Fuzzy PID-inspired Potential Field Path Planning for Quadrotors in Environmental Monitoring

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Abstract
This paper introduces a novel approach for quadrotor path planning referred to as the Fuzzy PID-inspired Adaptive Potential Field Method (FPID-APFM). Traditional Potential Field Methods (PFMs) face challenges like getting stuck in local minima, oscillating near obstacles, and requiring fine-tuning of parameters. To overcome these problems, the proposed method integrates a fuzzy inference system that dynamically adjusts key parameters, including the attractive force coefficient (k_a) and repulsive force coefficient (k_b). The idea behind this is inspired by PID controllers, where k_a functions similarly to the proportional gain (k_p), which helps the quadrotor move toward its goal, and k_b functions similarly to the integral gain (k_i), accounting for the cumulative effects of obstacles and reducing the significant deviations by the quadrotor. A damping factor, ζ, is also included to ensure smoother paths, especially in dynamic conditions. Through simulations in both static and dynamic environments, including scenario with wind disturbances, the results show that the method performs well. This approach proves to be a reliable and efficient solution for real-world path planning, enabling quadrotors to navigate safely while collecting environmental data.
Keywords: Fuzzy Adaptive Potential Field Method, Quadrotor Path Planning, Environmental Monitoring, Fuzzy Logic, PID Controllers.

1. Introduction

Quadrotors have emerged as vital tools in various modern applications, such as package delivery, surveillance, search-and-rescue operations, and environmental monitoring. In environmental applications, quadrotors are increasingly utilized for tasks such as measuring air quality, collecting temperature gradients, and monitoring pollution levels. These tasks often require navigating through dynamic environments with obstacles like trees, buildings, and moving objects. Reliable and safe path-planning strategies capable of handling both static and dynamic obstacles are essential for effective environmental monitoring.

One widely recognized approach in robotic path planning is the Potential Field Method (PFM), initially proposed by Khatib [1]. This method defines navigation by considering the target as an attractive force and obstacles as repulsive forces [2]. While PFM offers a straightforward framework, it faces challenges such as local minima, oscillatory behavior near obstacles, and a lack of flexibility to adapt to complex and dynamic real-world scenarios [3]. To resolve the limitations of the traditional PFM, researchers have proposed various enhancements. For instance, some studies have modified the repulsive force equations to improve obstacle avoidance. An example of this is the work by Ge and Cui, who introduced a new PFM in dynamic environments, adjusting the repulsive forces to better handle moving obstacles [4]. Additionally, integrating PFM with optimization algorithms has been explored to adapt to changing conditions. For example, a fusion pathfinding algorithm combining an optimized A-star algorithm with the artificial PFM has been proposed to enhance path-planning performance in complex environments [5]. In recent years, fuzzy logic has shown capability in enhancing the robustness of PFMs. By using rule-based reasoning, fuzzy logic provides a flexible framework that enables algorithms to adapt more effectively to uncertainties and variations in dynamic environments. Research efforts, including the works of Lin and Jou [4] and Zhao et al. [5], have demonstrated the ability of fuzzy logic to improve robot navigation. These studies show how fuzzy logic can overcome common challenges in traditional PFMs, making it a valuable tool for navigation in complex scenarios. In recent years, fuzzy logic has shown up as a promising approach to enhance the robustness of PFMs. Using rule-based reasoning, fuzzy logic enables algorithms to adapt more effectively to environmental uncertainties and dynamic variations. For example, the work of Wang [6] demonstrates the potential of fuzzy logic to improve robot navigation by overcoming critical challenges such as local minimum. Planning paths for quadrotors presents challenges that extend well beyond those faced by ground robots. Quadrotors navigate three-dimensional spaces and must comply with strict dynamic constraints, such as limits on lateral acceleration, to ensure their paths are both safe and practical. If these constraints are not considered, the result can be unsafe maneuvers or paths that are infeasible in real-world operations. While recent research has made progress in incorporating quadrotor dynamics into path-planning algorithms [7], many existing methods still struggle to solve the problem of real-world environments, particularly those involving dynamic obstacles.

