Journal of Robotics and Control (JRC)
Volume 5, Issue 2, 2024
ISSN: 2715-5072, DOI: 10.18196/jrc.v5i2.21540

Adaptive Vector Field Histogram Plus (VFH+) Algorithm using Fuzzy Logic in Motion Planning for Quadcopter

Khitam Mohammed [1*], Ali Aliedani [2], Alaa Al-Ibadi [3]
[1, 2, 3] Department of Computer Engineering, University of Basrah, Basrah, Iraq
Email: [1] engpg.khitam.mohamed@uobasrah.edu.iq, [2] ali.nabeel@uobasrah.edu.iq, [3] alaa.abdulhassan@uobasrah.edu.iq
*Corresponding Author

***Abstract*—This work introduces the adaptive version of the vector field histogram plus (VFH+) motion planning algorithm, which is designed for unmanned aerial vehicles, particularly quadcopters, to enhance its performance in navigation tasks. The method suggests incorporating fuzzy control to adaptively modify the VFH+ look-ahead distance parameter by analysis continuous environmental and motion conditions. Simulation tests were completed using different scenarios that varied in obstacle quantity, density, distribution, and size and waypoint quantity. Simulation results showed the successful outcomes of this strategy in enhancing quadcopter motion performance in various contexts. The results indicated notable enhancements in obstacle avoidance, smoother motion trajectories, and decreased travel time compared to the traditional VFH+ method. One of the most important aspects of creating real-time motion planning systems is handling uncertainty. This is accomplished by incorporating a fuzzy system knowledge base for automatic algorithmic modification into the planning process and employing advanced motion-planning techniques. The adaptive algorithm improves the quadcopter's ability to deal with high uncertainty levels by incorporating fuzzy logic for dynamic parameter adjustment, allowing for accurate and efficient navigation in various environments, even in uncertain conditions.**

***Keywords*—Quadcopter; Motion Planning; Fuzzy logic; Vector Field Histogram Plus VFH+ Algorithm; Parameters Tuning.**

I. INTRODUCTION

Quadcopters, also known as quadrotors or drones, are a specific class of unmanned aerial vehicles (UAVs) with the ability to vertically take off and land (VTOL). These UAVs are ideal for exploring remote regions and transporting necessary supplies to isolated locations due to their exceptional mobility and versatility in various scenarios [1][2]. Furthermore, UAVs have basic constructions and are reasonably priced. These factors have contributed to the rise in popularity of UAVs over conventional winged helicopters in recent years [3].

The geometry of a quadrotor aircraft consists of four independently mounted rotors on a rigid frame, as shown in Fig. 1. Quadrotor aircrafts can be found in a variety of forms and sizes, including the Parrot, Bebop, and foldable models. They are also coaxial quadrotors. These are little vehicles, limited by the speed at which their four rotors rotate. Two distinct quadrotor geometries are produced by the rotor position arrangements with respect to the main frame: the 'X' (cross) shape and the '+' (plus) shape, as shown in Fig. 2 [4][5].

In general, quadrotor technology is very useful for many applications because of its low cost, straightforward design, and VTOL capability, which is further improved by the use of sophisticated sensors and actuators. To maintain steady flight, non-consecutive rotors, each driven by a separate motor, spin in the same direction [6]. In surveillance and monitoring missions, quadcopters are essential because they provide the data necessary for border security, environmental monitoring, and firefighting operations [7]-[11]. They have been crucial in contactless food delivery services, particularly in tackling the issues posed by the COVID-19 pandemic [12][13]. They are also utilized in the provision of medical services by transporting medications and supplies to remote places.

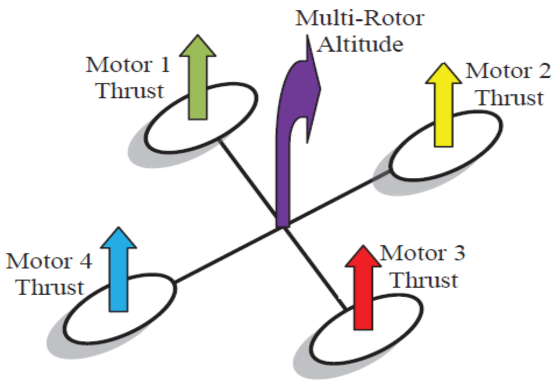

Fig. 1. The quadcopter structure [5]

Furthermore, their capacity to obtain excellent aerial photos is very helpful for aerial photography, enabling thorough evaluations of surroundings, infrastructure, and security situations [14].

Quadcopters contribute significantly to a variety of sectors and areas and offer creative solutions to logistical problems. These aerial robots can move independently to perform operations in challenging environments that are potentially hazardous or unreachable for human operators [15][16]. However, further technological obstacles must be removed before these UAVs can operate effectively and dependably in a variety of settings.

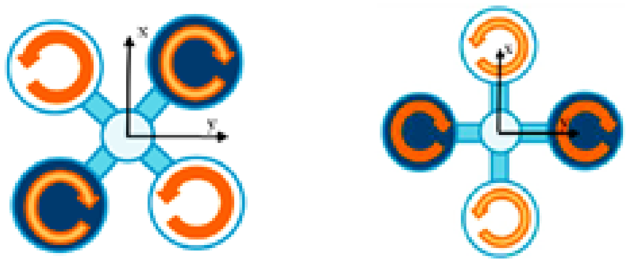

Fig. 2. Quadrotor configuration shape [4]

Motion planning is one of the most significant of these difficulties, as quadcopters must precisely coordinate their motions to prevent accidents and guarantee the effective completion of missions [17]-[20]. Motion planning for quadcopters is a major challenge that demands creative solutions for best results due to a number of technological issues. To efficiently determine an available path and provide a sufficient flight duration, it is necessary to find the best navigation paths and avoid obstacles as soon as possible. Short battery life may also make it difficult for the UAV to stay in the air and effectively complete certain tasks [21]-[24].

Moreover, it is imperative that the quadcopter avoid collisions with both stationary and moving obstacles. As a result, the quadcopter must create a safe path that shields it from any obstructions. Providing means for dynamic, successful plan revision becomes a requirement as surroundings change and new difficulties arise [25]. Energy consumption during flight time also represents one of the difficulties facing motion planning for quadcopters [26][27].

Thus, to achieve successful and efficient motion planning for quadcopters, a thorough examination of cutting-edge technological solutions that address these issues in depth and successfully is necessary.

Consequently, to allow UAVs to respond swiftly and efficiently to evolving issues, inventive motion planning methods are desperately needed. Planning activities may be made more effective, leading to smoother and more efficient navigation, by utilizing artificial intelligence technology and extensive analytical applications [27]-[31].

A variety of strategies have been suggested for UAV motion planning implementation. These methods are based on several factors, including the robot's capabilities, type of sensors, environment, and algorithms. They aim to progressively improve performance in terms of speed, distance, safety, cost, smoothness, and complexity [32][33]. Additionally, sensing mapping and replanning are other UAV planning strategies the literature discusses for operation under unpredictable environments [34]-[36]. Utilizing artificial intelligence extends to the enhancements to the vector field histogram (VFH) algorithm [37]. Specifically, artificial neural networks and fuzzy systems have been incorporated [38][39].

Technological breakthroughs have significantly changed how humans view the world and raised the bar for human–machine interaction by using complex control algorithms that convert human actions into numerical data that can be used in a variety of industrial domains.

Zadeh proposed fuzzy logic in 1965 to build and process models similar to those used by the human brain [40]. The goal of fuzzy logic is to simulate the complex, imperfect reasoning humans use to translate physical phenomena into information that computers or embedded systems can use. Fuzzy logic has been studied widely over the years due to its ability to solve complex issues without the need for explicit models. Furthermore, it has been effectively implemented in situations that were previously thought to be unbeatable. Within the FS domain, logic is defined in terms of sets. A fuzzy set is characterized by a range of membership grades. In contrast, classical sets are defined in terms of binary true or false values. Highly adaptive, fuzzy logic controllers are capable of handling a wide range of operating situations and various external and internal disturbances. Numerous fields find uses for fuzzy logic: antilock braking systems, cruise control systems, streamlined robotic control, automotive engine management, renewable energy management, aerospace propulsion, energy optimization, demand projection, predictive maintenance strategies, and more. The list is endless and serves as an example of fuzzy logic's adaptability and effectiveness in a variety of fields [41]-[44].

Thus, this work aims to explore and develop a new approach to quadcopter motion planning by integrating VFH plus (VFH+) algorithms with fuzzy logic to provide innovative solutions that contribute to overcoming technological challenges and enhancing quadcopters' ability to achieve optimal performance in various conditions and environments. The adapted and improved VFH+ overcomes the main shortcomings. The parameters were adjusted more interactively, with multiple different environmental conditions using fuzzy logic in this improved algorithm, so the proposed algorithm has the ability to avoid various obstacles in complex and simple environments, simultaneously improving the quadcopter's speed and success rate in reaching the target point while avoiding collisions. Due to the use of fuzzy logic to improve the algorithm, the improved algorithm proposed in this work was named FVFH+.

The main contribution of this article is the development and implementation of a motion planning system for the quadcopter using fuzzy logic. This system relies on an algorithm capable of adapting to changes in the system, enabling the drone to effectively deal with the variables in its environment. Similarly, a fuzzy controller can be incorporated into an inexpensive embedded system due to the ease of modifying and adapting the code.

Furthermore, the algorithm is designed to generate seamless, unobstructed trajectories for the quadcopter to navigate, demonstrating exceptional efficiency and rapid decision-making capabilities.

Thus, this article represents a significant contribution to the field of developing control systems for drones using fuzzy logic, providing a comprehensive system capable of adapting to changes and making fast and efficient decisions, which enhances the drone's ability to smoothly and accurately navigate different environments. The paper covers three primary sections. The first section reviews current histogram motion planning techniques and outlines their advantages and drawbacks to give a comprehensive overview of the approach and draw attention to any existing research gaps. These qualities are described based on the published research of the developers of the algorithms. The second section focuses on adapting histotrophic methods to ensure the robot moves smoothly and responds well to challenges. The final section contains results from experiments and testing of the presented algorithm. The flowchart for the study technique is shown in Fig. 3.

