An Adaptive Path Replanning Method for Coordinated Operations of Drone in Dynamic Urban Environments

Yu Wu, Kin Huat Low

Abstract—**Drones should be allowed to respond to dynamic urban environments and self-adjust their paths, safely and efficiently. Existing studies fail to develop a comprehensive approach to deal with drone encountering various dynamic changes over the course of flying. In this paper, an adaptive path replanning (APReP) method is proposed in discrete urban environments by considering the features of different types of dynamic changes, and the coordination among drones as well. First, various dynamic changes are concluded into three types. Three strategies are developed to conduct the path replanning for a single-drone operation under different combinations of dynamic changes. As the path replanning is extended to the operation involving multiple drones, the orders of planning are determined by task priority, path planning strategy and competition mechanism. A discrete rapidly-exploring random tree (DRRT) algorithm is presented to generate the path considering the characteristic of discrete urban environments. Simulation results demonstrate that DRRT algorithm is suitable for the path replanning problems considered, and the three proposed path replanning strategies are valid to cope with the corresponding types of dynamic change. Compare to other two algorithms, APReP algorithm is more efficient in large-scale problems with a number of dynamic changes.**

Index Terms — drones*; *urban environments*; *dynamic changes*; *path planning; rapidly-exploring random tree algorithm

I. INTRODUCTION

Usages and application with drones have become more and more popular in cities as they are efficient tools both in people's daily lives and some public affairs, especially in parcel delivery and surveillance tasks [1,2]. Air transportation business is a typical example to save time and manpower compared to the ground traffic [3]. Drones also can be deployed to sow or spray pesticides in agriculture [4], and they can track or patrol the specific target or area in emergency [5]. The concept of Urban Air Mobility (UAM) has been proposed by National Aeronautics and Space Administration (NASA) in 2017 to ensure the efficiency and safety of goods and passengers [6]. According to the plan, 'Air Taxi' will be a strong complement to the existing buses and subways in 2030 [7]. It can be expected that drones will play an increasingly important role in changing peoples' lifestyles.

With the growing number of flying drones in low-altitude urban environments, the flight safety and efficiency become the main concern, and the capacity of urban airspace should be estimated by reasonable methods [8]. A flight plan must be determined in advance to avoid the conflicts during flight. In the flight plan, the 3D path, start time and flight velocity of each drone must be included to fix their 4D paths. First, 3D paths can be calculated independently without considering the interferences among drones. A* [9], rapidly-exploring random tree (RRT) [10] and swarm-based algorithms [11] are common approaches. After collecting all the information on start time and flight velocity, the 4D path of drone maybe changed (even the flight task may be canceled) according to some rules of eliminating potential conflicts during flight [12]. In this way, the safety of flying drones can be guaranteed.

However, the above scheduling process is conducted before the tasks start, which fails to provide a solution in case of an emergency during drones' flying. An online path planning method is imperative to make a quick response to the dynamic changes and enable the task to be finished smoothly.

In this paper, the online path planning problem is considered in dynamic urban environments from the view of unmanned aerial system (UAS) traffic management (UTM), and the conceptual model is shown in Fig. 1.

As presented in Fig. 1, the offline flight information of drone must be known before it starts to fly. After having detected the dynamic changes, path replanning with different strategies is conducted according to the situations, and the coordination among drones also must be considered. Drones fly along the planned paths and repeat the above steps when detecting other dynamic changes. In this paper, modeling of dynamic changes in the discrete urban environments and development of path replanning algorithm are the focus. An adaptive path replanning (APReP) method is proposed to generate drones' paths considering the features of dynamical changes, the task

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priority of drones and the conflicts among drones. The main contributions of this work can be concluded as follows:

1. Various dynamic changes are classified into three types, and the corresponding path replanning strategies are formulated. The opportunity of conducting path replanning under discrete urban environments is also defined to make path replanning more efficient.

2. An APReP algorithm considering the task priority of drones and the path planning strategy is proposed. The orders of replanning for drones with the same task priority and path planning strategy are determined by introducing a competitive mechanism. Three strategies are used adaptively in this algorithm to modify the planned path with the minimum degree.

3. A discrete rapid-exploring random tree (DRRT) algorithm is developed to apply in the discrete environment. The check whether there is an obstacle between the current node and the spare node is unnecessary based on the flight rules of drone. Besides, the principles of generating the new node is changed considering that only a certain number of spare nodes can be selected in the discrete environment.

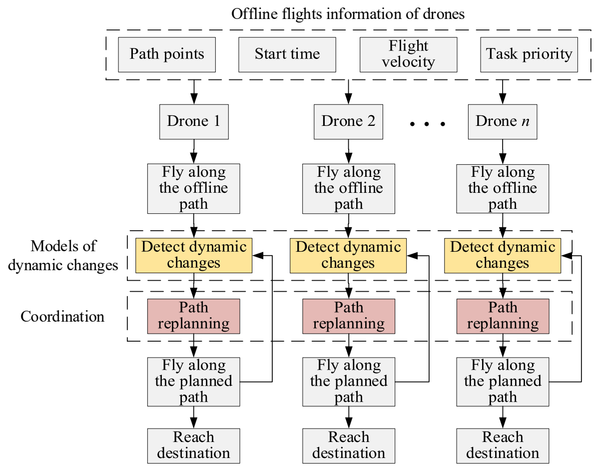


Fig. 1. Conceptual model describing the work in this paper

II. RELATED WORKS

There have been many literatures discussing the online path planning problem for a single unmanned aerial vehicle (UAV), and the emphasis is put on reducing the computation cost. A path planning algorithm without iterative process can save more computing time, and an anti-swing trajectory planning approach is proposed for a quadrotor slung load system in [13]. Meta-heuristic algorithms have been widely applied in UAV path planning problems, and comparison between genetic algorithm (GA) and particle swarm optimization (PSO) algorithm is made in [14]. The results show that GA produces superior trajectories to PSO algorithm with statistical significance.

Among the path planning algorithms, RRT is based on the random sampling and has been widely applied in various problems. RRT can generate a path very fast even in the complicated environment, which is suitable for online path planning. To further improve the performance of RRT in solution quality and computing speed, many improved versions are developed, and they can be concluded as the random extensions of unidirectional and bidirectional trees [15]. The operations are carried out mainly from developing the strategies of sampling nodes and changing the step size of search. In [16], a lower bound tree-RRT (LBT-RRT), which is a single-query sampling-based motion-planning algorithm, is proposed to obtain the near-optimal path. LBT-RRT can produce paths with higher quality than RRT and can run faster than RRT*. In [17], a Node Control (NC-RRT) algorithm is introduced to constrain the extended nodes of the tree and reduce the extension of invalid nodes. Besides, the strategy of changing the sampling area is designed to guide the exploration and improve the search speed. The sampling process in RRT also can be improved by combining with other intelligent algorithms, such as the artificial potential field algorithm [18], the neural network algorithm [19] and the inverse reinforcement learning algorithm [20]. To sum up, the quality of path is improved by guiding the search towards the optimal direction, thus reducing the randomness of search. Sometimes, it is achieved at the cost of increasing the computations, which may impair the ability of online planning. Besides, those improved versions of RRT are all used in the continuous environment, which may fail to conform to the characteristic of discrete environment.