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This paper presents an approach to solve these problems by introducing the Fuzzy PID-inspired Adaptive Potential Field Method (FPID-APFM). By dynamically adjusting the parameters of PFM using fuzzy logic, our approach takes inspiration from the PID control rules, where the attractive and repulsive forces are treated similarly to the proportional and integral gains in that controller. This dynamic adjustment enables the quadrotor to navigate complex and changing environments more effectively. The method adapts the parameters, such as the attractive and repulsive force coefficients, in real-time, reducing the risk of getting stuck in local minima or oscillating near obstacles. Constraints like maximum lateral acceleration are also incorporated to ensure the generated paths are not only feasible but also smooth and safe for real-world operations.

This paper is organized as follows: Section 2 presents an overview of PFM and PID techniques. Section 3 introduces the proposed FPID-APFM, explaining its design, fuzzy rules, and parameter adaptation mechanisms. Section 4 details the simulation results in testing a real-world scenario. Section 5 shows the pseudocode of this simulation. Finally, Section 6 concludes the paper with a summary of findings and practical implications.

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2. Quadrotor Dynamics

The quadrotor represents a nonlinear system characterized by six degrees of freedom. Its dynamics are commonly modeled using the Newton-Euler formulation. These dynamics are typically categorized into translational and rotational components, reflecting the system's full range of motion [8]:

2.1. Translational Dynamics

The translational motion of the quadrotor in the inertial frame is given by:

$$m\ddot{\mathbf{r}} = \mathbf{F}_g + \mathbf{F}_t + \mathbf{F}_d \tag{1}$$

Here, $\mathbf{r} = [x, y, z]^T$ denotes the position of the quadrotor in the inertial frame, while **m** represents the quadrotor's mass. The gravitational force is given by $\mathbf{F}g = [0,0,-mg]^T$, and the thrust force, $\mathbf{F}_t = R[0 \quad 0 \quad T]^T$, is expressed in the inertial frame using the rotation matrix **R**. Additionally, $\mathbf{F}^d$ accounts for aerodynamic drag and any external disturbances.

2.2. Rotational Dynamics

The rotational motion of the quadrotor is described using the Euler angles φ(roll), θ(pitch), and ψ (yaw):

$$\mathbf{I}\dot{\boldsymbol{\omega}} + \boldsymbol{\omega} \times (\mathbf{I}\boldsymbol{\omega}) = \boldsymbol{\tau} \tag{2}$$

Where $\boldsymbol{\omega} = [p, q, r]^T$, I is the inertia matrix and $\tau = [\tau_\phi, \tau_\theta, \tau_\psi]$ represents the control torques generated by the rotors.

2.3. Constraints on Quadrotor Dynamics

In real-world applications, quadrotors must operate within specific physical and operational limits to ensure their safety and functionality. These limits include restrictions on lateral acceleration, velocity, and roll angles, as well as the need to account for external factors like wind disturbances. This work considers the following key constraints:

2.3.1. Thrust and Voltage Constraints

The total thrust generated by the rotors is limited by the maximum voltage supplied to the motors:

$$F_t \le k_t V_{max} \tag{3}$$

where V_{max} is the maximum motor voltage, and k_t is the thrust coefficient. This ensures the generated forces remain within the hardware's operational limits.

2.3.2. Lateral Acceleration Constraint

To ensure smooth and safe navigation, the lateral acceleration is limited:

$$a_{lateral} = \sqrt{a_x^2 + a_y^2} \le a_{max,lateral} \tag{5}$$

where $a_{max,lateral}$ is the maximum allowable lateral acceleration

2.3.3. External Disturbances

Wind disturbances are modeled as forces acting along the x, y, and z axes. These forces are randomly varied within a specified range to simulate real-world environmental conditions:

$$F_{wind} = [F_{wind,x}, F_{wind,y}, F_{wind,y}] \tag{6}$$

The impact of these disturbances is incorporated into the total forces acting on the quadrotor.

3. Overview of Path Planning and Control Techniques

3.1. Potential Field Method

PFM is an important and functional approach in robotic path planning. The PFM at a specific point in the robot's configuration space is a scalar value derived from attractive and repulsive potentials. It considers the robot's environment as a field of forces, where the target acts as an attractive force pulling the robot toward it, while obstacles generate repulsive forces pushing the robot away. By reacting to the resulting force, the robot strives to move effectively toward its target while avoiding collisions.

