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# Collision Avoidance for Cooperative UAVs With Optimized Artificial Potential Field Algorithm

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**ABSTRACT** Unmanned aerial vehicle (UAV) systems are one of the most rapidly developing, highest level and most practical applied unmanned aerial systems. Collision avoidance and trajectory planning are the core areas of any UAV system. However, there are theoretical and practical problems associated with the existing methods. To manage these problems, this paper presents an optimized artificial potential field (APF) algorithm for multi-UAV operation in 3-D dynamic space. The classic APF algorithm is restricted to single UAV trajectory planning and usually fails to guarantee the avoidance of collisions. To overcome this challenge, a method is proposed with a distance factor and jump strategy to solve common problems, such as unreachable targets, and ensure that the UAV will not collide with any obstacles. The method considers the UAV companions as dynamic obstacles to realize collaborative trajectory planning. Furthermore, the jitter problem is solved using the dynamic step adjustment method. Several resolution scenarios are illustrated. The method has been validated in quantitative test simulation models and satisfactory results were obtained in a simulated urban environment.

**INDEX TERMS** Multi-UAV, trajectory planning, collision avoidance, artificial potential field, jitter problem.

## I. INTRODUCTION

The unmanned aerial vehicle (UAV) system has been widely researched recently due to the large-scale applications for warfare and civilian use in urban areas. The characteristics of the UAV system allow for the performance of dull, dirty, dangerous and deep (4D) tasks using an electronic device instead of people and it has the advantages of high flexibility, high adaptability and viability, no risk of casualties, low manufacturing cost and maintenance, etc. [1]. Due to the increasing complexity of the work environment, the increasing variety of tasks and the limited capacity of a single machine, multi-UAV collaborative tasks have become a significant development for UAV system applications. UAV cluster control can be achieved through multi-UAV collaboration, which not only reduces the burden on operators but also makes trajectory planning more reasonable and easier to control. To achieve this goal, the ability of collaborative control of UAVs must be improved [2].

The core of UAV collaborative task performance is multi-UAV cooperative trajectory planning and collision avoidance. In the civil aviation field, the Traffic Alert and Collision Avoidance System (TCAS) is a universally accepted last-resort means of reducing the probability and frequency of mid-air collisions between aircraft [3], [4]. There is also further research regarding TCAS logic [5]–[7]. In recent years, there have been many studies of UAVs [38], such as the Artificial Potential Field algorithm [9], ant colony algorithm [10], genetic algorithm [11], geometric optimization [12], colored petri net [13], Markov Decision Progress [14] and the combination and optimization of these algorithms. [15] presents a comprehensive and meticulous introduction and comparison of several collision avoidance algorithms and methods.

The artificial potential field (APF) algorithm has been widely used in UAV trajectory planning because of its simplicity, high-efficiency and smooth trajectory generation. The algorithm does not require a search of the global trajectory, the planning time is short, the efficiency is high, and it meets the requirements of being real-time and the safety of trajectory generation. The basic concept of APF is to consider the movement of the UAV in the planning space as a type of force motion in the virtual force field and the UAV moves to the target point under the composition of the attractive force and repulsive forces. Although the trajectory obtained using APF is not necessarily the shortest, its principle determines that it is smoother and safer than trajectories obtained by other methods, which better meets the requirements of

UAV trajectory planning and collision avoidance. Reference [16] combines the Lyapunov theorem with the artificial potential to solve the local minimum point problem. Reference [17] uses a simplified dynamic model in order to ensure the feasibility of the generated trajectory for the actual UAV. Reference [18] represents the bidirectional concept and provides a separation distance between vehicles so they can travel to the target point cooperatively. Reference [19] introduces an additional control force to translate the constrained UAV trajectory planning optimization problem to an unconstrained problem.

In this paper, an optimization algorithm based on APF has been implemented to achieve multi-UAV collaborative trajectory planning and collision avoidance. Not only has the problem of unreachable targets been solved, but UAV companions performing the same task have been considered as well, so that each UAV changes its trajectory to avoid collision with the rest of the UAVs and obstacles. The method is validated with several simulations using the MATLAB platform.

The layout of this paper is as follows. Section II states the ontology of the APF and the current problems of the traditional APF algorithm as well as the possible optimizations. Section III describes the proposed optimized APF algorithm, including the mathematical equation and pseudo-code. Section IV describes the simulation model established to test the proposed method and the obtained results in simulations and experiments. Finally, conclusions and future work are described in Section V.

