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A* Algorithm for Planning UAV Paths

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ABSTRACT

The present study examines the expanding utilization of unmanned aerial vehicles (UAVs), which can be classified into two categories: the first is a remote controlled aircraft, the second is an aircraft that can travel automatically due to the battery problem in a specific flight plan. The research community also piques interest in the creation and application of fresh algorithms for the autonomous monitoring and maneuvering of these vehicles. Today, UAVs are employed in a wide range of non-military tasks, including traffic management, environmental research, and weather forecasting. For autonomous moving and f three-dimensional flying robots (3D) planning path is an important problem. Two-dimensional path planning is used by unmanned aerial vehicles (UAVs) technique to find a shortest way across environmental obstacles so that the robots can complete the surroundings of assignments as quickly as feasible. The aim of this paper is locate the quickest path to the destination with Getting around barriers. The A* algorithm in this article is the recommended algorithm. UAVs were therefore used in real-time testing. The A* method thus demonstrates that the 21-meter path travels in 0.1069 seconds.

KEYWORDS: *Path Planning, A* Algorithm, Unmanned aerial vehicle*

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1. INTRODUCTION

Because of new study directions and innovative technologies that address the usefulness of path planning under different schemes, the field of path planning research has been done intensively. This area enables accurate tracking of a variety of situations for applications in the military and the civilian sector [1]. A UAV is a remote-controlled, autonomous, non-human aircraft. The primary body of a UAV consists of its skeleton, wing, motor drive, battery, engine, propeller and command panel. In addition to these main parts, the (UAV) additionally has cameras, numerous detectors, communication electronics, and electronic sensors. The UAV's historical development began about the middle of the 1800s, but it is gained prominence in the First and Second World Wars. During the Cold War, it also continued to develop due to an increase in pilot casualties and increased exploration and intelligence.

For the past ten years, a lot of focus has been based on the performance and design of unmanned aerial vehicles (UAVs) for both military and commercial purposes. The employment of unmanned aerial vehicles (UAVs) that can function autonomously in complex and dynamic environments has grown in popularity. As such, UAVs need to be equipped with emergency protocols. Finding the best or most efficient route between the pertinent locations under predetermined constraints is a common path planning task. Following the preparation of the plan flight, an unmanned aerial vehicle (UAV) that can identify enemy threats, carry out tasks in the air, and guarantee the safety of its targets is able to define their region. The advantages of UAVs include low cost, great reliability, mobility, and no need to worry about personal losses [2]. Unmanned Aerial Vehicles (UAVs) operate in a complex environment by evading essential barriers. To go over obstacles, UAV uses two types of classification: a traditional technique and an intelligent approach. The path planning is the foundational element of these independent flights. planning Path is the primary part of these autonomous flights, trip planning shows several things, such where you're going and how to cut the trip short and avoid obstructions [3].

As of now, for UAV route planning, Xiao et al. (2005) proposed a genetic technique-based UAV path planning method for challenging settings. It was demonstrated that the suggested algorithm discovered an unobstructed, non-optimal path in a rapidly changing environment. [4]. Jayesh et al. (2006) The algorithmic combination and recent data structure was put into practice as a fast and practical UAV path planning method. According to the RRT algorithm pathsThe Dijkstra algorithm path finds the fastest, obstacle-free path between any two locations on the road[5]. Akshay Kumar Guruji et al. (2016) Robots take over human functions in order to attain high speed ,efficiency, multiplicity, and good precision. In several industries, heavy lifting is done by robots. The suggested A* algorithm exhibits a good reduction in processing time with increased speed and determines the heuristic function's value immediately before to the phase collision, as opposed to doing it originally [6]. Mariusz and Patrick (2006) proposed a system for autonomously preparing UAV paths. The work was completed by looking over the implementation procedure and removing any upper bounds. Currently, the old plans that were in danger of being lost are being restored by contacting a planner to create new (probabilistic road maps) or (rapidly exploring random trees) plansThe final outcomes show how these techniques are applied in the field of unmanned aerial vehicles (UAVs) [7]. Aleksandar et al. (2010) The recommended quantity of intelligence-based path optimization approaches for the UAVs. We demonstrated that the Ant System approach may be used to optimize the UAV application in the map coverage scenario. By contrasting it with an additional technique, the nearest neighbor search, or NNS, implies that the technique finds a more accurate path more often than the NNS [8]. Jose and Felipe (2010) proposed a Dijkstra technique for UAV fixed-wing trajectory planning that is subject to field height variations. The EDA (Elevation Based Dijkstra Algorithm) is shown to dramatically reduce the computation time using the MDA (Modified Dijkstra Algorithm) technique [9]. Dong et al. (2010) examined the FVF-based method. For UAV path planning, the FVF (Fuzzy Virtual Force) technique is quick and easy to use. When the internet UAV path planning complex environment is outperformed by the FVF methodology [10]. Jinbae et al. (2017) suggested a self-sufficient strategy for improving UAV flight plan training. They used a sort of reinforcement learning system called Q-learning to remove barriers until the UAV arrived at its destination. A quicker arrival time is suggested by the suggested methodology [11].

