Cooperative Obstacle Avoidance Planning via A*-BDWA Fusion for Unmanned Aerial Vehicles

Feifan Ni, Bowen Jin, Xin Gao, and Quanbin Li*

Abstract—**Recent advances on the technology of Unmanned Aerial Vehicles (UAV) have greatly increased the complexity of application scenarios, emphasizing the relevance of current study on UAV obstacle avoidance. The cooperative obstacle avoidance and trajectory planning issues that UAVs come up with when navigating through environments full of obstacles are discussed in this paper. A set of modeling schemes for optimal path planning based on benchmarks, i.e. the shortest path, shortest flying time, and least energy consumption is generated. While integrating the traditional static global planning A* algorithm with sparse optimization and improve the Dynamic Window Approach (DWA), an A*-Bi-objective DWA (A*-BDWA) algorithm was proposed, which generates global paths using the sparsified A* algorithm, then performs optimization on local paths for UAVs with various attributes and complex environments by summing scores of weighting headings, obstacle distance, and sightline as an evaluation function. The propose scheme offers optimal path trajectory simulations and time measurements for two UAVs, resulting in better models for possibly extreme cases. Simulations indicate that the proposed scheme ensures safe, collision-free pathways and dynamic obstacle avoidance during dual UAV operations. Besides, changing weights of score has little effect on UAV flying time, demonstrating the stability and effectiveness of our approach. With various repetitive and difficult simulation conditions upon testing, the proposed scheme displays a high completion rate of 88.3% and the shortest flight time, proving stability and efficiency for significant practical implications.**

Index Terms—**A*-BDWA fusion, DWA, dynamic obstacle avoidance, evaluation function, sparse optimization, UAV**

I. Introduction

The cluster systems of unmanned aerial vehicles (UAV) provide various benefits over single UAV operations, including redundancy, resilience, and scalability. Hence, a wide range of applications has been enabled, which consists of cooperative search, reconnaissance, surveillance, target tracking, electronic countermeasures, as well as the assaults of clustering [1-6]. Global scholars have conducted active research with practical implementations on this topic, which improves the safe, efficient, and energy-efficient operation of UAVs in complicated situations [7-10], while the technical limitations on a variety of research fields are both stimulating and challenging.

Currently, the majority of research advances focuses on trajectory planning in single UAV, single target, and static obstacle scenarios. However, these studies exposed several shortcomings such as limited application situations, failure to consider the characteristics of natural motion on UAVs, and minimal flying autonomy. Previous schemes such as A-star [11, 12], Genetic method [13] and Dijkstra [14], were adopted on directly producing trajectory paths which match the selected criteria of goals, however, the shortage of capacity on these approaches for real-time adaptation to dynamic changes in the procedure of UAV, stands for a dominant weakness, calling for solution.

In recent study, a small portion of research scholars have examined how these dynamic impediments affect trajectory planning, often making use of artificial potential fields and local path planning methods such as DWA [15, 16]. These algorithms show exceptionally good performance in local path optimization since they dynamically optimize paths to help participants avoid obstacles in real-time. However, such kind of path planning might not always produce the globally optimal path; on the contrary, it might also result in local optimum traps on rare occasions.

Cooperative study on algorithms of global path planning and local route optimization may overcome the prior defects and solve the potential problems of UAV trajectory planning. However, due to their unique properties, integrating these algorithms turns out to be difficult. Some researchers have combined these different types of algorithms for real-time path planning in order to get around these restrictions. For example, it is possible to enable real-time dynamic obstacle avoidance by combining the A-algorithm and the Dynamic Window Algorithm (DWA) to increase motion trajectory smoothness [17-21]. For instance, the A*-BDWA algorithm, intent to solve the problems of obstacle avoidance trajectory planning upon cooperating multiple UAVs. After obtaining a global route through sparsely optimizing the A* algorithm, this approach applies modified DWA algorithm to search for locally optimal trajectories between nodes by concerning both static and dynamic obstacle avoidance, while its final trajectories may guarantee efficiency, economy, and safety.

In our study, an A*-BDWA fusion based approach is proposed to improve the capabilities of obstacle avoidance for dual UAVs by overcoming the constraints of local optimality in the DWA algorithm, and thereby providing potential solution to real-time dynamic obstacle avoidance, which results into significant savings on computational costs. Simulation results prove the effectiveness of our integrated algorithm in meeting its aims on appropriate planning for

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cooperative obstacle avoidance.

The keynote contributions in our study are summarized in the following manifolds:

i) A dynamic scheme which integrate the A* algorithm and a bi-objective dynamic window approach (BDWA) was proposed on collaborative obstacle avoidance path planning by UAVs. This approach offers an effective solution to the problem of dynamic obstacle avoidance in complex scenes by merging global path planning with optimized local paths.

ii) Sparse optimization on A* algorithm: An improved A* scheme with sparse optimization was derived by reducing redundant nodes through sparse optimization, and thereby improving the efficiency of global path planning, especially when handling path redundancy issues in complex scenes. This scheme exhibits high stability and wide applicability in complex dynamic scenes. It may still retain high efficiency and safety especially in situations where the speed and path planning of the drone display considerable variations.

iii) A dual-target dynamic window scheme was proposed to improve the evaluation function of BDWA, enabling the safety and effectiveness of two UAVs to complete their relevant tasks. Simulations demonstrate the validity of this algorithm in condition of various velocities and random obstacles, proving its stability and adaptability in complex scenes, and achieving a high task completion rate upon tests. Integrating the merits of global planning and local dynamic obstacle avoidance, the global optimality of UAV path and respond to alternating scenes in real time are both ensured, improving the efficiency upon executing the related tasks.

The rest of this paper are structured as follows. Section II shows the assumptions of complex environments and a brief description on UAV performance. The A* algorithm and its sparse optimization are presented in Section III, while the BWDA scheme is proposed in Section IV. Simulation trials and performance analysis are displayed in Section V. The last Section VI summarizes our conclusions and prospects.

II. Assumptions and Performance of UAV Operating Environments

A. Environment Assumptions

UAVs play a vital role in natural disaster rescue. They are helpful to monitoring crisis circumstances [22], offering communications among photographs, transporting materials [23], and allowing potential rescuers to carry out activities swiftly and effectively while minimizing casualties and losses caused by the disaster. In our study, forest fires are employed as an environmental context.

It is assumed that a forest fire takes place in a specified location, necessitating a timely reaction from appropriate individuals. A risky area is defined on the foundations of both terrain and wind direction, while rescue activities begin from one side [24], as seen in Fig. 1.

The most severe region of the fire is in the center of the area, marked by thick smoke, scattered burning objects [25], and weak signals [26], making it possible for rescuers to become disoriented or disconnected. UAVs are adopted for signal amplification and fire detection. Due to the UAVs' short durability, bi-objective UAVs must operate alternately to enable ongoing rescue operations.