## II. TRADITIONAL ARTIFICIAL POTENTIAL FIELD ALGORITHM

The artificial potential field algorithm is widely used in robot trajectory planning and collision avoidance because of its simple principle, uncomplicated structure and smooth trajectories generated. The algorithm does not need to search the global trajectory, and has a short planning time and high efficiency, which is very suitable for planning tasks that have strict requirements for real-time trajectory generation and security. APF does not generate the shortest trajectory, but it is the smoothest and safest. However, since the APF algorithm transforms all the information into a single force and controls the movement of the robot in the resultant direction, valuable information, such as the distribution of the obstacles, is omitted and thus, its trajectory planning ability is insufficient in some complex environments.

In 1986, Khatib first introduced the artificial potential field algorithm to the robot obstacle avoiding and trajectory planning. The philosophy of the artificial potential field approach can be schematically described as follows. The manipulator moves in a field of forces. The position to be reached is an attractive pole for the end effector and obstacles are repulsive surfaces for the manipulator parts [20].

To simplify the discussion, Khatib treated the UAV and the target point as particles and treated the obstacles or threat areas as circles, and then analyzed the APF model in two-dimensional space. The direction of UAV movement at an arbitrary position in the planned space is determined by the resultant force field formed by the gravitational field generated by the target and the repulsion field generated by the obstacles.

Khatib first considered the collision avoidance problem with a single obstacle O. The attractive potential field function and repulsive potential function can be represented as [20]:

$$U_{art}(x) = U_{goal} + U_{obs}(x) \tag{1}$$

$$U_{goal}(x) = \frac{1}{2}k_p(x - x_d)^2 \tag{2}$$

$$U_{obs}(x) = \begin{cases} 0.5\eta\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2, & \rho \le \rho_0 \\ 0, & \rho > \rho_0 \end{cases} \tag{3}$$

where $x$ and $x_d$ represent the spatial position of the UAV and the goal, respectively; $k_p$ and $\eta$ are attractive force gain coefficient and repulsive force gain coefficient, respectively; $\rho_0$ represents the limit distance of the potential field influence and $\rho$ is the shortest distance to the obstacle $O$.

After calculating the negative gradient of the gravitational potential field function, the corresponding attractive force function and repulsive force function are:

$$F_{goal}(X) = -grad\left[U_{goal}(x)\right] = -k_p(x - x_d) \tag{4}$$

$$\begin{aligned} F_{obs}(X) &= -grad\left[U_{obs}(x)\right] \\ &= \begin{cases} \eta\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)\frac{1}{\rho^2}\frac{\partial\rho}{\partial x}, & \rho \le \rho_0 \\ 0, & > \rho_0 \end{cases} \end{aligned} \tag{5}$$

The resultant force considering all the obstacles is:

$$F_{art} = F_{goal}(x) + \sum\nolimits_{obs=1}^{n} F_{obs}(x) \tag{6}$$

When constructing the repulsive function around the obstacle, Khatib chose a Force Inducing an Artificial Repulsion from the Surface (FIRAS, from the French) function. Other functions can be selected, such as the deformed Gaussian function, but it is necessary to ensure that the function and its derivative are continuous.

The traditional artificial potential field algorithm can easily converge on the local minimum point, and there is the problem of target unreachability, trajectory jitter in the narrow region and other phenomena. In response to these problems, the researchers have improved the traditional algorithm and offered many effective solutions.

### A. ABBREVIATIONS TARGET UNREACHABILITY PROBLEM

Target unreachability is the main problem of the traditional APF model. It refers to the situation where the UAV falls into the local potential minimum point before it reaches the target. The following three cases of this problem will be discussed:

Target point close to the obstacle. The traditional APF model does not consider the potential force change of the UAV when the target point is close to the obstacle. When the target point is near the obstacle, the UAV moves toward the target point under the attractive force of the gravitational potential field and suffers from a greater repulsive force because of the proximity to the obstacle. If in the process of approaching the target point, the repulsion force of the UAV is greater than the gravitational force, it cannot reach the target point [21].

The obstacle between and collinear with the target point and the UAV. If the obstacle is between the robot and the target and they are collinear, according to the definition of the traditional APF model, there must be a point at which the resultant force of the UAV becomes zero as the UAV moves to the target point. If there is no other external force, the UAV will stop at that point and will not reach the target point.

### B. NARROW CHANNEL

When the UAV encounters obstacle-intensive areas which cannot be bypassed as it moves to the target point, it must select some narrow channels as a viable trajectory. At this point the repulsion force of the obstacles around the channel may be much larger than the gravitational force of the target point, and if the UAV only depends on the resultant force in the traditional APF model to determine the next move, it may fail to find a channel in the tight obstacles, and the repulsive forces on both sides may trap the UAV into a local minimum point.

