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Obstacle Avoidance and Path Planning for UAV Using Laguerre Polynomial

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Abstract: Recently, path planning algorithms have been one of the primary and important functions of unmanned aerial vehicles (UAVs). Path planning algorithms in UAVs focused on path length, average path length, computation time, and standard deviation from the mean path length. In spite of this, it faced many difficulties and problems, such as many obstacles, path segmentation, and the increasing number of obstacles and paths in urban environments. This work proposes polynomial functions for path planning and obstacle avoidance. Since it enables us to plan the path in static internal environments, it enables us to plan the path quickly and with less computing time because it does not require high memory and does not require pre-compute of the path. Instead, the route is plotted in real time, Where the appropriate equation is entered into the program, so that the vehicle follows the curve of the entered equation. An accurate data set and metrics were used to measure the efficiency of the proposed method. The experimental results showed a clear improvement in the work of the polynomial function on A*, PSO and genetic algorithms, as this improvement appears very clearly when compared to the computing time, which was reduced by 15% in the method of polynomial functions where the path calculation took only parts of The second, as well as the path length was halved in the polynomial method as the results showed, which reduces the time of battery and memory consumption, the cost of calculating the path and the time to reach the goal.

Keywords: Path planning, Polynomial functions, Avoid obstacles, Unmanned aerial vehicle, Laguerre polynomial.

1. Introduction

Advances in autonomous aircraft technologies have become an irresistible trend in many countries. Military unmanned aerial vehicles (UCAVs) have been very important to many military systems worldwide because they operate in remote, dangerous, and populated environments [1]. The subject of path planning is one of the most important and most prominent aspects of the independent control unit in the UCAV, which one of its main objectives is to provide the best path from the starting point to the destination to which the aircraft is to be sent, taking into account the fixed and moving industrial and natural obstacles.

One ideal path for the drone trajectory planning scheme minimizes flight time, average altitude, fuel consumption, radar exposure, has the fewest obstructions, etc. [2].

With the development of defensive land-based weapons, it has been challenging to identify these threats. Therefore, to deal with these increasing difficulties, the researchers made a combat model that gradually moved away from the standard algorithms [3-5].

Path planning is a complex multi-objective optimization problem [6] that a workable solution can only solve without resorting to an improved solution. As it is necessary to obtain the three-dimensional path to solve the problem of low height, there are obstacles represented in the fact that the search space is very large in the three-dimensional environment. Thus, the time for the algorithm to find the path becomes relatively long. Therefore, finding a fast, efficient, and engineered custom route planning method is essential.

Polynomials have been used in drone trajectory planning applications. It was used in fixed and

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moving obstacles, which is done by entering the equation of the best path [7]. Many obstacles reduce the smoothness of the track from the start point to the end point, especially in turns.

At this time, deep learning approaches have emerged as the best practice in applications and fields such as image processing applications in general and path planning and obstacle avoidance applications [8]. Mainly, it was used for simultaneously planning a path and avoiding obstacles for a drone, and it obtained training a set of information representing visual clips of a particular environment. The path planning of the UAVs is done by their detection and positioning via sequential frames [9]. The convolutional neural network architecture allows two consecutive frameworks for object detection and Path planning. The result is that objects are surrounded by bounding, plus there are no other details like coordinates and maps [10]. Fig. 1 shows several types of UAVs used in the fields of surveillance, photography, and civil and military.

Determining the best path using a polynomial function is a method that gives the drone smoothness in overcoming curves and obstacles. In addition, it does not require a large memory to implement; this leads to unwanted problems, but these problems are unintended. Path planning tools often depend on the features of the moving object, so the drone's movement leads to a change in the realistic background that occurs in front of the aircraft, etc. This handicap is very prominent in the work of drones. Finally, valuable data about training or testing any proposed algorithm is one of the most critical challenges. The main contribution of this work is as follows:

i. A new method based on polynomial functions was proposed for trajectory planning.
ii. The proposed method was implemented on an MSI KATANA GF76 11UE laptop simulator. It has both Windows and Linux systems.
iii. Calculate performance factors speed and acceleration.