This scenario can be simplified to a classical and concise scene model of a single obstacle in a two-dimensional target plane, as depicted in Fig. 2. The subsequent definitions are presented as follows:

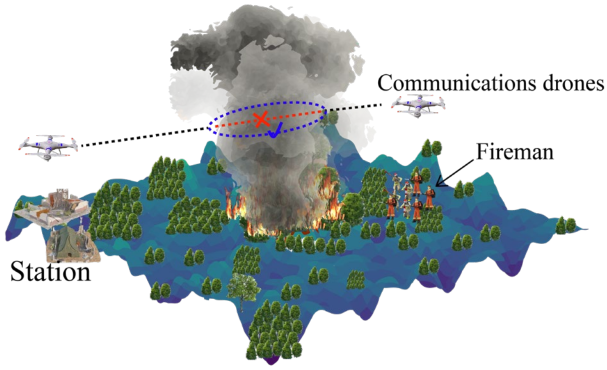


Fig. 1. 3D Scene model of fire detection by UAVs

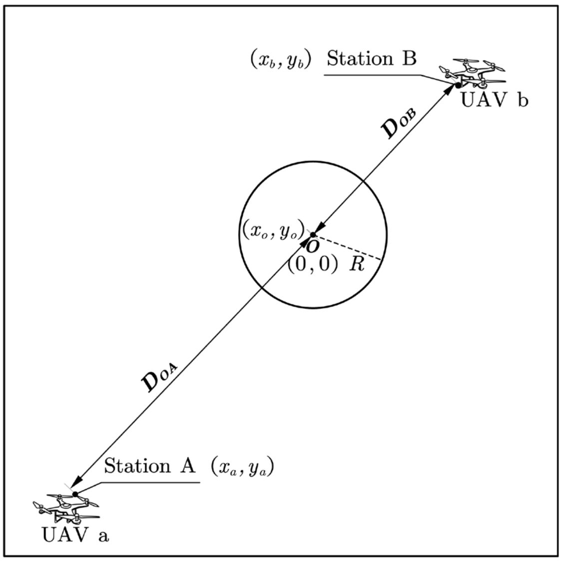


Fig. 2. A simplified scene model from complex environment

1) Target area and obstacles:

- Define the target region as a square with a diagonal length of L meters, representing the danger zone.
- Identify the region most impacted by the wildfire by drawing an obstacle circle with a radius of R and a center of O.

2) Bi-objective UAV stations:

- Define UAV station a as point A, which stands for the base station, and UAV station b as point B, which represents the terminal station.
- UAV stations A and B are located on either side of the obstacle circle radius R, both of which are on the extension of the radius. Note that Points A, B, and the center O are collinear. Euclidean distances from O to A and O to B are denoted as D_{OA} and D_{OB}, respectively.

3) Establish the Cartesian coordinate system:

- A two-dimensional Cartesian coordinate system was created, with the point A serving as the origin and the surrounding square sides serving as the x- and y-axes.

- The initial rectangular coordinates of points A, B, and O are denoted as (x_a, y_a), (x_b, y_b), and (x_O, y_O), respectively.

4) Consider the safety of UAV:

- To ensure adequate turning area for the UAV, 20% of its width was supplemented around the obstacle circle [27].

B. Performance description

In actual situations, the planning of UAV's trajectory will be affected by performance of its own and environmental factors. The elements of the UAV are illustrated as follows:

i) In initial positioning, UAVs a and b are located in stations A and B, respectively, both of which must fly to station B and station A along a specific path. Meanwhile, the UAV at station A is prioritized to arrive, while both of them move at a steady rate v and depart simultaneously.

ii) The turning radius of each UAV is minimized to r, while their angles on initial direction of UAVs a and b are denoted as θ_a and θ_b, respectively, meanwhile, denote $\omega = v/r$ as the angular velocity of UAVs.

iii) Assume that there is no possibility for UAVs meeting with each other (in other words, the line between two UAVs must always intersect with an obstacle) to prevent signal interference, which affects path planning. Besides, each UAV departing from the base station are in a full state, and those returning from the terminal are in a weak state.

III. Sparse Optimization of A* Algorithm

A. A Algorithm*

As a conventional scheme on heuristic searching, the A* algorithm is based on the fundamental design of its heuristic function, which is expressed by [11], [12]

$$f(n) = g(n) + h(n) \tag{1}$$

where $g(n)$ symbolizes the actual cost from the departure point to the current node, and $h(n)$ stands for the predicted cost from the current node to the destination node.

A heuristic function was adopted by A* algorithm to calculate the estimated cost from the goal point to the present location, and then decides the direction of path search with respect to this projected cost, boosting the validity and efficiency of this method.

Notably, variations in the number of UAVs may cause overlapping trajectories, resulting in potential collisions. To address this issue, we first forecast the routes of UAV a, and then consider it as an obstacle affecting route planning of UAV b. As a result, those paths of the two UAVs are restricted to the opposite sides of the line connecting points A and B, allowing for easier calculations upon operating.

B. Sparse Optimization on the A Algorithm*

The A* algorithm is effective at finding optimal paths on a raster grid, while the resulting paths frequently include a great number of redundant points. In order to enhance the computational efficiency of this model, it is essential to filter these global pathways while just finding and retaining the selected critical nodes instead [28]. This approach may ensure efficient optimization of the whole path.

In our approach, the strategy for traversing every three consecutive points is offered. If the line connecting the first and last locations does not intersect with any obstacles, the middle point can be regarded as redundant. Taking a circular obstacle as an example, the specific steps are presented on sparse optimization as follows. Let the set of path nodes be $\{A_i | i = 1, 2, 3 \cdots n\}$, where A_1 denotes the initial node and A_n stands for the final node. The angles formed by the vectors of neighboring nodes are calculated starting from $\overrightarrow{A_1A_2}$ and $\overrightarrow{A_2A_3}$ in order. Typically, there are two cases of removing redundant points, which are depicted in Fig. 3.

i) If the angle is 0, the three nodes are co-linear, and the middle node is redundant, which should be eliminated.

ii) If the angle is not 0, the three nodes are not co-linear. In this case, connect the two nodes adjacent to the middle node and determine whether the distance from the obstacle circle is greater than the safety distance.

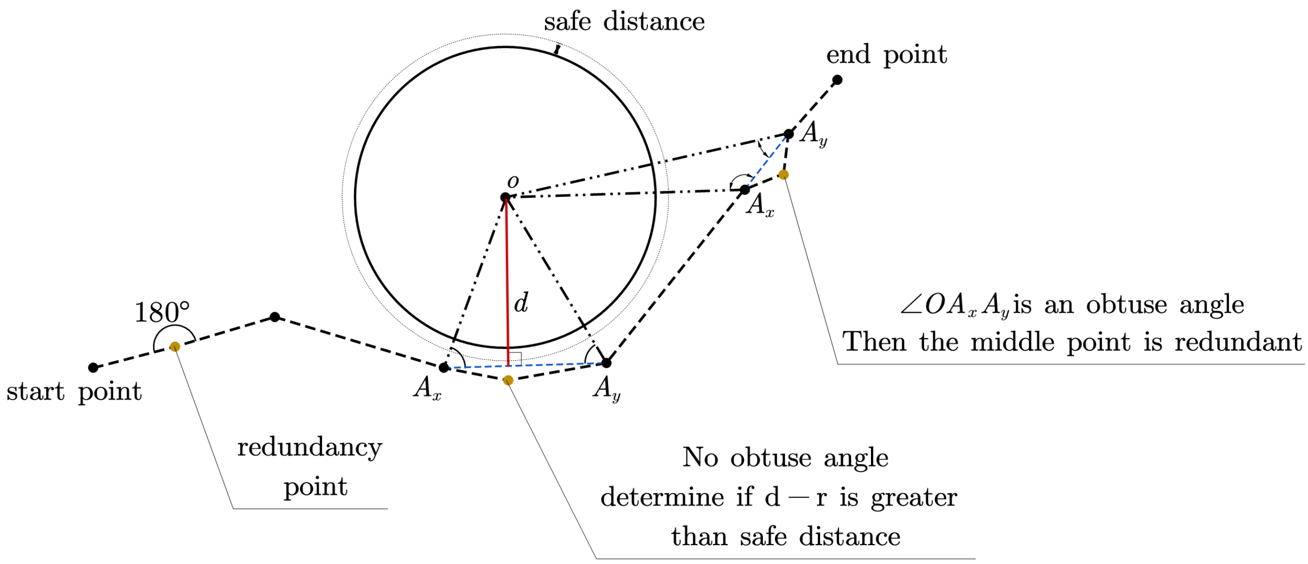


Fig. 3. Two cases of eliminating redundant points

The decision rule for redundant points is as follows: let O be the center for circle of an obstacle, while A_x and A_y can be marked as its two nodes.