### C. JITTER PROBLEM

The jitter phenomenon primarily occurs in the following two cases.

First, jitter occurs around multiple local minimum points. When the UAV is around several local minimum points, $\rho\left(X\left(n,m\right),X\left(n\right)\right)\leq\varepsilon$ indicates that the UAV has no substantial displacement among $m$-positions from step $n$ to step $n+m+1$, and the planned trajectory contains a periodic jitter, among them $m=2,3,\ldots$; and $\varepsilon$ is an infinitesimal.

Second, jitter caused by sudden changes of the resultant force. When the direction of the resultant force acting on the UAV around the obstacles changes, the direction of the UAV's next movement will undergo a large angle change, and the jitter phenomenon will occur. When the UAV moves, if the absolute value of the direction difference between two adjacent steps in continuous $N(N>2)$ steps satisfies $90^\circ<|\theta|<180^\circ$, it indicates that the UAV jitters.

When the UAV jitter phenomenon occurs in the process of movement, although the UAV may eventually reach the target point, the trajectory planning quality is significantly affected, which means its feasibility is very poor.

## III. THE OPTIMIZED APF ALGORITHM

The UAVs move toward the target point in 3D space. First, consider one UAV moves in the horizontal axis of the space and its 2D position is $X=(x,y)^T$. Then, the definition of the attractive potential function is:

$$U_{att}\left(X\right)=\frac{1}{2}k_{att}\left(X-X_{targ}\right)^2 \tag{7}$$

where $k_{att}$ is the proportional gain factor of the attractive potential field; $X$ is the position vector of the UAV in the potential field. Then, the attractive force $F_{att}(X)$ is the negative gradient of the attractive potential function:

$$\begin{aligned}F_{att}\left(X\right)&=-grad\left(U_{att}\right)\\&=-k_{att}\left(X-X_{targ}\right)=k_{att}\left(X_{targ}-X\right)\end{aligned} \tag{8}$$

The local minimum point problem of the APF has restricted the wide application of this algorithm. The root cause of the problem is that the target point is not the global minimum point of the entire potential field, and to solve this problem, the repulsive field function is improved [22]. By introducing the relative distance between the target and the UAV, the original repulsive potential field function is multiplied by a distance factor, $(X-X_{obs})^n$, to make the resultant force acting on the UAV at the target point become zero, so that the target point will still be the global minimum point of the entire potential field. For this reason, the attractive field function of the target remains unchanged, and the repulsive field function is modified to:

$$U_{rep}=\begin{cases}\frac{1}{2}k_{rep}\left(\frac{1}{\rho\left(X\right)}-\frac{1}{\rho_0}\right)^2\left(X-X_{targ}\right)^n, & \rho\left(X\right)\leq\rho_0\\0, & \rho\left(X\right)>\rho_0\end{cases} \tag{9}$$

where $k_{rep}$ is the proportional gain factor of the repulsive potential field; $\rho\left(X\right)$ is the shortest distance between the UAV and the obstacle in space; $\rho_0$ is the maximum impact distance of a single obstacle, which depends mainly on the movement speed and deceleration of the UAV, and when the distance between the UAV and the obstacle is greater than $\rho_0$, the repulsive potential field does not affect the movement of the UAV [23].

$\left(\mathrm{X}-\mathrm{X}_{\mathrm{targ}}\right)^{\mathrm{n}}=\left|\left(\mathrm{x}-\mathrm{x}_{\mathrm{targ}}\right)^{\mathrm{n}}\right|+\left|\left(\mathrm{y}-\mathrm{y}_{\mathrm{targ}}\right)^{\mathrm{n}}\right|$ is the relative distance between the UAV and the target point. Compared with the traditional APF repulsion function, the relative distance between the UAV and the target is introduced, which ensures that the target point is the only minimum of the entire potential field. Then, the repulsive force is the negative gradient of the repulsive potential function:

$$\begin{aligned}F_{rep}\left(X\right)&=-grad\left(U_{rep}\right)\\&=\begin{cases}F_{rep1}\left(X\right)+F_{rep2}\left(X\right) & \rho\left(X\right)\leq\rho_0\\0, & \rho\left(X\right)>\rho_0\end{cases}\end{aligned} \tag{10}$$