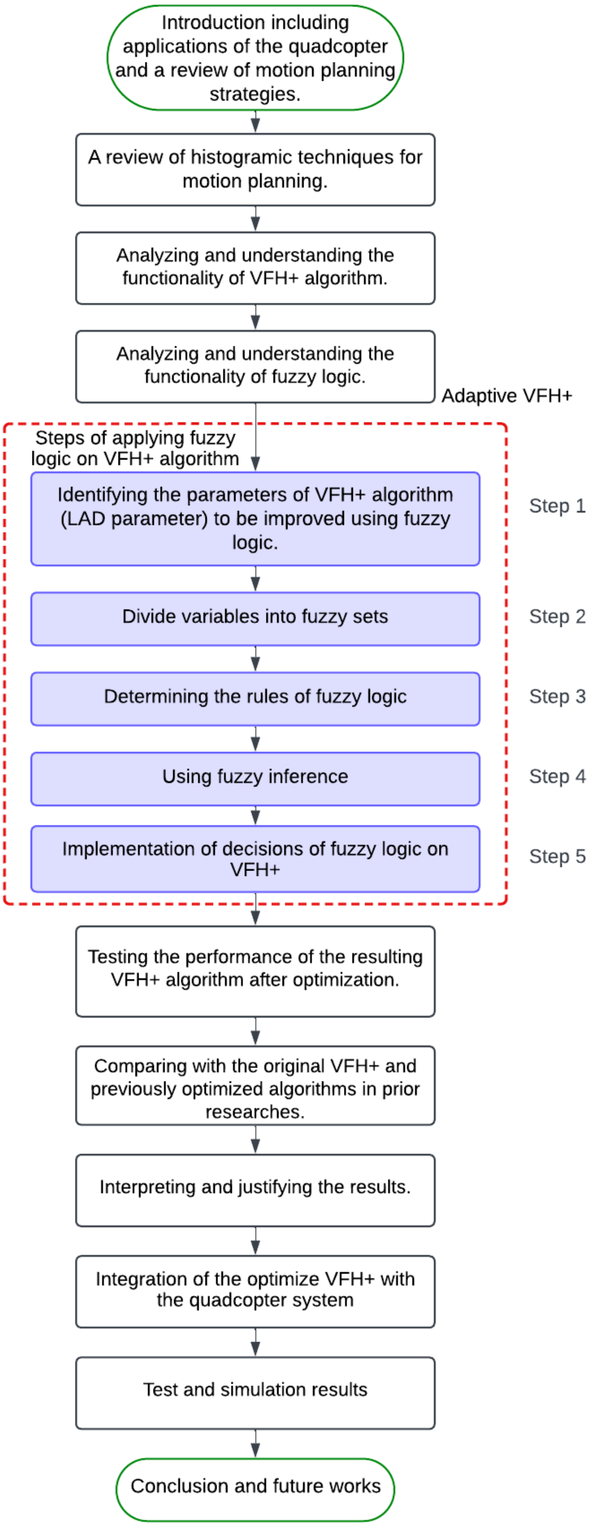

Fig. 3. The flowchart for the study technique

II. Overview of Motion Planning Using Vector Field Histogram Methods

For autonomous unmanned aerial vehicle (UAV) motion planning, histogram navigation techniques are essential for efficient path planning and obstacle avoidance. With the use of histograms, these techniques make use of data representation to help UAVs, such as quadcopters, make intelligent decisions by interpreting environmental information. Historic navigation techniques enable unmanned aerial vehicles (UAVs) to navigate intricate terrain on their own by generating spatial representations of the surrounding environment and avoiding obstacles while following predetermined paths.

Through the utilization of histograms to incorporate environmental information, these techniques facilitate UAVs' agile and precise navigation of intricate terrains, hence creating opportunities for applications in domains like airborne surveillance, mapping, and search-and-rescue. The rising advancement of UAV technology will mean that histogram navigation techniques will become more and more important in improving the autonomy and effectiveness of unmanned aerial systems.

Various methods for original vector field histogram method in a static environment have been developed, primarily designed for ultrasonic sensors.

In the following paragraph, a comprehensive examination of the majority of enhancements to both the original and VFH+ methods, as scrutinized by researchers, has been presented. We discussed the strengths and weaknesses of each method to pinpoint gaps and endeavor to address them in the algorithm proposed herein. It's notable that these algorithms offer extensive customization options, as evidenced by earlier studies and the range of adaptations detailed in subsequent paragraphs.

The standard Vector Field Histogram (VFH) was introduced in 1991 by J. Borenstein. This method offers the advantage of guiding a robot through narrow passages and alongside obstacles with balanced, oscillation-free movement. However, this method lacks consideration for the robot's dynamics and dimensions. To address this limitation, the VFH+ method was introduced, incorporating these factors into data reduction processes [45].

AH Hamad (2010). presented an improvement of the VFH algorithm using a neural network and a fuzzy algorithm to overcome its limitations to increase target guidance to improve the path planning of the mobile robot. This work modifies the vector field method (VFH) to enhance the path planning of a mobile robot using a neural-fuzzy algorithm, allowing it to traverse and avoid obstacles in a range of situations with efficiency. For obstacle detection, the system builds a backpropagation neural network, and for obstacle topology, it employs a different self-learning model. By utilizing the expertise of human experts, the fuzzy technique is utilized to direct the robot towards its intended destination. The method has difficulties with computational complexity, high training requirements, and sensitivity to parameter adjustment, even if it is good at avoiding obstacles and flexible in adapting to different settings [46].

BL Kazim (2010) introduce Modified Vector Field Histogram (MVFH) algorithm. This technology has been created to improve the process of determining the most efficient path and avoiding obstacles for a mobile robot. The algorithm relies on the concept of the "vector space" and demonstrates effectiveness in addressing environmental challenges, leveraging a neural network model to learn critical environmental conditions. The obstacle avoidance path is improved through the use of a digital filter, albeit requiring additional time. The complexity of the environment influences the time needed to reach the goal [47].

A. Babinec (2012) introduced an enhancement on the vector field histogram algorithm for mobile robot motion planning by substituting ultrasonic sensors with the Hokuyo URG-04LX Laser Distance Measurer, leading to enhanced distance measuring precision. The research enhances robot motion planning by using a laser scanner as the main sensor, which improves environment scanning accuracy and navigation precision in the vector field approach. The study suggests a VFH*-based technology that allows the robot to identify and evade moving impediments. Although these improvements have been successful in obstacle avoidance and navigation accuracy, consistently identifying moving obstacles is still a difficulty. The primary challenge is efficiently using the laser scanner to detect the positions, orientations, and velocities of moving obstacles, which may affect the effectiveness of obstacle avoidance. Implementing modifications to the VFH approach presents difficulties in algorithm development and may necessitate thorough testing to guarantee accurate functionality. This approach faces implementation challenges and requires comprehensive testing to guarantee precise functionality [48].

J. Senthil (2016) introduced a technique for motion planning of mobile robots in dynamic environments using the Vector Field Histogram (VFH) algorithm with the Spartan 3 FPGA processor. The advantages are the capability to navigate around obstacles and advance smoothly towards the destination due to the VFH algorithm and the effectiveness of parallel operation of the FPGA processor. The approach suffers difficulties in parameter tuning for good performance and is constrained in flexibility and scalability because it relies on hardware implementation [49].

Y. Yan, (2018) introduced VFH#, a local path planning method for intelligent vehicles, effectively navigating obstacles by addressing limitations in the previous VFH method. VFH# enlarges obstacles to avoid collisions, improves sensitivity issues, and achieved excellent results on an electric vehicle. While promising, there are still areas for improvement, highlighting the need for further research and refinement [50].

I. Ulrich (1998) developed and implemented the VFH algorithm to enhanced Vector filed histogram plus (VFH+). The VFH+ method selects free directions based on the maximum achievable robot speed, considering track circuits if applicable. It also addresses graph smoothness and allows for objective function modification, resulting in customizable robot behavior tailored to specific requirements. However, both VFH and VFH+ methods pose a challenge when the robot must choose between equal chances to avoid obstacles, as they lack foresight regarding future movements [51].

J. Gong, (2007) presented improved method based on VPH+ algorithm for local path planning in mobile robots using laser radar. By organizing identified problem locations into blocks, the technique enhances obstacle avoidance and allows for proactive avoidance of obstacles that are closer than is acceptable while preserving flexibility in restricted areas. VPH+ creates smoother trajectories by integrating a time-oriented cost function that takes into account the robot's speed and heading deviation from the objective direction. This optimizes the robot's path for the least amount of time needed to reach the goal. However, additional research may be necessary to ensure wider applicability and robustness due to issues like implementation difficulty and susceptibility to environmental changes [52].

I. P. Sary (2018) applied the Vector Field Histogram Plus (VFH+) algorithm to the field of obstacle avoidance for unmanned aerial vehicles. For obstacle avoidance, the VFH+ algorithm calculates steering angles by analyzing distance readings from lidar sensors. Utilizing the VFH+ algorithm has advantages such as its ability to produce steering commands in real time, allowing UAVs to safely navigate through obstacle-filled areas. Furthermore, the algorithm's potential for real-world implementation is illustrated by its successful use in simulation settings, as exemplified by the Gazebo environment running on RoS. To be robust in a variety of real-world circumstances, additional research may be necessary due to potential implementation complexity and susceptibility to environmental changes, among other restrictions [53].

Danial D. (2020) introducing a modified version named Vector Field Histogram +Dynamic (VFH+D), which exceeds the original version in navigating around moving obstacles, enhancing the robot's velocity, and increasing its efficiency in reaching destinations while preventing collisions. The update includes the implementation of cell occupancy decay and a new equation for obstacle vector size, simplifying parameter adjustment and reducing the number of iterations needed. Experiments showed that VFH+D improved performance by decreasing the average distance required to reach the target and increasing the average speed, making it more suitable for smart mobility applications. Using VFH+D effectively necessitates precise parameter control to maintain consistent performance and prevent bottlenecks in direct navigation. However, with this method, VFH+ failed to reach the target in 7 out of 10 trials [54].

B. Lee, (2023) presented a novel approach to improve robot navigation by utilizing data from several LiDAR sensors to accomplish full-spectrum sensing in all directions. This strategy enhances obstacle avoidance and increases navigation efficiency. Advantages include increasing the sensor range, streamlining the conversion process, and improving robot control and performance. Possible disadvantages of the suggested approach may involve process intricacy, resource use, programming complexities, and difficulties in cost management, which require additional research for a thorough assessment [55].

In conjunction with other global planning techniques, VFH+ is frequently utilized as a local planner to offer a dependable solution to the navigation problem. This is because it is quick and robust in obstacle avoidance. The biggest weakness in the VFH+ algorithm is that it requires fine-tuning of many parameters, which can be a challenge in many applications [47][56].

For UAVs and especially for quadcopters, if the advance parameters especially look ahead distance is not fine-tuned, this leads to the algorithm being unable to make effective decisions quickly, especially in complex environments [57]. Therefore, we seek in this research to develop an algorithm to solve these problems and gaps.

The research studies are summarized and compared in Table I. This table compares researchers' studies on using and improving the VFH algorithm in the field of movement planning for robots while avoiding obstacles, as well as clarifying the strengths and weaknesses of the original algorithms before improvement, as each technique is presented to improve the algorithm's skills in a specific context. The table shows the pros and cons of each approach. This comparison highlights the differences and advantages between the methods, providing readers with a comprehensive understanding of the different methods and the challenges they may face in the field of movement planning while avoiding obstacles using the histogram methodology.