- If there is one or more obtuse angles between $\angle OA_xA_y$ and $\angle OA_yA_x$, then the middle node is regarded as redundant, which can be removed.
- Otherwise, check if the distance from O to A_x and A_y is less than the predetermined safety distance. If the outcome is less, the point cannot be removed.

Similarly, another method for node screening is applied, which is denoted as $\{B_i | i = 1, 2, 3 \cdots n\}$. After applying the same operation, as depicted in Fig. 4, the number of nodes in the global paths of UAVs a and b is obviously reduced, improving speed and accuracy of path planning.

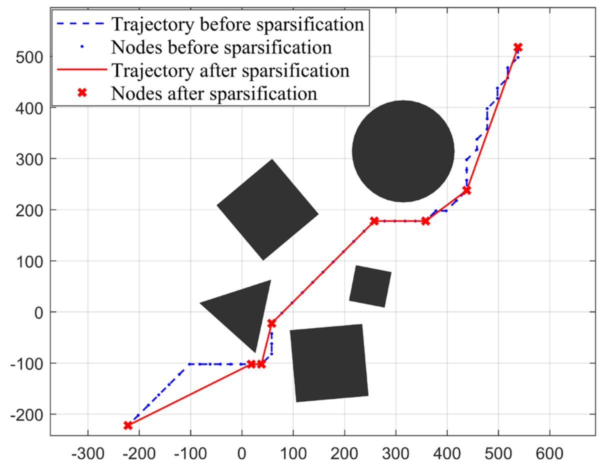


Fig. 4. Path after sparse optimization

In Fig. 4, the blue dashed line represents the original path generated by the A* algorithm, while the red solid line represents the actual path after sparse optimization. The sparse optimization scheme successfully addresses the issue of redundancy on path points, particularly excelling with irregular obstacles such as equilateral triangles and squares compared to circular ones. The improved path retains only a few key nodes, which considerably improves the efficiency of A* algorithm. This strategy not only minimizes redundant nodes in the path, but also ensures both the correctness and feasibility of path design, resulting into comprehensive improvement on computational efficiency and performance.

IV. The BDWA Algorithm

In parallel comparison to solving the issue of redundancy of global path point, the Dynamic Window Approach (DWA) algorithm is implemented to shape the model by integrating the sampling method and evaluation function [29]. Since the DWA algorithm works for single-target settings, adaptations must be done for its compatibility on dual UAV [30]. In this section, an improved scheme entitled as the Bi-objective Dynamic Window Approach (BDWA) is derived, which provides a stronger alternative comparing to DWA.

A. Traditional DWA algorithm

The main steps of conventional DWA are as follows:

Step 1) Sampling

UAVs a and b depart from different locations at the same time, with a minimum turning radius constraint of 30 meters due to their dynamic restrictions. Since both UAVs have the same linear velocity, the interval for altering their angular velocity (which are also known as the angular velocity sampling space or angular velocity window) may be calculated using $\omega = v/r$. It is possible to traverse each trajectory that UAV had anticipated over a pre-defined time interval by incrementally sampling its angular velocity.

Step 2) Prediction on directions

For the target environment situation, this study assumes that the time interval between each forward movement of UAV is dt. To ensure that the UAV's obstacle avoidance trajectory is forward-looking and acceptable, suppose that the prediction point is located p time intervals ahead, each point may involve projecting $p/_{dt}$ steps forward. However, UAV only moves one step in each actual time interval dt, and hence, the flight is completed inside that interval.

Step 3) Selecting optimal path via the evaluation function.

The evaluation function for the predicted path is given by:

$$Eval = w_h H + w_d D \tag{2}$$

where:

- Eval represents the total path score.
- H denotes the heading score of the prediction point.
- D stands for the distance score between the obstacle and the point for prediction.
- w_h and w_d symbols for the corresponding weight parameters, respectively.
- The prediction point is referred as the point located at p time intervals ahead, not the point where the UAV will take the next step.

The path with the highest total score is selected as the more optimal path for UAVs a and b to take a step forward.

The procedure for selecting optimal path for each UAV is summarized as below:

i) Calculate the prediction point heading score H.

Define the robot heading angle θ_i as the angle formed by heading of the expected point and the positive direction of the x-axis. Define the target angle θ_j as the angle formed by the line connecting the destination and prediction points, as well as the positive direction of the x-axis.

Let the deviation angle θ_p be the absolute value of the difference between θ_i and θ_j, which is denoted as

$$\theta_p = |\theta_i - \theta_j| \tag{3}$$

The heading score H reflects the difference between $180°$ and the deviation angle θ_p, which yields

$$H = 180° - \theta_p \tag{4}$$

According to (4), the smaller θ_p it is, the larger H will be acquired in practical tests.

ii) Calculate the predicted distance from obstacle score D.

Firstly, traverse and remove any anticipated spots that sit inside the obstacle circle. Then, the Euclidean distance is computed between each of the remaining predicted points and the edge of the obstacle. Finally, the minimum value of these distances is taken as the obstacle distance score D.

iii) Set the corresponding weight parameters of H and D, and calculate the evaluation function of total scores.

Step 4) Update the subsequent states for each UAV.

Every step forward of the UAV on the optimal path involves updating its current actual position, movement direction, and other relevant states via continuous sampling, prediction, and path optimization.

Step 5) Form a complete path for terminal UAV.

Repeat the Steps 1)-4) until UAV reaches the destination, and finally form a terminal trajectory path planning for each of the two UAVs.

B. BDWA algorithm

The main advantage of BDWA algorithm is its ability to offer an effective solution to the problem of avoiding signal interference between bi-objective UAVs, i.e., the precaution of collision. In contrast to traditional DWA-based schemes, BDWA incorporates a sightline score when performing the evaluation function, which renders more accurate outcomes. The fundamental principle of analyzing an obstacle distance score is illustrated in Fig. 5.

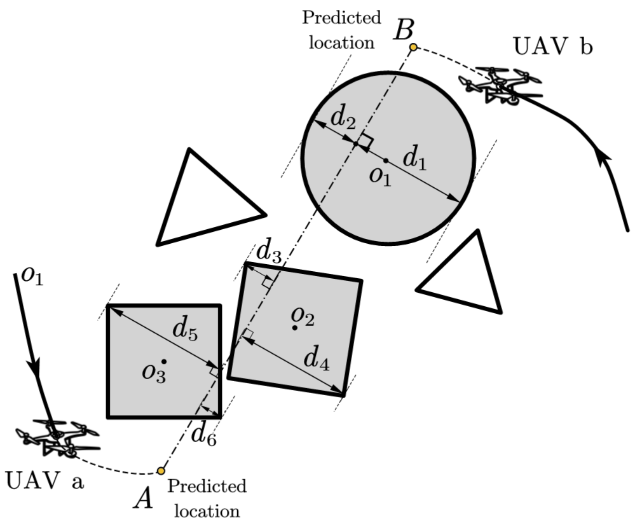


Fig. 5. Obstacle distance score analysis

The crucial steps of BDWA are presented as follows:

Step 1) Determine the obstacles that intersect the line of sight of the two UAVs:

Firstly, the predicted positions A and B of the two UAVs are connected to generate the line segment of AB, and then identify the obstacles intersecting this segment, which are represented by the gray obstacles in Fig. 5.