In the Cartesian coordinate system, the robot's position is represented as $q(x, y)^T$ [9]. So, the PF function can be stated as:

$$U(q) = U_{att}(q) + U_{rep}(q) \tag{7}$$

Where $U(q)$, $U_{att}(q)$ and $U_{rep}(q)$ are the total potential field, attractive potential generated by the target and repulsive potential generated by obstacles, respectively.

The attractive field between the robot and the target is formulated to direct the robot toward the desired target area.

$$U_{att}(q) = \frac{1}{2} \times k_a \times (q - q_d)^2 = \frac{1}{2} k_a {\rho_t}^2 \qquad (8)$$

k_a is the positive attractive coefficient for PF and q_d is the current position vector of the target. ρ_t is an Euclidean distance from the robot's location to the target location.

To ensure safe navigation, obstacles near the robot generate a repulsive force, pushing it away to prevent collisions. It should be noted that when obstacles are outside the defined range, they no longer influence the robot's movement, allowing it to focus on reaching the target. This behavior is mathematically represented by the repulsive potential function, which regulates the robot's motion based on its proximity to obstacles:

$$U_{rep}(q) = \begin{cases} \frac{1}{2} k_b \left(\frac{1}{d(q)} - \frac{1}{d_0}\right)^2 & d(q) \le d_0 \\ 0 & d(q) > d_0 \end{cases} \qquad (9)$$

k_b is the repulsive coefficient. d and d_0 are the distance between the robot and the obstacle and the distance of the obstacle's repulsive force field, respectively.

The total force acting on the robot, as shown in Fig. 1, comes from a combination of two components: the attractive and repulsive forces. The attractive force, calculated from the gradient of the attractive potential field, pulls the robot toward its target. On the other hand, the repulsive force, derived from the gradient of the repulsive potential field, pushes the robot away from obstacles. Together, these forces work to guide the robot's movement effectively [9].

$$F(q) = -\nabla U_{att}(q) - \nabla U_{rep}(q) \qquad (10)$$

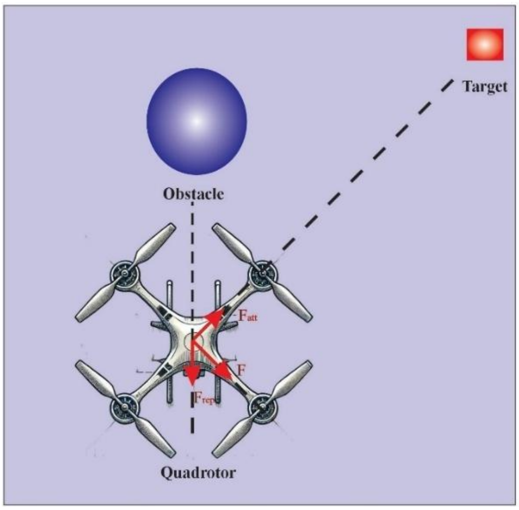


Fig. 1- Schematic illustration of the resultant force generated by the potential function for a quadrotor.

3.2. PID Control Method

PID control is a fundamental technique used in control systems to maintain desired outputs by adjusting control inputs based on the error between the desired and actual states of a system. The algorithm consists of three components: the Proportional (P) term, which produces an output proportional to the current error; the Integral (I) term, which accumulates past errors to eliminate steady-state error; and the Derivative (D) term, which responds to the rate of change of the error to counteract future error, thereby enhancing stability.

The weighting factors (k_p, k_i and k_d) of a PID controller can be adjusted to fine-tune its performance and achieve optimal system behavior.

$$CI(t) = k_p\, e(t) + k_i \int e(t) + k_d \frac{d}{dt} e(t) \qquad (11)$$

CI is the output of the PID controller. k_p, k_i and k_d are Proportional, Integral, and Derivative gains.

4. Fuzzy Potential Field Method

PF method is widely used in robotic path planning, faces several limitations that can reduce its effectiveness, particularly in dynamic and real environments. One of its primary challenges is the need for precise parameter tuning, especially the values of the attractive and repulsive forces. In addition to these issues, PFM also struggles with problems such as getting stuck in local minima [9]. By adjusting parameters in real-time, fuzzy logic helps PFM better adapt to changing conditions and enhances its overall performance. Fig. 2 illustrates the rule surface of a fuzzy inference system, depicting the relationship between two inputs, the error and its derivative, and the three outputs.