Compare to a single UAV, the online path planning problem for multiple UAVs are more complicated as the interference among UAVs must be considered. There are fewer studies on this topic, and the methods can be summarized as centralized and distributed approaches. Centralized approaches can generate the best trajectories for the whole UAV team, but it also leads to a large computation load of the central server, which reduces the efficiency. Distributed approaches can solve the above problems and make the centralized decision into a number of sub decision-making problems. Receding horizon control (RHC) has been applied in online path planning problem for a single UAV [21,22]. The distributed format of RHC and model predictive control (MPC) is the mainstream in online path planning for multiple UAVs. Under the framework of distributed decision-making, each UAV can generate the path in the near future considering the constraints only related to its own [23]. Some strategies are proposed to avoid the conflicts among UAVs, such as the consensus-based approach [24], accessibility strategy [25] and priority-based approach [26]. When the idea of RHC/MPC is introduced to distributed online path planning, each UAV is required to submit an optimal path without considering the plans of other aerial vehicles. Then the above strategies are used to determine the order of path planning at the current moment, and the UAV must take the planned paths of others into account when calculating its future path. Various path planning algorithms are applied when each UAV generates the path in the RHC format, such as A* [27], PSO [28], ant colony optimization (ACO) algorithm [29], adaptive grasshopper optimization algorithm (AGOA) [30] and improved grey wolf optimizer

(IGWO) [31].

In the aforementioned studies, a comprehensive consideration of various dynamic changes is lacked, and they should be concluded and classified into different types according to their features. Besides, although RHC can deal with the dynamic changes, it is started without considering their features, which may not be the most efficient strategy from the perspectives of computational load and the degree of modifying the original path. A general approach is needed to cope with dynamic changes according to their influence on drones' flights and modify the planned paths to the minimal degree. It is difficult especially when the number of drones is great, and the dynamic changes come from different aspects. To the best of our knowledge, there is little literature study on different online path planning strategies for multiple drones in dynamic urban environments.

III. MATHEMATICAL MODEL OF PATH REPLANNING PROBLEM

A general description on urban environments and drone's flight rules are presented first to show the basic principles in this path planning problem. Then different forms of dynamic changes are considered, and how they have an influence on the original path are analyzed. The goal of path replanning is to enable a number of drones accomplishing tasks as many as possible, and also to reduce the total arrival delay of drones to their respective destinations.

A. Background of urban environments and drone's flight rules

In the proposed framework describing the urban environments, named 'AirMatrix' [32], the low-altitude airspace is divided into many small cubes with the same size, as shown in Fig. 2.

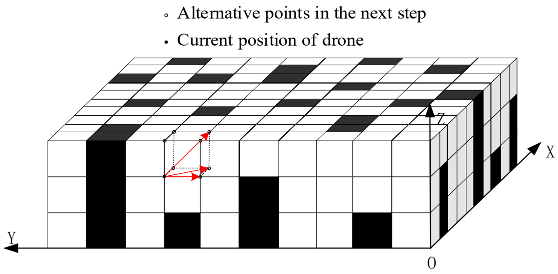


Fig. 2. Discrete urban environments described by 'AirMatrix'

In Fig. 2, the black cubes denote the buildings with different heights, and the drone can fly only in the white space and should keep certain distance from the buildings during flight. In real situations, the buildings are with various shapes, and they all can be enclosed by a certain number of cubes, like the operation in [12]. An example is given in Fig. 3.

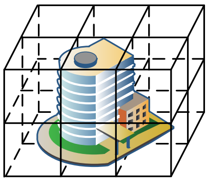


Fig. 3. The building with irregular shape enclosed by cubes

With the operation in Fig. 3, the building all can be modeled as cuboids to reduce the computation load of collision detection. Besides, to facilize the operation of traffic management, the vortexes of small cubes are set as the path points. The drone can choose the vortex of a connected edge, face diagonal or body diagonal as the next path point, and it flies along the straight line composed by two neighboring path points. When the path point overlaps with the buildings or exceeds the boundary of 'AirMatrix', it must be abandoned.

B. Path planning model for multiple drones under the framework of 'AirMatrix'

Under the developed framework of 'AirMatrix', the path points are the variables to be optimized in this path planning problem. Assume that the number of drones is N_D, the following constraints must be met to ensure the flight safety and efficiency.

1. Drones must fly within a certain space regulated by 'AirMatrix'

$$\begin{cases} x_s^i \in px, px = \{x_{min} + a \cdot o, o = 0,1,\dots,\frac{x_{max}-x_{min}}{a}\} \\ y_s^i \in py, py = \{y_{min} + a \cdot p, p = 0,1,\dots,\frac{y_{max}-y_{min}}{a}\}, s = \\ z_s^i \in pz, pz = \{z_{min} + a \cdot q, q = 0,1,\dots,\frac{z_{max}-z_{min}}{a}\} \end{cases}$$
$$1,2,\dots,N_{max,i}; i = 1,2,\dots,N_D \quad (1)$$

where x_{min}, x_{max}, y_{min}, y_{max}, z_{min} and z_{max} are the boundaries of 'AirMatrix', and *px*, *py* and *pz* are the sets of coordinate value of path points in the directions of OX, OY and OZ respectively. For example, $px = \{x_{min}, x_{min} + a, x_{min} + 2a, \dots, x_{max}\}$, $py = \{y_{min}, y_{min} + a, y_{min} + 2a, \dots, y_{max}\}$ and $pz = \{z_{min}, z_{min} + a, z_{min} + 2a, \dots, z_{max}\}$. Note that $N_{max,i}$ is the number of path points for drone i, and a is the edge length of a cube. According to Eq. (1), the position of drone i can be selected from a set of the discrete points $\{(x_s^i, y_s^i, z_s^i) | x_s^i \in px, y_s^i \in py, z_s^i \in pz\}$ defined in Fig. 2.

2. Path points must keep a certain distance away from the buildings

$$min\left\{\sqrt{(x_s^i - \tilde{x})^2 + (y_s^i - \tilde{y})^2 + (z_s^i - \tilde{z})^2}\right\} \geq a, (\tilde{x}, \tilde{y}, \tilde{z}) \in V_B \quad (2)$$

where V_B is the space of cubes occupied by the buildings, and $(\tilde{x}, \tilde{y}, \tilde{z})$ is a point which belongs to V_B. With the constraint in Eq. (2), the distance between the drone and a building must be no less than a.

3. Drones must reach their destinations respectively

$$\sqrt{(x_{N_{max,i}}^i - x_{tar}^i)^2 + (y_{N_{max,i}}^i - y_{tar}^i)^2 + (z_{N_{max,i}}^i - z_{tar}^i)^2} = 0 \quad (3)$$

where $(x_{tar}^i, y_{tar}^i, z_{tar}^i)$ is the destination for drone i.