Step 2) Calculate the minimum distance between AB and the boundary of each intersecting obstacle:

Identify two lines parallel to AB which only have one intersection with the gray obstacle. Compute the distances between these two lines and the AB segment, and take the minimum value as the final result. The three gray obstacles depicted in Fig. 5 are successively formulated by

$$d_{O1} = \min(d_1, d_2) \tag{5}$$

$$d_{O2} = \min(d_3, d_4) \tag{6}$$

$$d_{O3} = \min(d_5, d_6) \tag{7}$$

Step 3) Calculate the sightline distance.

Consider the minimum distance from AB to the boundary of each intersecting obstacle, then the maximum of these values is taken as the vision distance, which is expressed by

$$Sightline\ distance = \max(d_{O1}, d_{O2}, d_{O3}) \tag{8}$$

Step 4) Avoid the impact of excessively large sightline distance on the evaluation function.

While longer sightline distances suggest lower risk on task-specific goals, the effectiveness of evaluation function may be impaired. Hence, a maximum limit of 100 was set up, which only include the final sightline score computation if lower than this threshold. Calculations are formulated by:

$$S = \min(100, Sightline\ distance) \tag{9}$$

Accumulating the product of values on H, D, S and their respective weight parameters yields the evaluation function of the proposed BDWA algorithm, which is expressed by

$$Eval = w_h H + w_d D + w_s S \tag{10}$$

V. A*-BDWA DYNAMIC WINDOW ALGORITHM

The inherent capacity of global optimal planning on the A* algorithm makes up the tendency of BDWA falling into local optimization. Meanwhile, BDWA algorithm addresses the challenges of real-time dynamic obstacles originated from the A* algorithm. Hence, effective fusion on these two algorithms results in a trajectory-planning method with high reference value, where the flowchart is illustrated in Fig. 6.

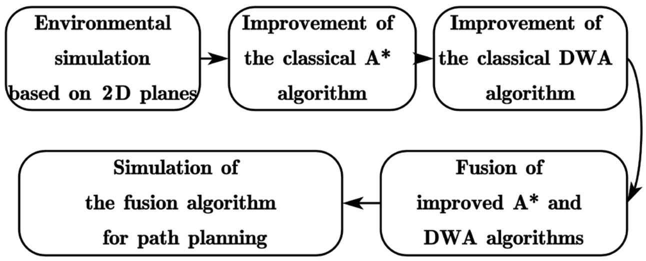


Fig. 6. Flowchart of fusing A* and DWA

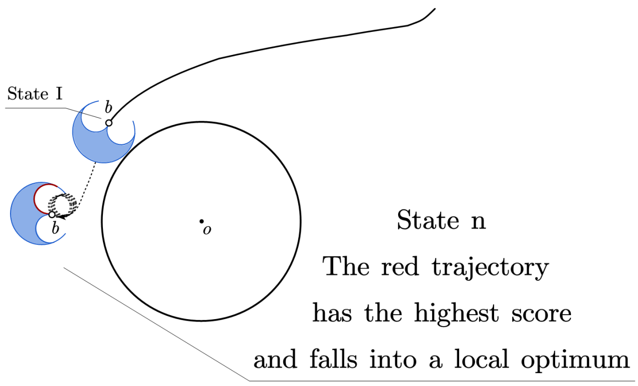


Fig. 7. Effect of large forward simulation time on the path.

A. Solutions to the Two Extreme Problems

In order to prevent UAV path planning from falling into two extreme cases, our discussions are presented as follows:

1) Range of the excessively estimated trajectory. If the range of estimated trajectory on UAVs is too wide to follow, a local optimum known as turning around in place" may be encountered, which is depicted in Fig. 7.

2) Range of inadequate Predicted Trajectory: When the predicted range of UAV is insufficient, it lacks capability on establishing an appropriate prediction path, which violates the restriction that the two UAVs are not allowed to meet. Such kind of situation is shown in Fig. 8.

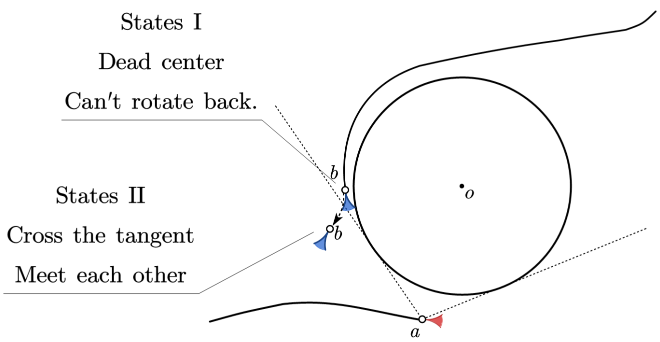


Fig. 8. Effect of too small forward simulation time on the path

With respect to the two case studies, it is discovered that changes in speed influence the maximum angular velocity, resulting in a bigger angle of clustering on the anticipated path line. Besides, higher speeds may bring about longer anticipated trajectories over the same time interval. Hence, it is crucial to establish a realistic forward simulation time.

To handle the two severe difficulties as mentioned above, modeling the forward prediction time *p* yields

$$p=\left[\frac{2\pi}{\frac{v}{r}\times 2}\right]+1 \tag{7}$$

where Parentheses [ ] denotes the estimated time, which is rounded to an integer of seconds.

Most notably, the essential target nodes for the iteration times of BDWA are filtered using sparse optimization based on the A* algorithm, which drastically eliminates redundant points and inflection points of no necessity, saving wasted travel. The proposed scheme generates a set of feasible paths, picks up the best instructions with respect to criteria of performance evaluation, and thereafter improving path planning for UAV. While dynamically adapting instructions to changing conditions on scenes and updating the states of UAVs in real-time while moving, the optimal global path planning are asymptotically achieved in this set of scenarios.

VI. Experiments and Performance

To test the feasibility and validity of the proposed model, our experimental study is performed in three set of scenarios: i) Tests of sampling on velocities of UAV ranging from [10, 30], and the simulations on trajectory and flight time of two UAVs under distances of times by 1000m; ii) Performance evaluation of UAV with the increment of obstacles while the location and size of object are random, with the involvement of analysis on the complexity, for instance, various speed of UAV in condition of alternating the distance between base station *A* and obstacles are simulated; iii) Comparison of the A*-BWDA fusion scheme and single DWA algorithm, in addition to stability analysis of A*-BWDA under scenes of complex environments, where the execution time of three algorithms (A*-BWDA, in contrast to A*-BWDA with no sparse optimization and single BWDA) are computed via line charts and violin plots to visualize the average value and distributions.

A. Prerequisites of Our Experimental Study

1) Environment Preparation

The experiments are conducted using software platform of MATLAB R2020a and later versions on a laptop with Windows 10 operation system (Intel Core i7-1165G7, 2.80 GHz CPU, and 32 GB RAM). A square with a diagonal length L of $4500m$ is established. The obstacle circle O has a radius r of $500m$, a distance D_{OA} of $1000m$ to base station *A*, and a distance D_{OB} of $3500m$ to the rescuer. The rectangular coordinates of A, B, and O are $(0,0)$, $(3128,3128)$, and $(707,707)$, respectively.

2) Initial state preparation of UAVs

Set the speed of both UAVs to be uniform at $v=10m/s$, with a minimum turning radius $r=30m$. As a result, the angular velocity ω ranges from $[-1/3,1/3]$. The weight of the heading score is 0.37, the weight of the distance to obstacle score is 0.6, and the sightline score weighs 0.8.

To select a reasonable initial heading angle for the UAV, the lengths of UAV trajectory are compared under various initial direction angles. The results are tabulated in Table I.