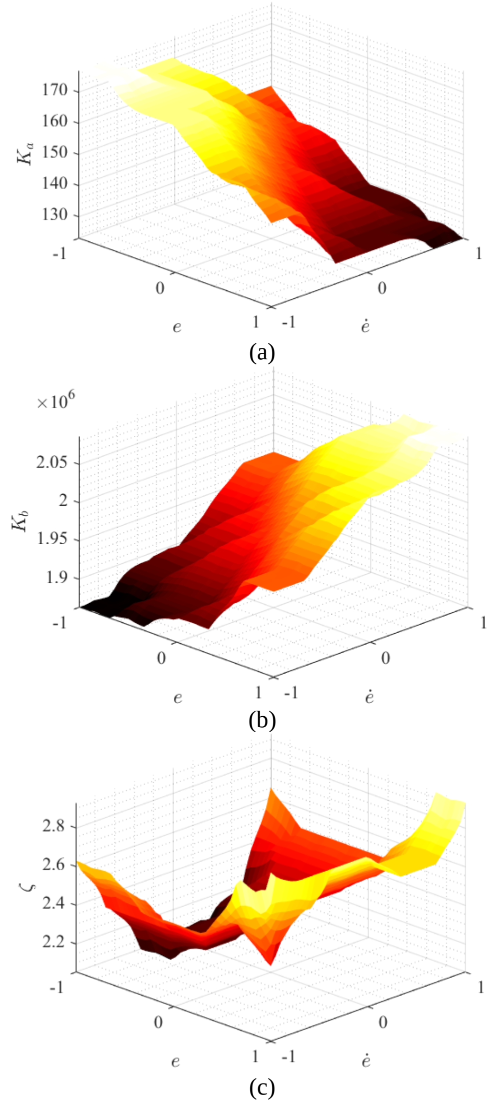


Fig. 2-Rule surface visualization of the fuzzy inference system (adapting from [10]) (a) k_a, (b) k_b and (c) ζ.

4.1. k_a, Attractive Coefficient

In PFM, k_a is crucial for influencing the robot's path and its approach to the target. Increasing k_a increases the attractive force, enabling the robot to move more quickly toward the target. Setting k_a too high may result in overshooting or oscillatory behavior, especially in dynamic environments. On the other hand, a lower k_a results in smoother and slower motion. This can be beneficial for precise navigation or when operating in areas with many obstacles.

The roles of k_p in a PID controller and k_a in the PF method are the same in concept because both parameters determine the strength of a system's response toward its target.

In a PID controller, k_p determines the intensity of the system's reaction to the difference between the current state and the desired value. A higher k_p accelerates the response to minimize the error but can create to overshooting or oscillations if set too high. In contrast, a lower k_p results in a more stable response, though it may slow down convergence.

Thus, both k_p in a PID controller and k_a in the PF method make a trade-off between speed and stability. Increasing their values makes the system respond faster but comes with the risk of instability while lowering them improves stability but slows down progress.

4.2. k_b, Repulsive Coefficient

In the PFM, the repulsive coefficient k_b plays a critical role in helping the quadrotor effectively avoid obstacles. A higher k_b increases the magnitude of the repulsive forces, allowing for stronger and more immediate responses to nearby obstacles. On the other hand, lowering k_b reduces the repulsive forces, making the movement smoother and more direct. However, this comes with the trade-off of a higher risk of collisions or not having enough clearance around obstacles.

The roles of k_i in a PID controller and k_b in the PF method share similarities in that both handle the effects over time k_i in error accumulation and k_b in obstacle avoidance.

In PID control, k_i corrects steady-state error by collecting past deviations from the desired value. A higher k_i helps eliminate steady-state error but can cause instability or oscillations if set too high. Similarly, k_b builds influence over the robot's path by continuously modifying its response based on the presence of obstacles.

Although the link between k_i and k_b isn't as straightforward as that between k_p and k_a, both parameters play a role in making long-term corrections. k_i does this by dealing with accumulated errors, while k_b ensures the robot avoids obstacles along its path.

4.3. ζ, Damping Factor

In our simulated PFM, the damping factor ζ is responsible for controlling the rate of change of the robot's velocity, influencing how the robot slows down as it approaches its target or navigates around obstacles. In other words, it is used to scale the force applied to the robot. A higher ζ results in a more damped response, reducing oscillations and overshooting, leading to smoother and more stable motion. However, if ζ is set too high, the system converges too slowly, so affecting the overall performance. In contrast, a lower ζ value reduces damping, allowing the robot to move more quickly toward the target, but this can increase the risk of instability, such as oscillations.

