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Unmanned aerial vehicle dynamic path planning in an uncertain environment

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SUMMARY

An unmanned aerial vehicle (UAV) dynamic path planning method is proposed to avoid not only static threats but also mobile threats. The path of a UAV is planned or modified by the potential trajectory of the mobile threat, which is predicted by its current position, velocity, and direction angle, because the positions of the UAV and mobile threat are dynamically changing. In each UAV planning path, the UAV incurs some costs, including control costs to change the direction angle, route costs to bypass the threats, and threat costs to acquire some probability to be destroyed by threats. The model predictive control (MPC) algorithm is used to determine the optimal or sub-optimal path with minimum overall costs. The MPC algorithm is a rolling-optimization feedback algorithm. It is used to plan the UAV path in several steps online instead of one-time offline to avoid sudden and mobile threats dynamically. Lastly, solution implementation is described along with several simulation results that demonstrate the effectiveness of the proposed method.

KEYWORDS: UAV; Dynamic path planning; Model predictive control algorithm; Mobile threats; Uncertain environment.

1. Introduction

Unmanned aerial vehicle (UAV) path planning has become one of the key technologies of UAV and has been widely investigated by scholars around the world. The main purpose of UAV path planning is to plan a flight path to the target with minimum comprehensive costs, that is, minimizing the probability of being destroyed and meeting the UAV performance constraints.[7,10,12,16,19] Borrowing a concept from hydrodynamic analysis[16] presents stream functions which satisfy Laplace's equation as a local-minima free method for producing potential-field-based navigation functions in two dimensions. These functions generate smoother paths (i.e. more suited to aircraft-like vehicles) than previous methods. In ref. [19], a novel combination of data structures and algorithms is presented as a fast and efficient practical approach to path planning for unmanned vehicles. This approach utilizes an architecture that integrates effective obstacle representation using an efficient Quadtree data structure, with path planning based on a modified Rapidly-exploring Random Tree (RRT) algorithm, and a path pruning technique based on Dijkstra's algorithm, resulting in rapid discovery of sub-optimal feasible paths.

Many methods or algorithms are employed to plan the UAV path; these methods include RRTs,[1] hybrid neural network,[8] ant colony optimization algorithm (ACO),[2,9,21,22] A* algorithm,[11] mixed integer linear programming (MILP),[13,14] and genetic algorithms.[20] Most of static path planning methods are executed prior to flying and are only suitable for avoiding static and known threats. UAVs are not well informed of all the information about the flight area in advance; thus, dynamic path planning is studied according to different environments. Xingguang and Demin[3] studied online path planning in adversarial environments, Shin, Leboucher and Tsourdos[4] under communication constraints, Babel[5] in a risk environment, and Wei, Yan and Yu;[2] Wong, Lin and Cheng;[6] Hyun, Kabamba and Girard;[15] and Zhang and Xi[17] with some uncertain information. In ref. [6], a path planning method dealing with uncertainties is proposed, where both uncertainties in mobile robot

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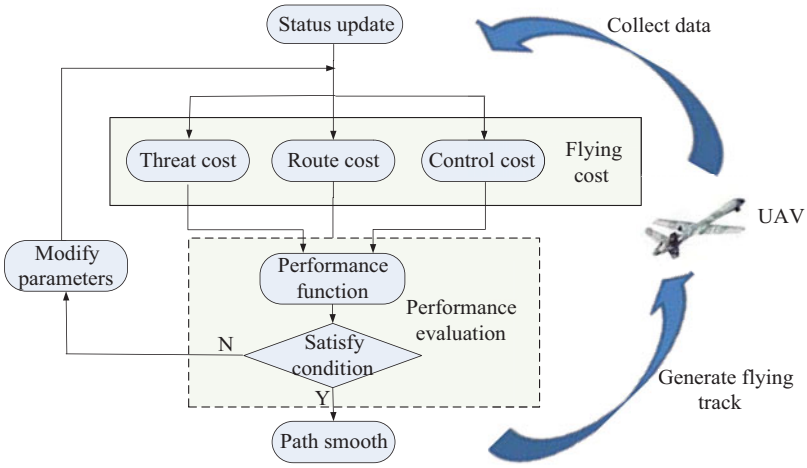


