Innovative Fuzzy PID Algorithm: Advancing Quadcopter Control with Adaptive Precision

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Abstract: The integration of fuzzy logic techniques into PID controllers shows promising advantages in quadcopter control. By incorporating fuzzy logic, the PID controller achieves enhanced adaptability and robustness, resulting in more dynamic and resilient control performance. This is achieved through the automatic adjustment of PID parameters based on real-time system feedback, enabling a control strategy that closely resembles human reasoning. Overall, the combination of fuzzy logic and PID control offers significant potential for improving quadcopter control in various environmental conditions.

Keywords: PID controller, Fuzzy logic, Quadcopter control

1. Introduction

In recent years, the utilization of quadcopters has significantly increased in various applications, ranging from aerial photography and surveillance to parcel delivery and search and rescue missions. Efficient control of quadcopters is essential to ensure stable flight and accurate maneuvering in dynamic environments. Traditional Proportional-Integral-Derivative (PID) controllers have been widely employed for quadcopter control due to their simplicity and effectiveness in tracking desired trajectories. However, PID controllers have limitations in adapting to uncertainties and variations in environmental conditions, leading to suboptimal performance in complex scenarios.

To address these challenges, researchers have turned to fuzzy logic techniques to enhance PID controllers’ adaptability and robustness. Fuzzy logic offers a more intuitive approach to control by incorporating linguistic variables and IF-THEN rules, enabling controllers to mimic human-like reasoning. This integration allows for automatic adjustment of PID parameters based on real-time system feedback, improving control performance in varying conditions.

Previous studies have demonstrated the effectiveness of fuzzy PID controllers in various control applications, including robotic systems, industrial processes, and unmanned aerial vehicles. However, there remains a need for further exploration and optimization of fuzzy PID controllers, particularly in the context of quadcopter control, where precise trajectory tracking and stability are crucial.

In this paper, we propose a fuzzy PID controller tailored for quadcopter control, aiming to improve adaptability, robustness, and performance compared to traditional PID controllers. We integrate fuzzy logic techniques into the PID control framework to enable dynamic adjustment of control parameters based on environmental conditions and system feedback. Through simulation studies and experimental validation, we aim to demonstrate the effectiveness and potential superiority of the proposed fuzzy PID controller in quadcopter control applications.

2. PID controller

To achieve precise tracking and good performance, PID type controllers are commonly used in cascade control systems [2]. In this process, the PID controller works closely by calculating the difference between the setpoint and the desired setpoint, and minimizing this difference by adjusting the control variable [1][2]. The relationship between the system error and the PID controller output is defined by Equation (1), where Equation (2) represents the difference between the desired output and the actual output.

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}$$

(1)
Where \( K_p \) is the proportional gain, \( K_i \) is the integral gain, and \( K_d \) is the derivative gain. Increasing \( K_p \) can reduce steady-state error, but excessively high values may lead to unstable oscillations. Increasing \( K_i \) can eliminate steady-state error in feedback systems, while increasing \( K_d \) can reduce overshoot and settling time of the feedback system output signal \([3][4]\). Figure 1 shows the block diagram of the PID controller.

![Figure 1: Simulink blocks of PID controller](image)

### 3. PID adjustment method

PID controllers have no understanding of the process plant, making them unable to adjust and respond to changes. Therefore, proper tuning is required to achieve satisfactory performance. One of the most commonly used methods is the Ziegler-Nichols method, which is divided into step response and frequency response rules. Both rules start with setting the integral and derivative gains to zero while increasing the proportional gain to a value that causes the system to oscillate \([5][6]\).

However, systems without sustained oscillation cannot be tuned using this method. In this work, the derived model adopts a manual tuning approach to adjust the PID parameters, as attempts using the Ziegler-Nichols method did not result in sustained oscillation. Increasing each PID gain affects the system's transient response, with the effects summarized in Table 1. The PID parameters obtained according to the listed rules are shown in Table 2.

The rules for manual tuning of PID parameters are as follows \([7][8]\):

1) Set \( K_p, K_i \) and \( K_d \) to zero.

2) Increase \( K_p \) until oscillations occur either completely or almost completely. If full oscillation cannot be achieved, it is suggested to set a long simulation time.