Similarly, in a PID controller, k_d determines how the system responds to the rate of change in the error signal.

It provides an effect to reduce overshoot and oscillations by accounting for how quickly the system is approaching the setpoint. A higher k_d value results in faster corrections by damping the system's response, helping to prevent overshoot. However, excessively high k_d values can lead to overcompensation.

In contrast, a lower k_d value produces quicker responses but may increase overshooting and system instability.

Therefore, both parameters help smooth the system's response, reduce oscillations, and ensure stability.

5. Simulation

Fig. 3 illustrates a schematic representation of the proposed path-planning system for a quadrotor tasked with environmental monitoring in a real environment. The orange path represents the nominal path that the FPID-APFM is designed to generate. The generated path enables the quadrotor to safely navigate toward its target while avoiding obstacles. Dynamic obstacles, such as moving birds, are highlighted by red circles, demonstrating the algorithm's ability to dynamically adjust the path in real-time. Static obstacles, like trees or stationary structures, are indicated by blue circles. This figure emphasizes the algorithm's capability to handle both static and dynamic obstacles, ensuring the quadrotor collects environmental data efficiently and safely in real-world scenarios.

Fig. 4 represents the 3D simulation results of a quadrotor path-planning algorithm within a cylindrical workspace. The environment contains a combination of static and dynamic obstacles, presenting a challenging scenario for safe navigation. The nominal path, shown in green, represents the path before considering environmental disturbances or obstacle interactions. The quadrotor path, depicted in blue, demonstrates the actual path followed by the quadrotor, reflecting its dynamic adjustments in response to obstacles and workspace constraints. The environment includes both static and dynamic obstacles. The static obstacles are represented by cyan and red points and remain fixed. In contrast, dynamic obstacles, shown in magenta and black, introduce an additional complexity as their positions change over time. The quadrotor's ability to avoid these moving obstacles while following the nominal path. In this simulation, the impact of wind on the path planning of quadrotors is modeled in three directions: X, Y, and Z. The wind values in each direction are simulated with a mean speed of 10 m/s and a variation factor.

Fig. 5 shows the velocity in all three axes, used to test the method's ability to adapt to wind forces in dynamic real-world conditions.

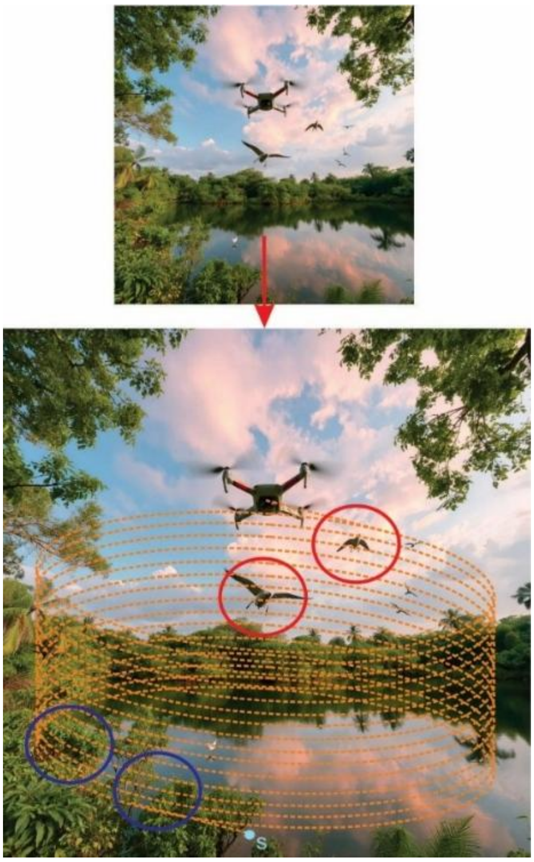
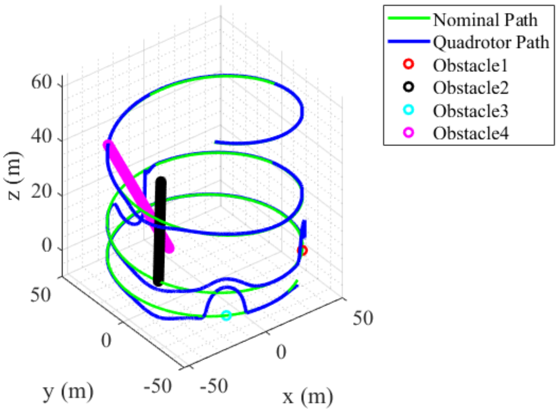
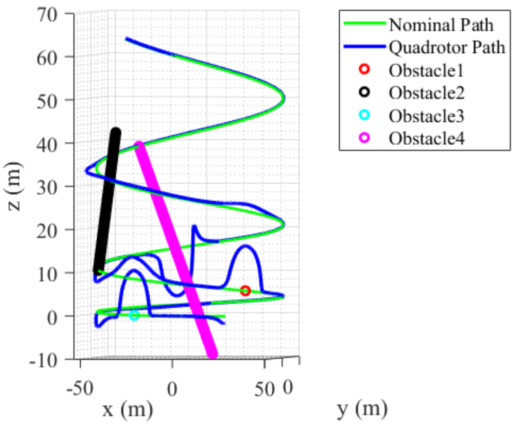