TABLE I. COMPARISON OF STUDIES VFH ALGORITHM FOR ROBOT MOTION PLANNING

Ref.	Researcher and Year	Method Used	Advantages	Limitation
[45]	J. Borenstein (1991)	VFH	• Minimal computational requirements.	• There are no considerations about geometry. • There is no concern given to the velocity of the robot. • Specifically engineered for ultrasonic sensors. • The active window has a square form. • Execution in a stable or unchanging setting.
[46]	AH Hamad (2010)	VFH with neural-fuzzy	• Increased target guidance and improved path planning efficiency for mobile robots. • Efficient obstacle avoidance in various scenarios.	• Computational complexity and high training requirements. • Sensitivity to parameter adjustment.
[47]	BL Kazim (2010)	Modification of VFH (MVFH)	• Improved path planning and obstacle avoidance for mobile robots. • Effectiveness in addressing environmental challenges and improving obstacle avoidance path.	• Increased time required to reach the goal in complex environments.
[48]	A. Babinec (2012)	VFH with Hokuyo URG-04LX Laser Distance Measurer	• Enhanced distance measuring precision. • Improved environment scanning accuracy and navigation precision. • Ability to avoid dynamic obstacles using VFH* technology.	• Continuous challenge in identifying moving obstacles using laser scanner. • Difficulties in implementing and comprehensive testing.
[49]	J Senthil (2016)	VFH with Spartan 3 FPGA processor	• The capability to navigate around obstacles. advance smoothly towards the destination. • Effectiveness of parallel operation of the FPGA processor	• Difficulties in parameter tuning for good performance. • Constrained in flexibility and scalability • Relies on hardware implementation.
[50]	Y Yan (2018)	Modification of VFH (VFH#)	• Improves obstacle avoidance and sensor sensitivity.	• Need for further research and improvements to enhance algorithm performance.
[51]	Borenstein and Ulrich (1998)	VFH+	• Geometry consideration. • The highest possible robot velocity consideration.	• Designed with ultrasonic sensors in consideration. • The active window's form is square. • Working in a fixed environment.
[52]	Gong (2007)	VPH+	• Enhances obstacle avoidance • Proactive avoidance of obstacles closer than acceptable • Preserves flexibility in restricted areas • Creates smoother trajectories • Integrates time-oriented cost function • Optimizes path for minimal time to reach goal	• Implementation difficulty • Susceptibility to environmental changes
[53]	Sary (2018)	VFH+	• Produces real-time steering commands • Safely navigates UAVs through obstacle-filled areas • Successful simulation uses in Gazebo environment running on ROS • Potential for real-world implementation	• Implementation complexity • Susceptibility to environmental changes
[54]	Danial D. (2020)	Modification of VFH+ with cell occupancy decay and a new equation for obstacle vector size	• Improved performance in dynamic obstacle avoidance. • Increased speed in reaching the target. • Simplification of parameter adjustment • Reduction in required iterations.	• Failure to reach the target in some trials.
[55]	B Lee (2023)	EVFH+	• Expands sensing range. • Simplifies conversion process. • Enhances robot control and performance	• Process complexity. • Resource consumption. • Programming intricacies. • Cost control challenges. • Further studies required for comprehensive evaluation

Table I presents a comprehensive comparison of several techniques employed in motion planning using the VFH algorithm, highlighting its strengths and constraints. To summarize, these methods provide varied benefits in the field of motion planning for robots, but they also have specific constraints that must be resolved for maximum performance in diverse situations.

The utilization of fuzzy logic technology can effectively tackle numerous issues and constraints faced in the motion planning of unmanned aerial vehicles (UAVs). Fuzzy logic can be employed to construct adaptive models that exhibit enhanced responsiveness to environmental changes. These models incorporate fuzzy knowledge to predict risks and dynamically adjust the path of unmanned aerial vehicles (UAVs) based on real-time sensor data.

Moreover, the VFH+ algorithm with fuzzy logic can enhance precision in distance determination and dynamic obstacle avoidance, resulting in the creation of avoidance paths that are both more precise and effective.

In addition, fuzzy logic can be employed to create control models that exhibit enhanced adaptability to variations in parameters and environmental variables, hence diminishing the system's susceptibility to parameter modifications.

The utilization of the VFH+ algorithm in conjunction with fuzzy logic can augment the system's capacity to swiftly and precisely make judgments in real-time, hence enhancing the efficiency of motion planning and obstacle avoidance.

By using these sophisticated methodologies, the efficiency of UAV control systems can be heightened, enhancing their capacity to adjust to variations in the surroundings and swiftly and efficiently make judgments to avoid obstacles [58]-[61].

III. Vector Field Histogram Plus VFH+

The VFH+ approach incorporates additional improvements to facilitate path planning and achieve better performance for obstacle avoidance. VFH+ employs a data reduction process across four stages to determine the most optimal direction towards the goal, building upon the VFH algorithm. The first three stages are utilized to construct a one-dimensional polar histogram based on a two-dimensional grid graph. The final stage is then used to determine the steering direction depending on the cost function and polar histogram [62]-[67].

By accounting for the drone's width and possible trajectories, the vector histogram plus (VFH+) method enhances the VFH algorithm. Instead of using the two-stage data reduction that the VFH algorithm utilizes, the VFH+ method uses a four-stage approach to achieve this. The two-dimensional Cartesian histogram grid is used by the VFH+ method to produce a one-dimensional main polar histogram in the first step, which accounts for the robot's breadth. When the primary polar histogram is generated, each obstacle cell in the active zone is increased to account for the robot's breadth. Each obstacle cell is expanded by the width of the quadcopter plus an extra safety zone. Therefore, r_{q+s}, where $r_{q+s} = r_{quadcopter} + r_{safety}$, is the safety area surrounding the obstacle as shown in Fig. 4 [68][69].

In order to generate primary polar histograms in the first, second, and third stages—as well as steering candidate directions VFH+ uses computational data that includes a histogram grid. The following stages are taken by the VFH+ algorithm:

A. Histogram Grid

For the ensuing computations, only the cells in an active window. Given that the center of the robot is situated in the middle of the active window's square form $w_s \times w$, the number of cells on the edge of the active window must be odd. The number of cells on the border of the active window and the number of sectors (k) are empirical parameters that are optional and dependent on a variety of variables, including the robot's reaction time. Fig. 5 illustrates an active window split into angular parts [70].

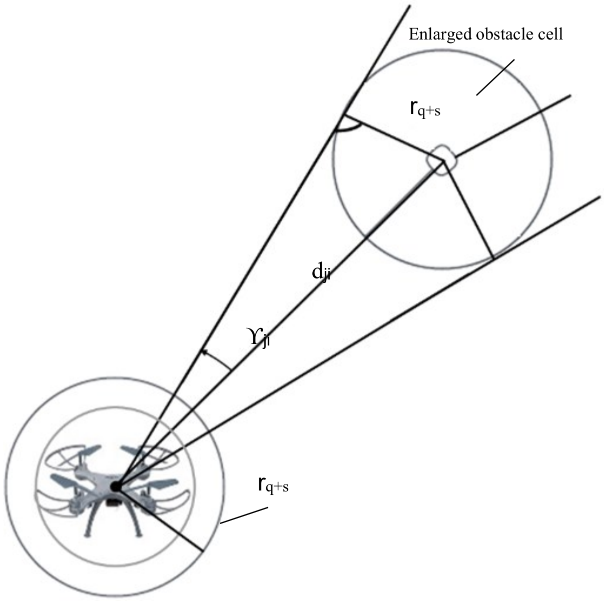

Fig. 4. The safety zone and width of the quadcopter (robot) are enlarging the obstacle

Equation (1) expresses the direction of an obstacle vector (β) from an active cell to the Vehicle Center Point (VCP) for each active cell (i, j) inside the 2D histogram grid:

$$\beta_{i,j} = tan^{-1}\left(\frac{y_i - y_0}{x_i - x_0}\right) \tag{1}$$

Where, x_0, y_0 are the quadcopter's current position coordinates, x_i, y_i are the active cell's coordinates.

In the original VFH technique, the robot's next step direction is determined by looking at only one histogram. In contrast, the VFH+ approach creates three histograms one at a time. Equation (2) is used to produce the first polar histogram, known as the principal one (H_p):

$$H_k^p = \sum_{ij=c*} m_{ij} \,.\, h'_{ij} \qquad i;\ j \in k \tag{2}$$

The coordinates of the active cell c^* in the active window C^* are represented by the values i and j, whilst the index k indicates the sector number.

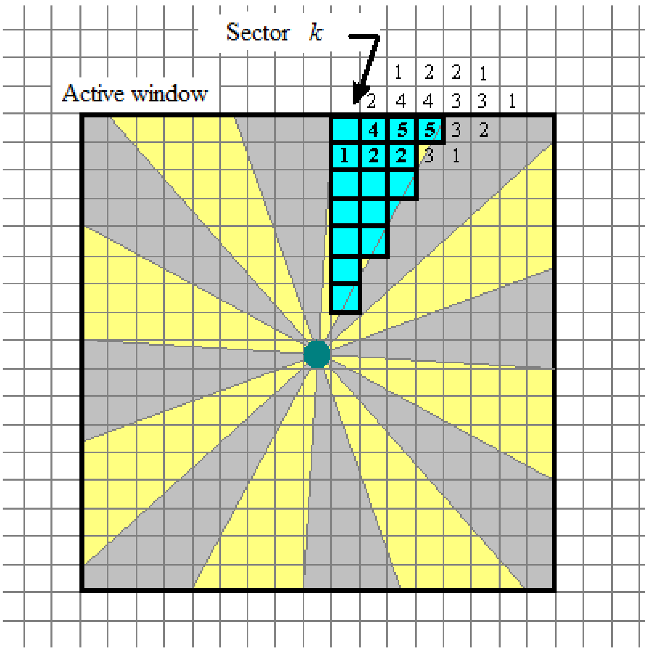

Fig. 5. Histogram Grid [66]

B. First stage Histogram Polar

The sensor that measures distances at each angle resolution d_i yields the Histogram Polar H_k^p. In an active window, the magnitude m_i and angle β_i of lidar sensor data are analyzed. The quadcopter's obstacles' positions (x_i, y_i). may be determined from the sensor readings. The quadcopter's location (x_0, y_0) is the source of β_i and the obstacle to the current window (x_i, y_i). One may use Equation (1) to write angular equations β_i Equation (3) represents the magnitude m_i of the certainty value measurement sensor c^*, along with the distances d_i in the active window:

$$mi = \left(c_{i,j}^*\right)^2 . \left(a - b . d_{i,j}^2\ d_i\right) \tag{3}$$

Where a, b are positive constants, $c_{i,j}^*$i; j the active cell's (i, j) confidence value, $d_{i,j}$ is the distance between the VCP and the active cell (i, j).