Bo Wang et al. (2018) Radar has been used for offer real-time target position feedback, anticipate the next target location-based step scenario, and carry out dynamic path planning using a combination of scenario forecast data and mixed feedback. The course for several moving targets was planned using the ant colony technique, and status positions and anticipated goal locations were obtained using Kalman filtering. This proposed strategy shows that the route is getting shorter and the amount of time required to reach the goal has decreased [12]. Jung Leng et al. (2006) PSO provided a unique way to formulate and solve 3D path planning problems. Their goal is to minimize the danger of enemy threats while reducing fuel usage [13]. Rosli Omar and Dawei (2010) Based on 2D frames, they proposed methods for 3D path planning. Additionally, they suggested the (VL) procedure, which in a region with polygonal barriers can show the quickest route connecting the starting and destination points. This demonstrates that it can be calculated effectively and is appropriate for real-time applications [14]. Han Tong et al. (2012) This study offers a solution technique to accomplish cooperation timing between groups of vehicles. A popular control strategy was established using the DPSO and Voronoi diagram. The results demonstrate that, for complex group assignments, the proposed genetic technique can be used with time constraints [15]. Ismail AL-Taharwa et al. (2008) In this paper, a controllable mobile robot is assisted in determining the best route through a grid environment between a start point and an end point using a genetic algorithm. Four nearby motions are carried out by the suggested control method, allowing road planning to adjust to complex search areas of low complexity [16]. Wang Honglun et al. (2015) For unmanned aerial vehicles operating at low altitudes (UAVs) operating at challenging terrain, these have three-dimensional (3D) path planning. They recommended using an interfering adaptive fluid system (IFDS) to find the best three-dimensional path in terms of flight height and path time. Better results are shown using the suggested technique [17]. Halil Cicibaş et al. (2015) developed a multi-criteria path planning model for unmanned long- and mid-air vehicles. They suggested the A* algorithm, which accounts for the dynamics of the environment, as the best course for UAV in terms of time, ,fuel consumption and range [18]. Mohammad Mozaffari et al. (2016) Flying base stations provide an ideal environment for the deployment of unmanned aerial vehicles. When compared to the traditional Voronoi cell assembly method using fixed UAV locations, the suggested distribution strategy has been demonstrated to boost the system's power efficiency by a factor of 20 [19]. Victor vladareanu et al. (2016). The algorithms and methods discussed in this work have been minutely researched, simulated, and recommended for use in low-level systems, high-level decision techniques, flight optimization procedures, and UAV motion strategies in unmanned aerospace projects. This study examines clever methods for using sensory information to optimize a UAV task plan [20].

Argel and Reagan (2014) Unmanned aerial vehicles (UAVs) with quadrotor types offer path planning, which lowers vehicle power consumption and prevents energy waste over time. In order to save energy and time, approach uses the Genetic Algorithm (GA) to determine the quickest route that avoids obstacles [21]. Fun-Hsun Tseng et al. (2017) In this investigation, data transfer is facilitated by civilian UAVs utilizing pre-existing 3G communication networks. In comparison to path-greedy and signal-greedy algorithms, The proposed technique shows that the Multi-Objective Genetic Algorithm, or MOGA, provides times (1.32 and 3.22) of enhanced signal quality[22]. Weiwei Zhan et. al (2014) This article addresses a problem of UAVs needing high survivability and low fuel consumption by examining an innovative algorithm designed for Unmanned Aerial Vehicles' path planning real-time in a 3D wide battlefield scenario. The algorithm can determine the best path between two waypoints in the target space while accounting for variables like path length, altitude, and detection likelihood. They therefore demonstrate the stability, convergence, and efficiency of the enhanced A* algorithm [23].