The second section in this paper explains related works, while the third section describes this article's fundamental principles and methodology. The fourth section explains the structure of the proposed method and all implementation details. The fifth and final section presents the research results and the future vision for developing the work.

In this research, polynomial functions are used because they do not need time to calculate the path, as the path is entered in the form of an equation after examining the environment that contains fixed obstacles.

Figure. 1 Several types of UAVs

2. Related work

Recently, several papers have been submitted on UAV path planning and obstacle avoidance. 3D path planning algorithm taxonomy based on deep learning shows superior performance, more powerful tools, and semantic features. Many path-determining algorithms have emerged, the most important of which are natural algorithms, the most famous of which are Ant colony optimization (ACO) and bee colony optimization (ABC) [11, 12].

The algorithms that simulate the movement of ants and bees in nature have unique features and distinctive characteristics in path planning and obstacle avoidance. Subsequently, new systems with exceptional performance in object detection were developed or proposed, such as the particle swarm algorithm and A* algorithm, with many improvements, which greatly improved the problems in path planning and obstacle avoidance [13-15].

In [16] a fuzzy gain-based dynamic ant colony optimization (FGDACO) for dynamic path planning is proposed to effectively plan collision-free and smooth paths with feasible path length and minimum time. The ant colony system's pheromone update mechanism was enhanced with a sigmoid gain function for effective exploitation during path planning. Collision avoidance was achieved through the proposed fuzzy logic control.

In [17] suggests an algorithm consisting of Three units. The first unit forms an optimized path by performing a hybrid particle swarm modified Frequency Racket Optimization (PSO-MFB) algorithm that reduces distance and track tracking softness standards. The second module detects any useless points generated by the proposal PSO-MFB Hybrid Algorithm Through a new local search (LS) algorithm integrated with the hybrid PSO MFB algorithm to be transformed into feasible solutions. The third unit is characterized by the discovery of obstacles and Avoidance (ODA), which is triggered when a moving robot detects obstacles inside its sensor area, allowing it to avoid hitting obstacles.

In [18], a strategy to increase the number of offspring using multi-domain reflection was proposed. Meanwhile, a second fitness assessment was made to delete unwanted offspring and keep the most useful individuals. can be improved to help effectively enhance the local search capacity and increase the probability of generation excellent people. Monte Carlo simulation of five examples from the library for travel the vendor problem was first performed to evaluate the effectiveness of the algorithms. Improved algorithms have been applied to unmanned surface vehicles' navigation, guidance, and control systems in a real marine environment. A comparative study reveals that the algorithm with multi-domain reflection excels with the desired balance of path length and time cost and has a shorter optimum path, faster convergence speed, and better durability than the others.

In [19], the basic potential field function of the traditional artificial potential field method is improved, and the traditional spherical potential field is proposed to be improved to the ellipsoidal potential field. The improved algorithm is compared and simulated in MATLAB in order to address the inefficiency of the traditional artificial potential field method in complex environments for obstacle avoidance. The findings demonstrate that the enhanced artificial potential field method enables the UAV to plan its obstacle avoidance trajectory with high efficiency and possibility in a challenging three-dimensional environment.

In [20], UAV trajectory planning using the Deep-Sarsa method and obstacle avoidance (UAVs) is presented. A technique of policy-reinforced learning known as Deep-Sarsa enables drones to avoid obstacles and move while determining the best route to the objective using a depth neural network. Compared to other algorithms, it has a major advantage over the dynamic environment. The Deep-Sarsa model is trained in a network environment and subsequently deployed in a ROS-Gazebo system for UAVs. According to the testing findings, drones can be guided to their objective without colliding when using the Deep-Sarsa model by trainers. Deep-Sarsa has never been developed for autonomous path planning and obstacle avoidance of drones in a dynamic environment.

