A review on path optimization algorithm for unmanned aerial vehicle (UAV)

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Abstract*— UAVs (Unmanned Aerial Vehicles) are crucial for tasks ranging from surveillance and reconnaissance to disaster response and remote sensing. UAVs are capable of doing 3D path planning, which entails identifying the most effective and obstacle-free route in a complex 3D environment. This planning process takes into consideration a variety of elements, including geometry, physics, and time constraints. Even though a lot of effort has been dedicated to solving the issue of UAV three-dimensional path planning, there is a noticeable absence of a thorough investigation on this subject. This is especially true in relation to the recently published studies that are primarily focused on this field. This study investigates the algorithms that have shown to be the most successful in terms of three-dimensional (3D) path planning for UAV in recent years. Based on the findings of this study, the methods that are utilized for planning the three-dimensional path of UAVs are classified into five distinct groups. The classifications comprise algorithms that depend on sampling, nodes, mathematical models, biotechnology, and multi-fusion methodologies. This section offers an in-depth examination and comparison of each category. Furthermore, taking into consideration the operational mechanism and temporal complexity of each technique, a comprehensive and practical analysis is presented for each of the approaches.

Keywords— Path planning, Sample based algorithms, Node based algorithms, Mathematical based algorithms, Bio-inspired algorithms, multi-fusion based algorithms.

I. Introduction

UAVs are very adaptable platforms employed in a variety of situations because of their remarkable agility and vertical landing capabilities. An UAV requires path planning to navigate from its starting position to its destination [1]. Path planning is a crucial element of the entire system when designing a mission [2]. Route planning is all about creating a path to a target in real-time, making sure to avoid obstacles and optimise a cost function. It also takes into account Kino dynamic restrictions. In addition, the factors that the UAV's mission must consider are the same issues that path planning addresses. Conventional 2D path planning algorithms struggle to navigate through intricate 3D terrains that are filled with different obstacles and unpredictable elements. Thus, there is an urgent need for 3D path planning algorithms to assist UAV navigation in difficult environments, like the target scene as shown in Figure 1.

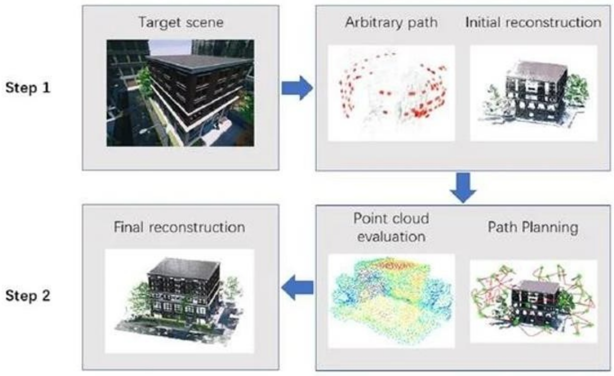

Fig. 1: 3D path planning of a target scene

Though more difficult than 2D, path planning in 3D situations has a lot of potential. The addition of dynamic constraints and the growing intricacy of kinematic constraints cause the difficulties to triple. In order to create a path that avoids collisions in a complex environment, it is important to use a variety of mathematical tools to accurately represent these limitations and preserve the relevant data. Finding a complete path in three dimensions is regarded as an NP-hard problem by optimization theory, which implies that no generally acknowledged solutions are currently in use in the sector.
Various methods have been introduced in recent years to tackle challenges related to 3D path planning in diverse settings. Environments in computer science involve a range of algorithms and approaches, including the Visibility Graph [3], which is centred on graph-based visibility analysis. Moreover, search techniques such as the Rapidly-exploring Random Tree (RRT) [4] and the Probabilistic Roadmap (PRM) [5] are used through random sampling. Efficient search techniques like Dijkstra's algorithm [6], A* algorithm [7], and D* algorithm [8] are also used. Bio-inspired planning algorithms are also integrated into the surroundings. This paper specifically concentrates on broadly applicable approaches. The smooth trajectory-producing manifold-based algorithm [9] is not included because it is only compatible with rigid body robots and ignores aerodynamic or hydromechanical effects.