Fig. 1. Diagram of dynamic path planning for the UAV.

localization and new objects localization are taken into account. The safeness of its proposed method is due to the mixing between the planning phase and the navigation phase. In ref. [15], a dynamic path planning method for swarming of UAVs in the urban environment is presented. For the missions of a team of UAVs in a complex environment, conflict-free paths for all vehicles are calculated dynamically in real-time using the latest information on the changes in the surroundings such as pop-up threats. Therefore, a hierarchical dynamic path planner is proposed that consists of an offline path planning and a real-time model predictive trajectory generator. In this framework, many existing and proven off-line algorithms can be deployed for globally optimal path planning.

Dynamic path planning is more flexible than static path planning. However, it often requires different methods for different situations. The avoided objects in the environments mentioned above are complex but still static. In this study, path planning can avoid not only static and known threats but also dynamic threats. Some of the algorithms used in static path planning are not suitable for the avoidance of dynamic threats. Therefore, hybrid path planning algorithms are being studied by several scholars. For example, with the advantage of parallelism of genetic algorithms, static and dynamic planning can be combined; however, the planning results depend on the selection of the fitness function,[23–25] the calculation is complex, and the convergence speed of the algorithm is low.

The mobile threat avoidance problem in UAV path planning is the primary focus of this study. According to the real-time position, velocity, and direction angle information of the mobile threat, the potential trajectory of the threat is predicted and the UAV path is adjusted in the UAV performance constraints to avoid the threat.

2. Dynamic Path Planning with the Model Predictive Control (MPC) Algorithm

2.1. MPC algorithm overview

Dynamic real-time optimal or sub-optimal path planning is more feasible than offline global optimal path planning and can avoid not only static threats but also mobile and sudden threats because of the frequent changes in the battlefield environment. The model predictive control (MPC) algorithm is a real-time relative optimal algorithm instead of an offline global optimal algorithm; the algorithm was proposed by J. Richalet in 1978. It consists of three components: prediction model, rolling optimization, and feedback control. The function of the prediction model is to predict the system output through historical information and future input. The method is not completed offline in one time but in several online steps that involve rolling optimization and a feedback algorithm. The method emphasizes the model's function rather than its structure. Thus, it can be applied to dynamic path planning for UAVs.

The dynamic path planning method with the MPC algorithm is shown in Fig. 1.

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In UAV dynamic path planning, route, control, and threat costs are calculated under the premise of predicting mobile threats to obtain the performance function. The MPC algorithm is employed to optimize the path and minimize the overall costs.

Supposing that a UAV flies at a constant altitude, the UAV flies and avoids threats in two-dimensional (2D) space. The UAV changes its flying direction by modifying the lateral acceleration. A nonlinear prediction model is established with formulas (1), (2), and (3) according to the aircraft's kinematics equation.

$$x(k+1) = x(k) + s\cos\varphi(k+1), \tag{1}$$

$$y(k+1) = y(k) + s\sin\varphi(k+1), \tag{2}$$

$$\varphi(k+1) = \varphi(k) + (\alpha(k)/v(k)) \times \Delta t, \tag{3}$$

$$s = v(k) \times \Delta t,$$

where x and y are the positions of the UAV in a 2D place; v is velocity; j is the flight tilt angle; a is the lateral acceleration which must be below limit value U, that is, $|\alpha| < U$; Δt is the sampling cycle; and k is the kth sampling cycle.

2.2. Performance function of UAV path

The control parameters are optimized in the MPC algorithm to minimize the performance function, which would have an effect on the prediction model and modify the UAV path online. The performance function consists of threat, route, and control costs. Threat cost originates not only from a static threat source but also from a mobile threat source. Route cost can be described as fuel consumption cost. This cost is calculated based on the voyage distance to the target and it must meet the maximum flight distance constraint. Control cost is produced when the flight direction is changed; it is determined by lateral acceleration.