TABLE I
THE OPTIMAL TRAJECTORIES OF THE TWO UAVS WITH DIFFERENT INITIAL HEADING DIRECTIONS ARE

a Angle(°)	b Angle(°)	a time spent	b time spent
0	−180	519	693
18	−162	495	663
36	−144	492	672
54	−126	492	675
72	−108	490.5	642
90	−90	489	688.5

It can be found that the initial angle of UAV *a* falls within the interval $[36°, 72°]$, while the initial angle of UAV *b* falls within the interval $[-144°, -108°]$. The sum of the operating time by both UAVs, which is shorter compared to other angles, conforms to the conditions of optimal path planning. As a result, our study may have the assumption that the initial travel direction of UAV *a* is $\theta_1=45°$, i.e., the angle with the positive direction of the *x*-axis is 45°, and similarly, the initial path direction of UAV *b* is $\theta_2=135°$.

B. Experiments of Obstacle Avoidance by the proposed A*-BWDA Fusion Algorithm

1) Experimental results of rate variations on UAV a

The constant rate of UAV *a* is controlled to change within the range of [10, 30] m/s, with selected sample values of 10 m/s, 20 m/s, and 30 m/s upon testing. Most notably, all other parameters remain the same as our prior study, with the goal of ensuring the priority of arrival for UAV *a*. Simulations on parameters of machine flights and trajectory are illustrated in Table II and Fig. 9, respectively.

TABLE II
TIME OF DIFFERENT A-MACHINE SPEEDS CORRESPONDING TO A, B FLIGHTS

Machine flight speed (m/s)	Machine flight time (s)	Machine flight time (s)
10	472	640
20	472	558
30	474	476

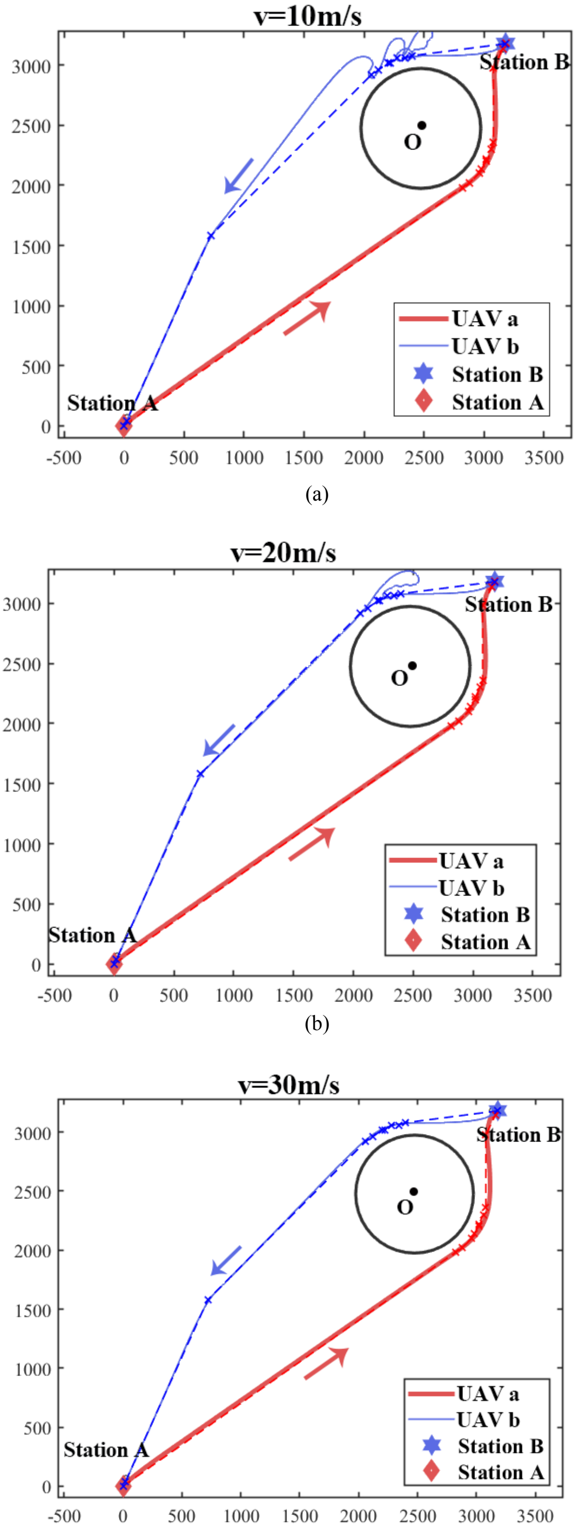


Fig. 9. Trajectory of flighting for UAV *a* with variable speeds

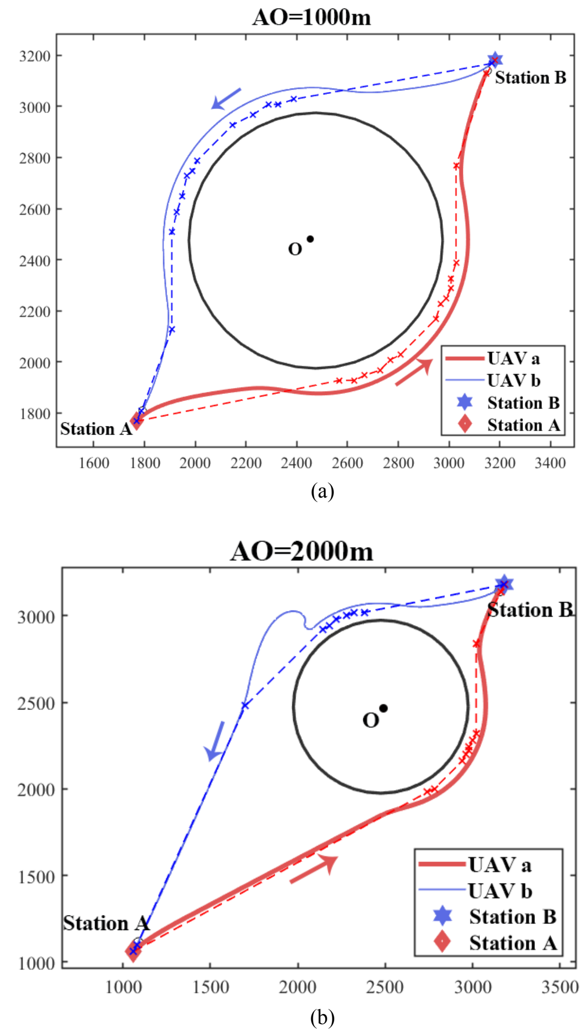
In Fig. 9, the thick red solid line and the thin solid line represents the trajectories of UAVs *a* and *b*, respectively. It is clear that as the speed of the fully charged UAV increases, the waiting time for the low-battery UAV substantially decreases, which can be entirely disappeared in some cases. This improves efficiency of overall rescue and saves crucial time. Furthermore, the data demonstrates that regardless of changes in the speed of UAV, A*-BDWA model performs proper and consistent simulations on the flight paths of both UAVs. This not only demonstrates the validity of proposed scheme under diverse speed conditions, but also displays its applicability and dependability in a variety of scenarios, prospecting its significant potential and applications in real-world rescue operations.