The goal of this research is to find the shortest path for Unmanned Aerial Vehicles (UAVs) using two-dimensional (2D) route planning algorithms that consider local obstacles.

Fractures commonly occur in the near-wellbore zone of injection wells in Western Siberian fields.

2. Materials and methods

Path Planning is a technique that measures the distance between two locations to ascertain the best route between them. Multiple variables or factors must often be entered for path planning tasks, including the starting position, the goal position, and any impediments. Algorithms employ multiple steps to find a 2D path. To get to this path at the best cost, path planning algorithms are applied from a beginning point to a destination point. many alternate routes planned using road planning algorithms. Various strategies are used to find the most appropriate path planning [24].

2.1. A Star (A*) Algorithm

In computer science, this algorithm finds the shortest path among others. It can be applied, for instance, to the resolution of the traveling salesman problem (TSP). Similar to this, it is frequently used in game development to determine the shortest route for players to take in order to reach the objective. An algorithmic approach that is intuitive is the A* algorithm. To put it briefly, the "best fit" algorithm determines which nodes are the shortest between a starting point and a destination node. A* One of the greatest and most often used methods for charting and navigating is the search algorithm. To calculate the total cost, multiply the cost of the road by an intuitive cost. The technique effectively creates a path on the chart that can be walked between several nodes or points. The route with the lowest total cost is recommended. This computer method, which is widely used in path finding and charting, generates a path that may be effectively traveled between the points known as nodes. algorithms used in computer science to solve problems using a heuristic method [25].

An algorithm of approach to heuristics is the A* algorithm. Heuristic costs are added to the highway price to determine the final cost. Preference is given to the least complete price path. Thus, you are not required to visit every node. As shown in Figure 1 the nodes of the sample A* algorithm.

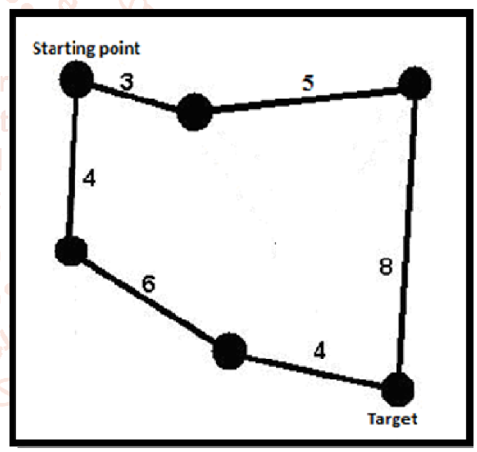

Figure 1. An example of an A* algorithm node.

Since its initial introduction in 1963, A* has gained popularity as a technique for path planning and graphics switching. An easy-to-use function-based approach for practical path planning is the A* algorithm. It uses the best initial search to find the least expensive path from a starting node to a destination node. The 2D implementation algorithm of this path planning has been significantly and well-developed. Still, there are computational issues with the 3D application. Then, without taking into account various disturbances, the experimental use of this method for unmanned aerial vehicles was investigated; nevertheless, no proof of its viability, efficiency, or convergence was found. To construct a connected network chart, some researchers divide the target area into multiple portions using the two-dimensional Voronoi map. The article describes an

A* algorithm that aims to achieve high survival rates and minimal fuel consumption for unmanned aerial vehicles by providing real-time path planning on a 3D large-scale battlefield. As shown in Figure 2 the A* algorithm's flow diagram.

One category of admissible heuristic algorithms is the A* algorithm. This is due to the algorithm's usage of the following function to determine distance:

$$f(n)=g(n)+h(n)$$

As the equation indicates,
f(n): heuristic function,
g(n): The cost of moving from the starting node to the current node,
h(n): Estimated distance from the current node to the destination node.