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This study primarily focuses on evaluating the efficiency of each algorithm and determining the ideal algorithm. In intricate 3D terrains filled with numerous obstacles, path planning algorithms aim to generate paths that steer clear of collisions while minimizing travel distance and energy consumption. To develop a realistic route that can adjust to different uncertainties, all of these factors must therefore be taken into account. Furthermore, explored in this work are the ideas of global and local minima.

Section 2 defines problems for future discussion and looks at contentious subjects that require clarification. In-depth classification of 3D path planning methods is covered in Section 3. Every category is carefully examined in this paper, which also offers a long list of algorithms in each domain together with an explanation of the fundamental ideas. Section 4 explores subjects in need of explanation and provides concise explanations of the problems for additional discussion. Section 5 evaluates the suitability of each strategy by analyzing its distinctive characteristics. The last part offers a synopsis of the work and addresses possible directions for more investigation.

II. Preliminary Material

Unmanned aerial vehicles, which can operate independently without human assistance, are commonly utilized. When confronted with intricate circumstances in either outdoor or indoor settings. In order to navigate through different environments, a path planner is required to determine the optimal route. Path planning refers to the process of determining a suitable route or trajectory for a moving object, such as a robot or vehicle, to navigate from one location to another while avoiding obstacles and adhering to certain constraints. Referring to the literature in references [10,11,12,13], 3D path planning for UAVs involves finding the best trajectory for an unmanned aerial vehicle in a three-dimensional space, considering factors like obstacles, mission goals, and limitations.

This paper assumes that UAVs will fly in a three-dimensional space (R^3), referred to as the workspace, denoted as w. There are many obstacles in the workspace(w) named as (w_o) and (i^{th}) is the iteration number allotted to them. W_{free} is the actual workspace available for UAV to fly without the obstacles. The initial position $X_{initial}$, the goal position X_{goal} and the workspace available W_{free} altogether constitute for the path planning. Figure 2 illustrates an example of $X_{initial}$ & X_{goal} in the workspace.

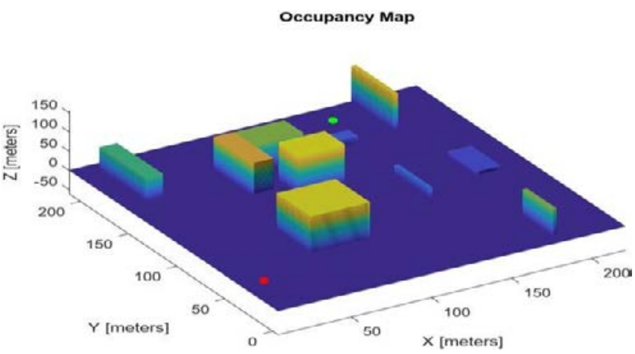

Fig. 2: Initial (green) & Goal (red) position in the 3D workspace (w) [14].

Additionally, the following definitions are provided:

Path Planning: Given a function δ: [0, T] of bounded variation where $\delta(0) = X_{init}$ and $\delta(T)=X_{goal.}$ If there is a method, denoted as Φ, that can ensure the absence of any obstacles δ in the path τ for every τ in the interval [0, T], then Φ is referred to as Path Planning.

Optimal Path Planning: If there is a route planning issue with an initial state, a goal state, obstacles, and a cost function (c) that maps paths to non-negative real numbers, If a process meets the criteria 1 to discover a path δ', and c(δ') is the minimum of c(δ) for all viable paths δ, then δ' is the best path and Φ' is the optimal path planning. Figure 3 shows an example of path planning in workspace available (W_{free}) from $X_{initial}$ to reach X_{goal}.

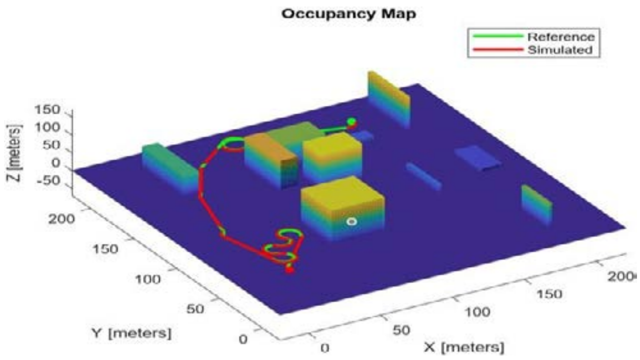

Fig. 3: Path planning from $X_{initial}$ to reach X_{goal} in obstacles embedded 3D workspace (w) [14].