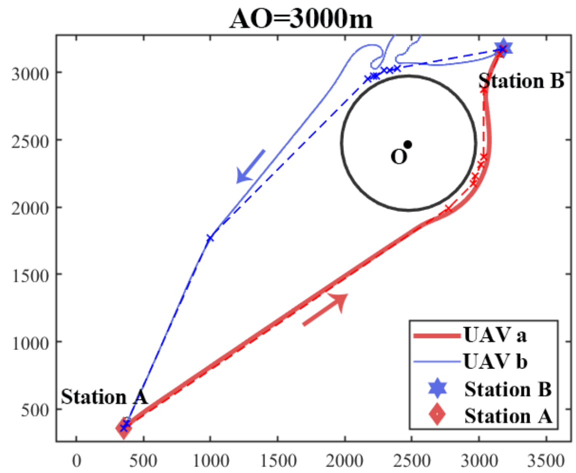
2) Experimental results of different distances between base station A and obstacle O

The purpose of adjusting the distance between obstacle *O* and base station A to 1000m, 2000m, and 3000m, while still maintaining other parameters is for UAV a to reach its target. Simulation results are illustrated in Fig. 10, and the time of flighting are summarized in Table III.

TABLE III
FLIGHT TIME OF TWO UAVS WITH DIFFERENT DISTANCES

OA length (m)	UAV *a*'s flight time (s)	UAV *b*'s flight time (s)
1000	235	234
2000	349	325
3000	422	535
4000	521	733





(c)

Fig. 10. Diagrams of different trajectory for bi-objective UAVs and two base stations

Seen from Fig. 10, the position of Base Station A has a considerable impact on rescue efficiency. The closer Base Station A is to the catastrophe region, the sooner the fully charged UAV may arrive at the rescue site, while UAV with lower battery may avoid lengthy time on waiting. However, in real-world settings, practical concerns such as the impact from disaster on neighboring signals must also be taken into account. Hence, combining the location of the base station with the speed of low-battery UAVs considerably improves the efficiency of rescue. Furthermore, applying A*-BDWA not only efficiently calculates the pathways of UAVs, but also prioritizes UAV a, resulting into much faster time of response under a variety of scenarios. Combining this model with practical operation restrictions offers crucial options on optimizing rescue plans and thereafter improving efficiency.

C. *Evaluation and Comparison*

In this subsection, an extended experiment was adopted for comprehensively evaluating performance of A*-BDWA, measuring its robustness, scalability, and adaptability.

1) Increasing Environmental Complexity

The simulations described above were carried out in an environment with only one obstacle. To further evaluate the method and illustrate its practicality, the complexity of environment was strengthened. We added the number of obstacles in the original location while changing their shape and size. Additionally, obstacles were randomly distributed throughout the target regions, while some of which are capable of performing regular movement. The results are displayed in two subplots at Fig. 11.

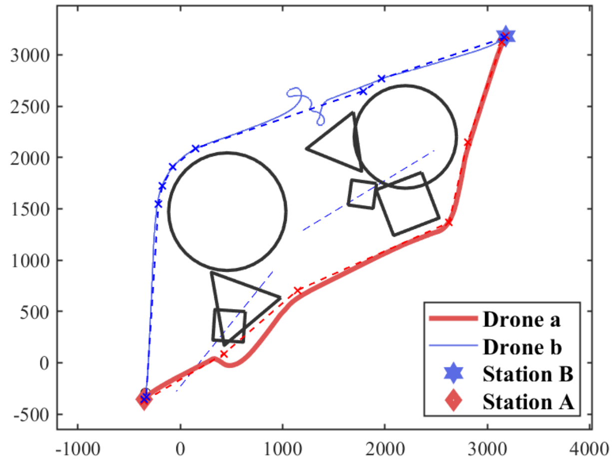
As illustrated in Fig. 11(a), five obstacles of various forms were generated at random inside the defined region, as well as two random pathways on simulating dynamic obstacles. The two UAVs successfully avoided obstacles and completed their flight tasks effectively and safely while being controlled by the A*-BDWA algorithm.

Fig. 11(b) presents flight times of the two UAVs obtained using this approach in 100 random situations. The success rate of this task-specific execution is 88.3 %. Among the accomplished tasks, the average duration of flight for UAV a is 570 seconds, and for UAV b is 662 seconds.

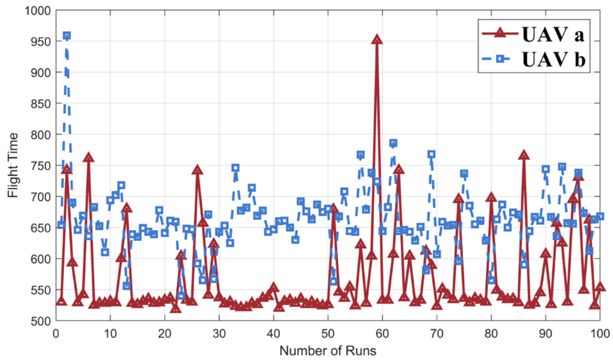
In our trials, we discovered considerable differences in the flying times of the UAVs between different runs. Due to alternations on environmental variables such as the random location and shape of obstacles, these changes may have a substantial impact on the procedure of pathfinding.

2) Comparison with the Original A-BDWA Algorithm*

To demonstrate the superiority of the integrated algorithm over the original single algorithm, a comparison between the two is essential. The difference of algorithms was assessed from two perspectives: the path results of the old and new algorithms in a simple environment, while the stability and success of the A*-BDWA fusion in complicated scenes.



(a)



(b)

Fig. 11. Simulation in a Complex Environment

The performance analysis was divided into two parts, one is for pathing results of algorithms in simple scene, the other shows stability analysis of fusion scheme in complex scenes.

a) Comparing Path Results of Old and New Algorithms in a Simple Scene

Fundamental setting is established as follows. Three fixed obstacles are initially set up, while the navigation routes of UAVs are planned using both single DWA and the proposed A*-BDWA fusion algorithm for comparison. The simulation results are illustrated in four diagrams in Fig. 12.

As depicted in Fig. 12(a) and Fig. 12(b), the flight path calculated by the standalone DWA algorithm contains some redundancies since the UAV only changes direction when it approaches obstacles. In this case, two UAVs have flight durations of 638 seconds and 597 seconds, respectively. However, applying the A*-BDWA fusion approach yields reduced time duration of flighting on UAVs to 592 seconds and 581 seconds, respectively, which indicates evidence on increased efficiency and lower energy consumption.

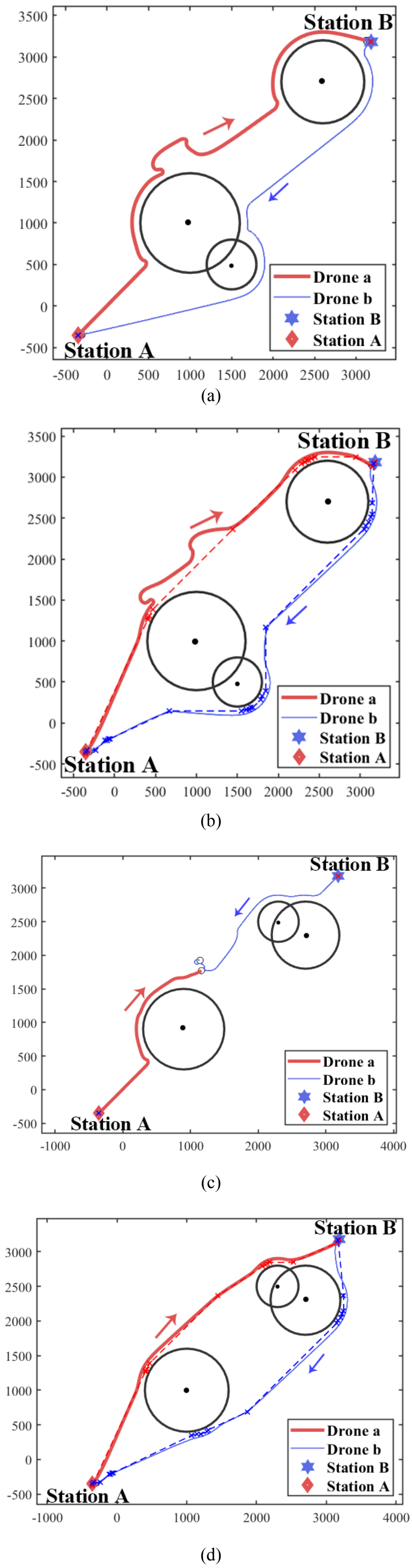


Fig. 12. Comparison between the proposed A*-BWDA fusion and the standalone DWA algorithm.