One of the biggest problems of path planning algorithms is computing time; it is the time it takes for the algorithm to calculate the path from the starting point to the target point, so it was focused on and solved in the proposed algorithm in this paper.

3. The basic principles

3.1 Path planning

Path planning is finding the first path start to reach the target point. In general, a system appears the distance between force and conduction has been determined as consumed energy or time. The need for path planning algorithms is to transform high-level descriptions of tasks into Low-level charts for buy orders.

3.2 Obstacle avoidance

In UAVs, obstacle avoidance is one of the most critical applications that avoids collision and keeps the vehicle on course to the target. In unmanned air vehicles, it is a hot topic citation needed. In general, the concept of obstacle avoidance means the urgent need to use UAVs in urban areas for military and civilian applications in general, where they can be of great benefit in urban warfare. Obstacle avoidance usually differs from route planning, where one is usually performed in an interactive environment. At the same time, the other involves pre-calculating an obstacle-free route in which the controller guides the UAVs. With the recent advances in the UAV sector, there is an urgent need for obstacle avoidance features for unmanned vehicles and, therefore, optimal obstacle avoidance [21].

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3.3 A* algorithm

It is a node-based search algorithm to find the shortest path between the starting and target points. It is a non-automatic algorithm used to traverse the map to find the best route to take. A* was initially designed to traverse the graph to help build vehicles that could find their path. It is one of the most popular and widely used graph traversal algorithms.

Another thing that makes A* a mighty algorithm is weighted graphs in the implementation. A weighted graph uses numbers to represent the cost of each course of action. This is because the algorithms can choose the path with the lowest cost and find the best path in terms of distance and time. A heuristic algorithm sacrifices optimality with precision and accuracy to solve problems faster and more efficiently.

All images contain variable nodes or points the algorithm must define to reach the final node. All paths between these nodes have a numeric value, considered a path specifier. The total of all discovered routes and tracks gives you the route's cost.

First, the algorithm calculates the cost for all of its adjacent nodes, n, and selects the nodes whose cost is the least. This process is repeated until the contract expires and there are no new contracts, so the cost of passing all the tracks is determined. Then, the algorithm thinks of the best path between the detected paths. If *f(n)* represents the final cost, then it can be denoted as [22]:

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

Where:

$g(n)$ = cost of traversing from one node to another will vary from node to node.

$h(n)$ = heuristic approximation of the node's value. It is not an absolute value but an approximation cost.

3.4 Polynomial function

A polynomial function is the simplest, most used, and is one of the most important mathematical functions. It also covers a huge number of operations. These operations represent algebraic expressions with specific conditions. Learning and understanding polynomial operations are necessary because of their extensive applications.

In this paper, Let's learn what polynomial functions are, their types, and what graphs use. A polynomial function in standard form is [23]:

$$f(x) = a_n x^n + a_{n-1} x^{n-1} + \dots + a_2 x^2 + a_1 x^1 + a_0 x^0 \tag{2}$$

This algebraic expression is called a polynomial function in variable x. Here,

- $a_n x^n + a_{n-1} x^{n-1}$, … $a_0 x^0$ are real number constants.
- $a_n x^n$ can't be equal to zero and is called the leading coefficient.
- n is a non-negative integer.

4. The proposed algorithm

In this proposal, a start point is defined, an end or stop point, obstacles are defined, and find the optimal waypoint using the polynomial function of the fourth and fifth degree besides improvising it using the A* search algorithm while making sure that the restraining *ts* on velocity and acceleration are satisfied. This approach uses advanced mathematical computation with reflection to AI as an investigator. The main advantage lies behind the meagre cost compared to CNN models.

We used the Python language program with the introduction of path determination equations for polynomial functions of the fourth and fifth degree while building the environment used in this Paper through Python language. After that, the program reads the obstacles in the environment and draws the path through the equations of polynomial functions. The method is easy to implement as it does not need a large memory with a low cost compared to other algorithms, as well as a decrease in the calculation time of the algorithm.