The performance function in UAV dynamic path planning is described as formula (4).

$$J(k) = T_t J_t(k) + T_c J_c(k) + T_d J_d(k) + T_w J_w(k). \tag{4}$$

The first item, J_t is the mobile threat cost; T_t is the weight of the mobile threat cost. The second item, J_c is the control cost; T_t is the weight of the control cost. The third item, J_d is the route cost; T_d is the weight of this cost. The fourth item, J_w is the mobile threat cost; T_t is its weight. Threat cost is the primary consideration in this study. Thus, the weights are set as

$$T_t = T_w = 0.4;\ T_c = T_d = 0.1.$$

3. UAV Path Planning Cost Description

3.1. Mobile threat cost

According to the current position, velocity, and direction angle of the mobile threat, its trajectory in the next several sampling cycles is predicted. The mobile threat cost is then calculated based on the relative position of the mobile threat and UAV. Considering that the path of the mobile threat is predicted repeatedly online, it is predicted only in five sampling cycles each time. $(x_t(k), y_t(k))$ is the measured position of the mobile threat in the kth sampling cycle. $(x_t(j|k), y_t(j|k))$ is the predicted position of the mobile threat in the jth sampling cycle based on information in the kth sampling cycle.

Mobile threat cost is described as

$$J_t(k) = \frac{T_t}{N} \sum_{j=k+1}^{k+N} [J_t(j|k)], \tag{5}$$

where N is the predicting steps and is set at 5.

$$J_t(j|k) = \frac{1}{\sqrt{(x(j) - x_t(j|k))^2 + (y(j) - y_t(j|k))^2}}.$$

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The Kalman filter algorithm is used to predict the path of the mobile threat in the next five steps, that is,

$$(x_t(\,j\,|\,k),\, y_t(\,j\,|\,k)), \quad j = k+1,\ k+2, \ldots, k+5.$$

The object is supposed to move in constant altitude. The motive model can be simplified as

$$r(k) = A(k)r(k-1) + Bw(k-1), \tag{6}$$

where r_k is the state variable in the kth sampling cycle, which consists of the position and velocity in x and y directions, respectively. It can be expressed as: $[x_t(k),\, v_{tx}(k),\, y_t(k),\, v_{ty}(k),\, \omega(k)]^T$. $w(k-1)$ is Gaussian white noise whose mean value is zero. Thus, formula (1) can be modified as

$$\begin{bmatrix} \hat{x}_t(k) \\ \hat{v}_{tx}(k) \\ \hat{y}_t(k) \\ \hat{v}_{ty}(k) \\ \hat{\omega}(k) \end{bmatrix} \cong \begin{bmatrix} 1 & \frac{\sin(\omega_t T)}{\omega_t} & 0 & -\frac{1-\cos(\omega_t T)}{\omega_t} & 0 \\ 0 & \cos(\omega_t T) & 0 & -\sin(\omega_t T) & 0 \\ 0 & \frac{1-\cos(\omega_t T)}{\omega_t} & 1 & \frac{\sin(\omega_t T)}{\omega_t} & 0 \\ 0 & \sin(\omega_t T) & 0 & \cos(\omega_t T) & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_t(k-1) \\ v_{tx}(k-1) \\ y_t(k-1) \\ v_{ty}(k-1) \\ \omega(k-1) \end{bmatrix} + \begin{bmatrix} 0.5T^2 & 0 & 0 \\ T & 0 & 0 \\ 0 & 0.5T^2 & 0 \\ 0 & T & 0 \\ 0 & 0 & T \end{bmatrix} w(k-1), \tag{7}$$

where $x_t(k)$ is the object position in x direction in the kth sampling cycle, $y_t(k)$ is the object position in y direction, $v_{tx}(k)$ is the velocity in x direction, $v_{ty}(k)$ is the velocity in y direction, and $\omega(k)$ is the lateral acceleration.

The dynamic equation is established by measuring data. Therefore, the observation equation is established as

$$m(k) = H(k)r(k) + w_v(k), \tag{8}$$

where H is the observation function, and $w_v(k)$ is the observation noise that is independent and identically distributed with $w(k)$.