III. Types of UAV 3D path planning methods

Among the well-known methods are Artificial Potential Field [15], Probabilistic Roadmaps, and Rapidly exploring Random Trees. The classification of the current approaches for 3D path planning algorithms is shown in Figure 4.

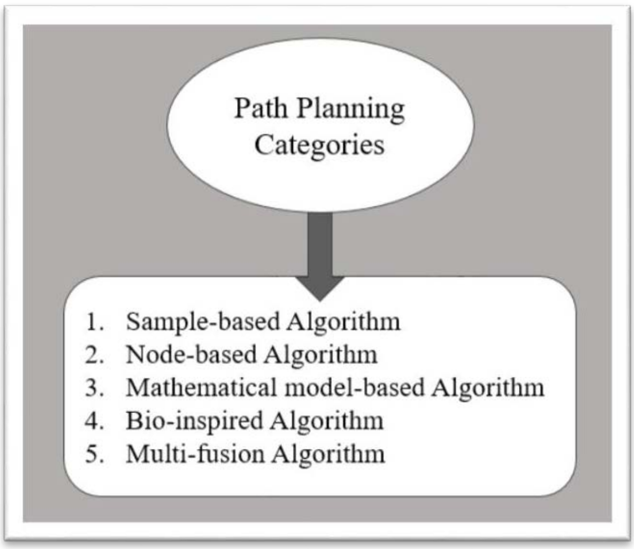

Fig. 4: 3D Path planning categorization.

This document categorizes all techniques for planning the three-dimensional paths of UAVs. The content can be classified into five distinct categories, each of which includes a range of approaches that adhere to specific features. While the present study concentrates on the special features of each category, the following sub-sections provide thorough methodology for each category.

A. Sample-based Algorithm

Sample-based algorithms are computational techniques that depend on generating and assessing random samples from a specified distribution or space. These algorithms are especially valuable in situations where precise calculation or thorough searching is not feasible because of the vast size of the problem or the complexity of the environment. Sample-based algorithms can efficiently estimate numbers, make judgements, or optimise functions by utilising random sampling techniques such as Monte Carlo methods or randomised optimisation. These methods are extensively used in fields such as machine learning, optimisation, and simulation to address problems that cannot be solved with deterministic approaches.

This research categorizes sample-based algorithms into 2 different sub-categories: Passive and Active. An algorithmic process that is actively running or carrying out a particular task is referred to as an active algorithm. Rapidly-exploring Random Trees (RRT) can independently create a skeletal structure that guides towards the objective using its unique processing method. Passive techniques, such as Probabilistic Roadmaps (PRM), are capable of generating a road network map from a starting node to a destination. However, there are multiple paths available, so a combination of search algorithms is required. Algorithms for planning the three-dimensional paths of UAVs.

The challenge requires the use of multi-fusion- based algorithms. Based on this information, this research categorizes a group of algorithms that are unable to develop a single path on their own, and labels them as passive. Passive includes elements such as those found in each sub-category. The techniques used in this project include 3D Voronoi diagrams [16] and Rapidly-exploring Random Graphs [17]. The study introduced the RRT∗ algorithm, borrowing the asymptotic optimality of the RRG while preserving a tree structure instead of a graph. For asymptotic computational complexity, the RRG and RRT∗ algorithms have no substantial overhead compared to the RRT algorithm as shown in Figure 5. Probabilistic Roadmaps (PRM), Kino-dynamic Probabilistic Roadmaps (K-PRM) [13], Sampling-based Probabilistic Roadmaps (S-PRM) [12], Visibility Graphs, and Corridor methods are all techniques used in motion planning. The Dynamic Domain RRT (DDRRT) [18] and RRT-Star (RRT*) [19] are two algorithms.