Furthermore, the standalone DWA algorithm occasionally fails to achieve signal isolation and safe flight for the two UAVs, which are exhibited in Fig. 12(c) and Fig. 12(d). Without the global planning support of the A* algorithm, pathways planned by the standalone DWA algorithm, may cause the UAVs flying to the same side of an obstacle, resulting into potential encounters or even collisions, posing major safety issues. In contrast, the proposed A*-BDWA fusion scheme offers reliable calculations on trajectories for the two UAVs, assuring accuracy and safety of flying.

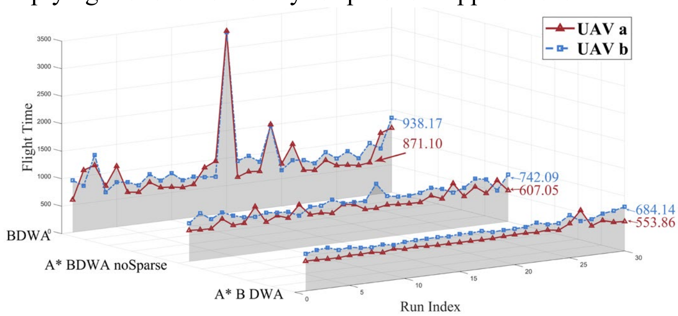
b) Stability Evaluation of Fusion Algorithms in Complex Scenes.

For better analysis on the stability of A*-BWDA fusion approach due to the fact that simple and identical situations are insufficient for assessment, more complex scenes with a range of unforeseen barriers were set up, keeping the level of complexity constant, while the experiments were repeated by several times to test the actual time of execution.

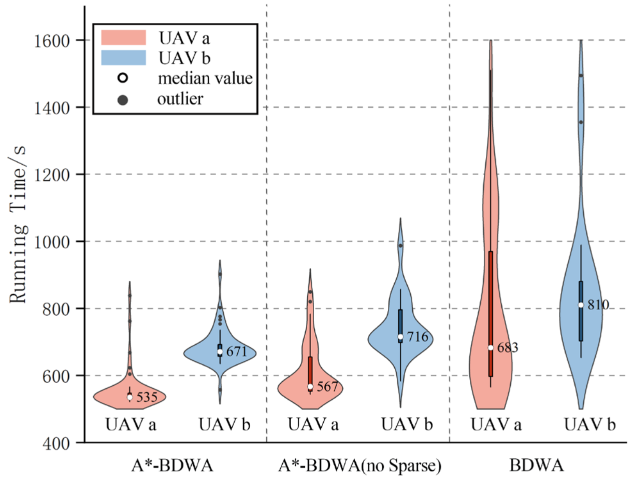
In this case, complexity means that the quantity of obstacles in the environment is constant, while both of their types and sizes randomly fluctuate within a particular range, and positions of these obstacles are randomly distributed in a small scope of area upon restriction. To assess the success rate of the fusion method, a large number of repetitive trials was tested, recording the time of each flight and the chance of success, as shown in Fig. 13.

Fig. 13(a) depicts the flight times of the three algorithms (A*-BDWA, A*-BDWA with no-sparse optimization, and single BDWA) in difficult scenarios. It can be shown that the UAV controlled by the A*-BDWA algorithm takes less execution time to accomplish the navigation task in most circumstances, while still maintaining high stability, which is not by chance. The BDWA algorithm, on the other hand, has the longest and most sparsely distributed flight time, with the average flight length of the two UAVs under its control being 871 seconds and 938 seconds, respectively, which is 5 minutes more than the flight time of the other two methods. This suggests that the A*-BDWA algorithm is more efficient in path planning and better suited to handle complex and dynamic scenes in real-world environments.

Fig. 13(b) depicts the runtime violin charts of the three algorithms for comparison. Each algorithm has two runtimes: UAV *a* and UAV *b*. This subplot shows that the A*-BDWA method has a highly concentrated distribution of runtimes, implying that it is more stable than other algorithms in the same setting of complexity. The single BDWA algorithm, on the other hand, has the widest distribution of runtimes, implying the least reliability for practical application.



(a)



(b)

Fig. 13. Line graphs and violin-box plots on the flight times of two UAVs under three algorithms

TABLE IV
NUMBER OF SUCCESSFUL RUNS AND SUCCESS RATE OF THE THREE ALGORITHMS

	Number of successes	success rate
A*-BDWA	106/120	88.3%
A*-BDWA (no-sparse)	78/120	65.0%
BDWA	52/120	43.3%

Table IV displays the success rate in accordance with the number of successful runs of the three algorithms upon our test. It is indicated that A*-BDWA has the maximum number of completed task executions, with a success rate of 88.3%. The success rates for A*-BDWA (no-sparse) and BDWA are 65.0% and 43.3%, respectively, which are much lower than those for A*-BDWA. As a result, the A*-BDWA algorithm is better suited to various real-time scenes, which is prone to complete the tasks more safely and effectively.

In sum, the conventional DWA method lacks adaptability for dealing with settings in which numerous UAVs are operating simultaneously. The proposed A*-BWDA fusion scheme provides an alternative approach for less operating time, safety ensurance and improved efficiency, for better performance of UAVs. Upon handling multi-UAV trajectory planning tasks in more complex environments, A*-BDWA algorithm shows advantages in contrast to A*-BDWA and BDWA, exhibiting higher efficiency, safety, and stability.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, an optimal trajectory planning method for bi-objective UAVs under two-dimensional environment is investigated. Combining the standard A* algorithm with the dynamic window approach (DWA), an A*-BDWA algorithm is derived to address the defects of traditional A* algorithm, which include a large number of redundant keynote points and inefficient process upon searching. The proposed A*-BWDA fusion scheme is oriented for dynamic obstacle avoidance trajectory planning for bi-objective UAVs, which address the task-specific limitation of single-target on DWA algorithm. Experimental study presents the improvement of execution time, efficiency and safety, with evidence on the ideal obstacle avoidance trajectory in condition of variations on simulated environment, proving its efficiency and wider applicability for multi-objective path planning using UAVs.

In future work, we plan to update the evaluation function of BDWA algorithm by introducing a regulating factor so as to increase the robustness of our approach. We also intend to design a few ablation tests to check the stability of proposed A*-BDWA scheme in a variety of practical scenes. Besides, alternative methods on heuristic searching and deep learning -based schemes are potential matches on fusion, which are also within the scope of our subsequent investigation.

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REFERENCES

[1] M. R. Brust and B. M. Strimbu, “A networked swarm model for UAV deployment in the assessment of forest environments,” in *2015 IEEE Tenth Int. Conf. Intell. Sen., Sen. Networks Inform. Process. (ISSNIP)*, Apr. 7-9, 2015, Singapore, pp. 1-6.

[2] W. Khawaja, V. Semkin, N. I. Ratyal, Q. Yaqoob, J. Gul, and I. Guvenc, “Threats from and countermeasures for unmanned aerial and underwater vehicles,” *Sens.*, vol. 22, no. 10, 3896, 2022.