In this example, $H(k)$ is set as

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}.$$

From formula (6), we obtain

$$r(k) = [x_t(k|k-1),\, v_{tx}(k|k-1),\, y_t(k|k-1),\, v_{ty}(k|k-1),\, \omega(k|k-1)]^T.$$

Thus, we can derive $(x_t(\,j\,|\,k),\, y_t(\,j\,|\,k))$ with formulas (7) and (8) according to the position, velocity, and acceleration of the kth sampling cycle. Then, we derive the mobile threat cost with formula (5).

3.2. Control, path, and static threat costs

Control, path, and static threat costs can be described as formulas (9), (10), and (11).

$$J_c(k) = \alpha(k), \tag{9}$$

$$J_d(k) = \sqrt{(x(k) - x_o)^2 + (y(k) - y_o)^2}, \tag{10}$$

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$$J_w(k) = \sum_{i=1}^{R} k_i P_i(k), \tag{11}$$

where α_k is the lateral acceleration in the kth sampling cycle. (x_o, y_o) is the target position of the UAV.

Formula (10) has R static threats, such as radar and missile. k_i is the weight, and $P_i(k)$ is the ith static threat cost. Supposing that the firing radius is $R_{\min}$ and the maximum firing radius is $R_{\max}$, then the cost is

$$P_i(k) = \begin{cases} 1 & (d(k) < R_{\min}) \\ 1/d(k) & (R_{\min} \le d(k) \le R_{\max}), \\ 0 & (d > R_{\max}) \end{cases} \tag{12}$$

where $d(k)$ is the distance between the UAV and the static threat in the kth sampling cycle.

3.3. Performance optimization

The purpose of optimizing the UAV path is to minimize overall costs, which include control, threat, and route costs. When the current position of the UAV is known, static threat, and route costs are determined. Control cost changes with lateral acceleration α_k. Mobile threat cost is related to the trajectory ahead and is also determined by lateral acceleration α_k. Thus, the UAV path is optimized by modifying lateral acceleration α_k.

4. Examples

4.1. Mobile threat avoidance example

We suppose that a mobile threat, which could be a tank or armored car, exists, and current position, velocity, and prior trajectory are known. The potential trajectories are then predicted with formula (7) based on the information. The concrete steps are as follows:

(1) Measurement of the current position, velocity, and acceleration of the mobile threat. Based on this information, the next five sampling cycle positions of the mobile threat are predicted.
(2) According to the predicted trajectory of the mobile threat, the UAV path is adjusted to avoid the threat.

Example 1: We suppose that a UAV plans to fly from the position of (10, 20) km to the position of (45, 56) km. Two mobile threats are present nearby. This situation is illustrated in Fig. 2(b). Although the two mobile threats are far from the UAV in the starting position, the positions of the two mobile threats change dynamically and may be close to the UAV when the UAV flies to its destination. During the flight when no threats exist, the UAV flies straight to its destination as can be seen in Figs. 2(b) and 2(c). The UAV and the right mobile threat get closer after a period of time because they move in opposite directions. The potential trajectory of the mobile threat is predicted by the previous trajectory, and the UAV adjusts its flight direction and avoids the threats in advance as shown in Figs. 2(d) and 2(e). Thus, the UAV flies to its destination safely. The entire flight trajectory of the UAV is shown in Fig. 2(a). This example shows that both the minimum flight and the avoidance of mobile threats are considered.

4.2. UAV dynamic path planning in a complex environment

Example 2: In complex conditions, not only mobile threats but also static threats, such as radar and anti-aircraft gun, are considered in UAV path planning. This example has a total of 17 static and 2 mobile threats. The positions of the static threats are known as shown in Table I. However, the trajectories of the mobile threats are unknown. The static threats have four types of threats, namely, radar, missile, anti-aircraft gun, and atmosphere threat. The main difference among these four types of threats is the threat radius as shown in Table II.

Static threat cost can be calculated with formula (12). The UAV flight to the destination is shown in Fig. 3.