4. For two drones, the time interval of passing the same

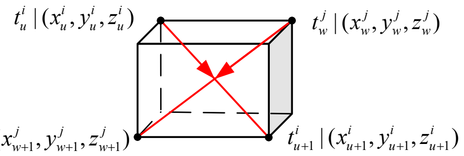
path point must be greater than a certain value to avoid the conflict.

$$|t_u^i|(x_u^i, y_u^i, z_u^i) - |t_w^j|(x_w^j, y_w^j, z_w^j)| > \Delta t$$
$$if\ x_u^i = x_w^j, y_u^i = y_w^j, z_u^i = z_w^j$$
$$i \neq j, i, j \in \{1,2,\dots,N_D\}, u = 1,2,\dots,N_{max,i}, w = 1,2,\dots,N_{max,j} \quad (4)$$

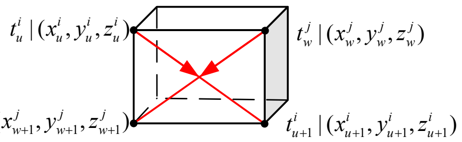
where $t_u^i|(x_u^i, y_u^i, z_u^i)$ denotes the time information of path point (x_u^i, y_u^i, z_u^i), and Δt is the defined safe time interval.

5. For two drones, right-angle collision is forbidden to ensure the flight safety.

To make a better understanding, an example of right-angle collision is presented in Fig. 4.



a) Path segments are the body diagonals



b) Path segments are the face diagonals

Fig. 4. Right-angle collision between drones

In Fig. 4, although drone *i* and *j* are both safe at the four path points, they will collide with each other at the intersection point of two path segments. To avoid the conflict, the following equation must be met.

$$t_u^i > t_{w+1}^j \ or\ t_w^j > t_{u+1}^i$$
$$if \begin{cases} x_u^i + x_{u+1}^i = x_w^j + x_{w+1}^j \\ y_u^i + y_{u+1}^i = y_w^j + y_{w+1}^j \\ z_u^i + z_{u+1}^i = z_w^j + z_{w+1}^j \end{cases} \quad (5)$$

Eq. (5) denotes that the two drones can avoid the right-angle collision by staggering the time of reaching the intersection point.

C. *Modeling of dynamic changes*

Dynamic changes defined in this work are the factors that have an influence on the planned offline flight path. In general, the dynamic changes can be classified into three categories. The details are explained as follows:

1. Fixed no-fly zones

The fixed no-fly zones mean the static zones appeared after the generation of offline paths, and they will remain in the same space during the drones' flying. The fixed no-fly zones can be caused by the newly appeared weather (such as the strong wind) or military control. Drones must change their original path to bypass them. Note that, the change of drone's destination also belongs to this category because the drone also must avoid the zones which are not considered before to reach the new destination.

2. Cooperative drones

Cooperative drones are those which have registered their flight information on the UTM system, and their flight paths are known to the existing drones. In real situation, urgent tasks such as rescue and tracking, must be implemented immediately, and there may be conflicts between the flight paths of the existing drones and the cooperative drones. In this case, the paths of existing drones must be replanned.

3. Non-cooperative drones

For the drones which have not registered their flight information on the UTM system, they are defined as the non-cooperative drones. Their future flight paths are unknown to the existing drones [33]. Only the current positions of those drones can be obtained. The existing drone must replan its path to avoid colliding with the non-cooperative drones. Note that, the flying birds have the similar characteristic with the non-cooperative drones.

In summary, there are three types of dynamical changes affecting the original paths of drones, and reasonable responses must be made to ensure the flight safety and accomplish the respective tasks.

D. *Performance Index for the evaluation of path replanning*

First of all, the path replanning should allow more drones to accomplish their tasks in the low-altitude airspace, so the initial (or the first) index is set as the number of drones accomplishing tasks. From the perspective of operation efficiency of drones, shorter arrival delay is desired, and the total arrival delay of drone is set as the second index. Assume that the number of drones accomplishing tasks is N_A, the two indices of evaluating the performance of path replanning can be formulated into the following equations:

$$J_1 = max(N_A) \quad (6)$$

$$J_2 = min \sum_{i=1}^{N_A} (at_i - ot_i) \quad (7)$$

where at_i is the actual arrival time of drone *i*, and ot_i is the original arrival time of drone *i*. Note that J_1 represents the greatest number of drones accomplishing a given task, whereas J_2 is the shortest arrival delay of the drones in total.

IV. ADAPTIVE PATH REPLANNING APPROACH FOR A SINGLE DRONE

In this section, the path replanning approach for a single drone is discussed. Different from the path replanning strategy in the continuous space, the opportunity of conducting path replanning is regulated under 'AirMatrix'. Then path replanning strategy under a single type of dynamic change is developed. In a real situation, a drone may meet more than one type of dynamic changes at the same time, and adaptive path replanning approach under such cases is designed to deal with those complicated situations.

A. *Opportunity of conducting path replanning*

The path replanning begins by deciding the opportunity of taking actions. In a continuous space, when dynamic changes are detected, UAVs conduct the online path planning process at regular intervals [34], and this simple strategy cannot be applied directly under 'AirMatrix' because the drone must fly along the straight line composed by two neighboring path points with the constant velocity. A diagram is shown in Fig. 5 to explain the opportunity of conducting path replanning under 'AirMatrix'.

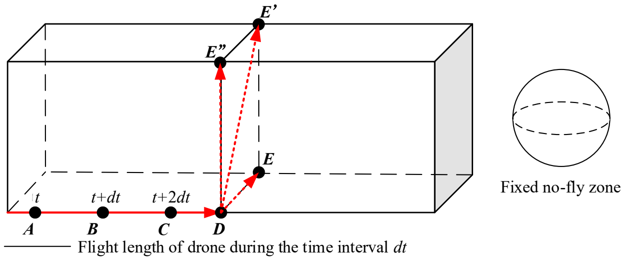


Fig. 5. Opportunity of conducting path replanning

In Fig. 5, *A*, *B* and *C* are three positions of drone corresponding to three adjacent sample moments (denoted as *t*, *t*+*dt* and *t*+2*dt* respectively), and the drone flies along the line $\overline{AD}$ with the flight velocity v_i. The flight information on the line $\overline{AD}$ is forbidden to be modified once the drone is enroute on the line $\overline{AD}$. Although the drone has detected the static no-fly zone at point *A*, path replanning is not conducted immediately because the drone will be still on the line $\overline{AD}$ (at point *B*) at the next sample moment (*t*+*dt*). The same is true for point *B*. When the drone reaches point *C*, path replanning can be started as the drone will arrive at point *D* and fly beyond the line $\overline{AD}$ before the next sample moment (*t*+3*dt*). The points *E*, *E*' and *E*" can be the candidates of the next path point when the path replanning is conducted at the sample moment (*t*+2*dt*). Even if the path replanning is conducted at point *A*, the newly generated path cannot be executed by the drone immediately until it reaches point *D*. Besides, dynamic changes occurring between the sample moments *t* and *t*+2*dt* may make the new path generated at the sample moment *t* invalid, and new path must be generated one more time at point *C*. With the above analysis, path replanning can be conducted at the last sample point of the current flight segment. In this way, the effectiveness of path replanning can be guaranteed, and the planned path can be executed to the maximum extent.

B. Strategy of path replanning considering a single type of dynamic change

According to the above descriptions, the strategies of addressing different types of dynamic changes are designed below.