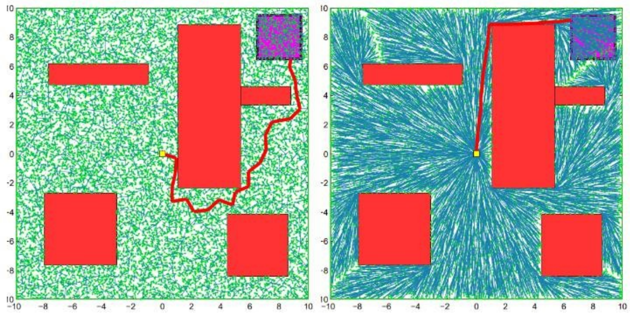

Fig. 5: Comparison of RRT & RRT*, both iterated with sample space of 20,000 samples [17].

Four series can be merged: the PRM series, the Voronoi series, the Artificial Potential Field series, and the RRT series. There is no way for the basic style of each series to find the best way for everyone around the world. Yang [4] developed a path free of impediments by using the Rapidly exploring Random Tree (RRT) technique. However, it is important to note that RRT lacks both a re-planning mechanism and the capacity to optimize the generated path. Therefore, enhanced versions such as RRT*, DDRRT, and RRG have been suggested to address this issue. Xiao et al. [5] suggested an enhanced Probabilistic Roadmap algorithm and integrated it with the A* algorithm to address the limitation of PRM in generating an ideal path independently. The Voronoi map construction approach does not have the capability to Create the most efficient path. However, it is prone to getting stuck in local minima. To address this issue, Sigurd et al.[15] proposed combining Voronoi with a navigation function to obtain an obstacle avoided path.

B. Node-based Optimal Algorithm

Node-based algorithms are computational methods that work by expressing issues or data using nodes and edges, creating a structure similar to a graph. Nodes often symbolise things or data points, whereas edges indicate relationships or connections between them. These algorithms utilise the structure of the graph to carry out tasks such as moving around the network, finding specific elements, or improving efficiency. Typical instances include graph traversal methods such as breadth-first search (BFS) and depth-first search (DFS), as well as graph-based optimisation approaches like Dijkstra's algorithm for finding the shortest pathways. Node-based algorithms are extensively employed in diverse fields such as computer networking, social network analysis, and computational biology, owing to their adaptability and effective modelling of intricate relationships.

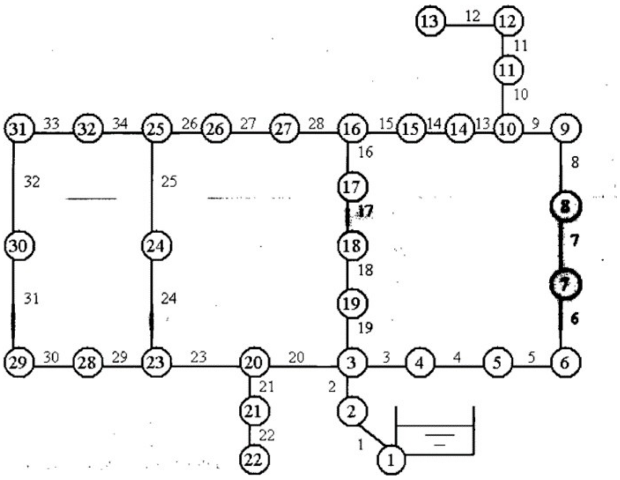

Fig. 6: An example of Hanoi water distribution network, it shows optimal solution [23].

This class of algorithm comprises, among others, Dijkstra's Algorithm, the A* Algorithm, the Lifelong Planning A* Algorithm (LPA) [20], the Lazy Theta* Algorithm [21], the Dynamic A* Algorithm (D*), the D*-Lite [22], the Harmony Search Algorithm [23]. This approach falls under the category of dynamic Programming. After creating a map or graph, the initial step is to define a cost function. Next, every node and arc is carefully analyzed to find the path with the most affordable cost. Musliman et al. [6] demonstrated that Dijkstra's methods are capable of determining the shortest path in a given graph. Filippis et al. [7] suggested a heuristic way to determine the cost for minimizing the number of states in Dijkstra's algorithm. This led to a faster convergence solution that saved time. Stentz was the first person to suggest Dynamic A*(D*). This program utilizes sensors to adjust the weights of its edges in order to create a temporal map. Many individuals currently opt for D* due to its ability to maintain stability. Harmony Search (HS), originally described by [23], Provides a solution for problems that linear programming cannot address. High school (HS) can change the planned route to find the fastest, most efficient way to get to the destination. In a study by [24], this technique was used to unmanned aerial vehicles (UAVs) to achieve optimization of aerial coverage.