Among which:

$$\begin{aligned}F_{rep1}\left(X\right)=k_{rep}\left(\frac{1}{\rho\left(X\right)}-\frac{1}{\rho_0}\right)\frac{1}{\rho^2\left(X\right)}\cdot\left(X-X_{targ}\right)^n\\\cdot\frac{\partial_\rho\left(X\right)}{\partial\left(X\right)}\end{aligned} \tag{11}$$

$$\begin{aligned}F_{rep2}\left(X\right)=-\frac{n}{2}k_{rep}\left(\frac{1}{\rho\left(X\right)}-\frac{1}{\rho_0}\right)^2\cdot\left(X-X_{targ}\right)^{n-1}\\\cdot\frac{\partial\left(X-X_{targ}\right)}{\partial\left(X\right)}\end{aligned} \tag{12}$$

$F_{rep1}(X)$ and $F_{rep2}(X)$ are two component forces of $F_{rep}(X)$. Before the UAV reaches the target point, it is impossible to produce a situation where the resultant force is zero, which solves the target unreachability caused by the distance between the target and obstacle being too short.

In addition to the obstacles, the article also considers the effect of other UAVs on the studied UAV. The APF algorithm considers the space in which the obstacles are located as repulsive force fields, while the other UAVs in the space can be considered moving obstacles with position and speed, so they also produce repulsion. In practice, the safety distance of the UAV is usually much larger than its volume. The APF algorithm can provide the UAVs with the sensitive ability of collision avoidance, and the speed in this situation can be ignored when the repulsive force between the two UAVs is studied. Likewise, there are local minimum problems after considering the influence of other UAVs, so a distance factor $(X_i - X_{targ})^n$ is multiplied as the solution of the repulsive potential function. Then, the repulsive potential function generated by the other UAV is:

$$U_{mut}(i) = \begin{cases} \sum_{j=1}^{m} \frac{1}{2} k_{rep} \left( \frac{1}{\rho(X_{ij})} - \frac{1}{\rho_0} \right)^2 (X_i - X_{targ})^n, \\ \qquad \rho(X_{ij}) \leq \rho_0 \\ 0, \quad \rho(X_{ij}) > \rho_0 \end{cases} \tag{13}$$

Similarly, the repulsive force generated by the other UAV is the sum of the negative gradient of the potential function, which is similar to the above formulas and is no longer listed.

After handling collaborative trajectory planning and collision avoidance, the potential field trap problem and the jittering phenomenon are also studied. The potential field trap refers to the situation when the UAV moves to a certain position where the angle between the direction of the resultant force and the direction of the UAV's movement is *180* degrees. The UAV will continue to plan a trajectory, but the actual movement has stopped. The jitter problem occurs when the resultant force direction of the UAV continuously changes suddenly near the obstacles, causing the UAV to waver. From the definition, the potential field trap is a special type of jitter phenomenon. The dynamic step adjustment method is used to solve these problems.

The dynamic step adjustment method not only changes the direction of the UAV movement appropriately but also reduces the step when the resultant force directions of two adjacent steps significantly changes, so that the UAV can gently escape the jitter area. At this point, the next step of the UAV should be:

$$\begin{cases} x_{n+1} = x_n + f * l * \cos\left(\theta_{n-1} + \frac{1}{2}\Delta\theta_n\right) \\ y_{n+1} = y_n + f * l * \sin\left(\theta_{n-1} + \frac{1}{2}\Delta\theta_n\right) \end{cases}$$
$$\theta_o < |\Delta\theta_n| < 180^\circ \tag{14}$$

where $\Delta\theta_n$ is the angle of the directions of two adjacent steps, and $\theta_o$ is threshold set according to the actual situation. $|\Delta\theta_n| > \theta_o$ indicates that the UAV begins to jitter. $f$ is the jitter factor, which is set to adjust the step length.

The pseudo-code of the optimized algorithm is shown in Algorithm 1. Therein, the jitter judgement is in bold. At the start of the code, the algorithm calculates the attractive force and repulsive forces of the UAV. The jitter judgement detects whether the UAV falls into a jitter state. Finally, all the UAVs complete the trajectory planning.

## IV. SIMULATIONS

The optimized method was run in a PC with a 2.7 GHz quad-core processor and 8 GB of RAM. The operating system was Windows 10. The code has been written and compiled in MATLAB 2016. The general parameters are illustrated in Table 1, and the results of multi-UAV APF trajectory planning are displayed in Figures 1, 4 and 6, and Fig. 8 provides a clear three-dimensional city application of this method.