1. Fixed no-fly zones

When the minimum distance between the remaining planned path and the fixed no-fly zones is smaller than the threshold value d_{safe}, 3D path is replanned one time to bypass those fixed no-fly zones and the buildings. The path planning algorithm applied in this case will be introduced in Section V. The flight velocity of drone will be kept the same to reduce the degree of modification.

2. Cooperative drones

In this case, the drone can keep safe by just changing its flight velocity. To facilitate traffic management, the flight velocity of drone only can be chosen from very specific values, i.e., V_H, V_M and V_L, which mean high speed mode, middle speed mode and low speed mode respectively. The drone will fly with the updated velocity in the rest of path. When there is more than one feasible flight velocity, the smaller one will be chosen to leave room for increasing flight velocity in future. If the drone cannot keep away from the cooperative drone with any of the three flight velocities, it will hover and repeat the above process at the next sample moment.

3. Non-cooperative drones

The remaining path of drone cannot be generated one time, and RHC is introduced to generate the path point in the near future. Detectors are installed on the drone. As the detection ability is limited, the non-cooperative can be detected only when the distance between the drone and the non-cooperative drone is smaller than the detection range (denoted as d_{det}), RHC-based path replanning is conducted, and only the 3D position of the next path point will be calculated. As the number of spare path points is small, enumeration method is used to check their feasibility. Note that, the non-cooperative drones will not follow the flight rules defined in 'AirMatrix'. To ensure the safety of existing drones, the following strategy is applied, as shown in Fig. 6.

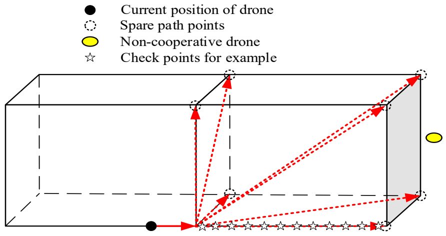


Fig. 6. Method of checking the spare path points in RHC-based path replanning

The straight line between the spare path point and the last path point is divided into a certain number of segments evenly. The positions of equal diversion points must be checked with the current position of non-cooperative drone. If any of the distance is greater than the threshold value (denoted as d'_{safe}), the corresponding spare path point will be treated as an unfeasible one. Among the feasible spare path points, the next path point will be selected according to the following cost function:

$$J_{RHC,i} = |x_{sp} - x_{tar}^{i}| + |y_{sp} - y_{tar}^{i}| + |z_{sp} - z_{tar}^{i}| \tag{8}$$

where (x_{sp}, y_{sp}, z_{sp}) is the position of spare path point, and $J_{RHC,i}$ denotes the Manhattan distance between the spare path point and the destination. If none of spare path points is feasible, the drone will hover at the last path point and repeat the above steps at the next sample moment.

When the non-cooperative drone is not within the detection range, the RHC-based path replanning will be terminated. The remaining flight path will be generated one time considering the influence of buildings and the fixed no-fly zones.

To sum up, the drone conducts a one-time path replanning when the states of dynamic changes can be known in advance, and an RHC-based path replanning is applied when facing non-cooperative drones. Besides, in most cases, the drone can just either change the flight velocity or 3D path to deal with the dynamic changes. Replanning 4D path is implemented only when modifying 3D path fails to result in a safe path.

C. Path replanning approach combining different types of dynamic changes

In real flight, more than one type of dynamic changes may occur at the same time, and the situation becomes complicated. An adaptive path replanning approach is needed to cope with different combinations of dynamic changes. According to the discussion in Section IV. B, the path replanning strategies can be classified by two different criteria. The first one is based on the domain of path planning, i.e., one-time planning and RHC-based planning. When one-time planning and RHC-based planning are both required at the same time (for example, cooperative and non-cooperative drones are detected at the same time), RHC-based planning will be carried out because one-time planning is one special case of RHC-based planning when the planning domain is the whole rest path.

The second criterion is based on the degree of modification, i.e., changing flight velocity and 3D path. It is clear that changing 3D path has greater degree of modification than changing flight velocity. For example, when fixed no-fly zones and cooperative drones are detected simultaneously, changing 3D path only is enough to guarantee a safe path. An adaptive path replanning approach is presented in Fig. 7.

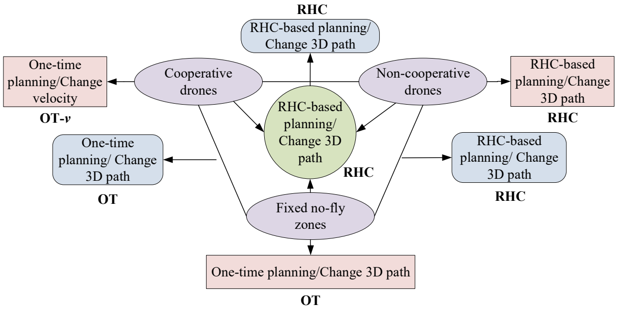


Fig. 7. An adaptive approach of path replanning for a single drone (the abbreviation of corresponding approach is also defined in this figure)

In Fig. 7, the proposed approach contains three strategies, i.e., OT-v, OT and RHC. All combinations of the three cases in Section IV. B are involved, and the path replanning strategy corresponding to each possible situation is shown. Note that neither one-time nor RHC-based 4D path planning is included because it is just reserved as an alternative when the strategy of 3D path planning is not effective. Besides, to deal with the most complicated case, RHC strategy is adopted, which happens as long as the non-cooperative drone occurs.

V. ADAPTIVE PATH REPLANNING ALGORITHM FOR MULTIPLE DRONES

When multiple drones are all affected by dynamic changes, the coordination among them must be considered. Their orders of path planning need to be determined. A competitive mechanism is introduced to solve this problem. In the proposed path replanning approach, a path planning algorithm is needed only in OT strategy, and the DRRT algorithm is designed to generate the remaining path. As for the other two strategies, the enumeration method is adopted as the number of alternatives is small, and the one with the best fitness value will be selected.

A. Determination of drones' path planning orders by a competitive mechanism

At each sample time, the drone can be classified into different types according to their current states and the strategies of plan replanning, as shown in TABLE I.

TABLE I. THE TYPES OF DRONES AT EACH SAMPLIE TIME

Type	Description
1	Drones cannot conduct path replanning
2	Drones can conduct path replanning
2-1	Drones adopt the OT-v strategy
2-2	Drones adopt the RHC strategy
2-3	Drones adopt the OT strategy

For the drones type 1, they just fly following the planned paths, and determination of drones' path planning orders is conducted only for drones type 2. The following regulations are made to reflect both the priority and competitiveness among drones type 2.

1. Drones with high task priority conduct path replanning earlier

When they conduct path replanning, the constraints contain the buildings, dynamic changes, the generated future paths of drones type 1 and the future paths of drones type 2. Obviously, the drones with higher task priority will consider fewer constraints when conducting path replanning.

2. For the drones with the same task priority, the corresponding path replanning strategy with fewer number of optional variables are conducted path replanning earlier.