C. Mathematical based Algorithm

Mathematical algorithms are computing approaches that extensively rely on mathematical ideas and techniques to solve issues or optimise objectives. These algorithms frequently require converting issues into mathematical models, establishing objective functions, and utilising mathematical optimisation or analysis techniques to discover answers. Illustrative instances encompass linear programming for the purpose of optimisation, numerical integration techniques for the resolution of differential equations, and statistical algorithms for the study and inference of data. Mathematical algorithms play a crucial role in a wide range of disciplines including engineering, economics, physics, and computer science. They offer systematic methods for addressing intricate issues and extracting valuable information from data.

Two primary categories of mathematically based algorithms are linear programming and optimal control [25]. Among the optimisation problems covered by linear programming are mixed-integer linear programming [26], binary linear programming [27], nonlinear programming [28,29], and others. This algorithm takes almost all factors into account and sets up a cost function to evaluate the current option until the best path is found as shown in Figure 7. Figure 8 illustrates the algorithm planning with a fundamental mathematical model.

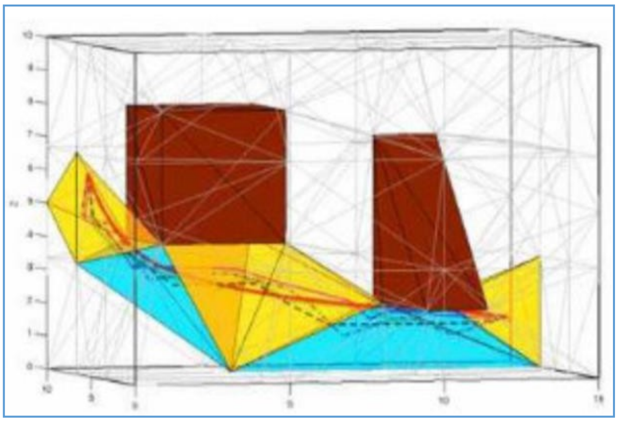

Fig. 7: Path planning using optimal channel & five trajectories; 1) centre of gravity, 2) centre of inspheres, 3) centres of common faces, 4) middle of common faces, 5) B-spline curve for 5 convex fragments [27].

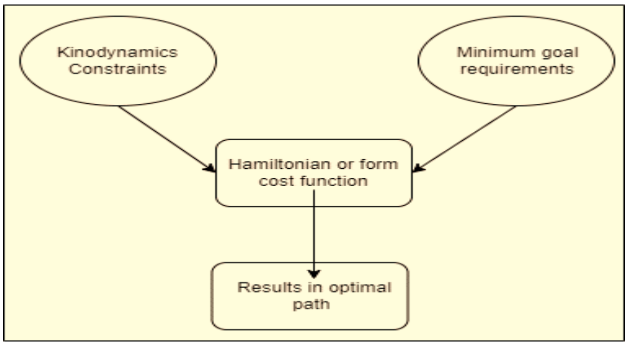

Fig. 8: Steps for mathematical based problem solving

Miller [25] addressed the issue of optimal path planning. To generate a boundary value problem, the control framework combines a cost criterion and a Hamiltonian function. The Boundary Value Program (BVP) algorithm generated a path that closely mirrored the actual route, ensuring global optimization. It is very hard to do the maths when you add more factors because they cause more evaluations of the recursive functions. Binary Linear Programming [27] produces a simple framework or roadmap by removing a significant amount of information, hence simplifying Mixed-Integer Linear Programming (MILP) [28].

D. Bio-Inspired based Algorithm

Bio-inspired algorithms are computational techniques that derive inspiration from biological systems and processes in order to address intricate challenges. These algorithms imitate the actions of natural systems such as evolution, swarm intelligence, or neural networks in order to accomplish tasks related to optimizations, pattern recognition, or decision-making. Illustrations are of genetic algorithms, which imitate the process of natural selection and genetic recombination to seek for the most advantageous solutions, or ant colony optimization, which replicates the foraging behavior of ants to solve issues involving combinatorial optimization. These algorithms harness the efficiency and flexibility observed in biological systems to effectively handle complex computer problems. The Evolutionary Algorithm (EA) [29] and the Neural Network (NN) algorithm [30] are the two categories into which this study separates bio-inspired algorithms. The reason for this division is their analysis at various levels. Many methods are included in evolutionary algorithms, including genetic algorithms (GA) [31], memetic algorithm [32], particle swarm optimization (PSO) [33], ant colony optimization (ACO) [34], and shuffling frog leaping algorithm [35]. Figure 6 shows the optimal route, which shows the person who is the fittest.