Polynomial functions of the fourth and fifth degree were used because the functions of the fourth degree are more flexible and thus used for easy curves. In contrast, the polynomial functions of the fifth degree are used for sharp and difficult curves.

The required environment is entered so that it moves simultaneously to the target point after specifying a set of points to extract the required equation using the mathematical concept of polynomial functions to draw the path curve. This is often the shortest path to the goal and is computed with the least computing time because it does not depend on an algorithm to calculate the path.

4.1 Performance appraisal requirements

In this paper, the performance of the proposed methods and algorithms is evaluated using the following concepts:

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- **Distance (d):** The path length from the starting point to the destination point, measured by meter.
- **Time of arrival (t):** This is when it takes for the vehicle to reach the target measured by second (s).
- **Velocity (v):** It is the drone's speed over the path from the start point to the end, measured by meter over second (m/s).
- **Computing time:** This is the time it takes for the algorithm to find the path, measured by second (s) or minute (min.).
- **Fitness**: It represents the amount of vehicle preservation on the trajectory and is calculated by the following equation:

$$F = L \times (1 + error) \quad (3)$$

F is fitness, L is Length of path.

4.2 Case1: Fourth degree Laguerre polynomial

In this case, the Laguerre polynomial function of the fourth degree is implemented by the following relationship [17]:

$$x = \sum_{i=0}^{n-1} \left(w_x(i,0) \times \frac{C \times (n-i)}{10} \right) + w_x(n,0) \quad (4)$$

$$y = \sum_{i=0}^{n-1} \left(w_y(i,0) \times \frac{C \times (n-i)}{10} \right) + w_y(n,0) \quad (5)$$

Where:
C is constant in range (0,51,1).
w_x , w_y; rate of x and y at each point of the path.

The equation of the polynomial function of the fourth degree is applied to plan the path and avoid obstacles, where in this case, we get the least number of turns, speed, acceleration, and latency; this was applied to a fixed environment.

4.3 Case 2: Fifth degree Laguerre polynomial

In this case, the Laguerre polynomial function of the fifth degree is implemented by the following relationship [18]:

$$x = w_x(n,0) \times 5\tau + \sum_{i=0}^{n-1} \big((w_x(i,0) \times (1-K) + (n+1-i) \big) \quad (6)$$

$$y = w_y(n,0) \times 5\tau + \sum_{i=0}^{n-1} \Big(\big(w_y(i,0) \times (1-K \big) + (n+1-i) \Big) \quad (7)$$

K is constantly less than 1.
w_x , w_y; rate of x and y at each point of the path.
τ is an equation variable.

The fifth degree's equation of a polynomial function is applied for trajectory planning. Avoidance, where we get, in this case, the least number of revolutions, velocity, acceleration, and latency, with increased cornering intensity to observe the behavior of the vehicle in sharp turns in terms of speed, acceleration, and latency, and this was applied to a static environment, Fig. 2 UAV speed.

When the UAV is launched, we notice a gradual increase in speed and a decrease in acceleration until it reaches a sharp turn. The UAV's speed is almost zero, so it can cross the curve. Then after passing the curve, the vehicle begins to accelerate until it reaches the target.

4.4 Case3: Apply A* algorithm

In this case, the A* algorithm is implemented, where the algorithm begins to search for the target, takes each point of the environment, and starts searching for the target point. This function has been applied by using Python 3.10; this was applied to 4 statements, start and goal, ten runs, and 130 iterations, in order to reveal the robustness of this algorithm.

5. Result and discussion

This paper formed a static internal computer environment consisting of 11 obstacles. The starting and target points were determined for four cases, and for ten runs each run, 120 iterations were made each, with obstacles represented in black, starting points in green, target points in red and vehicle in orange. We introduced the path planning and obstacle avoidance method for the drone. The average speed, arrival time, path length, average path length from the starting point to the target point, the aircraft's accuracy in following the path to the target point, and the standard deviation from the average path length are calculated. The fourth and fifth-degree polynomial function method was applied, after which the A * algorithm was applied for the same environment, and the results of the above determinants were calculated.