**TABLE 1. Parameter values and definitions.**

| Parameter | Value | Definition |
|---|---|---|
| k | 8 | Attractive gain coefficient |
| $m$ | 2 | Repulsive gain coefficient |
| $d$ | 1 | Influence radius of the obstacles |
| $l$ | 0.05 | Step length of the UAVs |
| $J$ | 300 | Amount of steps |
| $\theta_o$ | 1.57 | Threshold for judging jitter |
| f | 0.2 | Jitter factor |

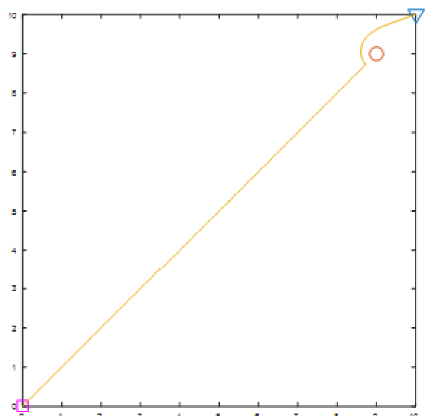

**FIGURE 1. The obstacle collinear with the target point and the UAV, and the target within the reach of the obstacle.**

### A. THE SOLUTION OF THE PROBLEMS EXISTING IN THE TRADITIONAL APF ALGORITHM

The simulation model is used to illustrate the method's improvement for solving the local minimum problem. As shown in Fig. 1, the target point (10, 10) is within the range of influence of the obstacle (9, 9), and they are collinear. The situation includes the above two cases in the target

**Algorithm 1** Pseudo-Code of Optimized APF

```
Input: start position, target position, the number of UAVs N, the number of obstacles, the positions of the obstacles, the
       step length, thestep amount J, the jitter factor, the attractive gain coefficient, the repulsive gain coeffient, the
       influence radius of the obstacles, the angle threshold θ0
Output: trajectories of all the UAVs D
for j = 1 : J do
    for i = 1 : N do
        Calculate the value and direction of the attractive force of the target point;
        Calculate the values and directions of all the repulsive forces of the obstacles and the other UAVs;
        Calculate the angle difference of the adjacent two step Δθ;
        Jitter judgement:
        while |Δθ| > θ0 do
            Adjust the length of the next step;
            Adjust the direction of the resultant force;
            if no collision then
                break;
        if UAV i reaches the target position then
            break;
        else
            D[i][j]=the coordinate of the step j of UAV i;
    if all the UAVs have reached the target position then
        break;
return D;
```

unreachable problems. When the UAV moves from the start point (0, 0) to the position approximate to the obstacle (9, 9), it is located on the connection between the target point and the obstacle. According to the traditional APF algorithm, it will stop because of the balance of gravitation and repulsion. The simulation result shows that the UAV can smoothly bypass the obstacle and continue tracking the target under the special position relationship using the improved APF algorithm.

The waypoints of the trajectory near the obstacle and target point are listed in Table 2, and the distance between the UAV and the edge of the obstacle is calculated. From the scatter plot (Fig. 2), the minimum distance is greater than 0.2, which is the safe distance to prevent the UAV from collision.

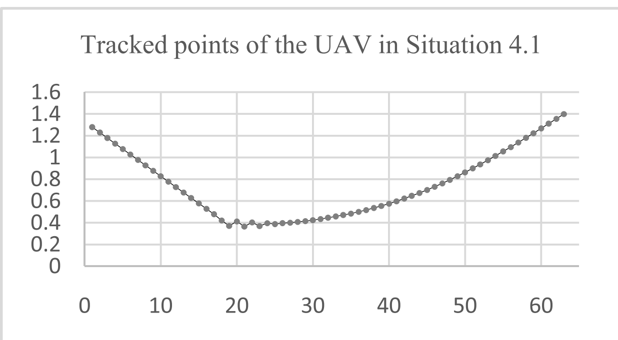


**FIGURE 2.** The tracked points of the trajectory in Situation 4.1.

Figure 3(a) and 3(b) compare the trajectories of the common APF algorithm trajectory planning and the trajectory planning with dynamic trajectory adjustment mentioned above to eliminate jitter. Compared with (a), (b) significantly eliminates the jitter, essentially achieving smooth collision avoidance.

### B. MULTI-UAV THROUGH COMPLEX SITUATION OF HORIZONTAL MULTIPLE OBSTACLES

The simulation model is primarily used to simulate the trajectory planning of a multi-UAV collaborative flight in a city. The starting positions of the UAVs are located on the west and south sides of the coordinate system, and the obstacles form several complex narrow channels between the target point and the starting positions. Six UAVs move from the starting position through the 30 obstacles and track the target point, and the simulation result is shown in Fig. 4.