Among the three strategies, OT-v strategy has the fewest optional variables, and the whole remaining path must be checked to satisfy all constraints. Therefore, the drones type 2-1 conduct path replanning earlier to address fewer constraints.

In RHC strategy, only the next path point will be generated, and it is selected from a small number of feasible spare path points. The second place is given to the drones type 2-2.

As for the OT strategy, a large space is provided to search the remaining path, which has the most optional variables and the highest success rate in path replanning. The drones type 2-3 will additionally consider the generated future paths of drones type 2-1 and 2-2, which adds the difficulty of generating remaining 3D path.

3. Drones with the same task priority and path replanning strategy should make a competition to determine their orders

Those drones first generate the remaining paths or the next path points respectively without considering the future paths of others. The orders are decided according to their estimated remaining travel time (ERTT), and the drones with shorter ERTT will conduct path replanning earlier. This competition mechanism is designed based on the thinking that drones with shorter ERTT are likely to finish their tasks earlier to free up space for others, and they should conduct path replanning with fewer constraints. The mathematical form of calculating ERTT for one-time path planning and RHC-based path planning are listed below.

$$ERTT_{one}^{i} = dis_i / v_i \tag{9}$$

$$ERTT_{RHC}^{i} = (dis_{i-x} + dis_{i-y} + dis_{i-z})/v_i \quad (10)$$

where dis_i is the length of the remaining 3D path, and v_i is the current flight velocity of drone *i*. In RHC-based path planning, as the remaining 3D path has not been decided, the Manhattan distance is regarded as the estimated length.

The above regulations of determining drones' path planning orders can be summarized in Fig. 8.

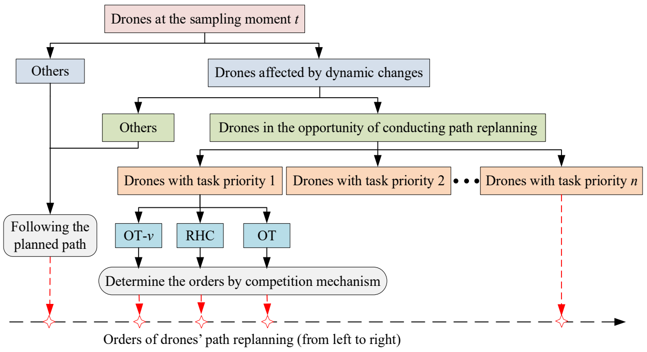
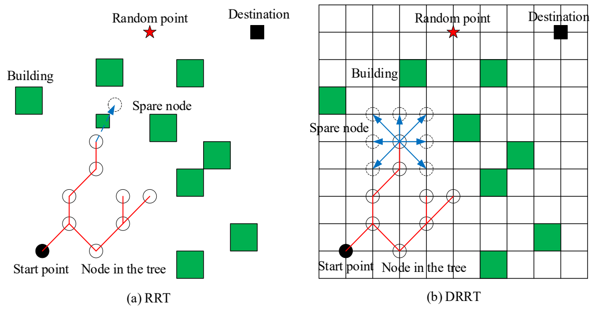


Fig. 8. Regulations of determining drones' path replanning orders

In Fig. 8, the dash line with arrow denotes the timeline of each drone conducting path replanning, and the drones following the planned path will determine their future paths first at each sample time. The task priorities of drones are represented with Arabic numerals, and a smaller number indicates a higher task priority. The drones with task priority *n* conduct the path replanning last.

B. *Modification of RRT in OT strategy to adapt to discrete urban environments*

RRT is selected to generate the remaining 3D path one time in this work because it can obtain a good path within a short time, which is fit for the online path planning problem. The original form of RRT is applied in the continuous space, and some modifications must be undertaken to make it suitable solving this 4D path planning problem in discrete urban environments. Fig. 9 is provided to show the modification of DRRT compared to the original RRT.



(a) RRT (b) DRRT

Fig. 9. Comparison between DRRT and RRT

In RRT, the check whether there is an obstacle between the current node and the spare node must be conducted, and only the spare node passing the check can be added to the tree nodes. While it is unnecessary to perform such a check in DRRT because there cannot be buildings between the current node and the spare node according to the flight rules of drone. Besides, as the spare nodes are discrete in DRRT, it often fails to extend the tree node toward the direction of random point. In DRRT, the spare node which has the smallest distance to the random point will be added to the tree nodes. To further explain the DRRT, the current position of drone T_0 is set as the tree node, and the union of all the tree node is assumed as *TR*. The destination assumes to be *D*, and the steps of DRRT algorithm are presented in Algorithm 1.

Algorithm 1 DRRT algorithm

```
1: $T_0 \in TR, T_c = T_0$
2: while $||T_c - D|| > \sqrt{3}a$
3:     $mark$=0
4:     while $mark$==0
5:         Generate a random point $T_R \in A$
6:         for $i = 1: length(TR)$
7:             $dis(i) = ||T_R - TR(i)||$
8:         end
9:         $T_s = arg\{min(dis)\}$
10:        List the spare path points $SP$ following by $T_s$
11:        if $SP \neq \emptyset$ then
12:            $mark$=1
13:        end
14:    end
15:    for $j = 1: length(SP)$
15:        $dis'(j) = ||T_R - TR(j)||$
17:    end
18:    $T_b = arg\{min(dis')\}$
19:    $T_b \in TR$
20:    $T_c = T_b$
21: end
```

The operator $||\cdot||$ is used to calculate the distance between two points, and A is the defined space in 'AirMatrix'. When the destination D can be the next path point of the new tree node T_b according to the flight rules, the search process ends, and the 4D path is generated.

In *line* 5, to accelerate the search process, the destination can be selected as the random point with a certain probability to force the exploration toward the destination. This approach has been applied in many modified versions of RRT algorithm [10]. *Lines* 10 and 17 are different from the original RRT as the drone can only reach specific path points according to the flight rules. Note that if none of the spare path points is feasible in *line* 10, it will turn to *line* 5 immediately. A new random point is generated again to continue the search process.

C. *Flow of APReP algorithm*

In Section IV and V, the details of APReP algorithm for multiple drones are explained, and the flow of this algorithm is shown in Fig. 10.

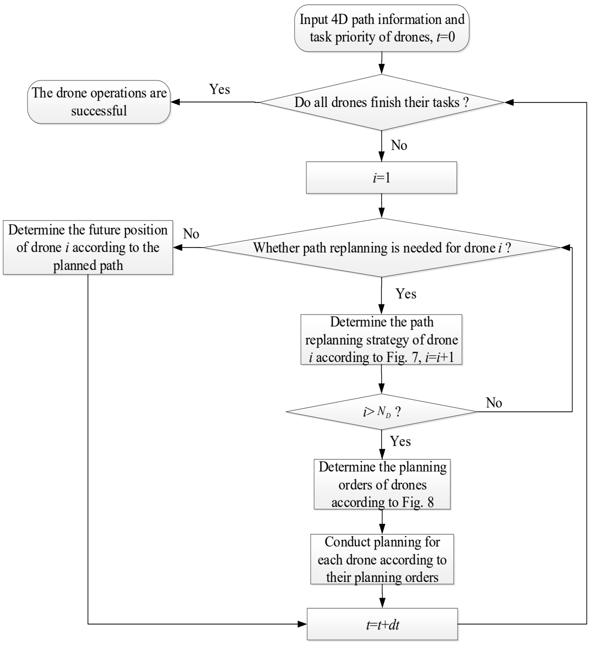


Fig. 10. Flow chart of APReP algorithm integrating Section IV and V

In Fig. 10, the flow generally contains three parts, i.e., checking, ordering and planning. At each sample time, a drone is checked whether path replanning is needed, and which path replanning strategy is applied. Then the orders of path planning are determined considering the task priority, path replanning strategy and competition results comprehensively. Each drone carries out path replanning in order, and their future paths are generated. The proposed APReP algorithm take different types of dynamic changes into account and can address them by modifying the planned paths with the minimum degree, which also coordinates the motion of drones successfully.