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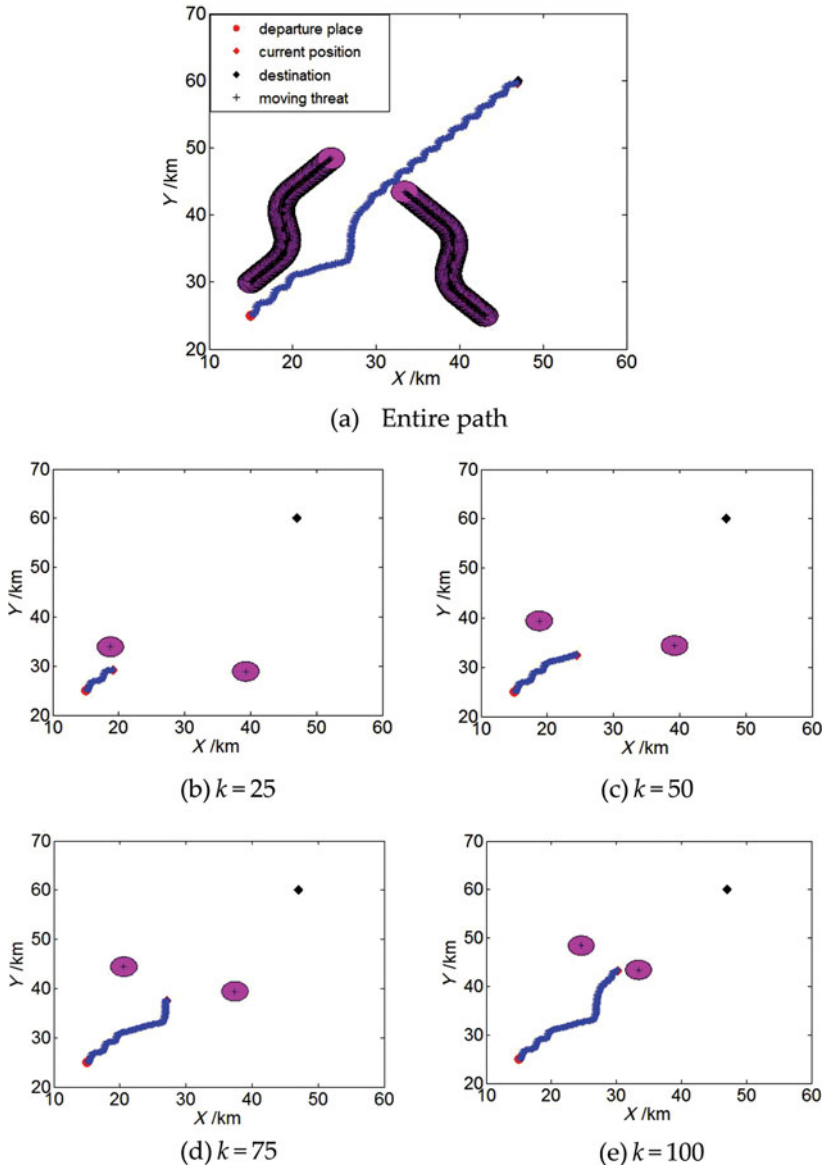


Fig. 2. UAV path planning to avoid mobile threats.

The positions of all the static and mobile threats in the 25th sampling time are marked in Fig. 3(b). Path planning focused on the static threats because the mobile threats are far from the UAV. As shown in Fig. 3(c), the UAV adjusts its path to avoid the static threat on its path. In Fig. 3(d), one of the mobile threats moves toward the UAV; thus, its path is predicted in advance and the UAV changes its path to avoid the mobile threat. Figures 3(b)–3(f) show the positions of the threats and the UAV in several sampling cycles. The entire process of the flight is shown in Fig. 3(a).

Three other simulation examples are performed to verify the effectiveness of the algorithm.

Figures 4(a)–4(c) provide three additional examples in a complex environment. In the first example, the two mobile threats are on the different sides of the UAV and are far from it. Therefore, path planning mainly considers the static threats. In the second example, the two mobile threats are on the same side of the UAV and move in the same direction. Thus, path planning mainly considers the nearer mobile and static threats. In the third example, one of the mobile threats moves straight. Thus, its trajectory can be easily predicted in advance. Given that the mobile threats are predicted to move away from the UAV, the UAV performs planning even in the direction close to the mobile threats during its flight to avoid several static threats. The positions of the threats are different in these three examples. The UAV completes its flight safely in all these examples as can be seen in Fig. 4.