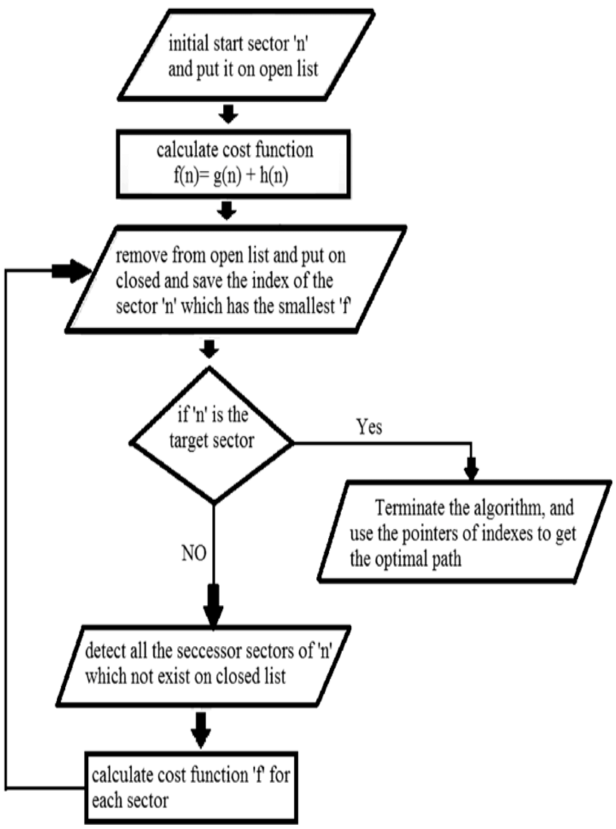

Figure 2. Diagram of the A* algorithm flow

2.1.1. A* Algorithm operation:

This algorithm operates in the following ways.

At each step, the algorithm selects the node with the lowest value, which is the most significant node, and removes it from the queue.

This node has a fee to access it, and if you notice, the function f (n) includes this value. This node updates the values of all nearby nodes.

The method repeatedly runs through the previous steps until the destination reaches the target node (priority queue in the priority queue) or until there isn't a node in the queue.

3. Simulation and Application

It is desirable to fast progress through practice and build 3D path planning systems for autonomous mobile robots, based on complex 2D path planning algorithms.

By using unmanned aerial vehicles, the quickest route is reached among the obstacles created by the simulation setting by utilizing the recommended procedures and avoiding barriers between the source and the objective. The most widely used methods for autonomous mobile robots are those based on the A* algorithm.

Three elements make up the produced map: the impediment, the starting position, and the end point (target). This map was made with Matlab. To find a 3D path in algorithms, a few stages are needed. First, barrier height data are collected from a local starting point to an endpoint. The shortest path planning and the height of these obstacles are then used to determine the UAV's maximum altitude. several alternate route plans that use 2D path scheduling algorithms depending on obstacle heights. Various methods are employed to identify the best path planning strategy. The result of the A* algorithm's path planning is the blueline.

3.1. first test media in two dimensions

The path planning algorithm is applied, as shown in Figure 3. The A* algorithm is the suggested algorithm. There are three distinct barriers, each with a varied length and width, as seen in the pictures. Two obstacles measure forty by forty meters, and the other three measure twenty by sixty meters.

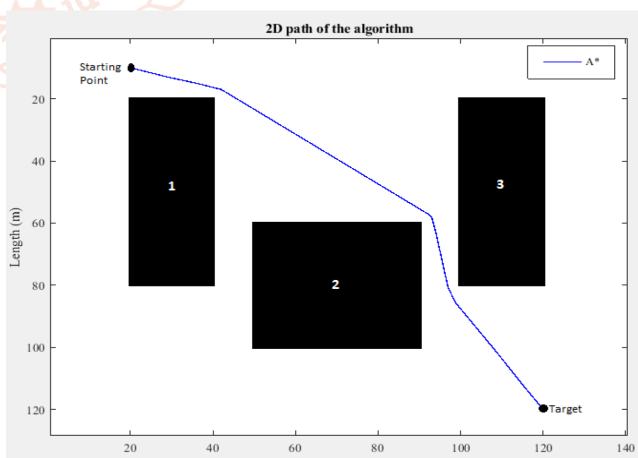

Figure 3. The algorithm's 2D way.