Among the three path replanning strategies, OT and RHC also can be applied independently to deal with different types of dynamic changes. In other words, path replanning can be conducted by using OT or RHC strategy only, but the results will be inferior to the APReP algorithm. This is because the RHC-based algorithm lacks a global view in path planning, and only the best path point in the next step is selected. This mechanism may lead to many detours during drones' flying, which will increase the time of accomplishing tasks. On the other hand, the difference between APReP algorithm and OT-based algorithm lie in their way of addressing cooperative and non-cooperative drones. When path replanning is conducted, OT-based algorithm always generates new 3D path from the current position of drone to the destination. This action equals to reserve a number of path points in the space. Actually, those reserved path points will be abandoned when facing the non-cooperative drones, which makes the drone be a dog in the manger and reduces the search space of other drones.

VI. SIMULATION STUDIES

To investigate the rationality and superiority of the proposed APReP method for coordinated online planning of drones, simulations testing different functions of the method are designed. In the first group of simulations, A*, ACO, RRT* and DRRT algorithm are used to generate the flight path for a drone, and comparison are made among the four algorithms. In the second scenario, the path replanning strategies under different types of dynamic changes are verified. Comprehensive simulations with 90 drones are conducted in Section VI. C, and all types of dynamic changes are set to test the performance of APReP algorithm. Three algorithms are applied to solve this complicated path replanning problem, and the statistical results are analyzed.

There are a certain number of buildings distributed in 'AirMatrix'. The ranges of 'AirMatrix' in OX, OY and OZ directions are [0, 1800] m, [0, 1800] m, and [0, 90] m respectively. The settings of other parameters are listed in TABLE II.

TABLE II. PARAMETERS SETTINGS IN SIMULATIONS

Item	a	Δt	dt	d_{safe}	d'_{safe}
Value	30 m	5 s	1 s	15 m	20 m
Item	d_{det}	V_H	V_M	V_L	
Value	100 m	15 m/s	10 m/s	5 m/s	

The parameters in TABLE II is got considering the flight performance of drone and the detection and computation abilities of devices equipped on the drone. The safe flight distance between drones is also taken into account. As the sample time interval dt is set to 1s, the elapsed time for the drone to calculate the future path should be no more than 0.1s to leave enough time for the control system to execute the generated the path. All the results are obtained by running the programs on a desktop with Intel(R) Xeon(R) CPU E5-1630 3.70 GHz.

A. Comparison among several path replanning algorithms in OT strategy

Among the three path replanning strategies, the OT strategy requires a fast algorithm with high accuracy. To verify the rationality of using DRRT, A*, ACO and RRT* are introduced to make comparisons. The steps of RRT* are the same with those of the DRRT, and the rewire operations are added after each search process. The parameters settings of ACO are taken from Ref. [35], and the probability of selecting the destination as the random point in RRT* and DRRT are both set as 0.5.

The start point and destination are set as (750, 810, 60) and (1770, 1710, 90) respectively. With the above settings, the paths generated by A*, ACO, RRT* and DRRT are shown in Fig. 11. RRT* and DRRT are run independently for 50 times, and the best results of the two algorithms are presented in Fig. 11. Note that, as it is not clear to see the 3D paths in the urban environments distributed with buildings, only the graph of 2D view is presented, and the important information of the paths are all included. To further discuss the qualities of paths and the computing time, important data from the four algorithms are summarized in TABLE III, and the statistical results of RRT* and DRRT are listed in TABLE IV.

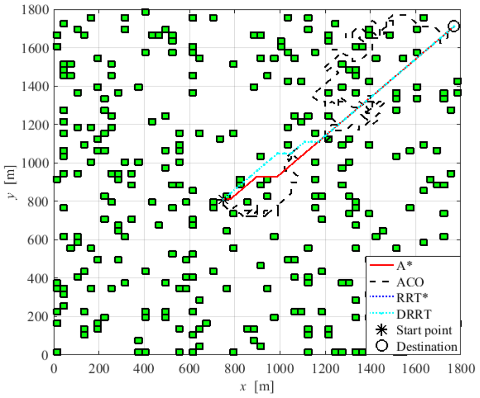


Fig. 11. Paths generated by different algorithms (2D view)

TABLE III. PATH PLANNING RESULTS WITH FOUR ALGORITHMS

Algorithm	A*	ACO	RRT*	DRRT
Path length	1405.2 *m*	7481.1 *m*	1421.4 *m*	1421.4 *m*
Computing time	3.66 *s*	1604.83 *s*	0.12 *s*	0.021 *s*

TABLE IV. STATISTICAL RESULTS OF RRT* AND DRRT (THE AVERARE VALUES OF 50 INDEPENDENT RUNS)

Algorithm	Path length	Computing time	Number of nodes
RRT*	1475.29 *m*	0.12 *s*	41.41
DRRT	1508.1 *m*	0.028 *s*	43.8

In Fig. 11, the drone can fly to the destination with the paths generated by the four algorithms, and the path generated by ACO makes many detours, which is not a good path compared to the other three algorithms. In TABLE III, A* spend 3.66*s* to search out the optimal path, and the elapsed time is longer than the sample time interval 1*s*, which cannot be realized in online path planning. For RRT* and DRRT, their best path is the same in 50 independent runs, and DRRT spend fewer time to obtain the path. To make a further analysis, in TABLE IV, RRT* performs better than DRRT in terms of path length, and the average path length increases by only 4.9% and 7.3% compared to A* for RRT* and DRRT respectively. While the computing time of RRT* is larger, and the number of nodes in the two algorithms is approximately the same. RRT* can obtain shorter path at the cost of performing the rewire operations at the end of each search process, which will increase the extra computing time. However, the improvement of path quality is not so significant because the number of adjacent nodes which can be selected in the rewire operations is small in discrete urban environments, and a notable rise is led in computing time. DRRT can meet the requirement of online computing proposed at the beginning of Section VI. In general, DRRT is qualified for solving this online path planning problem and can generate a good path within short computing time.

B. Verifications of path replanning strategies under different types of dynamic changes

In this section, the proposed three path replanning strategies, i.e., OT, OT-*v* and RHC are tested respectively. To make the offline path of drone affected by the dynamic changes intentionally, the fixed no-fly zone, cooperative drone and non-cooperative drone are all set to locate or bypass the same path point (1020, 1080, 90) on the offline path of drone. Fig. 12 shows the 2D views of paths avoiding the fixed no-fly zone.

