveness and real-time performance of the proposed method, various simulation experiments are carried out. The simulation results show that the improved DA proposed in this paper can complete the real-time path planning task for the hybrid UAV/UGV system efficiently in different states, such as the static and dynamic environment, static and dynamic target. Furthermore, the comparison experiments show that the improvements of the proposed method are effective. In future work, the real world applications will be further studied to test the real performance of the proposed approach, and some new methods for the hybrid UAV/UGV system will be presented to further improve the efficiency of the real-time path planing method.

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