Table 1 displays the outcomes of the path in the aforementioned graphic. The path from the starting location to the destination is computed in two dimensions. The A* algorithm shows that the 27-meter path is moving in 0.3980 seconds.

3.2. first experimental 3D media

Once the drone and the obstruction have been measured in height, As shown in Figure 4 that the first obstacle is 60 meters high, the heights of the second and third are respectively 40 and 60 meters.

When the drone reaches a height of 45 meters, the algorithm determines the path length, suggesting that the height is not the same as the second barrier. This allows the drone to bypass the second obstacle and arrive at the destination point faster.

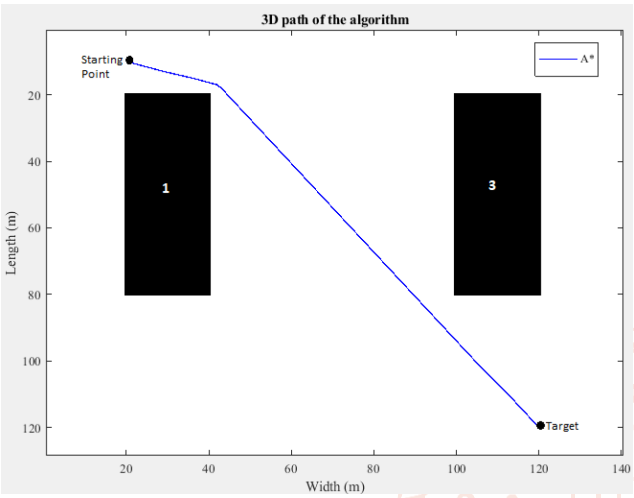

Figure 4. The algorithm's 3D way.

Table 1 displays the outcomes of the path in the aforementioned graphic. A three-dimensional path is computed from the starting location to the destination. The A* algorithm shows that the 21-meter path is moving in 0.1069 seconds.

3.3. Second experimental 2D media

The path planning algorithm is applied, as shown in Figure 5. The A* algorithm is the suggested algorithm. As can be seen in the pictures, there are four different obstacles, each with a different length and width. First, there are four obstacles: the first is 30 meters wide by 10 meters long; second, it is 30 meters wide by 20 meters long; third, it is 30 meters wide by 30 meters long; and fourth, it is 30 meters wide by 40 meters long.

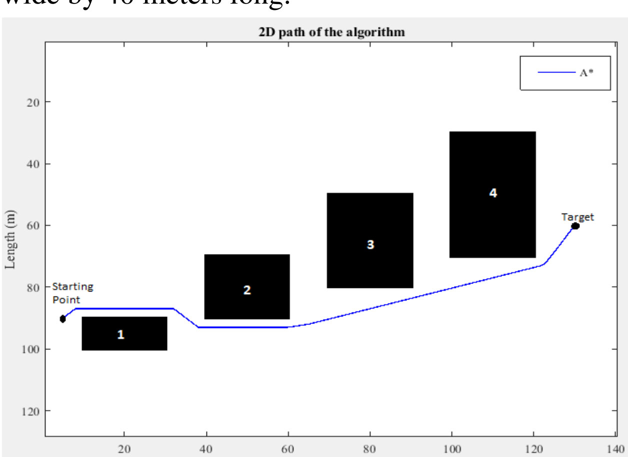

Figure 5. The algorithm's 2D way.

Table 1 displays the outcomes of the path in the aforementioned graphic. The path from the starting location to the destination is computed in two dimensions. The A* algorithm shows that the 70-meter path is moving in 0.3877 seconds.

3.4. Second experimental 3D media

Upon evaluating the drone's height in relation to the obstacle, as shown in Figure 6 that the first obstacle is 10 meters high, followed by obstacles that are 20 meters high, 30 meters high, and 40 meters high. When the drone reaches a height of 35 meters, the algorithm determines the length of the path, showing that the height is less than the second obstacle. By doing this, the drone can go faster to the destination by avoiding the first, second, and third obstacles.