3) Slightly increase \( K_d \) to reduce the oscillation period to one cycle. Running simulations with shorter stop times can be used.

4) Increase \( K_i \) until steady-state is close to the setpoint, and there is single oscillation around the setpoint.

5) Repeat these rules until the desired output is achieved.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>( K_p )</th>
<th>( K_i )</th>
<th>( K_d )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overshoot(%)</td>
<td>Increase</td>
<td>Increase</td>
<td>Decrease</td>
</tr>
<tr>
<td>Rise time(s)</td>
<td>Decrease</td>
<td>Decrease</td>
<td>Minor change</td>
</tr>
<tr>
<td>Setting time(s)</td>
<td>Minor change</td>
<td>Increase</td>
<td>Decrease</td>
</tr>
<tr>
<td>Steady-state error</td>
<td>Decrease</td>
<td>Eliminate</td>
<td>No effect(Theoretically)</td>
</tr>
<tr>
<td>Stability</td>
<td>Degrade</td>
<td>Degrade</td>
<td>Improved(Small ( K_d ))</td>
</tr>
</tbody>
</table>

### Table 2: The gains of PID parameters for PID controller

<table>
<thead>
<tr>
<th>Variable</th>
<th>( K_p )</th>
<th>( K_i )</th>
<th>( K_d )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position ((x,y),) Altitude ((z))</td>
<td>0.50</td>
<td>0.10</td>
<td>1.00</td>
</tr>
<tr>
<td>Attitude ((\phi, \theta, \psi))</td>
<td>1.00</td>
<td>0.01</td>
<td>0.10</td>
</tr>
</tbody>
</table>
4. Fuzzy Controller

Manual tuning methods are a convenient way for PID controllers to obtain reasonable results because they offer an intuitive approach and require minimal process knowledge. However, obtaining gains that yield reasonable results may take a long time, and determining whether the final settings are optimal can be challenging. Moreover, there is no guarantee that the system will reach a persistent and stable solution, which could potentially put the entire factory at risk. Due to the limited understanding of process plants by PID controllers, they cannot adjust themselves automatically when the system faces changes [9]. Therefore, heuristic methods, especially fuzzy logic techniques, are integrated into PID controllers to ensure that the desired outputs are achieved and parameters are automatically adjusted when changes are applied to the system.

Fuzzy logic is a powerful tool that does not require precise knowledge of mathematical models [10]. By leveraging human understanding of the factory in the control design process and decision-making process, fuzzy control is based on fuzzy set theory, linguistic variables, and fuzzy inference [11][12]. Fuzzy control systems consist of fuzzification, fuzzy rule base, fuzzy inference, and defuzzification, as shown in Figure 2 illustrates the general diagram of a fuzzy inference system [13].

**Figure 2: Fuzzy inference system**

For position, altitude, and attitude control of quadcopters, the inputs are errors (representing the difference between the desired trajectory and the generated trajectory) and the rate of change of errors. According to Figure 2, these inputs, represented as crisp values, are fed into the fuzzy inference system and transformed into linguistic variables through the fuzzification process. In the fuzzification process, prior knowledge is required to determine the ranges of input variables in order to map the input variables to discrete intervals.

Fuzzy logic controllers require a rule base and fuzzy set outputs to adjust PID parameters. The type of rule base chosen in this paper is Mamdani-type, which is a multi-input multi-output (MIMO) system, as it accepts 2 inputs and generates 3 outputs, namely $K_p$, $K_i$, and $K_d$. For position and altitude control, the fuzzy set inputs are set as $e(t) \in [-10,10]$ and $de(t) \in [-15,15]$, while for attitude control, they are set as $e(t) \in [-0.5,0.5]$ and $de(t) \in [-50,50]$. These regions are depicted in Figure 3 (position and altitude) and Figure 4 (attitude).