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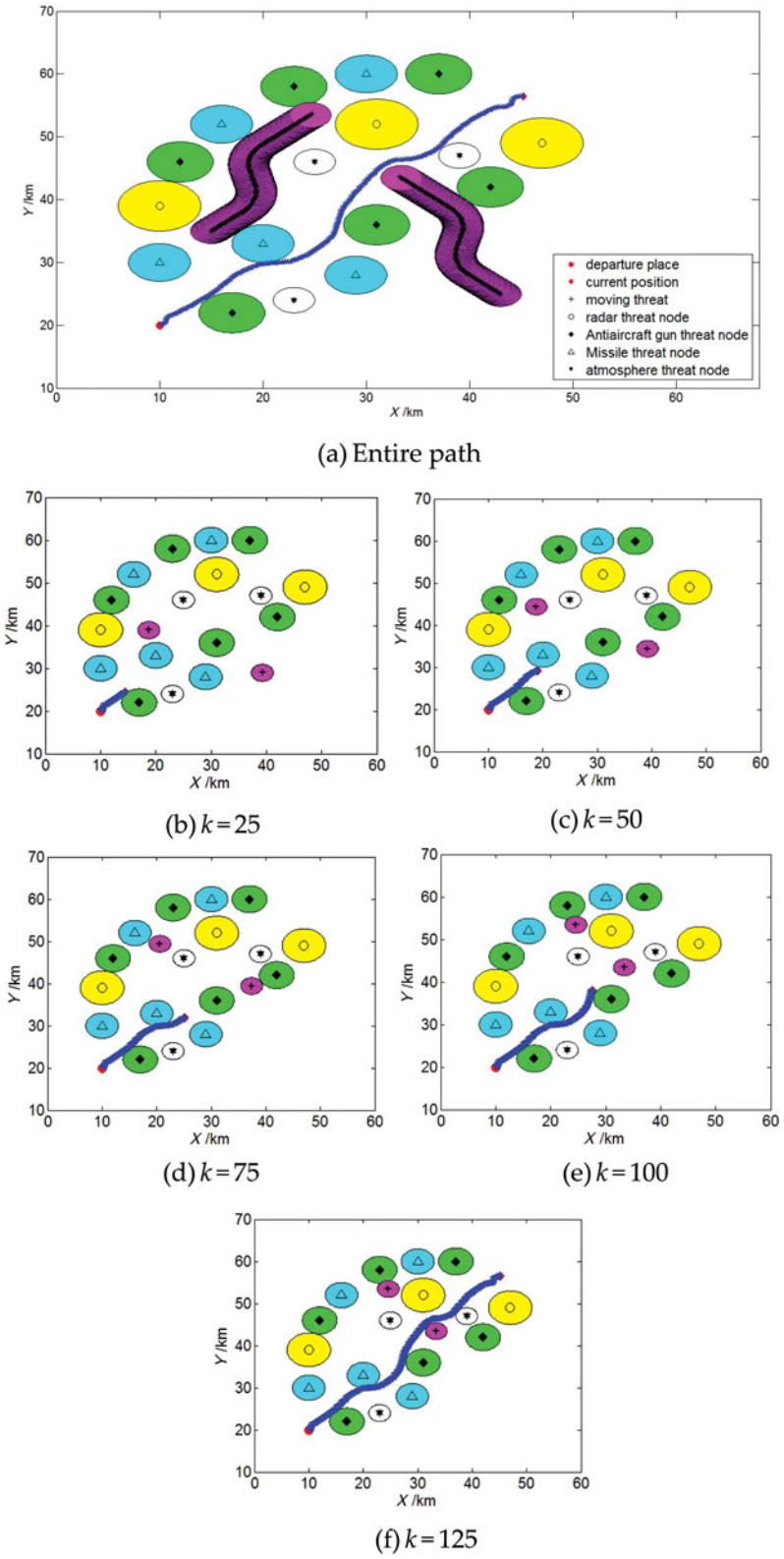


Fig. 3. UAV path planning in a complex environment.