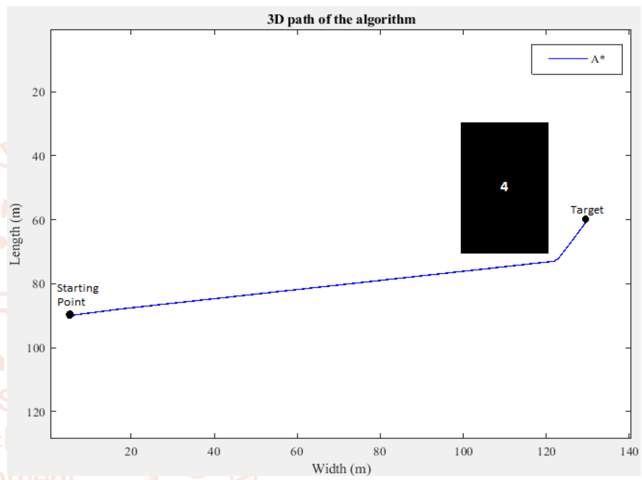

Figure 6. The algorithm's two-dimensional path.

Table 1 displays the outcomes of the path in the aforementioned graphic. A three-dimensional path is computed from the starting location to the destination. The A* algorithm shows that the 21-meter path is moving in 0.3877 seconds. Table 1 displays the outcomes of the two distinct test medium pathways.

Table 1. Path planning line length performance in meters and 2D and 3D path planning algorithm performance in seconds.

Figure		Time of A* algorithm (sec)	Path length of the A* algorithm
First Environment	33	0.3980	27
	44	0.1069	21
First Environment	55	0.2661	70
	66	0.3877	21

As shown in Figure 7 an autonomous aircraft flying in a real-time testing environment. There are three obstacles, and the heights of each obstacle vary. Determined are the routes from the starting position to the end point. The first obstacle is 30 meters high, the second is 15 meters, and the third is 40 meters high.

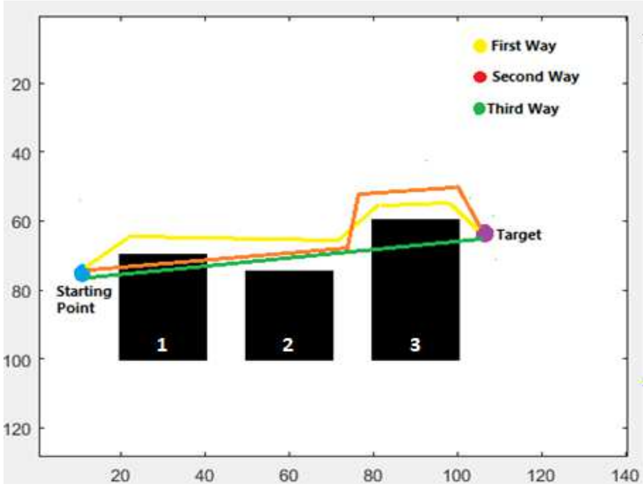

Figure 7. UAV test environment.

The results of the UAV test environment are shown in Table 2. The photographs on the unmanned aerial vehicle's flight route as shown in Figures 8, 9, and 10.

Table 2. Energy consumption at different heights.

Method	Height of Drone (m)	Distance in meters	Speed of the drone (m/s)	The cost of batteries (v)	Battery usage percentage (%)
First Method	20	264	5	3400	14.430184
Second Method	35	249	5	3400	15.464194
Third Method	45	264	5	3400	15.785886

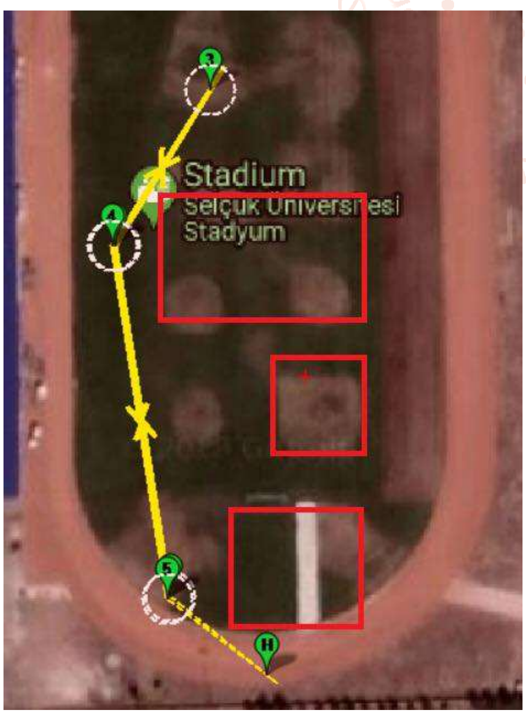

Figure 8. First-way drone height of 20 meters.