C. Second Stage Histogram Binary

After getting a polar histogram, the process of histogram binary H^b is performed. This technique makes advantage of data processing, such as hysteresis properties, where the tuning process yields the lowest threshold T_{low} |and maximum threshold T_{high} | . In order to transform polar obstacle density (POD) into binary numbers, open (0) and closed (1)[71].

$$h_{k.i}^b = 1\ \ if\ h_{k.i}^p\ > Thigh$$

$$h_{k.i}^b = 0\ \ if\ h_{k.i}^p\ < T_{low}$$

$$h_{k.i}^b = h_{k.i-1}^b \quad \text{Others}$$

D. Third Stage the Masked Polar Histogram

The masked polar histogram H_m is used to determine if a region is possible for the robot to pass through based on its circular movement when avoiding obstacles, as seen in Fig. 6 [72][73].

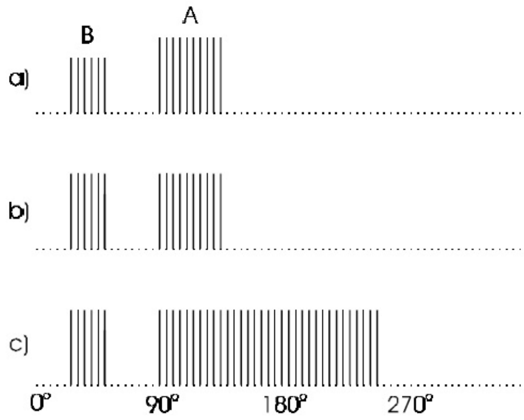

Fig. 6. The Primary polar histogram, binary polar histogram, and masked polar histogram representations [51]

E. Forth Stage Steering Direction

Based on the various candidate directions the VFH+ algorithm determines which direction to drive the robot in, as shown in Fig. 7.

Fig. 8 illustrates that the VFH+ algorithm's functioning might be summarized using a flowchart.

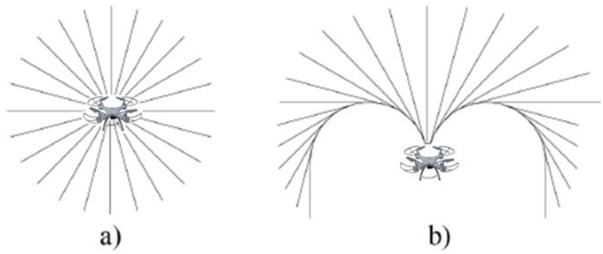

Fig. 7. Quadcopter (robot) trajectories

IV. Fuzzy Logic

Numerous real-world applications have made use of the fuzzy logic system. Fuzzy logic systems are utilized to derive sophisticated non-linear systems since they are non-linear expressive systems between input and output variables. The process of designing a control system begins with the analysis and formulation of the dynamic behavior of the system that has to be regulated. Next, a control algorithm is developed with the aim of accomplishing predetermined control objectives. In essence, the majority of genuine systems in the world are conformal. Unlike conventional probabilistic models, fuzzy logic systems operate on a distinct premise. Systems using fuzzy logic operate without assuming anything about the operation of a probability distribution model. Because of this distinction, unstable systems can benefit greatly from the fuzzy logic system [72]-[74].

Fuzzy logic (FL) is one of the algorithms used in obstacle avoidance. Fuzzy algorithms use a method similar to how people come at questionable conclusions. Robots or autonomous systems can decide what is the "truth" or "untruth" of a situation by using fuzzy logic [75][76]. The system can listen for and react to sensory data under specific conditions thanks to this algorithm. Robots that employ fuzzy logic for obstacle avoidance are able to make judgments based on data, including speed and distance and can react cautiously enough to the information they receive [77]-[79].

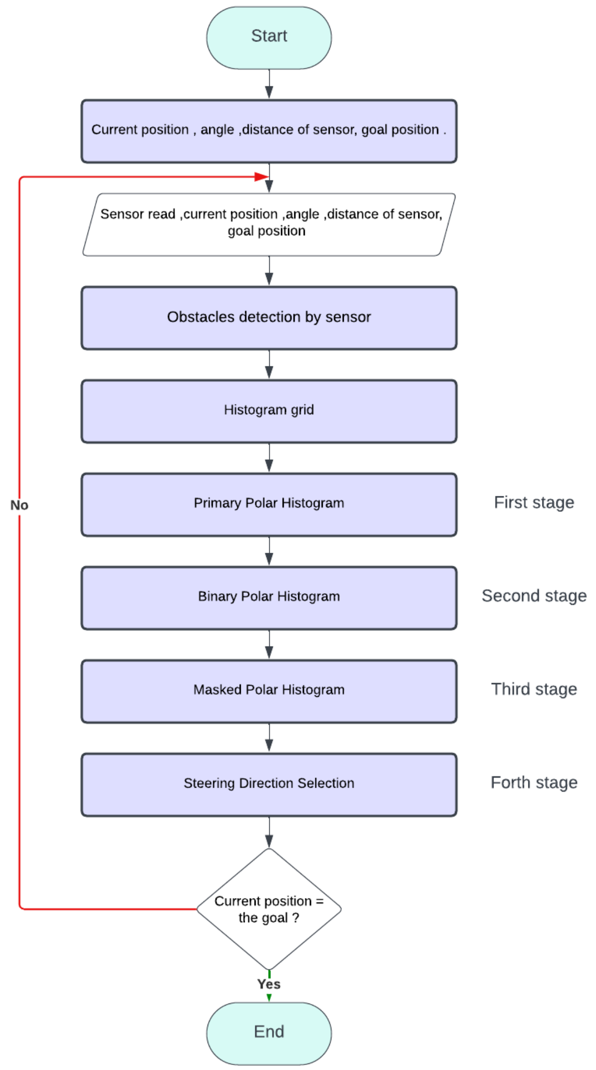

Fig. 8. VFH+ algorithm flowchart

The fuzzy logic system is a logical system that is based on the principles of ambiguity and handling imprecise or ambiguous situations. The objective of this system is to handle and analyze ambiguity and uncertainty in information by employing a collection of linguistic and logical rules that assess performance based on a set of explicit criteria.

The process of working with fuzzy logic can be elucidated by the following steps:

- Identifying Fuzzy Variables: First, we determine the variables that are manipulated or assessed using fuzzy logic. These factors may encompass the level of obstacles present in the environment and the concentration of path points.
- Fuzzy Range Division: Fuzzy variables are partitioned into a collection of fuzzy values, such as "low," "medium," and "high."
- Constructing Knowledge Base: A collection of language rules is established to govern the decision-making process, taking into account the imprecise values of the variables. For instance, if the density of obstacles is low and the number of path points is low, then it is advisable to reduce the lookahead distance.
- The fuzzy inference process utilizes knowledge rules and fuzzy variables to produce fuzzy outputs according to the given inputs.
- Fuzzy Processing Operation: Following the fuzzy inference, the fuzzy outputs are transformed into actual values or close approximations of actual values using a fuzzy logic inference engine.
- Utilization of Fuzzy Rules: The fuzzy rules employ the actual outputs and suggested values to enhance the system by making decisions and implementing algorithms.

These processes are applicable not just in this system but also in several domains such as smart systems, robot control, industrial control systems, and decision support systems.

V. Adaptive VFH+ by Fuzzy Logic

In this research, we implemented and tested an algorithm optimized by fuzzy logic for quadcopter navigation in an unknown workspace. The developed fuzzy control system features two inputs and one output. Fuzzy logic rules were manually mapped to represent human knowledge and address real-time needs of our algorithm. The system autonomously determines an appropriate fuzzy lookahead distance, calculated based on inputs reflecting environmental conditions and their changes.

Our efforts to enhance the VFH+ algorithm led us to a research initiative focused on integrating fuzzy logic to optimize the selection of the predefined lookahead distance a critical parameter in the algorithm [46][79]. Initially, we engaged in manual tuning using trial and error methodologies across diverse environments, varying in obstacle density and the number of waypoints, both directly influencing the optimal lookahead distance. To elevate the system's intelligence, we introduced fuzzy logic for autonomous decision-making, leveraging real-time environmental data. The fuzzy logic framework enabled the creation of a self-adapting system capable of dynamically adjusting the lookahead distance based on surroundings. This approach empowers the algorithm to navigate environments with varying complexities, ensuring efficient obstacle avoidance and path planning [80]-[84]. The system of motion planning using fuzzy logic and the construction of fuzzy system are shown in Fig. 9 and Fig. 10.

The seamless integration of fuzzy logic into the VFH+ algorithm results in a significantly improved system that autonomously adapts to different scenarios, achieving a more intelligent and versatile robotic navigation capability. This fusion not only enhances adaptability but also establishes the groundwork for autonomous decision-making in dynamic and unpredictable environments.

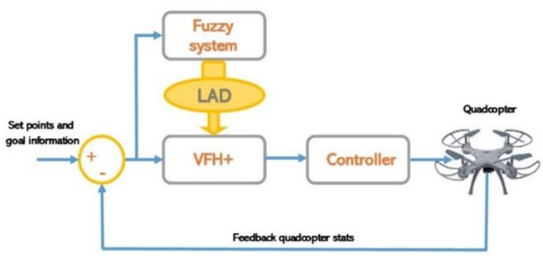

Fig. 9. Motion planning system for quadcopter

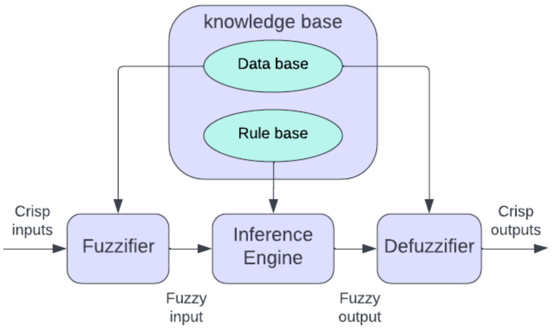

Fig. 10. The construction of fuzzy system authors and affiliations

A. *Look Ahead Distance Based on Fuzzy Logic*

Our fuzzy logic system, with inputs of obstacle density and path waypoints, outputs an adaptive lookahead distance in quadcopter navigation Fig. 11, Fig. 12, and Fig. 13 respectively.