After applying Eqs. (4) to (7) to the environment of this paper, we get the optimal path shown in Fig. 2 to 4, and 6. The results shown in Table 1 represent a comparison between the proposed methods and method of A*.

Through the results shown in Table 1, we note through the comparison between the method of polynomial functions and the algorithm that the computing time in the case of polynomial functions is faster than the processing time in the algorithm, which reduces the memory required to calculate the

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Table 1. Comparison among polynomial 4th, polynomial 5th and A* algorithms used in this paper

Cases	Start point	Goal point	Method	min. Path length (m)	Average path length (m)	average traveling Time (s)	Average speed (m/s)	Computing Time (min.)	Standard deviation (SD)
case.1	(3,0.2)	(9.5,5)	Polynomial 4th Degree	17.5	15.6	20	0.78	0.63	1.9
case.1	(3,0.2)	(9.5,5)	Polynomial 5th Degree	19	13.3	24	0.8	0.55	5.7
case.1	(3,0.2)	(9.5,5)	A* algorithm	15.6	9.2	35	0.26	4.3	6.4
case.2	(0.8,5.8)	(6,5)	Polynomial 4th Degree	9.8	12.5	43	0.32	0.34	2.7
case.2	(0.8,5.8)	(6,5)	Polynomial 5th Degree	14.7	7.3	22	0.33	0.64	7.4
case.2	(0.8,5.8)	(6,5)	A* algorithm	20.1	11.4	47	0.25	4.7	8.7
case.3	(2,7)	(5.8,1)	Polynomial 4th Degree	15.3	11.5	19	0.63	0.5	3.8
case.3	(2,7)	(5.8,1)	Polynomial 5th Degree	18.6	12.7	25	0.5	0.53	5.9
case.3	(2,7)	(5.8,1)	A* algorithm	14.3	9.5	33	0.28	4.7	4.8
case.4	(7.8,3)	(6,6)	Polynomial 4th Degree	9.7	11.0	41	0.26	0.37	1.3
case.4	(7.8,3)	(6,6)	Polynomial 5th Degree	13.4	8.1	23	0.35	0.65	5.3
case.4	(7.8,3)	(6,6)	A* algorithm	21.6	12.9	42	0.3	4.2	8.7

Table 2. Comparing the effectiveness of polynomial method with other algorithms in path length

cases	Path length (m)						
	polynomial 4th	polynomial 5th	A*	FLACO [16]	FGDACO [16]	Hybrid PSO-MFB [17]	CGA [18]
1	17.5	19	15.6	28.97	31.47	14.786	35.50
2	9.8	14.7	20.1	38.74	43.78	14.7953	70.37
3	15.3	18.6	14.3	74.33	77.12	14.796	74.67
4	9.7	13.4	21.6	---	---	14.8083	115.19