The drone is 20 meters high, as can be seen in the picture below. The suggested algorithm overlooks the second obstacle when we attempt the first path in the simulated environment since its height is greater than that of the second obstacle. It shows the route that's shown in Figure 9.

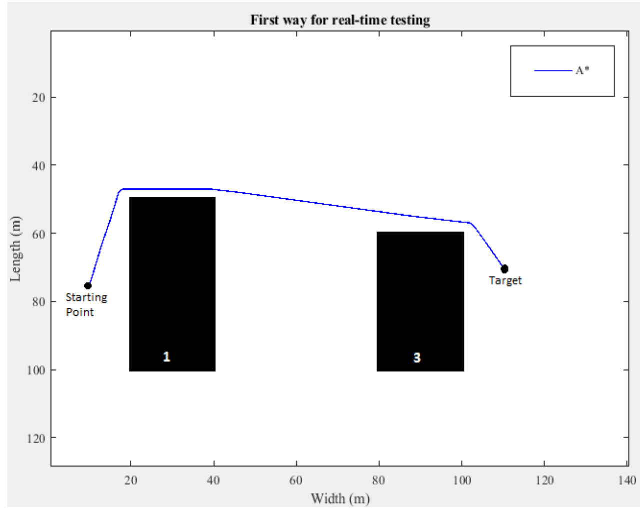

Figure 9. First method for testing in real time.

The computation of a three-dimensional path is done between the starting and destination locations. With the A* algorithm, the 40-meter path appears to be moving in 0.3056 seconds.

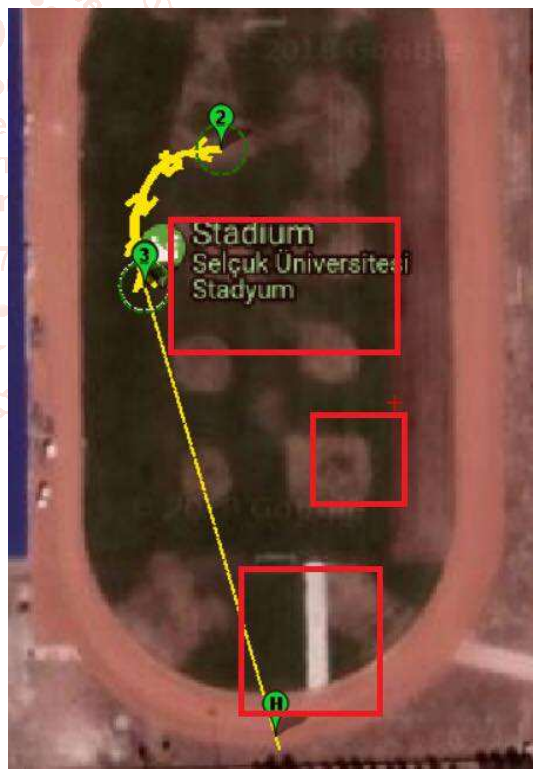

Figure 10. Drone Height 35m for second way.

When the drone was 35 meters high, we tried the second route in the simulated environment. The drone height was greater than the first and second barriers, therefore when the algorithm ran, it disregarded the 30 and 15-meter heights. The route that was mapped is shown in the following Figure 11.

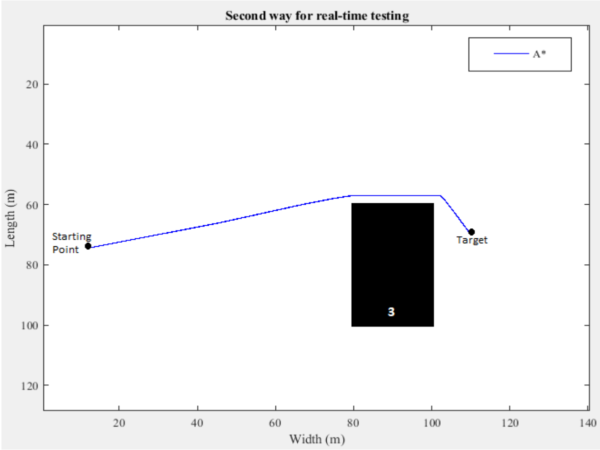

Figure 11. First method for testing in real time.