The experiment result in Fig. 4 demonstrates that under the improved APF algorithm, when the obstacles form narrow channels, the UAVs can overcome the local minimum value, adjust their trajectories according to the sizes and directions of the potential forces and consider the spatial positions of other UAVs in the same coordinate system to avoid obstacles and UAV companions and successfully track the target point. Figure 5 describes the distance between UAV 5 and six obstacles on its trajectory in red color. From the six scatter plots, the optimized APF algorithm guarantees the safe distance of the UAV. In the process, the UAVS can overcome many complex cases of the target unreachable problem mentioned above and eliminate various jitter states instead of vibrating in a certain position for a long time, which achieves the purpose of the experiment.

**TABLE 2.** Units for magnetic properties.

| Number | x | y | Number | x | y | Number | x | y |
|---|---|---|---|---|---|---|---|---|
| 1 | 8.096373 | 8.096373 | 22 | 8.644941 | 8.808131 | 43 | 9.048161 | 9.644808 |
| 2 | 8.131728 | 8.131728 | 23 | 8.659332 | 8.856016 | 44 | 9.093065 | 9.666799 |
| 3 | 8.167083 | 8.167083 | 24 | 8.620556 | 8.887582 | 45 | 9.138544 | 9.687574 |
| 4 | 8.202439 | 8.202439 | 25 | 8.618208 | 8.937527 | 46 | 9.184481 | 9.707319 |
| 5 | 8.237794 | 8.237794 | 26 | 8.604954 | 8.985738 | 47 | 9.230776 | 9.726207 |
| 6 | 8.273149 | 8.273149 | 27 | 8.600607 | 9.035549 | 48 | 9.277348 | 9.744401 |
| 7 | 8.308505 | 8.308505 | 28 | 8.60122 | 9.085545 | 49 | 9.324131 | 9.762047 |
| 8 | 8.34386 | 8.34386 | 29 | 8.606895 | 9.135222 | 50 | 9.371069 | 9.779274 |
| 9 | 8.379215 | 8.379215 | 30 | 8.617431 | 9.184099 | 51 | 9.418119 | 9.796195 |
| 10 | 8.414571 | 8.414571 | 31 | 8.632557 | 9.231756 | 52 | 9.465245 | 9.812904 |
| 11 | 8.449926 | 8.449926 | 32 | 8.651956 | 9.27784 | 53 | 9.512416 | 9.829483 |
| 12 | 8.485281 | 8.485281 | 33 | 8.675284 | 9.322064 | 54 | 9.55961 | 9.845998 |
| 13 | 8.520637 | 8.520637 | 34 | 8.702178 | 9.364215 | 55 | 9.606807 | 9.862503 |
| 14 | 8.555992 | 8.555992 | 35 | 8.732268 | 9.404147 | 56 | 9.654005 | 9.879007 |
| 15 | 8.591347 | 8.591347 | 36 | 8.76519 | 9.44178 | 57 | 9.701202 | 9.895512 |
| 16 | 8.626703 | 8.626703 | 37 | 8.800589 | 9.477091 | 58 | 9.7484 | 9.912017 |
| 17 | 8.662058 | 8.662058 | 38 | 8.838132 | 9.510114 | 59 | 9.795597 | 9.928521 |
| 18 | 8.683863 | 8.722271 | 39 | 8.877509 | 9.540927 | 60 | 9.842794 | 9.945026 |
| 19 | 8.716889 | 8.759812 | 40 | 8.918439 | 9.569646 | 61 | 9.889992 | 9.961531 |
| 20 | 8.666946 | 8.75742 | 41 | 8.960668 | 9.596417 | 62 | 9.937189 | 9.978035 |