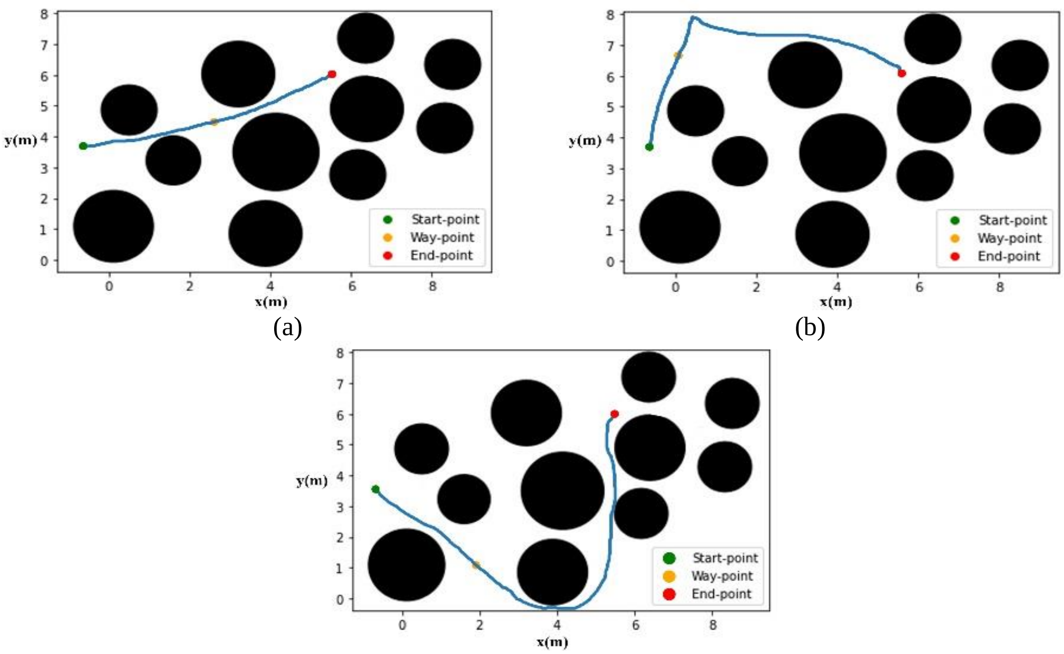

Figure. 3 Comparison of the three proposed methods at the case.2: (a) polynomial 4th, (b) polynomial 5th, and (c) A*

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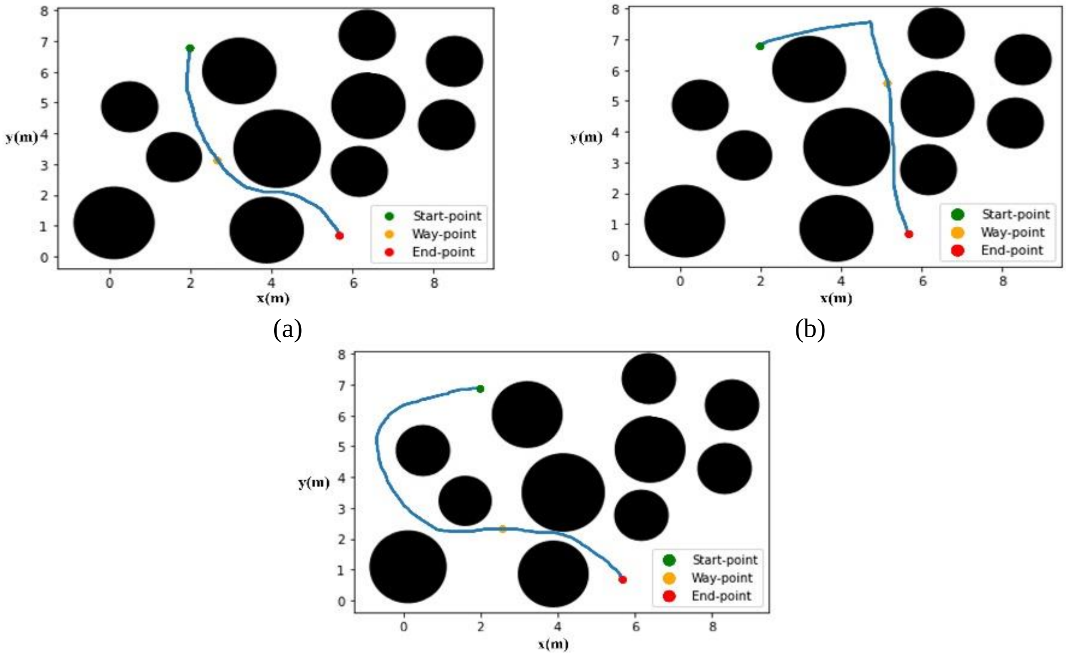


(a) (b)

(c)

Figure. 4 Comparison of the three proposed methods at the case.3 (a) polynomial 4th, (b) polynomial 5th, and (c) A*