Fig. 3- Problem visualization (AI assisted).





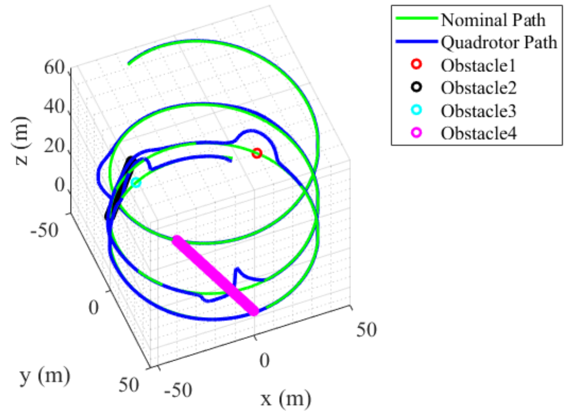


Fig. 4- Three different views of the 3D simulation illustrating the quadrotor's path planning.

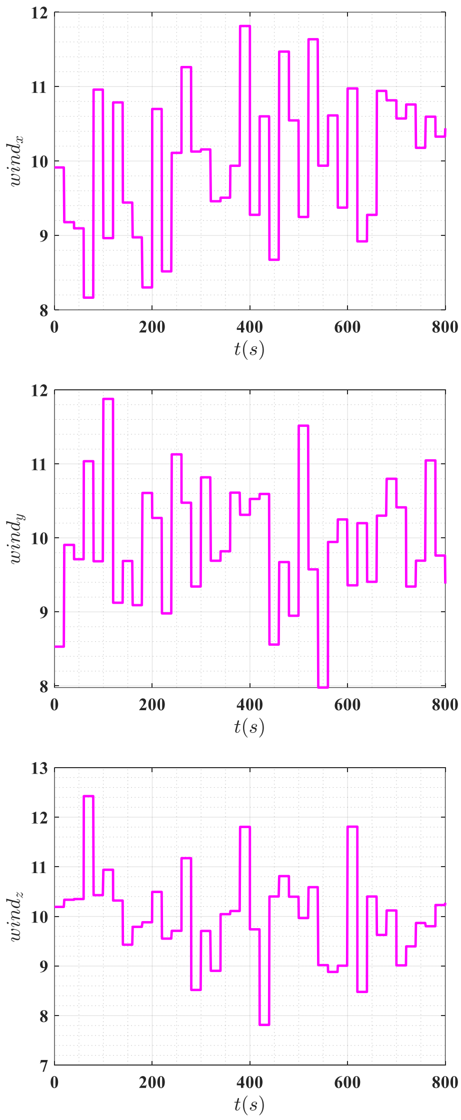


Fig. 5- Wind speed variation in the X, Y, and Z direction over time.