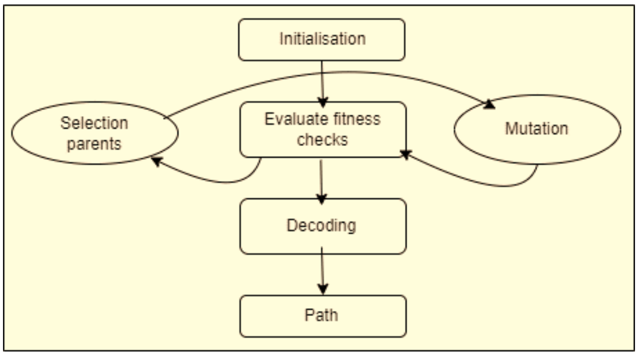

Fig. 9: Path planning evolution

The goal of the neural network approach is to give a dynamic depiction of brain functions. In a same vein, the artificial potential field technique draws the robot to previously undiscovered places all over the surroundings. Constructing a shunting equation guarantees that while negative UAV activity stays in one location, positive UAV activity can spread across all uncharted space. A multitude of factors in NP-hard issues can be problematic for classical linear programming. For this reason, the evolutionary algorithm [29] was developed. Premature convergence is a potential issue with these algorithms, too, as the crossing operator chooses values randomly. In robotics, Kroumov et al. [30] applied neural network technique to achieve a globally optimal path.

Rohit et al. [36] proposed a method that combines swarm intelligence, optimization, and dynamic decision-making to create an intelligent and efficient path planning tool based on the flying patterns of hummingbirds as shown in Figure
10. The Artificial Hummingbird technique demonstrated superior performance compared to traditional path planning in terms of path length, obstacle avoidance, and mission completion time. For UAV path planning in 3D environment, Sameer et al. [37] introduced a Matrix-based Genetic Algorithm (MGA) with the aim of enhancing convergence speed and computation time. Brijesh et al. [38] pondered upon the Adaptive Mayfly Algorithm for UAV path planning and obstacle avoidance in indoor environment.

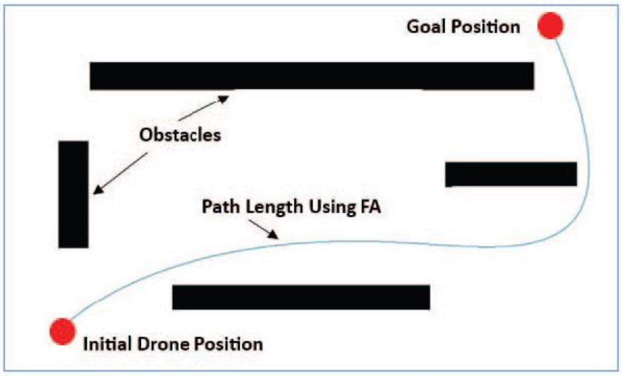

Fig. 10: Navigation of Drone Using Firefly Algorithm (FA) [36].

E. Multi-fusion (Hybrid) based Algorithm

Multi-fusion algorithms are computational strategies that combine numerous sources of information or methodologies to tackle complicated problems more efficiently than using individual methods alone. These algorithms leverage the advantages of many models, data sources, or algorithms to attain exceptional performance in tasks such as classification, prediction, or optimizations. Multi-fusion algorithms can enhance robustness and accuracy by combining several information streams or computational techniques. Illustrations encompass ensemble approaches such as random forests in the field of machine learning, which amalgamate predictions from numerous decision trees, or multi-objective optimizationsalgorithms that concurrently optimize multiple contradictory objectives. Multi-fusion algorithms areutilized in diverse fields such as data mining, picture processing, and system optimization. These algorithms exploit complementary information to achieve improved computing results. This work so classifies algorithms of this kind as multi-fusion-based algorithms, which are produced by fusing several algorithms to generate an optimal path ona global scale.