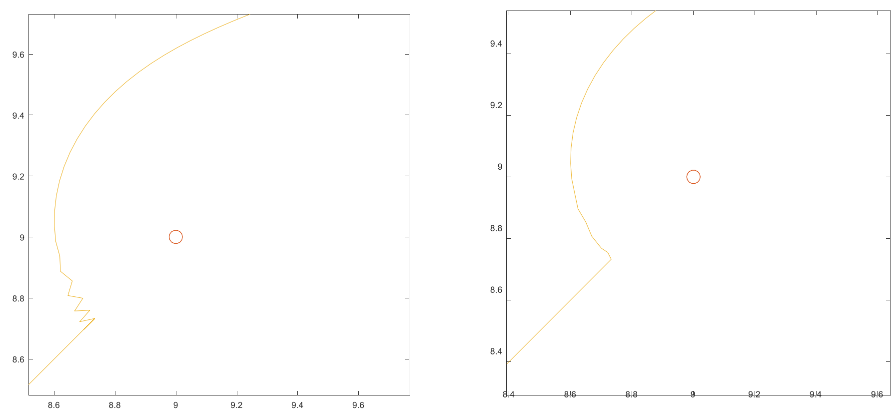


**FIGURE 3.** The trajectory (a) without jitter control and (b) with jitter control.

### *C. MULTI-UAV THROUGH COMPLEX SITUATION OF VERTICAL MULTIPLE OBSTACLES*

The simulation model is primarily used to simulate the situation of multi-UAVs handling vertical obstacles during collaborative flight trajectory planning. In most working environments of UAVs, vertical obstacles are more common than horizontal obstacles, usually bridge holes, windows, etc., so a more common vertical obstacle distribution was selected for the experiment. Six UAVs distributed at different heights start to move from the west side of the coordinate system, select different channels of the vertical obstacles to pass through according to their respective potential effects and reach the target point together.

The experimental results in Fig. 6 show that multiple UAVs select different channels to pass through the vertical obstacle. It is worth noting that the coincidence of the UAV trajectories in Fig. 6 does not mean that the repulsive force between multiple UAVs is lost, but illustrates that there is an arrival sequence of the UAVs because of the different lengths of the trajectories. The explanation of this situation is detailed in Fig. 7, using 3 neighboring UAVs as an example.

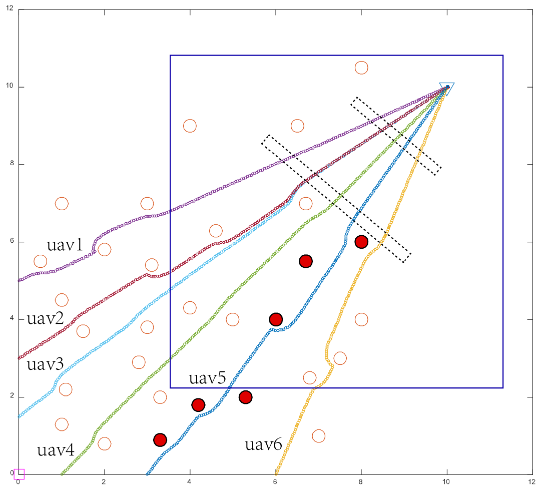


**FIGURE 4. Multi-UAV through complex situation of horizontal multiple obstacles.**

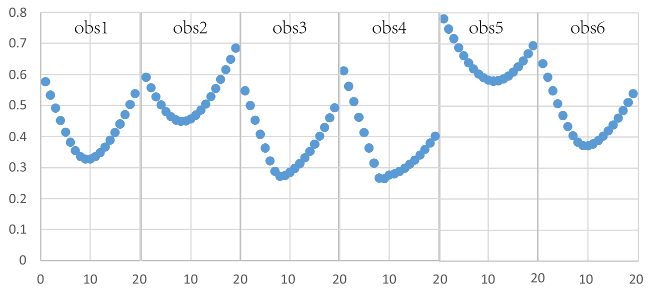


**FIGURE 5. Multi-UAV through complex situation of horizontal multiple obstacles.**

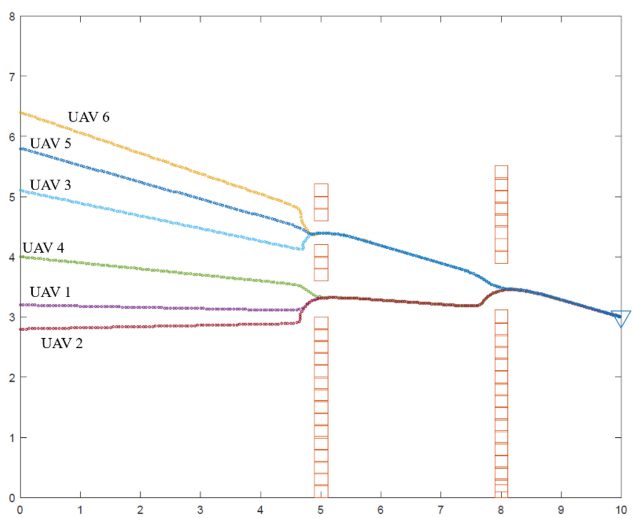


**FIGURE 6. Multi-UAV through complex situation of vertical multiple obstacles.**

## D. THE APPLICATION OF THE SIMULATION IN AN URBAN ENVIRONMENT

The experiment selects a group of UAVs in the complex urban environment to move toward the target point. During the flight, the UAVs must consider the gravitational potential of the target point, the horizontal and vertical repulsion potential fields of the buildings, and the three-dimensional repulsion potential fields of the other UAV companions. The horizontal trajectory planning is shown in section 4.2 and the vertical trajectory planning is shown in section 4.3.