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Table I. Positions of the static and mobile threats.

Object		Position (x, y)/km
Static threat	Radar	(10, 39)(31, 52) (47, 49)
	Missile	(10, 30)(16, 52) (20, 33)(29, 28) (30, 60)
	Antiaircraft gun	(12, 46)(17, 22) (23, 58)(31, 36) (37, 60)(42, 42)
	Atmosphere threat	(23, 24)(25, 46) (39, 47)
Moving threat	Departure	(15, 35)
	Destination	(43, 25)
UAV	Departure	(10, 20)
	Destination	(45, 36)

Table II. Threat radius of the static threats.

Threat type	Effective firing radius/km	Maximum detection radius/km
Radar	4	120
Missile	3.5	100
Antiaircraft gun	3	6
Atmosphere threat	2	7

Table III. Parameters of the UAV.

Item name	Value
Empty UAV weight	350 kg
Oil weight	295 kg
Maximum payload	204 kg
Maximum takeoff weight	1020 kg
Maximum flight speed	204 km/h
Patrol speed	111–130 km/h
Combat radius	926 km
Continuous flight time	>24 h

With the same threats as examples, the ACO algorithm is used to plan the UAV path shown in Figs. 5(a) and 5(b). In Fig. 5(a), the mobile threats do not move to the trajectory of the UAV; thus, the UAV can arrive at its destination safely. However, in Fig. 5(b), one of the mobile threats moves to the trajectory of the UAV; thus, the UAV cannot avoid it.

These examples show that compared with the ACO algorithm, the method that combines prediction and MPC is more suitable for path planning in complex environments with both static and mobile threats.

4.3. UAV dynamic path planning in a complex environment

4.3.1. Dynamic simulation. MAK VR-Forces is a powerful and flexible force simulation tool. A dynamic simulation platform is built based on MAK. In this platform, a UAV model is built (shown in Fig. 6). The parameters of the UAV are shown in Table III.

A dynamic simulation of example 1 is performed in MAK platform as shown in Fig. 7.

5. Conclusion

In this study, not only static threats but also mobile threats are avoided effectively in UAV path planning. We focused on the problem of avoiding mobile threats during UAV flight. The MPC algorithm was used to predict the trajectories of mobile threats according to the current position, velocity, and lateral acceleration of these threats. Threat costs were estimated based on the current and potential distances between the UAV and the threats. The UAV dynamic sub-optimal path