Problems that cannot be best solved by a single proposed approach alone can be addressed by multi-fusion algorithms. A 3D PRM to build a roadmap in an area free of obstacles and used a 3D grid to show the surrounds. At finally, the most effective path was obtained by integrating a state-of-the-art A* algorithm with nodes. Masehian et al. [39] suggested methodology which combined a visibility graph, Voronoi diagram, and potential field (VVP) to assess the extension of the VVP algorithm to 3D space. This method shows a useful balance between maintaining safety and finding the shortest path. Scholer et al. [40], to address the three-dimensional path planning problem, used a hybrid method that integrated the visibility graph with Dijkstra's algorithm, or geodesics. There are numerous strategies that fall under this category; however, it is not possible to describe them all here. For an optimal solution, Patle et al.

[41] proposed a hybrid of fuzzy logic and the firefly algorithm to establish a multitude of controller features. This method optimises path and time in a manner that the standalone algorithms were incapable of as shown in Figure 11.

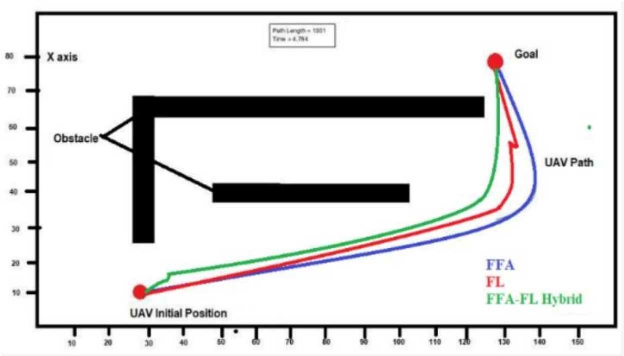

Fig. 11: Comparison of firefly-fuzzy controller [41].

This study separates multi-fusion algorithms into two groups based on how they work [42-43].

- More than one algorithm for planning the way that work together to find the best one. This is known as "Algorithm Integration" in this work.
- Combining several path planning methods. For it to work, one procedure must end and another must begin right away. This study calls this ‘Algorithm ranking’. Each subclass has multiple typical algorithms in Table 1.

Table 1: Typical multi-fusion-based algorithms

Sub-category	Examples of common methods in each group
Integrated Algorithms	Three algorithms utilized include the visibility graph, Voronoi diagram, and potential field (VVP) algorithms. Moreover, there are Voronoi potential field algorithms and neural network potential field algorithms available.
Rank of algorithms	Optimal algorithms based on Voronoi Nodes, PRM Nodes, GIS-MCDA, visibility graph Nodes, and visibility graph Geodesics.

IV. Results and Discussion

At first, sampling-based algorithms compile a sample of the surroundings as nodes. After that, they link the nodes using a "near" strategy, a depth-first search procedure, or another approach. Ultimately, these techniques are starting to investigate the best path to the objective. Usually, this kind of approach is simple to understand how to apply. Thus, they can be applied to both static and live planning. Node-based algorithms only care about nodes and don't care about how a map is usually made. In normal circumstances, they work with node information to calculate weights based on the distance between nodes and find the most efficient path globally. This method can utilize different types of parents, such as Initialize, Mutation, Crossover, and Selection. Look at the fitness theory Decode Path methods can be used to find the world best solution, and they can be used online.

Algorithms based on mathematical models try to provide a standardized representation of the whole region for best control. It defines stringent bounds for the cost function and describes practically all the mechanical and dynamic restrictions with mathematics. This kind of approach now functions adequately enough thanks to the advancement of computer technology; however, it typically taxes the computer's processor. If the internet goes down, you can still use these steps. Bio-inspired algorithms are basically heuristic techniques that perform well with NP problems and intricate unstructured constraints. Changing it takes a long time each time, but this kind of algorithm finds the best approach by doing so. Only offline operation of this kind of software is possible. The best features of many algorithms are combined in multi-fusion-based algorithms to determine the most economical and optimal solution available. Many times, you need consider how to obtain knowledge and save time simultaneously. Sometimes a couple basic relative strategies together can produce a quite decent online method. Table 2 gives an approximation of the processing time for every category, together with its real-time usability and compatibility with static (S) or dynamic (D) settings, based on the supplied study. Charts on static or dynamic contexts and the real-time applicability of the algorithms covered previously are shown in Figures 12 and 13 according to Table 2.