**Figure 3: The inputs membership functions of position and altitude**
Meanwhile, the fuzzy set outputs are configured based on $K_p \in [K_{p_{\min}}, K_{p_{\max}}], K_i \in [K_{i_{\min}}, K_{i_{\max}}]$ and $K_d \in [K_{d_{\min}}, K_{d_{\max}}]$. The fuzzy set outputs for position and altitude are set as $K_p \in [0.5, 5.0], K_i \in [0.1, 1.0]$ and $K_d \in [1.0, 10.0]$, as shown in Figure 5; while for attitude, they are set as $K_p \in [1.0, 10.0], K_i \in [0.01, 0.10]$ and $K_d \in [0.1, 1.0]$, as illustrated in Figure 6. These fuzzy sets are calibrated on the interval $[0, 1]$. The degree of membership functions is defined by triangular membership functions.
The Mamdani-type fuzzy controller utilizes IF-THEN rules to form linguistic representations of fuzzy logic, known as membership functions. Based on seven linguistic variables, 49 membership function rules are formed for each output. The membership function rules for the quadcopter are listed in Table 3 and Table 4 [14].

The final process of the fuzzy controller is defuzzification, where the outputs obtained from fuzzy inference are presented in linguistic form. To be fed into the PID controller, these outputs must be converted into crisp numbers. For Mamdani-type fuzzy controllers, the most common method of defuzzification is centroid method, with the specific calculation defined in Equation (3).

\[
\text{Output} = \frac{\sum_{i=1}^{q} \mu_i(w_i)w_i}{\sum_{i=1}^{q} \mu_i(w_i)}
\]  

(3)

Table 3: Fuzzy rules for Kp and Ki

<table>
<thead>
<tr>
<th>Error changes,</th>
<th>Error, e</th>
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<tbody>
<tr>
<td>&amp;e</td>
<td>NB</td>
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<tr>
<td>NB</td>
<td>M</td>
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<tr>
<td>NM</td>
<td>B</td>
</tr>
<tr>
<td>NS</td>
<td>VB</td>
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<tr>
<td>Z</td>
<td>VVB</td>
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<td>PS</td>
<td>VB</td>
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<tr>
<td>PM</td>
<td>B</td>
</tr>
<tr>
<td>PB</td>
<td>M</td>
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Table 4: Fuzzy rules for Kd

<table>
<thead>
<tr>
<th>Error changes,</th>
<th>Error, e</th>
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<tbody>
<tr>
<td>&amp;e</td>
<td>NB</td>
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<td>NB</td>
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<td>NS</td>
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<td>PS</td>
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<td>PM</td>
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<td>PB</td>
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5. Fuzzy PID Controller

The outputs generated by the fuzzy logic controller, K_p, K_i, and K_d, are fed into the PID controller to form a fuzzy PID controller. Figure 7 illustrates the general block diagram of the fuzzy PID controller, and Equation (4) defines the fuzzy PID controller [9][14][15][16].

\[
u(t)_{FPID} = (K_p + K_{pd})e(t) + (K_i + K_{id}) \int_0^t e(t)dt + (K_d + K_{dd}) \frac{de(t)}{dt}
\]

(4)

The minimum and maximum variable ranges of PID controller gains are obtained through trial-and-error simulations using the PID controller. The same values are used in Equations (5), (6), and (7) to
simulate the fuzzy PID controller, as depicted in Figure 8 [9][15][17].

\[ K_{pr} = \frac{K_p - K_{p\min}}{K_{p\max} - K_{p\min}} \]  
\[ K_{ir} = \frac{K_i - K_{i\min}}{K_{i\max} - K_{i\min}} \]  
\[ K_{dr} = \frac{K_d - K_{d\min}}{K_{d\max} - K_{d\min}} \]  

Figure 8: The Simulink blocks of self-tuning Fuzzy PID controller

6. Conclusion

Our creation of the fuzzy PID controller has the potential for improved effectiveness compared to traditional PID controllers. By integrating fuzzy logic techniques, our controller can adapt more dynamically to changes in the environment and system dynamics. The linguistic variables and IF-THEN rules in the fuzzy logic system allow for a more intuitive and human-like control strategy, enabling smoother and more precise control actions. Additionally, the automatic adjustment of PID parameters based on fuzzy logic reasoning enhances the controller's robustness and adaptability, leading to better performance, especially in complex and uncertain systems like quadcopter control. Overall, the fuzzy PID controller has the potential to outperform traditional PID controllers by offering enhanced adaptability, robustness, and performance.

References