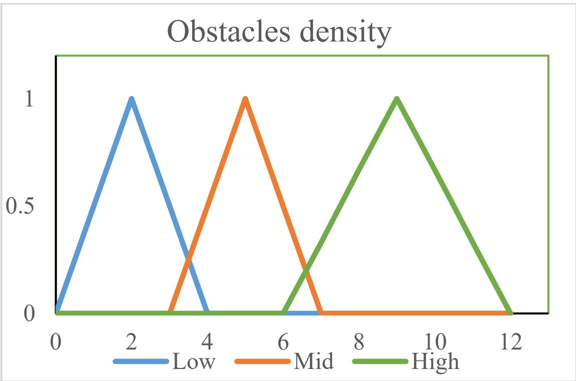

Fig. 11. First Input of Fuzzy system obstacle density membership

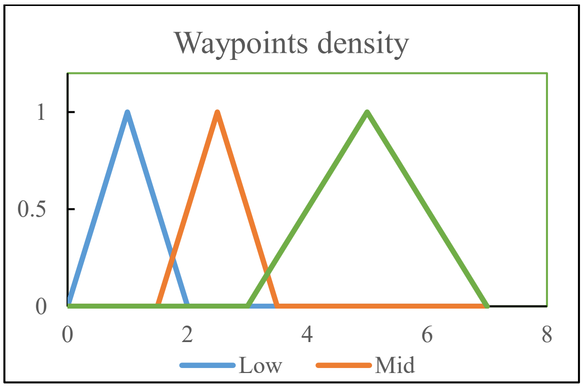

Fig. 12. Second Input waypoints density membership of fuzzy system

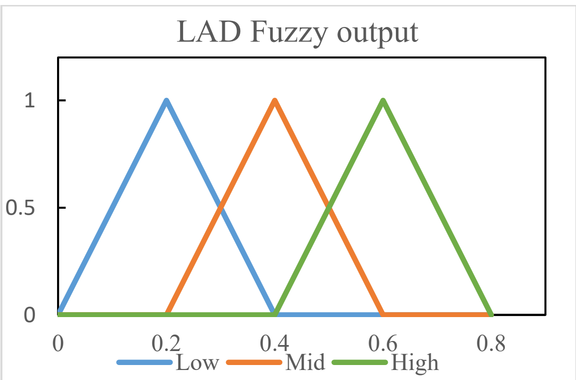

Fig. 13. Output of fuzzy system look ahead distance membership

The fuzzy rule base is shown in Table II. This system dynamically adjusts the lookahead distance based on real-time changes in environmental conditions, enhancing adaptability in varying obstacle densities and path complexities. Integrated into the VFH+ algorithm, this approach contributes to intelligent and autonomous decision-making, establishing a robust foundation for versatile robotic navigation.

TABLE II. FUZZY RULE BASE

Obstacle No. / Waypoint No.	L	M	H
L	L	M	H
M	M	M	L
H	L	H	H

The input obstacles and waypoints are defined with linguistic variables ***Low(L), Mid(M), High(H)***, while considered as a triangular type. The Fuzzy inference rules for selecting the winning LAD are as follows:

*If obstacle density is **L** AND waypoints is **L** Then LAD is **L**.*
*If obstacle density is **M** AND waypoints is **L** Then LAD is **M**.*
*If obstacle density is **H** AND waypoints is **L** Then LAD is **H**.*
*If obstacle density is **L** AND waypoints is **M** Then LAD is **M**.*
*If obstacle density is **M** AND waypoints is **M** Then LAD is **M**.*
*If obstacle density is **H** AND waypoints is **M** Then LAD is **L**.*
*If obstacle density is **L** AND waypoints is **H** Then LAD is **L**.*
*If obstacle density is **M** AND waypoints is **H** Then LAD is **H**.*
*If obstacle density is **H** AND waypoints is **H** Then LAD is **H***

The algorithm was tested in several different environments to comprehensively evaluate its performance. Nine different scenarios were selected, representing a diverse range of environments with varying obstacle densities and numbers of path points.

These scenarios encompassed a spectrum of obstacle densities, ranging from low to medium to high, as well as a variation in the number of path points, including scenarios with few, moderate, and many points.

Through these tests, the algorithm's responsiveness and performance were assessed across different environments, considering transportation requirements and distances required to reach the final destination.

This information was utilized to fine-tune the fuzzy logic rules and improve the algorithm's performance in each scenario, ensuring its optimal adaptation to changes in the environment and surrounding conditions.

VI. TEST AND SIMULATION RESULT

Utilizing the MATLAB statistical analysis program in a simulation environment is the optimal method for examining and analyzing the technologies utilized for the flying of UAVs, particularly quadcopters. The motion planning of these UAV was investigated in the research, and they were operated along a predetermined trajectory with the capability to manipulate the UAV's equations in order to reach the intended destination without facing any obstacles.

To assess the performance of the enhanced algorithm, multiple environments were utilized in a MATLAB simulation system, incorporating obstacles of various shapes, sizes, and quantities, along with numerous path points. The quadcopter's goal and initial location were established for each environment, and the quadcopter's position was monitored using on-board sensors.

Numerous simulations were conducted for each scenario, exceeding a hundred trials for both the traditional and improved algorithms, as outlined in Table III, maintaining identical initial conditions across all tests. The traditional VFH+ algorithm achieved success in reaching the target in only 80 out of 100 simulations, as detailed in Table IV. Fig. 14 to Fig. 22 illustrate the paths taken in each of the nine fuzzy logic cases, comparing them with the outcomes of the traditional algorithm. The prior looking distance value was fixed at the optimal value for each case, determined through experimentation and testing.

Our findings suggest that the proposed FVFH+ algorithm boasts a higher success rate in navigating congested indoor environments, a quicker arrival rate, a reduced deviation rate from the original path, and, in most instances, a relatively shorter path length. These improvements stem primarily from algorithmic enhancements, allowing for real-time adjustments to the traveler's advance view during flight based on encountered conditions such as obstacles. In interpretation, we posit that the improved algorithm incorporates more effective information, facilitating more accurate decision-making regarding the optimal path to follow.

TABLE III. SUCCESS RATE TO REACH THE GOAL

Algorithm	Trials	Success rate	Obstacle collision
VFH+	100	80%	80%
FVFH+	100	100%	100%

The number of waypoints and obstacles in each of the nine environments varied during the experiments, which resulted in variations in the path's length, travel duration, and optimal Look-Ahead distance. The configurations are as follows:

- The first environment has a small number of waypoints and few obstacles.
- The second environment has a few waypoints and a moderate number of obstacles.
- The third environment has a small number of waypoints and a lot of obstacles.
- In the fourth scenario, there are a moderate number of waypoints and few obstacles.
- The fifth environment comprises a moderate quantity of waypoints and obstacles.
- The sixth setting has a fair number of obstacles and a high number of
- There are a lot of waypoints and few obstacles in the seventh environment.
- There are a lot of waypoints and a medium number of obstacles in the eighth environment.
- A lot of waypoints and obstacles can be found in the ninth environment.

Fig. 14 to Fig. 22 successively display the simulation results for each of the nine fuzzy logic situations, which correspond to the various environments. These simulation results show the paths followed by the optimized algorithm in comparison to the traditional method's simulation results. Table V presents a summary of the findings for each scenario in terms of path length, time, and error rate.

Simulations of the improved algorithm were implemented using fuzzy logic in various environments, each characterized by different obstacle and path point densities. The density of obstacles and path points directly influences the determination of the prior looking distance, which is then compared to the traditional method that employs a fixed prior looking distance length. The flight period is predetermined before the start of the flight.

The Table IV provides data for every technique, including the variables' minimum (min), maximum (max), average (avg), and standard deviation (stdev) values. By highlighting elements like path planning and execution accuracy and efficiency, the data provides an understanding of the performance characteristics of the algorithms in the examination.

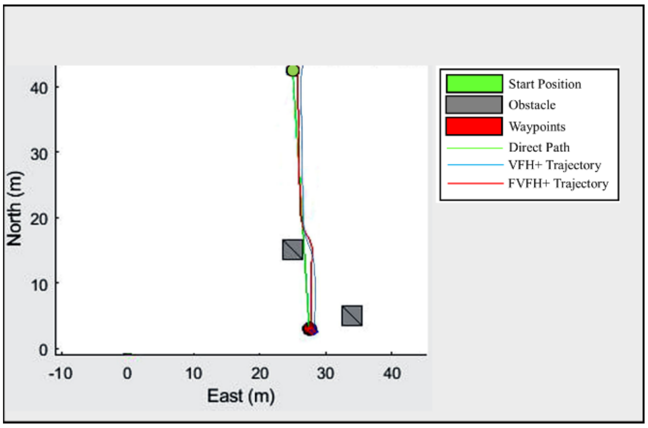

Fig. 14. Simulation result of quadcopter motion planning in environment with low number of obstacle and low waypoints using VFH+ and FVFH+

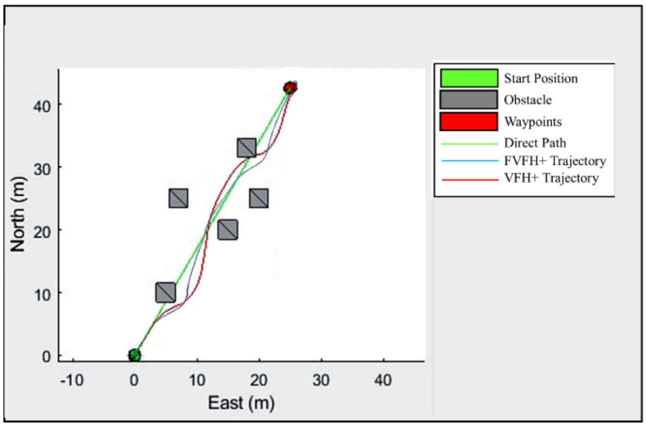

Fig. 15. Simulation result with medium number of obstacle and low waypoints using VFH+ and FVFH+

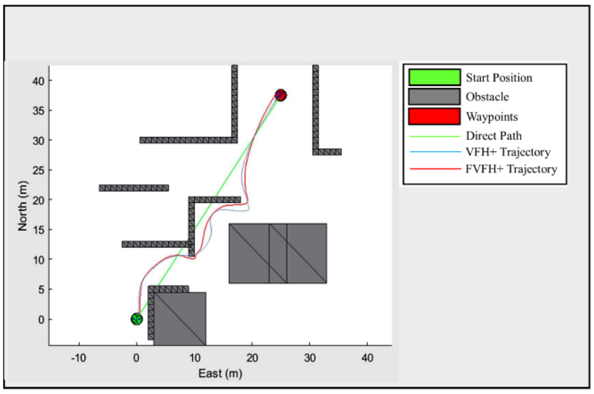

Fig. 16. Simulation result with high number of obstacle and low waypoints using VFH+ and FVFH+

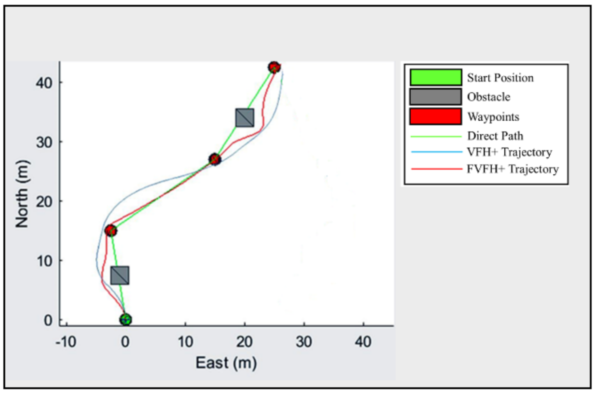

Fig. 17. Simulation result of quadcopter motion planning in environment with low number of obstacle and medium waypoints using VFH+ and FVFH+