The computation of a three-dimensional path is done between the starting and destination locations. With the A* algorithm, the 36-meter path appears to be moving in 0.3060 seconds.

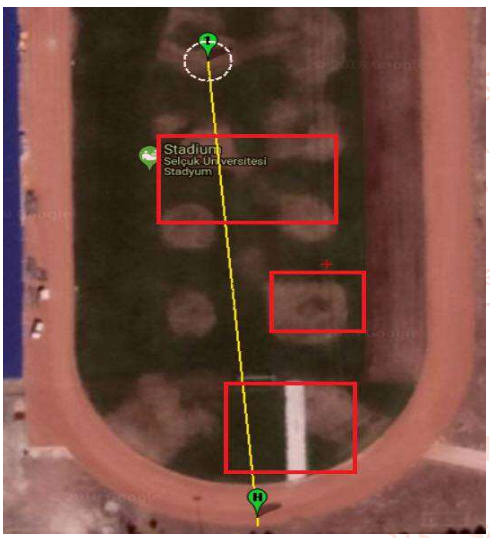

Figure 12. 3rd method for 45-meter drone height.

We attempted the third method in the simulation scenario when the drone height reached 40 meters. Because the drone height above the height allowed for the three obstacles, the algorithm ignored them when it was running. It is therefore estimated from the beginning point to the goal without any hindrances. The route that was plotted is displayed in Figure 13 below.

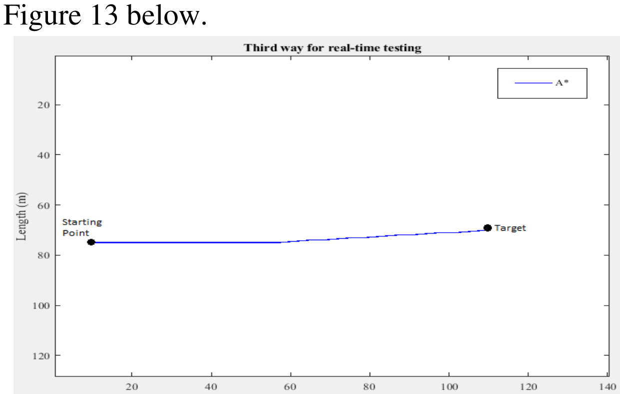

Figure 13. Third-party real-time testing method.

When the battery is fully charged, it is equal to 16.8 V, and when it is empty, it is equal to 13.2 V. The results show that more obstacles are eaten the higher the UAV.

The A* algorithm yields different results in the two experimental conditions when we compare the results. Our method provides superior outcomes in 3D situations when comparing 2D and 3D environments. Consequently, in three-dimensional environments, the A* algorithm demonstrates that it increases in shorter path length and shorter time. Consequently, unmanned aerial vehicles are employed in this capacity. Table 3 below displays the simulation environment's outcomes.

Table 3. Real-time testing outcomes from a three-dimensional simulation.

The outcome of a three-dimensional simulation	A* Algorithm	
	Time (seconds)	The ideal route (m)
First Method	0.3056	40
Second Method	0.3060	36
Third Method	0.1276	66

4. Discussion

The A* algorithm yields different results in the two experimental conditions when we compare the results. Our method provides superior outcomes in 3D situations when comparing 2D and 3D environments. As a result, in three-dimensional environments, the A* algorithm demonstrates that it increases in shorter path length and shorter time. Consequently, unmanned aerial vehicles are employed in this capacity. contrasting the outcomes of the real-time test with the simulation, as indicated in Table 4.

Table 4. Real-time test and simulation results in 2D and 3D are compared every second.

Figure		The star algorithm in seconds	
		Simulation	Testing in Real Time
First Environment	3	0.3980	0.02
	4	0.1069	0.005
First Environment	5	0.2661	0.01
	6	0.3877	0.02

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