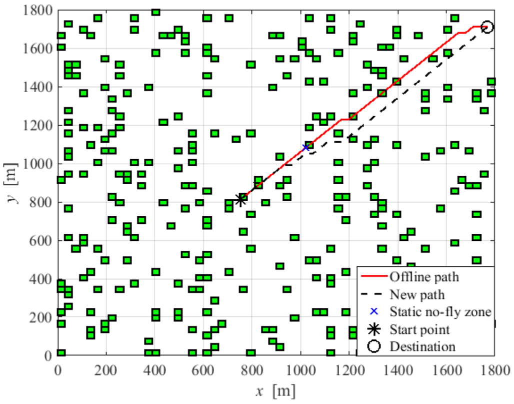


Fig. 12. Path replanning caused by the fixed no-fly zone (2D view)

In Fig. 12, the drone abandons the offline path when the fixed no-fly zone is detected, and new path is generated by DRRT, which can both avoid the fixed no-fly zone and the buildings and make the drone reach the destination. The path replanning is conducted just when the drone is near the fixed no-fly zone, which ensures that the offline path is executed to the maximum degree.

For the OT-*v* strategy, the offline 3D path is not changed when avoiding a cooperative drone. Only the information of flight velocity is provided in Fig. 13.

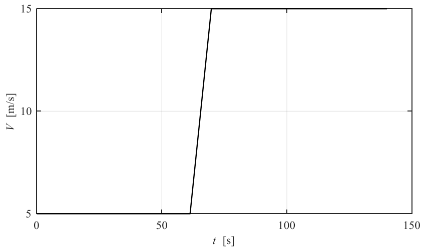


Fig. 13. Change of flight velocity when avoiding a cooperative drone

When *t*=69*s*, the flight velocity of drone changes from 5 *m*/*s* to 15 *m*/*s* to bypass the cooperative drone, and the flight velocity remains to be 15 *m*/*s* in the rest of path. It costs only 3.1*ms* to compute the new flight velocity of drone, which is far less than the required elapsed time (0.1*s*).

When facing the non-cooperative drone, the situation become more complicated, and it will take longer time to escape. Fig. 14 shows the process of avoiding the non-cooperative drone.

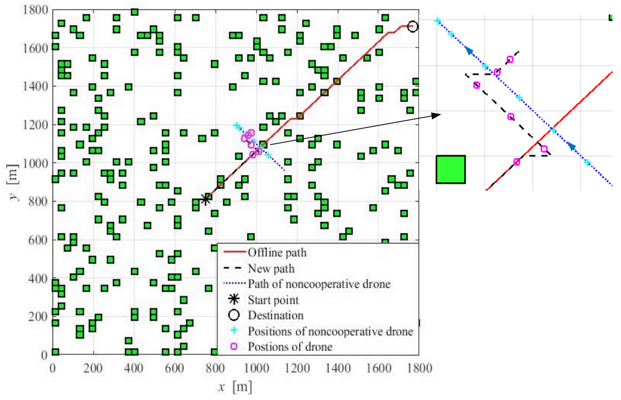


Fig. 14. Process of path replanning when avoiding the non-cooperative drone (2D view)

Note that the new path is incomplete as only the new path points generated by RHC strategy is calculated, and the rest of path can be generated by DRRT. In Fig. 14, the positions of two drones at the same moment are marked, which can show the 4D path information at some critical moments clearly. Moreover, the distance between the two drones is presented in Fig. 15.

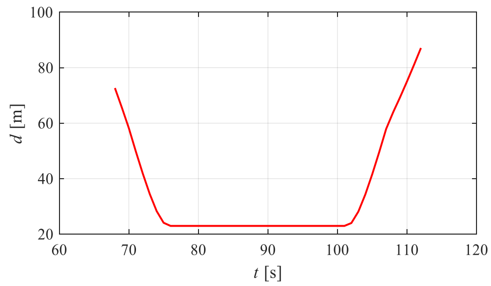


Fig. 15. Distance between two drones over time in RHC strategy

During this period, the distance between the two drones is always greater than the safe value ($d'_{safe} = 20$ m), which indicates the validity of the proposed RHC strategy. Besides, the average elapsed time of computing the 3D path is 1.2*ms* when applying the RHC strategy.

The above results demonstrate that the path replanning strategies are effective in dealing with different types of dynamic changes, and new path can be generated to keep the drone safe and make it reach the destination.

C. Comprehensive simulations under 90 drones with different algorithms

To further explain the advantages of the proposed APReP algorithm, a simulation containing 90 drones are carried out, and all types of dynamic changes involved in this work are set. The offline 4D flight paths of drones are referred to [12], which are obtained by running A* and GA on the platform of 'AirMatrix' considering the real urban environments. The task priorities of drones are denoted as 1, 2, 3, 4, 5, and a number of fixed no-fly zones are distributed within the boundaries of 'AirMatrix'. Five drones (No. 8, 28, 40, 57 and 65) are assumed to change their destinations after they start their travels for 10 *s*, and one drone (No. 90) cancels its travel plan. Ten cooperative drones with urgent tasks are set to disturb the original flight plan. Besides, ten non-cooperative drones are added to increase the difficulty of path replanning. As it is an online path planning problem with many drones, it is not visual to show the path of each drone. It is more appropriate to present the states of drones during flight. TABLES V and VI are designed to record drones' flying status.

TABLE V. MOMENT FOR DRONES APPLYING OT STRATEGY FOR THE FIRST TIME

Order	No.	Start time (*s*)	Moment (*s*)	Order	No.	Start time (*s*)	Moment (*s*)
1	D64	35	40	46	D69	1035	-
2	D32	66	76	47	D30	1105	1107
3	D57	70	80	48	D10	1126	1126
4	D60	72	-	49	D7	1134	1134
5	D25	78	78	50	D46	1154	**1154**
6	D51	91	108	51	D22	1159	1159
7	D47	99	-	52	D9	1176	-
8	D14	102	102	53	D40	1199	**1199**
9	D37	108	108	54	D79	1199	1199
10	D63	113	134	55	D74	1202	1202
11	D71	146	1691	56	D29	1246	1246
12	D89	152	-	57	D8	1256	**1256**
13	D26	226	226	58	D52	1264	1266
14	D4	263	**263**	59	D27	1277	1277
15	D70	273	**273**	60	D80	1317	-
16	D23	323	323	61	D59	1321	1327
17	D49	330	330	62	D20	1342	**1342**
18	D13	337	340	63	D67	1342	1342
19	D39	364	397	64	D87	1376	1376
20	D68	367	367	65	D48	1380	-
21	D83	382	382	66	D17	1385	1385
22	D81	416	416	67	D82	1395	1395
23	D84	444	444	68	D28	1404	**1404**
24	D78	467	477	69	D24	1412	1415
25	D45	489	492	70	D50	1420	1420
26	D38	549	-	71	D34	1423	1423
27	D21	550	583	72	D16	1510	1515
28	D2	558	561	73	D19	1511	1511
29	D33	575	575	74	D65	1514	**1514**
30	D77	608	628	75	D66	1525	1535
31	D75	627	627	76	D86	1533	1533
32	D62	632	650	77	D6	1539	-
33	D31	636	638	78	D5	1547	**1547**
34	D35	640	**640**	79	D1	1617	1617
35	D54	646	664	80	D61	1626	-
36	D3	653	653	81	D36	1644	1644
37	D42	653	658	82	D85	1661	-
38	D41	714	-	83	D72	1686	1691
39	D73	737	-	84	D56	1704	1722
40	D58	749	749	85	D55	1745	-
41	D43	797	**797**	86	D76	1749	1749
42	D44	857	871	87	D12	1785	-
43	D15	866	**875**	88	D53	1797	1797
44	D18	901	-	89	D11	1811	-
45	D88	986	-	90	D90	1817	**cancel**