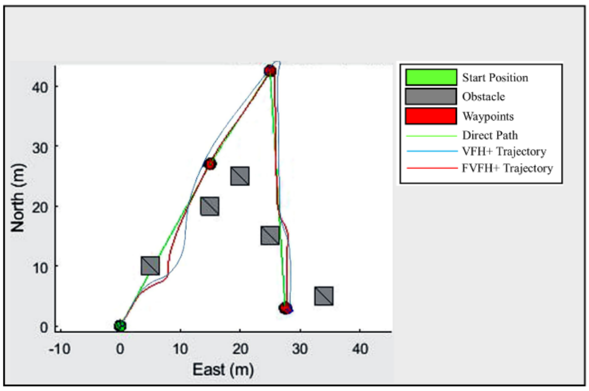

Fig. 18. Simulation result with medium number of obstacle and medium waypoints using VFH+ and FVFH+

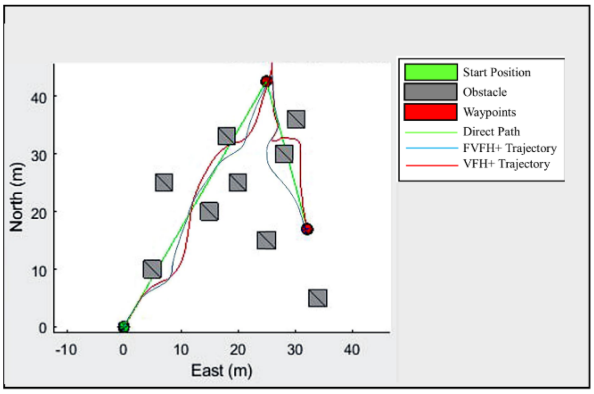

Fig. 19. Simulation result with high number of obstacle and medium waypoints using VFH+ and FVFH+

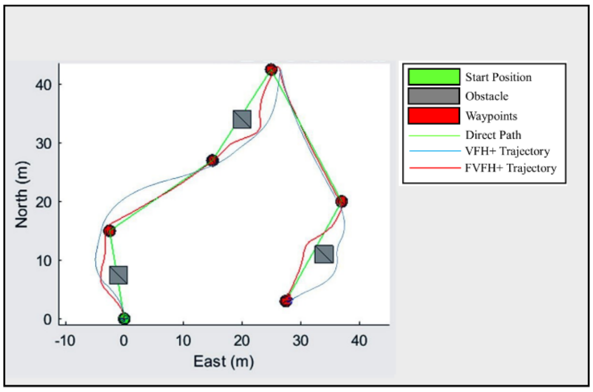

Fig. 20. Simulation result with low number of obstacle and high waypoints using VFH+ and FVFH+

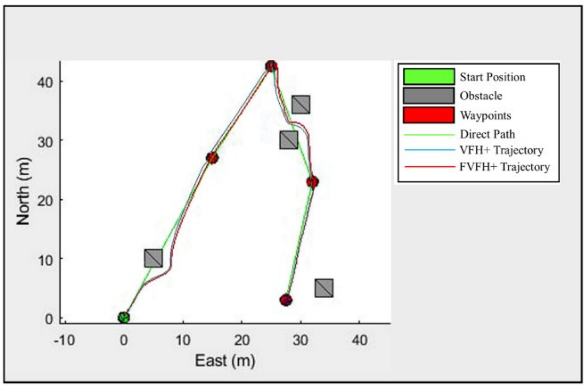

Fig. 21. Simulation result with medium number of obstacle and high waypoints using VFH+ and FVFH+

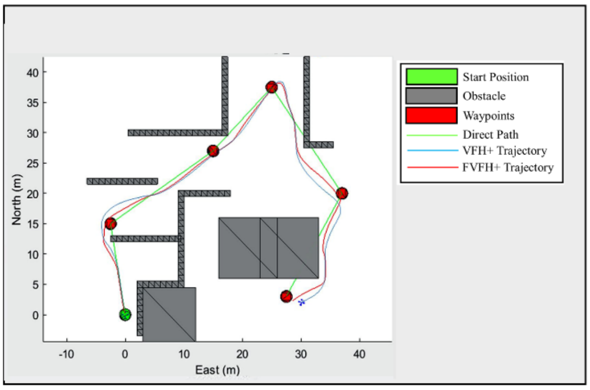

Fig. 22. Simulation result of quadcopter motion planning in environment with high number of obstacle and high waypoints using VFH+ and FVFH+

Table V shows a performance comparison of two algorithms, VFH+ and FVFH+, using various measures. Here is an analysis of the content:

- Algorithm: Specifies the algorithms according to comparison, VFH+ and FVFH+.
- Look ahead distance [m]: Refers to the distance ahead of the quadcopter's current position that is considered for path planning.
- Desired path length [m]: Indicates the intended path length that the quadcopter aims to follow.
- Time traveled [sec]: Represents the time taken by the quadcopter to travel the desired path.

- Trajectory length [m]: Refers to the length of the actual trajectory followed by the quadcopter.

The suggested algorithm, FVFH+, performs significantly better than the original VFH+ algorithm without modifications, according to the data in Table IV. This conclusion is bolstered by other important points: intended Path Length Performance: FVFH+ has a far greater overall average of the intended path length than VFH+. This suggests that there is greater potential for the suggested algorithm to produce paths that satisfy the necessary goals.

- Travel Time: The total average travel time demonstrates that, in comparison to VFH+, FVFH+ requires substantially less time to accomplish the required path. This shows that path planning and execution could be done more efficiently.
- Actual Trajectory Length: FVFH+ is able to decide on more suitable and direct paths as evidenced by the much shorter trajectories it generates when compared to VFH+.

TABLE IV. TABLE OF PERFORMANCE COMPARISON OF VFH+ AND FVFH+ ALGORITHMS BASED ON LOOK-AHEAD DISTANCE

Algorithm	Look ahead distance [m]	Desired path length [m]	Time traveled [sec]				Trajectory length [m]			
			min	max	avg	stdev	min	max	avg	stdev
VFH+	0.1-0.8	99.84	122.73	2,069.47	510.59	79.03	106.42	143.52	119.17	14.49
FVFH+	0.1-0.8	99.84	141.14	333.68	244.29	25.66	101.08	121.73	110.9306	7.80

TABLE V. COMPARISON OF VFH+ AND FVFH+ ALGORITHMS PERFORMANCE IN VARIOUS SCENARIO CONFIGURATIONS BASED ON OBSTACLE AND WAYPOINTS QUANTITY

No.	Ref. Fig. no.	Obstacle No.	Waypoints No.	Actual path length	VFH+			FVFH+		
					Trajectory length	Travel time	Error	Trajectory length	Travel time	Error
1	14	Low	Low	40.23	53.71	156.9	2.5%	45.43	131.53	1.14%
2	15	Medium	Low	49.3	65.38	197.44	2.40%	56.47	154.89	1.27%
3	16	High	Low	45.24	62.9	288.38	2.80%	52.63	152.51	1.40%
4	17	Low	Medium	56.72	78.1	340.54	2.70%	64.23	181.03	1.17%
5	18	Medium	Medium	89.62	109.92	485.17	1.80%	99.69	274.26	1.01%
6	19	High	Medium	74.87	94.23	430.05	2%	87.38	237.08	1.43%
7	20	Low	High	99.84	120.97	510.11	1.70%	112.66	302.74	1.14%
8	21	Medium	High	71.47	88.54	370.64	1.90%	80.29	226.42	1.10%
9	22	High	High	97.57	118.54	499.27	1.70%	115.7	301.31	1.57%

In summary, the Table clearly shows that the proposed FVFH+ algorithm outperforms the original VFH+ algorithm without enhancements, highlighting the importance of using improvements and advancements in path planning to enhance the efficiency and accuracy of navigation operations in robots.

Moreover, in situations where the advance sight distance was very short, the traditional method failed to detect obstacles that were in close proximity to the quadcopter. This caused the UAV to follow paths that might be unnecessary or more extended, resulting in increased time consumption. It is worth noting that the advance viewing distance in the traditional method remained fixed throughout the entire flight period, set before departure.

In contrast, the improved method FVFH+ demonstrated success in all conditions and environmental changes. The new method exhibited adaptability to varying environmental conditions and obstacles by dynamically adjusting the advance sight distance during the flight.

VII. CONCLUSION

In conclusion, this study presents a significant improvement to the VFH+ motion planning algorithm, enhancing its performance in the navigation domains of autonomous quadcopters. The key innovation lies in the integration of fuzzy logic control to dynamically adjust algorithm parameters, allowing for better adaptation to changing environments with various fixed obstacles. The simulation, conducted in diverse environments with varying obstacle distributions and waypoints, demonstrates the proposed FVFH+ algorithm's effectiveness.

The adaptive nature of the algorithm, facilitated by fuzzy control, enables real-time adjustments to VFH+ parameters based on continuous environmental and motion condition analysis. Simulation results showcase the algorithm's superior performance compared to the conventional VFH+, particularly in the successful navigation of various environments. Metrics such as success rate, arrival rate, deviation rate, and path length highlight the algorithm's efficiency and effectiveness. The importance of this research extends to the broader field of motion planning for quadcopters, emphasizing the role of fuzzy control in improving performance in complex and changing environments. The adaptive algorithm presented in this study, in contrast to fixed-parameter algorithms, demonstrates a capability to continuously self-adjust, enhancing the quadcopter's ability to handle uncertainty and navigate effectively.

Furthermore, the study acknowledges the increasing importance of quadcopters in various applications, from healthcare to logistics, and underscores motion planning's critical role in ensuring safe and successful operations. The proposed FVFH+ algorithm aligns with the continuous pursuit of developing technologies that make quadcopters more adaptable to diverse scenarios and challenges. Overall, this research contributes significantly to the advancement of motion planning techniques for quadcopters, providing a framework that combines traditional methods with fuzzy logic control for enhanced adaptability and performance in real-world environments.

The suggested algorithm has certain limitations, such as its sensitivity to changes in illumination, weather, and topographical features. These variables could affect how well the algorithm performs; hence, adaptive mechanisms and robustness testing are needed to guarantee dependable operation in a variety of scenarios. Furthermore, the fuzzy control and continuous environmental analysis processes may introduce delays, which could impair the system's responsiveness in rapidly changing situations. The proper implementation and efficacy of the algorithm in practical situations will depend on resolving these issues.

VIII. FUTURE WORK

- Experimental verification: Run real-world experiments to ascertain how well the suggested FVFH+ algorithm performs in varied conditions.
- Enhanced multi-sensor system integration: To improve decision-making capabilities and supply more information, investigate enhancing integration with multi-sensor systems, including cameras and other environmental sensors.
- Development of machine learning algorithms: Research methods for applying machine learning techniques to enhance algorithm performance in handling a wider range of complicated scenarios.
- Perform thorough robustness testing to assess the algorithm's effectiveness under different unfavorable scenarios, including sensor failure, connectivity outages, and unanticipated environmental changes.

REFERENCES

[1] M. Pouzesh and S. Mobayen, "Event-triggered fractional-order sliding mode control technique for stabilization of disturbed quadcopter unmanned aerial vehicles," *Aerospace Science and Technology*, vol. 121, p. 107337, 2022.