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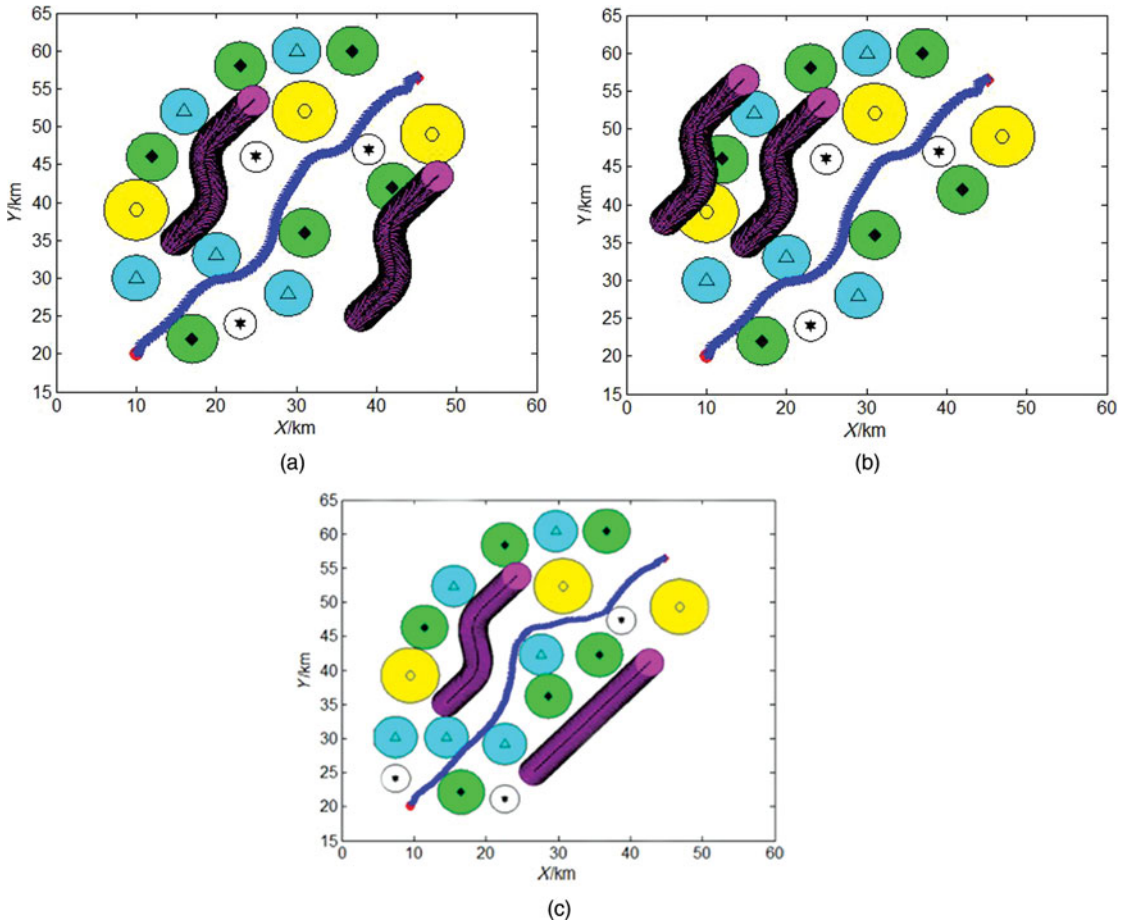


Fig. 4. Three additional examples in a complex environment.

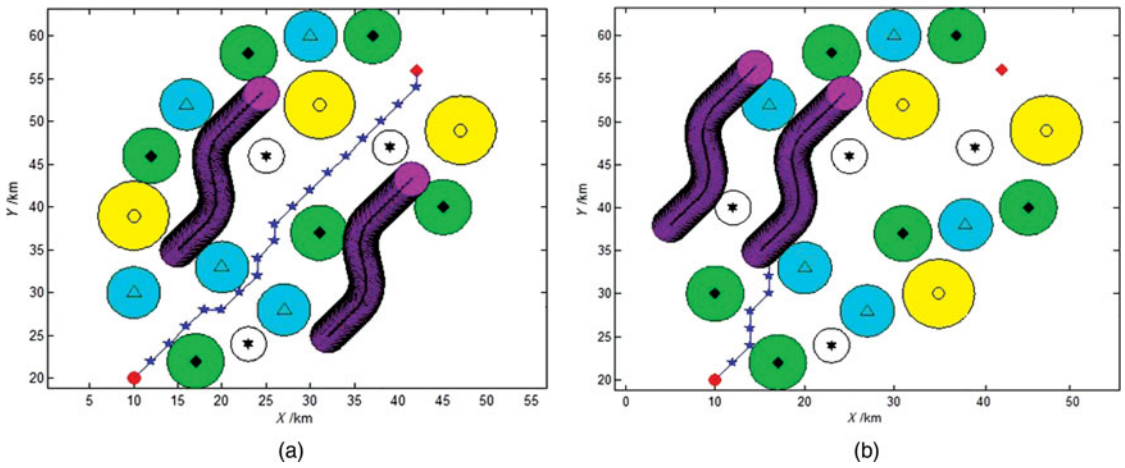


Fig. 5. UAV path planning with the ACO algorithm.

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Fig. 6. UAV model in MAK.



Fig. 7. Simulation of example 1 in MAK.

was planned by combining control and route costs. The analytical results, extensive simulation studies, and preliminary experimental demonstrations illustrate the viability of the proposed method.

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