6. Pseudocode

The pseudocode presented in Section 9 outlines the key steps of the algorithm, providing a clear understanding of the proposed method's functionality. It offers a detailed abstraction to ensure that the logic is practical for implementation

7. Conclusion

This study introduces a path-planning method for quadrotors designed for environmental data collection in dynamic and complex real-world conditions. The approach uses PFM while overcoming its key challenges, such as instability near moving obstacles. By incorporating a fuzzy logic framework, the method enhances adaptability and decision-making through its flexible, rule-based structure, making it more robust in uncertain scenarios. Practical considerations, such as lateral acceleration limits, are also integrated into the design to ensure safety and operational feasibility. Furthermore, the connection between PID control gains and potential field components highlights their shared behaviors and principles. The proportional gain ($\mathrm{k_p}$) aligns with the attractive force coefficient ($\mathrm{k_a}$) in PFM, driving the system toward its target. The integral gain ($\mathrm{k_i}$) corresponds to the path repulsive coefficient ($\mathrm{k_b}$), correcting steady-state errors over time for improved accuracy. Similarly, the derivative gain ($\mathrm{k_d}$) relates to the damping factor (ζ), which reduces oscillations and enhances stability. This analogy underscores the unified principles of control and optimization in both methods, providing a framework for developing reliable and accurate path-planning systems. Simulation results show the effectiveness of the proposed approach (FPID-APFM), demonstrating its ability to generate smooth, safe, and efficient paths. Table 1 summarizes the correspondence between PID controller gains and PFM components, highlighting their respective applications.

Table 1- Mapping PID Gains to Potential Field Components and Their Applications

PID Gain	PF Coefficient	Application
$\mathrm{k_p}$	$\mathrm{k_a}$	Determines the strength of the attractive force guiding the system toward its target.
$\mathrm{k_i}$	$\mathrm{k_b}$	Influences long-term corrective effects (obstacle avoidance vs. steady-state error correction).
$\mathrm{k_d}$	ζ	Dampens oscillations and ensures the system remains stable.

Fig. 6, Fig. 7 and Fig. 8 illustrate the variation of the coefficients over a 800-second simulation. These figures show how the fuzzy inference system dynamically adjusts the attractive and repulsive force coefficients in response to the error and its derivative at each second. As clearly seen in the figures, the fuzzy rules continuously adapt the coefficients, reflecting the system's ability to fine-tune these parameters in real-time to ensure smooth path planning. This dynamic adjustment process is key to overcoming challenges such as oscillatory behavior and local minima, allowing the quadrotor to navigate more effectively in both static and dynamic environments.

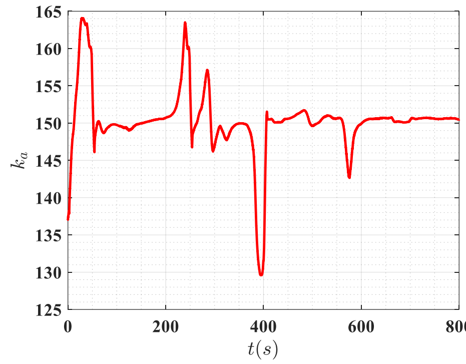


Fig. 6- The variation of k_a in the potential field method over time.

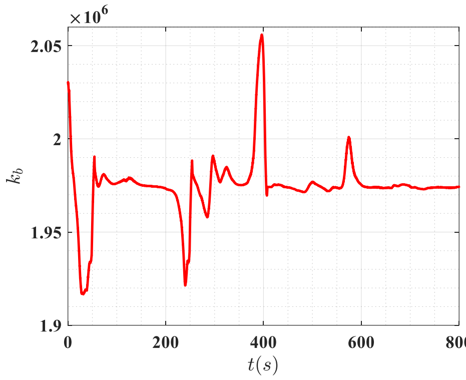


Fig. 7- The variation of k_b in the potential field method over time.

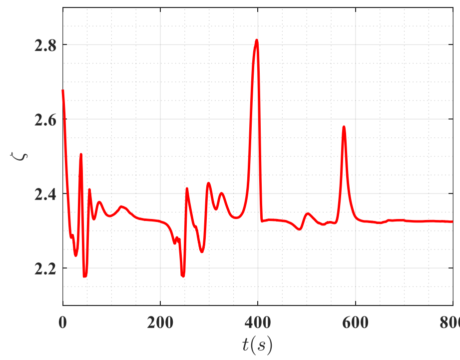


Fig. 8- The variation of ζ in the potential field method over time.