[2] G. Farid *et al*., "Modified A-Star (A*) Approach to Plan the Motion of a Quadrotor UAV in Three-Dimensional Obstacle-Cluttered Environment," *Applied Sciences*, vol. 12, no. 12, p. 5791, 2022.

[3] B. N. Abdul-Samed and A. A. Aldair, "Outdoor & Indoor Quadrotor Mission," *Iraqi Journal for Electrical And Electronic Engineering*, 2020.

[4] R. Singh, R. Kumar, A. Mishra, and A. Agarwal, "Structural analysis of quadcopter frame," *Materials Today: Proceedings*, vol. 22, pp. 3320-3329, 2020.

[5] B. N. A. Samed and A. A. Aldair, "Design Tunable Robust Controllers for Unmanned Aerial Vehicle Based on Particle Swarm Optimization Algorithm," *Iraqi Journal for Electrical & Electronic Engineering*, vol. 15, no. 2, 2019.

[6] M. F. Ahmed, M. N. Zafar, and J. Mohanta, "Modeling and analysis of quadcopter F450 frame," in *2020 international conference on contemporary computing and applications (IC3A)*, pp. 196-201, 2020.

[7] B. Chen, "Research on AI application in the field of quadcopter UAVs," in *2020 IEEE 2nd International Conference on Civil Aviation Safety and Information Technology (ICCASIT)*, pp. 569-571, 2020.

[8] M. F. Ahmed, M. N. Zafar, and J. Mohanta, "Modeling and analysis of quadcopter F450 frame," in *2020 international conference on contemporary computing and applications (IC3A)*, pp. 196-201, 2020.

[9] R. Al Jaber, M. S. Sikder, R. A. Hossain, K. F. N. Malia, and M. A. Rahman, "Unmanned aerial vehicle for cleaning and firefighting purposes," in *2021 2nd International conference on robotics, electrical and signal processing techniques (ICREST)*, pp. 673-677.2021 ,

[10] Y. Akbari, N. Almaadeed, S. Al-Maadeed, and O. Elharrouss, "Applications, databases and open computer vision research from drone videos and images: a survey," *Artificial Intelligence Review*, vol. 54, pp. 3887-3938, 2021.

[11] P. Radoglou-Grammatikis, P. Sarigiannidis, T. Lagkas, and I. Moscholios, "A compilation of UAV applications for precision agriculture," *Computer Networks*, vol. 172, p. 107148, 2020.

[12] Á. Restás, "Drone applications fighting COVID-19 pandemic—Towards good practices," *Drones*, vol. 6, no. 1, p. 15, 2022, doi: 10.3390/drones6010015.

[13] D. M. Harfina, Z. Zaini, and W. J. Wulung, "Disinfectant spraying system with quadcopter type unmanned aerial vehicle (UAV) technology as an effort to break the chain of the COVID-19 virus," *Journal of Robotics and Control (JRC)*, vol. 2, no. 6, pp. 502-507, 2021, doi: 10.18196/jrc.26129.

[14] B. Chamberlain and W. Sheikh, "Design and Implementation of a Quadcopter Drone Control System for Photography Applications," in *2022 Intermountain Engineering, Technology and Computing (IETC)*, pp. 1-7, 2022.

[15] M. Idrissi, M. Salami, and F. Annaz, "A review of quadrotor unmanned aerial vehicles: applications, architectural design and control algorithms," *Journal of Intelligent & Robotic Systems*, vol. 104, no. 2, p. 22, 2022, doi: 10.1007/s10846-021-01527-7.

[16] T. Shakeel et al., "A Comparative Study of Control Methods for X3D Quadrotor Feedback Trajectory Control," *Applied Sciences*, vol. 12, no. 18, p. 9254, 2022.

[17] A. Marchidan and E. Bakolas, "Collision avoidance for an unmanned aerial vehicle in the presence of static and moving obstacles," *Journal of Guidance, Control, and Dynamics*, vol. 43, no. 1, pp. 96-110, 2020.

[18] J. Wang, M. Q.-H. Meng, and O. Khatib, "EB-RRT: Optimal motion planning for mobile robots," *IEEE Transactions on Automation Science and Engineering*, vol. 17, no. 4, pp. 2063-2073, 2020.

[19] C. Zhou, B. Huang, and P. Fränti, "A review of motion planning algorithms for intelligent robots," *Journal of Intelligent Manufacturing*, vol. 33, no. 2, pp. 387-424, 2022, doi: 10.1007/s10845-021-01867-z.

[20] X. Xiao, B. Liu, G. Warnell, and P. Stone, "Motion planning and control for mobile robot navigation using machine learning: a survey," *Autonomous Robots*, vol. 46, no. 5, pp. 569-597, 2022, doi: 10.1007/s10514-022-10039-8.

[21] B. Song, Z. Wang, and L. Zou, "An improved PSO algorithm for smooth path planning of mobile robots using continuous high-degree Bezier curve," *Applied Soft Computing*, vol. 100, p. 106960, 2021.

[22] J. Yu, Y. Su, and Y. Liao, "The path planning of mobile robot by neural networks and hierarchical reinforcement learning," *Frontiers in Neurorobotics*, vol. 14, p. 63, 2020.

[23] J.-A. Delamer, Y. Watanabe, and C. P. Chanel, "Safe path planning for UAV urban operation under GNSS signal occlusion risk," *Robotics and Autonomous Systems*, vol. 142, p. 103800, 2021.

[24] M. N. Zafar and J. Mohanta, "Methodology for path planning and optimization of mobile robots: A review," *Procedia computer science*, vol. 133, pp. 141-152, 2018.

[25] A. Israr, Z. A. Ali, E. H. Alkhammash, and J. J. Jussila, "Optimization methods applied to motion planning of unmanned aerial vehicles: A review," *Drones*, vol. 6, no. 5, p. 126, 2022.

[26] D. Van Huynh, T. Do-Duy, L. D. Nguyen, M-.T. Le, N.-S. Vo, and T. Q. Duong, "Real-time optimized path planning and energy consumption for data collection in unmanned ariel vehicles-aided intelligent wireless sensing," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 4, pp. 2753-2761, 2021, doi.org/10.1109/TII.2021.3114358.

[27] S. Poudel, M. Y. Arafat, and S. Moh, "Bio-Inspired Optimization-Based Path Planning Algorithms in Unmanned Aerial Vehicles: A Survey," *Sensors*, vol. 23, no. 6, p. 3051, 2023.

[28] N. Abu, W. Bukhari, M. Adli, and A. Ma'arif, "Optimization of an Autonomous Mobile Robot Path Planning Based on Improved Genetic Algorithms," *Journal of Robotics and Control (JRC)*, vol. 4, no. 4, pp. 557-571, 2023, doi: 10.18196/jrc.v4i4.19306.

[29] S. Aradi, "Survey of deep reinforcement learning for motion planning of autonomous vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 740-759, 2020.

[30] V. Dwaracherla, S. Thakar, L. Vachhani, A. Gupta, A. Yadav, and S. Modi, "Motion planning for point-to-point navigation of spherical robot using position feedback," *IEEE/ASME Transactions on Mechatronics*, vol. 24, no. 5, pp. 2416-2426, 2019.

[31] L. Claussmann, M. Revilloud, D. Gruyer, and S. Glaser, "A review of motion planning for highway autonomous driving," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 5, pp. 1826-1848, 2019.

[32] F. Noroozi, M. Daneshmand, and P. Fiorini, "Conventional, Heuristic and Learning-Based Robot Motion Planning: Reviewing Frameworks of Current Practical Significance," *Machines*, vol. 11, no. 7, p. 722, 2023, doi: 10.3390/machines11070722.

[33] N. Abu, W. Bukhari, M. Adli, S. Omar, and S. Sohaimeh, "A Comprehensive Overview of Classical and Modern Route Planning Algorithms for Self-Driving Mobile Robots," *Journal of Robotics and Control (JRC)*, vol. 3, no. 5, pp. 666-678, 2022, doi: 10.18196/jrc.v3i5.14683.

[34] T. Sandakalum and M. H. Ang Jr, "Motion planning for mobile manipulators—a systematic review," *Machines*, vol. 10, no. 2, p. 97, 2022.

[35] C. Tonola, M. Faroni, M. Beschi, and N. Pedrocchi, "Anytime informed multi-path replanning strategy for complex environments," *IEEE Access*, vol. 11, pp. 4105-4116, 2023, doi: 10.1109/ACCESS.2023.3235652.

[36] A. Mazen, M. Faied, and M. Krishnan, "Tuning of Robot Navigation Performance Using Factorial Design," *Journal of Intelligent & Robotic Systems*, vol. 105, no. 3, p. 50, 2022, doi: 10.3389/fnbot.2020.00063.

[37] S. Sahloul, D. B. H. Abid, and C. Rekik, "An hybridization of global-local methods for autonomous mobile robot navigation in partially-known environments," *Journal of Robotics and Control (JRC)*, vol. 2, no. 4, pp. 221-233, 2021.

[38] V. Kramar, O. Kramar, and A. Kabanov, "Self-Collision Avoidance Control of Dual-Arm Multi-Link Robot Using Neural Network Approach," *Journal of Robotics and Control (JRC)*, vol. 3, no. 3, pp. 309-319, 2022.

[39] S. Dey, N. M. Reang, A. Majumder, M. Deb, and P. K. Das, "A hybrid ANN-Fuzzy approach for optimization of engine operating parameters of a CI engine fueled with diesel-palm biodiesel-ethanol blend," *Energy*, vol. 202, p. 117813, 2020.

[40] L. A. Zadeh, "The role of fuzzy logic in modeling, identification and control," in *Fuzzy Sets, Fuzzy Logic, and Fuzzy Systems: Selected Papers by Lotfi A Zadeh: World Scientific*, pp. 783-795, 1996.

[41] J. R. García-Martínez, E. E. Cruz-Miguel, R. V. Carrillo-Serrano, F. Mendoza-Mondragón, M. Toledano-Ayala, and J. Rodríguez-Reséndiz, "A PID-type fuzzy logic controller-based approach for motion control applications," *Sensors*, vol. 20, no. 18, p. 5323, 2020.

[42] S. Kambalimath and P. C. Deka, "A basic review of fuzzy logic applications in hydrology and water resources," *Applied Water Science*, vol. 10, no. 8, pp. 1-14, 2020.

[43] M. Woźniak, A. Zielonka, and A. Sikora, "Driving support by type-2 fuzzy logic control model," *Expert Systems with Applications*, vol. 207, p. 117798, 2022.

[44] F. Valdez, O. Castillo, and C. Peraza, "Fuzzy logic in dynamic parameter adaptation of harmony search optimization for benchmark functions and fuzzy controllers," *International Journal of Fuzzy Systems*, vol. 22, no. 4, pp. 1198-1211, 2020.

[45] J. Borenstein and Y. Koren, "The vector field histogram-fast obstacle avoidance for mobile robots," *IEEE transactions on robotics and automation*, vol. 7, no. 3, pp. 278-288, 1991.