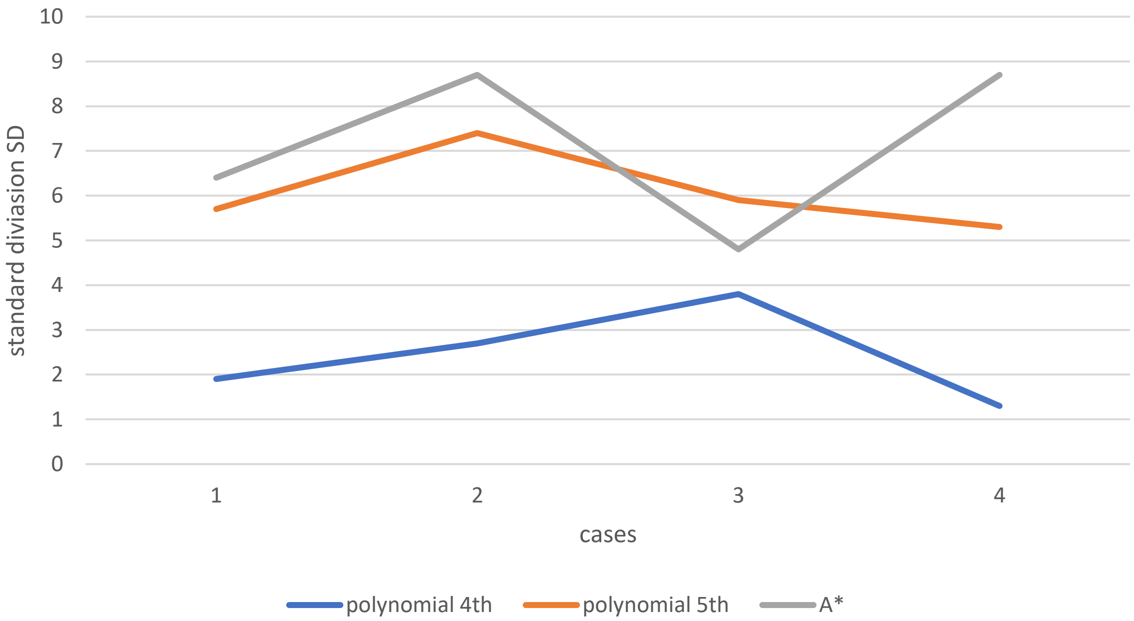
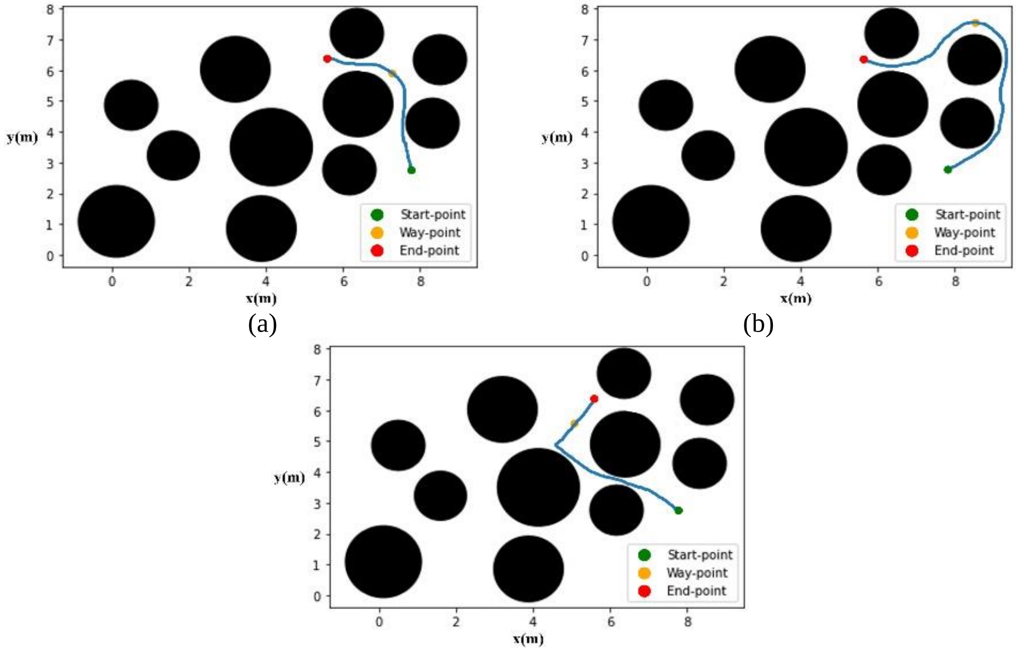