Fig. 9, Fig. 10, Fig. 11 and Fig. 12 present 2D plots depicting the variation in distance to the first, second, third, and fourth obstacles over time, respectively. Each plot features a blue oscillatory curve that reflects changes in distance, showing dynamic interactions between the quadrotor and its surroundings. A red horizontal line is included as a minimum threshold, serving as a safety limit or collision boundary. The periodic behavior in the curves indicates moments when the UAV approaches obstacles, highlighting the method’s responsiveness in maintaining a safe distance accordingly.

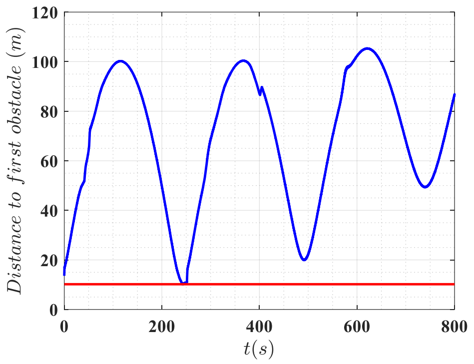


Fig. 9- Distance variation to the first obstacle over time.

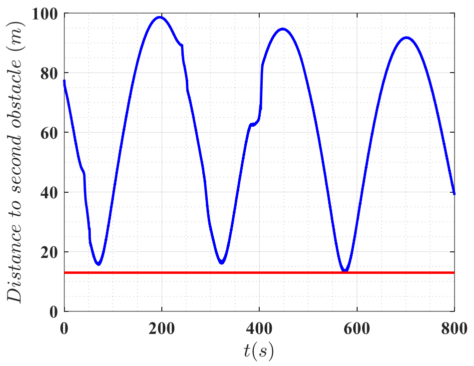


Fig. 10- Distance variation to the second obstacle over time.

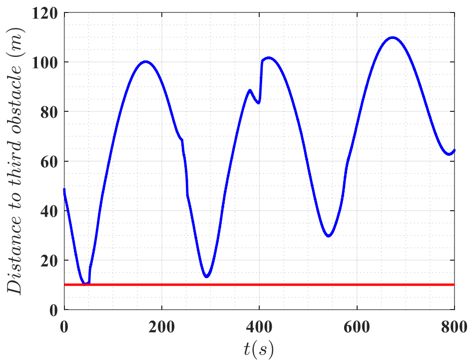


Fig. 11- Distance variation to the third obstacle over time.

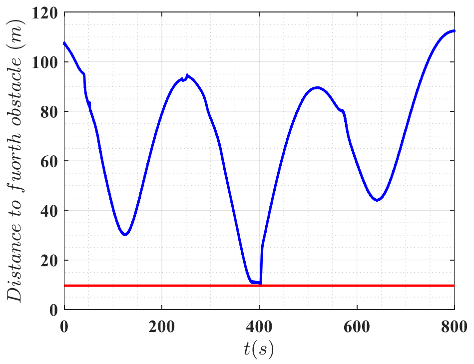


Fig. 12- Distance variation to the fourth obstacle over time.

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9. Appendix

- ✓ *Initialize simulation parameters*
  - $rx = Obstacle\ radius$
  - $nf = Obstacle\ radius\ scaling\ factors$
  - $V_{max} = Maximum\ voltage$
  - *Acceleration limits*
  - $dt = Time\ step$
  - $0 \to T = Simulation\ duration$
  - $\varphi\_max = Maximum\ roll\ angle$
- ✓ *Generate nominal path*
  - x_g, y_g *and* z_g
- ✓ *Set initial obstacle positions*
  - *Define initial positions*
  - *Assign dynamic velocities*
- ✓ *Initialize robot position*
- ✓ *Load fuzzy inference system*
- ✓ *Main simulation loop*:
  - *Evaluate fuzzy gains*
  - *For each obstacle*:

    $d_{obs} =$ *distance between the robot and obstacle*

    $d_0 = rx \times nf$
  - *Calculate repulsive force*
  - *If* $d_{obs} < d_0$:

    Compute repulsive forces
  - *else*

    Set repulsive forces to zero
  - *end*
  - *Calculate attractive force*
  - *Compute total forces*
  - *Considering wind effect*
  - *Apply constraints*
  - *Update robot position*
  - *Compute robot velocity, acceleration*
  - *Update obstacle positions*
  - *Update error values*

    $e = nominal\ path - generated\ path$
  - *Normalize error values*
- ✓ end