[46] A. H. Hamad and F. B. Ibrahim, "Path Planning of Mobile Robot Based on Modification of Vector Field Histogram using Neuro-Fuzzy Algorithm," *Int. J. Adv. Comp. Techn*., vol. 2, no. 3, pp. 129-138, 2010.

[47] B. I. Kazem, A. H. Hamad, and M. M. Mozael, "Modified vector field histogram with a neural network learning model for mobile robot path planning and obstacle avoidance," *Int. J. Adv. Comp. Techn*., vol. 2, no. 5, pp. 166-173, 2010.

[48] A. Babinec, M. Dekan, F. Duchoň, and A. Vitko, "Modifications of VFH navigation methods for mobile robots," *Procedia Engineering*, vol. 48, pp. 10-14, 2012, doi: 10.1016/j.proeng.2012.09.478.

[49] J. S. Kumar and R. Kaleeswari, "Implementation of vector field histogram based obstacle avoidance wheeled robot," in *2016 Online international conference on green engineering and technologies (IC-GET)*, pp. 1-6, 2016.

[50] Y. Yan, Y. Du, and W. Zhou, "Study on the local path planning for intelligent vehicles based on an improved VFH method," *International Journal of Embedded Systems*, vol. 10, no. 6, pp. 445-452, 2018, doi: 10.1504/IJES.2018.095747.

[51] I. Ulrich and J. Borenstein, "VFH+: Reliable obstacle avoidance for fast mobile robots," in *Proceedings, 1998 IEEE international conference on robotics and automation*, vol. 2, pp. 1572-1577, 1998, doi: 10.1109/ROBOT.1998.677362.

[52] J. Gong, Y. Duan, Y. Man, and G. Xiong, "VPH+: An enhanced vector polar histogram method for mobile robot obstacle avoidance," in *2007 International Conference on Mechatronics and Automation*, pp. 2784-2788, 2007.

[53] I. P. Sary, Y. P. Nugraha, M. Megayanti, E. Hidayat, and B. R. Trilaksono, "Design of obstacle avoidance system on hexacopter using vector field histogram-plus," in *2018 IEEE 8th International Conference on System Engineering and Technology (ICSET)*, pp. 18-23, 2018.

[54] D. Díaz and L. Marín, "VFH+ D: An improvement on the VFH+ algorithm for dynamic obstacle avoidance and local planning," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 9590-9595, 2020, doi: 10.1016/j.ifacol.2020.12.2450.

[55] B. Lee, W. Kim, and S. Lee, "An Extended Vector Polar Histogram Method Using Omni-Directional LiDAR Information," *Symmetry*, vol. 15, no. 8, p. 1545, 2023.

[56] S. Choi, E. Kim, and S. Oh, "Real-time navigation in crowded dynamic environments using Gaussian process motion control," in *2014 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3221-3226, 2014, doi: 10.1109/ICRA.2014.6907322.

[57] S. Raikwar, J. Fehrmann, and T. Herlitzius, "Navigation and control development for a four-wheel-steered mobile orchard robot using model-based design," *Computers and Electronics in Agriculture*, vol. 202, p. 107410, 2022, doi: 10.1016/j.compag.2022.107410.

[58] L. Chen, X. Hu, B. Tang, and Y. Cheng, "Conditional DQN-based motion planning with fuzzy logic for autonomous driving," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 4, pp. 2966-2977, 2020.

[59] A. Sakalli, T. Kumbasar, and J. M. Mendel, "Towards systematic design of general type-2 fuzzy logic controllers: analysis, interpretation, and tuning," *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 2, pp. 226-239, 2020.

[60] M. N. Mansor, A. A. Abd Samat, A. I. Tajudin, N. Salim, K. Daud, and S. F. Abd Shukor, "Self tuning of PI controller for speed control of DC motor by using fuzzy logic controller," in *2021 6th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE)*, vol. 6, pp. 1-6, 2021.

[61] S. Khesrani, A. Hassam, O. Boutalbi, and M. Boubezoula, "Motion planning and control of nonholonomic mobile robot using flatness and fuzzy logic concepts," *International Journal of Dynamics and Control*, vol. 9, no. 4, pp. 1660-1671, 2021.

[62] P. Pappas, M. Chiou, G.-T. Epsimos, G. Nikolaou, and R. Stolkin, "Vfh+ based shared control for remotely operated mobile robots," in *2020 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, pp. 366-373, 2020.

[63] X. Wang, M. Cheng, S. Zhang, and H. Gong, "Multi-UAV Cooperative Obstacle Avoidance of 3D Vector Field Histogram Plus and Dynamic Window Approach," *Drones*, vol. 7, no. 8, p. 504, 2023, doi: 10.3390/drones7080504.

[64] T. Dong, Y. Zhang, Q. Xiao, and Y. Huang, "The Control Method of Autonomous Flight Avoidance Barriers of UAVs in Confined Environments," *Sensors*, vol. 23, no. 13, p. 5896, 2023, doi: 10.3390/s23135896.

[65] J. Lee, Y. Cho, C. Nam, J. Park, and C. Kim, "Efficient obstacle rearrangement for object manipulation tasks in cluttered environments," in *2019 International Conference on Robotics and Automation (ICRA)*, pp. 183-189, 2019, doi: 10.1109/ICRA.2019.8793616.

[66] Y. Chen, G. Bai, Y. Zhan, X. Hu, and J. Liu, "Path planning and obstacle avoiding of the USV based on improved ACO-APF hybrid algorithm with adaptive early-warning," *IEEE Access*, vol. 9, pp. 40728-40742, 2021, doi: 10.1109/ACCESS.2021.3062375.

[67] S. Woo, C. Park, D. Lee, and S.-y. Lee, "Collision avoidance for unmanned aerial vehicles based on safety radius of the formation geometry," in *2020 20th International Conference on Control, Automation and Systems (ICCAS)*, pp. 179-183, 2020.

[68] W. Chen, C. Yang, and Y. Feng, "Shared control for omnidirectional mobile robots," in *2019 Chinese Control And Decision Conference (CCDC)*, pp. 6185-6190, 2019, doi: 10.1109/CCDC.2019.8833017.

[69] H. Dong, C.-Y. Weng, C. Guo, H. Yu, and I.-M. Chen, "Real-time avoidance strategy of dynamic obstacles via half model-free detection and tracking with 2d lidar for mobile robots," *IEEE/ASME transactions on mechatronics*, vol. 26, no. 4, pp. 2215-2225, 2020.

[70] C.-F. Wu, Y.-L. Wang, L. Ma, and A. Rakić, "VFH+ Based Local Path Planning for Unmanned Surface Vehicles," in *2021 IEEE International Conference on Recent Advances in Systems Science and Engineering (RASSE)*, pp. 1-6, 2021, doi: 10.1109/RASSE53195.2021.9686856.

[71] L. A. Zadeh, "Fuzzy logic," in *Granular, Fuzzy, and Soft Computing*, pp. 19-49, 2023.

[72] K. Mittal, A. Jain, K. S. Vaisla, O. Castillo, and J. Kacprzyk, "A comprehensive review on type 2 fuzzy logic applications: Past, present and future," *Engineering Applications of Artificial Intelligence*, vol. 95, p. 103916, 2020, doi: 10.1016/j.engappai.2020.103916.

[73] A. Jain and A. Sharma, "Membership function formulation methods for fuzzy logic systems: A comprehensive review," *Journal of Critical Reviews*, vol. 7, no. 19, pp. 8717-8733, 2020, doi: 10.1080/21642583.2021.1907259.

[74] J. Zheng, B. Liu, Z. Meng, and Y. Zhou, "Integrated real time obstacle avoidance algorithm based on fuzzy logic and L1 control algorithm for unmanned helicopter," in *2018 Chinese Control And Decision Conference*, pp. 1865–1870, 2018, doi: 10.1109/CCDC.2018.8407430.

[75] A. Nasrinahar and J. H. Chuah, "Intelligent motion planning of a mobile robot with dynamic obstacle avoidance," *Journal on Vehicle Routing Algorithms*, vol. 1, no. 2–4, pp. 89–104, 2018.

[76] H. A. Al-Mosawi, A. Al-Ibadi, and T. Y. Abdalla, "An Adaptive Parallel Fuzzy And Proportional Integral Controller (APFPIC) For The Contractor Pneumatic Muscle Actuator Position Control," in *2022 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, pp. 1-6, 2022.

[77] M. R. Mohd Romlay, A. Mohd Ibrahim, S. F. Toha, P. De Wilde, I. Venkat, and M. S. Ahmad, "Obstacle avoidance for a robotic navigation aid using fuzzy logic controller-optimal reciprocal collision avoidance (FLC-ORCA)," *Neural Computing and Applications*, vol. 35, no. 30, pp. 22405-22429, 2023.

[78] F. Valdez, "A review of optimization swarm intelligence-inspired algorithms with type-2 fuzzy logic parameter adaptation," *Soft Computing*, vol. 24, no. 1, pp. 215-226, 2020.

[79] M. Wu, S.-L. Dai, and C. Yang, "Mixed reality enhanced user interactive path planning for omnidirectional mobile robot," *Applied Sciences*, vol. 10, no. 3, p. 1135, 2020, doi: 10.3390/app10031135.

[80] Y. Niu, H. Qazi, and Y. Liang, "Building a Flexible Mobile Robotics Teaching Toolkit by Extending MATLAB/Simulink with ROS and Gazebo," in *2021 7th International Conference on Mechatronics and Robotics Engineering (ICMRE)*, pp. 10-16, 2021.

[81] F. A. Andrade *et al*., "Unmanned aerial vehicles motion control with fuzzy tuning of cascaded-pid gains," *Machines*, vol. 10, no. 1, p. 12, 2021, doi: 10.3390/machines10010012.

[82] B. Wu, T. Cheng, T. L. Yip, and Y. Wang, "Fuzzy logic based dynamic decision-making system for intelligent navigation strategy within inland traffic separation schemes," *Ocean Engineering*, vol. 197, p. 106909, 2020, doi: 10.1016/j.oceaneng.2019.106909.

[83] S. A. Mostafa, R. Darman, S. H. Khaleefah, A. Mustapha, N. Abdullah, and H. Hafit, "A general framework for formulating adjustable autonomy of multi-agent systems by fuzzy logic," in *Agents and Multi-Agent Systems: Technologies and Applications 2018: Proceedings of the 12th International Conference on Agents and Multi-Agent Systems: Technologies and Applications*, pp. 23-33, 2019.

[84] D. Phan, A. Bab-Hadiashar, M. Fayyazi, R. Hoseinnezhad, R. N. Jazar, and H. Khayyam, "Interval type 2 fuzzy logic control for energy management of hybrid electric autonomous vehicles," *IEEE Transactions on Intelligent vehicles*, vol. 6, no. 2, pp. 210-220, 2020, doi: 10.1109/TIV.2020.3011954.