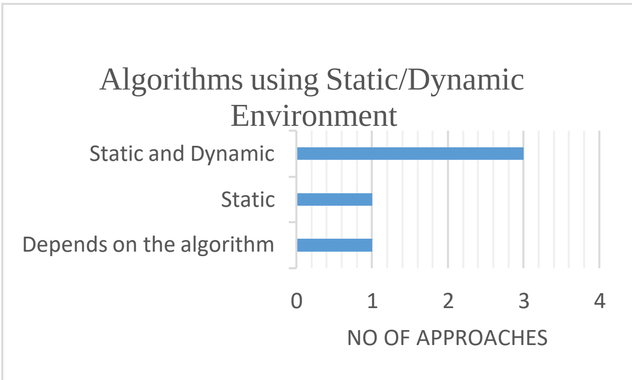

Fig. 12: Application of algorithms in static & dynamic environment

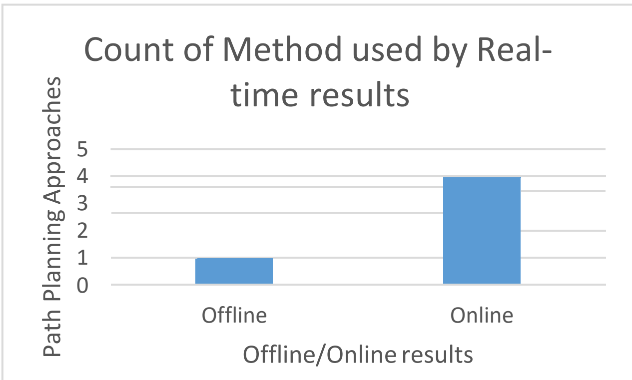

Fig. 13: Real-time results of path planning algorithms

Table 2 illustrates different parameters for different algorithm types.

Approach Used	**Algorithms in each method**	**Time Equations**	**Static/Dynamic Environments**	**Real-time Results**
Sampling based algorithms	Voronoi, RRT, PRM, K-PRM, S-PRM, Visibility Graphs, Corridor-Map, DDRRT, RRT*	$0(n * \log(n)) \leq T \leq 0(n^2)$	Static and Dynamic	Online
Node-based algorithms	Djikstra's Algorithms, A*, D*, LPA, Theta*, Lazy Theta*, D*-Lite, Harmony Search	$0(m * \log(n)) \leq T \leq 0(n^2)$	Static and Dynamic	Online
Mathematical model-based algorithms	Among them are non-linear programming, binary linear programming, mixed-integer linear programming and optimal control.	Depends on the mathematical equation.	Static and Dynamic	Online
Bio-inspired algorithms	shuffled frog leaping algorithm, particle swarm optimization, ant colony optimization, genetic algorithm, neural network	$T \geq 0(n^2)$	Static	Offline
Multi-fusion-based algorithms	VVP, Firefly-fuzzy algorithm, PRM-node based algorithm, GIS-MCDA algortihm, Visibility Graph Optimal algorithms based on nodes and visibility.	$0(n * \log(n)) \leq T$	Depends on the algorithm	Online

V. Conclusion

At this time, UAVs function efficiently in three-dimensional environments containing a multitude of obstacles, as demonstrated by the path planning methods analysed in this article. The objective is to provide an exhaustive analysis of 3D path planning for UAVs. This paper investigates five distinct type of approaches utilised in the 3D path planning of an unmanned aerial vehicle (UAV). Furthermore, the implementation of hybrid or multi-fusion-based methodologies is addressed in this work. The majority of the work is performed in static and dynamic environments, according to the results. A mathematical approach is the only method that conducts research by utilising equations derived and parameters considered. All bio-inspired algorithms draw inspiration from natural phenomena and have demonstrated efficacy in resolving diverse problems. In conclusion, the multi-fusion approach is superior to all others due to its ability to incorporate the benefits of multiple algorithms. In comparison to offline applications, the practicality of real-time results in online applications is considerable.

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