Figure. 5 Standard deviation SD between polynomial functions and A*

path and avoid obstacles and thus makes the time required to reach the Aiming is faster and easier which reduces the cost needed to determine the trajectory, plus the polynomial functions give the least number of turns in the trajectory which reduces the effort of the drone, in turn, to avoid obstacles. However, the A* algorithm is more accurate in trajectory and target identification. From Eq. (3), the error indicates the deviation of the UAV from the lane; If the deviation of the UAV from the lane is zero, then: $F = L$.

The value represents the total distance from the start point to the end point and the cost of the necessary path. Fig. 2 to 4 compare the three methods used in this paper.

Table 2 shows a comparison between the methods used in this paper and several algorithms used in path planning. The comparison shows the efficiency of the polynomial functions method and its ability to plan the shortest path to the goal and low computing time. Fig. 5 shows the standard deviation between polynomial functions and the A* Algorithm.



(a) (b) (c)

Figure. 6 Comparison of the three proposed methods at the case.4 (a) polynomial 4th, (b) polynomial 5th, and (c) A*

Table 3. Comparing the effectiveness of polynomial methods with other algorithms in computation time

cases	Computation time (min.)				
	polynomial 4th	polynomial 5th	A*	Hybrid PSO-MFB [17]	CGA [18]
1	0.63	0.55	4.3	3.425	1.8
2	0.34	0.64	4.7	3.189	2.9
3	0.5	0.53	4.7	3.704	26.9
4	0.37	0.65	4.2	3.368	39.1

In Table 3, we clearly show the importance and efficiency of the proposed method compared to the rest of the methods in terms of computing time. In the first case, the Computation time in the polynomial functions was less than 14% from an A* algorithm, less than 19% from the PSO-MFB algorithm, and less than 35% from the CGA algorithm, and this applies to all other cases.

6. Conclusion

In this paper, two types of polynomial functions were used, a fourth-degree polynomial and a fifth-degree polynomial, and compared with the results of an algorithm A* in terms of path length, vehicle speed, arrival time, vehicle accuracy in maintaining the path, the time it takes for the algorithm to calculate the path, and finally, Acceleration; it was found after applying all these methods that the polynomial functions method gave improved results in the time needed to calculate the path, as it was fast and free of complexity, as well as the vehicle speed was relatively constant. There were no significant stops compared to the algorithm A* and the low cost and ease of calculating the path in the method Polynomial functions.

In the future, this method can be used in multiple UAVs, calculating the path, avoiding obstacles, and reaching the goal quickly and safely.

Conflicts of Interest

We confirm that there is no conflict of interest in this work.

Author Contributions

“Conceptualization, and Methodology, L. A. Hassnawi, and H. N. Abdullah; Software, B. S. Shihab; Validation, B. S. Shihab and H. N. Abdulla; Formal analysis, B. S. Shihab; investigation, B. S. Shihab; resources, B. S. Shihab; data curation B. S. Shihab; Writing—original draft preparation, B. S. Shihab; Writing—review and editing, H. N. Abdullah and L. A. Hassnawi; visualization, H. N. Abdullah; supervision, H. N. Abdullah and L. A. Hassnawi;

project administration, H. N. Abdullah and L. A. Hassnawi.

A List of Abbreviations

Abbreviation	meaning
FLACO	fuzzy logic-based ant colony optimization
FGDACO	fuzzy gain-based dynamic ant colony optimization
PSO-MFB	Particle Swarm Optimization-Modified Frequency Bat
CGA	conventional genetic algorithm

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