[3] J. Chen, Y. Zhou, Q. Lv, K. K. Deveerasetty, and H. U. Dike, “A Review of Autonomous Obstacle Avoidance Technology for Multi-Rotor UAVs,” in *2018 IEEE Int. Conf. Inform. Automat. (ICIA)*, Wuyishan, China, Aug. 11-13, 2018, pp. 244-249.

[4] N. Gao, S. Jin, and X. Li, “3D deployment of UAV swarm for massive MIMO communications,” *IEEE J. Sel. Area Commun.*, vol. 39, no. 10, pp. 3022-3034, Oct. 2021.

[5] S. Wu, K. Zhang, S. Niu, and J. Yan, “Anti-interference aircraft-tracking method in infrared imagery,” *Sens.*, vol. 19, no. 6, 1289, 2019.

[6] Z. Yue, B. Lian, C. Tang, and K. Tong, “A novel adaptive federated filter for GNSS/INS/VO integrated navigation system,” *Meas. Sci. Technol.*, vol. 31, no. 8, 85102, pp. 1-11, 2020.

[7] Z. Zhang, Q. Zhang, J. Miao, F. R. Yu, F. Fu, J. Du, and T. Wu, “Energy-efficient secure video streaming in UAV-enabled wireless networks: a safe-DQN approach,” *IEEE Trans. Green Communi. Network.*, vol. 5, no. 4, pp. 1892-1905, Dec. 2021.

[8] H. Jin, X. Jin, Y. Zhou, P. Guo, J. Ren, J. Yao, and S. Zhang, “A survey of energy efficient methods for UAV communication,” *Veh. Commun.*, vol. 41, no. 6, 100594, pp. 1-21, Jun. 2023.

[9] T. Li, J. Zhang, M. S. Obaidat, C. Lin, Y. Lin, Y. Shen, and J. Ma, “Energy-efficient and secure communication toward UAV networks,” *IEEE Int. of Things J.*, vol. 9, no. 12, pp. 10061-10076, Dec. 2021.

[10] G. Aiello, K. P. Valavanis, and A. Rizzo, “Fixed-wing UAV energy efficient 3D path planning in cluttered environments,” *J. Intell. Robot. Syst.*, vol. 105, no. 3, 60, pp. 1-13, Jul. 2022.

[11] Q. Jiang, Z. Li, Q. Guan, and S. Guan, “Research on UAV path planning based on improved A* algorithms,” *J. Ordnance Equip. Eng.*, vol. 41, no. 9, pp. 160-164, Sep. 2020.

[12] J. Chen, M. Li, Z. Yuan, and Q. Gu, “An improved A* algorithm for UAV path planning problems,” in *2020 IEEE 4th Inform. Technol., Network., Electron. Automat. Control Conf. (ITNEC)*, Jun. 12-14, Chongqing, China, pp. 958-962.

[13] M. Gabli, E. M. Jaara, and E. B. Mermri, “A genetic algorithm approach for an equitable treatment of objective functions in multi-objective optimization problems,” *IAENG Int. J. Comput. Sci.*, vol. 41, no. 2, pp. 102-111, 2014.

[14] L.-S. Liu, J.-F. Lin, J.-X. Yao, D.-W. He, J.-S. Zheng, J. Huang, and P. Shi, “Path planning for smart car based on Dijkstra algorithm and dynamic window approach,” *Wireless Commun. Mobile Comput.*, vol. 2021, no. 1, p. 8881684, 2021.

[15] Z. Lin, M. Yue, G. Chen, and J. Sun, “Path planning of mobile robot with PSO-based APF and fuzzy-based DWA subject to moving obstacles,” *Trans. Inst. Meas. Control*, vol. 44, no. 1, pp. 121-132, 2022.

[16] Y. Hu, H. Long, and M. Chen, “The analysis of pedestrian flow in the smart city by improved DWA with robot assistance,” *Sci. Rep.*, vol. 14, no. 1, p. 11456, May 2024.

[17] X. Ji, S. Feng, Q. Han, H. Yin, and S. Yu, “Improvement and fusion of A* algorithm and dynamic window approach considering complex environmental information,” *Arab. J. Sci. Eng.*, vol. 46, pp. 7445-7459, Feb. 2021.

[18] Y. Li, R. Jin, X. Xu, Y. Qian, H. Wang, S. Xu, and Z. Wang, “A mobile robot path planning algorithm based on improved A*

algorithm and dynamic window approach," *IEEE Access*, vol. 10, pp. 57736-57747, 2022.
[19] X. Yin, P. Cai, K. Zhao, Y. Zhang, Q. Zhou, and D. Yao, "Dynamic path planning of AGV based on kinematical constraint A* algorithm and following DWA fusion algorithms," *Sens.*, vol. 23, no. 8, 4102, pp. 1-15, 2023.
[20] Q. Wang, J. Li, L. Yang, Z. Yang, P. Li, and G. Xia, "Distributed multi-mobile robot path planning and obstacle avoidance based on ACO–DWA in unknown complex terrain," *Electron.*, vol. 11, no. 14, p. 2144, 2022.
[21] X. Li, X. Hu, Z. Wang, and Z. Du, "Path planning based on combination of improved A-star algorithm and DWA algorithm," in *2020 2nd Int. Conf. Arti. Intell. Adv. Manu. (AIAM)*, Oct. 15-17, 2020, Manchester, United Kingdom, pp. 99-103.
[22] A. Khan, S. Gupta, and S. K. Gupta, "Emerging UAV technology for disaster detection, mitigation, response, and preparedness," *J. Field Robotics*, vol. 39, no. 6, pp. 905-955, Sep. 2022.
[23] M. Saponi, A. Borboni, R. Adamini, R. Faglia, and C. Amici, "Embedded payload solutions in UAVs for medium and small package delivery," *Machines*, vol. 10, no. 9, 737, pp. 1-15, 2022.
[24] R. Turner, "Point patterns of forest fire locations," *Environ. Ecolog. Stat.*, vol. 16, no. 2, pp. 197-223, 2009.
[25] P. Ragbir, A. Kaduwela, D. Passovoy, P. Amin, S. Ye, C. Wallis, C. Alaimo, T. Young, and Z. Kong, "UAV-based wildland fire air toxics data collection and analysis," *Sens.*, vol. 23, no. 7, 3561, 2023.
[26] W. Nie, Z.-C. Han, Y. Li, W. He, L.-B. Xie, X.-L. Yang, and M. Zhou, "UAV detection and localization based on multi-dimensional signal features," *IEEE Sens. J.*, vol. 22, no. 6, pp. 5150-5162, Mar. 2022.
[27] R. Szczepanski, "Safe artificial potential field-novel local path planning algorithm maintaining safe distance from obstacles," *IEEE Robot. Automat. Lett.*, vol. 8, no. 8, pp. 4823-4830, Aug. 2023.
[28] S. A. Gunawan, G. N. Pratama, A. I. Cahyadi, B. Winduratna, Y. C. Yuwono, and O. Wahyunggoro, "Smoothed A-star algorithm for nonholonomic mobile robot path planning," in *2019 Int. Conf. Inform. Commun. Technol. (ICOIACT)*, Jul. 24-25, 2019, Yogyakarta, Indonesia, pp. 654-658.
[29] S. Zhang and T. Zhao, "Mobile robot path planning in 2D space: a survey," *Highlights Sci., Eng. Technol.*, vol. 16, pp. 279-289, 2022.
[30] H. Yang and X. Teng, "Mobile robot path planning based on enhanced dynamic window approach and improved A* algorithm," *J. Robot.*, vol. 2022, no. 1, p. 2183229, 2022.

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