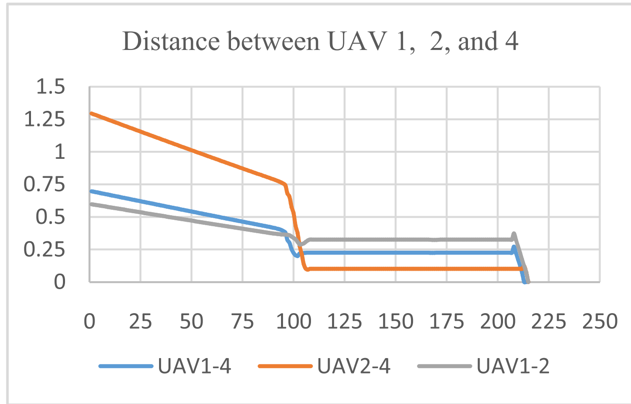


**FIGURE 7. Distance between UAV 1, 2, and 4.**

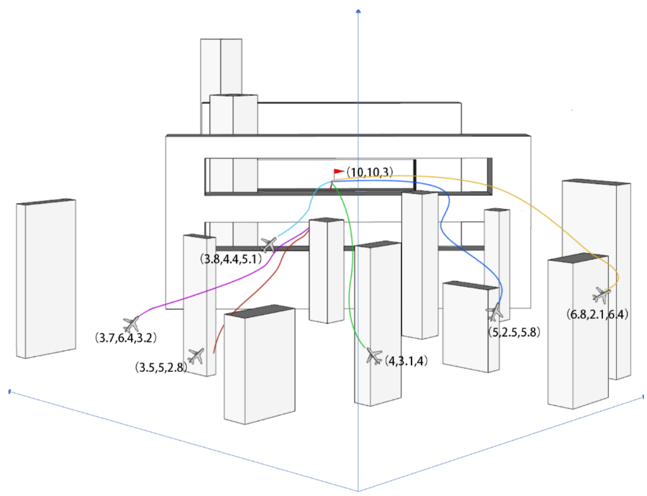


**FIGURE 8. Multi-UAV in urban environment.**

Figure 8 shows the 3D UAV collision avoidance model in the blue square frame of Fig. 4. In the process of moving from the starting point to the target, the UAV may encounter many typical obstacles, such as buildings, mountains, fire threats, other vehicles and so on. The obstacles can be simplified as cuboids [19]. The coordinates of the UAV start positions are (3.7, 6.4, 3.2), (3.5,5,2.8), (3.8, 4.4, 5.1), (4, 3.1, 4), (5, 2.5, 5.8) and (6.8, 2.1, 6.4), while the target point coordinates are (10, 10, 3). Before the UAVs reach the first skyscraper, they move to avoid horizontal buildings and other UAVs. As they move through the first and second skyscraper and reach the target point, they avoid obstacles vertically. In the process of UAV trajectory planning, the group of UAVs reach the target point successfully without hitting any obstacle buildings or UAVs.

## V. CONCLUSION AND FUTURE WORK

This paper presents the development and application of the traditional APF algorithm, proposes optimizations to eliminate its disadvantages, and considers the influence of the

UAV companions. The motivation for the optimized APF algorithm is to determine a method which can provide safe and smooth trajectories for a UAV to perform tasks efficiently, and to support the follow-up research for the trajectory planning and collision avoidance of the UAV system. The main contributions of this paper are as follows.

1) An improvement to solve the various situations of the target unreachable problem which prevents the traditional APF algorithm from being used in UAV trajectory planning area is proposed, and all the possible situations have been tested in the simulation models.
2) The interaction among a group of UAVs that perform a task together is considered in the optimized method. The method successfully simulates the UAV companions as dynamic obstacles and allows the UAV to plan every step while considering the target point, obstacles and UAV companions.
3) The method is validated using MATLAB 2016 and the test includes 6 UAVs and 30 obstacles in both the horizontal and vertical direction. Then, a 3D figure of the method applied in an urban environment is given in which 6 UAVs move to two targets as two groups.

Beyond that, to accomplish the fundamental purpose of UAV trajectory planning and collision avoidance, future work for the optimization of our method will consider the velocity and acceleration of every UAV and dynamic obstacles, which can better fit the requirements of the actual task performed by the UAV system. Additionally, we plan to validate this method with experiments in real urban environments with fixed-wing UAVs.

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