TABLE VI. DRONES CONDUCTING PATH REPLANNING MORE THAN ONCE DURING FLIGHT

No.	Start time (*s*)	OT-*v* (*s*)	OT (*s*)	RHC (*s*)
D4	263	-	263; 349; 350	332; 340;
D5	1547	-	1547; 1717	1696; 1699; 1702; 1705; 1710; 1713
D8	1256	-	1256; 1267	-
D15	866	-	875; 919; 922	915; 920
D20	1342	1451	1342	
D28	1404	-	1404; 1407; 1418	-
D35	640	-	640; 707; 724	677; 680; 683; 686; 688; 690; 692; 694; 696; 699; 683; 701; 703; 705; 722
D40	1199	-	1199; 1212	
D43	797	868	797	-
D46	1154	-	1154; 1276;	1266; 1268; 1270; 1272; 1274
D65	1514	-	1514; 1525	-
D70	273	-	273; 358	354

Except for the drone No. 90, the other 89 drones can all accomplish their tasks. 18 drones are unaffected by the dynamic changes, and they fly with the offline path respectively. The item 'Moment' in TABLE V means the time conducting the path replanning. Most of drones are influenced by the fixed no-fly zones, and OT strategy is used when they start to fly or after they have flown for a few seconds. In TABLE VI, the offline paths of drones No. 20 and 43 are disturbed by the cooperative drones. Six drones are interrupted by the non-cooperative drones, and the RHC strategy is usually conducted several times. To generate the remaining path after using the RHC strategy, OT strategy is followed. Note that drone No. 4 conducts OT strategy twice in two consecutive seconds because it fails to search out a feasible path at the first try, and it hovers and use the OT strategy again at the next sample time. It takes drone No. 35 about 50*s* to avoid the non-cooperative drone. The total time of accomplishing all tasks is 2044*s*, and the arrival delay for each drone is shown in Fig. 16.

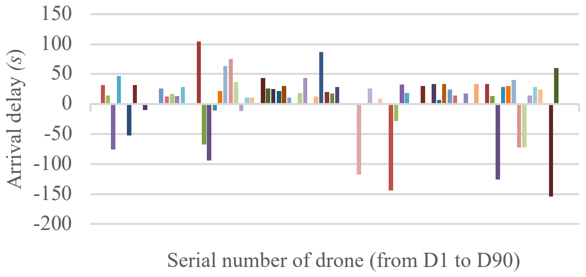


Fig. 16. Arrival delay of each drone accomplishing task

Most drones reach the destination later than their original arrival time due to the influence of dynamic changes. There are also some drones spending fewer time reaching the destination because they increase their flight velocities or search out shorter path when conducting path replanning. The total arrival delay for all drones accomplishing tasks is 510. 62*s*.

Next, comparison will be made among the APReP algorithm, RHC-based algorithm and the OT-based algorithm with the same settings in this section. The results are analyzed below.

With the RHC-based algorithm, the simulation is terminated when t=3387*s* because the consuming time of drone operations has far surpassed that in the proposed APReP algorithm. There are still 19 drones flying, and the performance of RHC-based algorithm is too far behind compared to the APReP algorithm. In general, relying on RHC strategy is not a good way in path replanning.

As there are random factors (such as the characteristic of IRRT algorithm and varying flight velocity of non-cooperative drones), the APReP and OT-based algorithm are run 30 times independently, and the statistical data are listed in TABLE VII.

TABLE VII. COMPARISON BETWEEN APReP AND OT-BASED ALGORITHM

	Maximum		Average		Minimum		Std	
	APReP	OT	APReP	OT	APReP	OT	APReP	OT
J_1	89	89	89	89	89	89	0	0
J_2	678.64*s*	707.25*s*	497.32*s*	566.48*s*	303.48*s*	328.85*s*	105.86*s*	128.48*s*

In TABLE VII, the value of initial index is the same, and the secondary index must be further compared. Drones reach their destinations with fewer arrival delay with APReP algorithm, and APReP algorithm is more stable than OT-based algorithm. Besides, *T*-test is conducted on the two set of data obtained from APReP and OT-based algorithm (values of J_2 in 30 independent runs) to judge whether the two set of data can be distinguished under the confidence coefficient of 0.05. The hypothesis is rejected, and the results obtained from the two algorithms come from different distributions statistically. To sum up, the quality of generated path in the OT-based algorithm is worse than that in APReP algorithm. Besides, from the perspective of computing resource, it will take longer time to execute the OT strategy compared to OT-v and RHC strategies, which is also a limiting condition to adopt the OT strategy in path replanning process.

VII. CONCLUSION

The path replanning problem for coordinated operations of drone in discrete urban environments is studied in this paper to respond to various dynamic changes and make drones accomplish their tasks. Literature investigation shows that the coordinated online path planning problems for UAVs are solved mainly based on the distributed RHC format, which lacks a flexible response according to different features of dynamic changes. An APReP method is proposed to deal with the above problem.

First, the discrete urban environments and flight rules of drones are defined under the framework of ‘AirMatrix’. Then the path planning model considering the constraints of a single drone flying and conflicts between two drones are established. The dynamic changes are classified into three types based on their influences on drones’ flight. A two-layer index is designed to evaluate the efficiency of drone operations from both the global view and the individual drone.

To respond to the dynamic changes effectively, the opportunity of conducting path replanning for a single drone is regulated. Then three strategies are developed to cope with three types of dynamic changes respectively. On this basis, an adaptive path replanning approach considering all possible combinations of dynamic changes is presented.

When multiple drones are involved, their orders of path planning must be determined, and the task priority and path replanning strategy of drones are the key factors. A competition mechanism is introduced when the orders cannot be decided by the above two factors. Besides, RRT is modified to make it suitable for solving this discrete path planning problem.

In the simulation studies, the advantage of DRRT is verified by comparing with A*, ACO and RRT*. DRRT can obtain a good path within shorter time, which makes it competent in this online path planning problem. Then the validity of OT, OT-v and RHC strategy are tested by three scenarios. Finally, the rationally and superiority of the APReP algorithm are explained in a comprehensive simulation by comparing with OT-based algorithm and RHC-based algorithm. In the future, the modeling of dynamic changes can be more explicit to reflect their features, and the constraints of communication distance and the signal strength among drones can be taken into account when designing the path planning algorithm. Besides, the energy consumption of drone can be considered as a factor to influence the strategy of online path planning.

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