Aviation Electronics, Information Technology, Telecommunications, Electricals, and Controls (AVITEC) 41
Vol. 7, No. 1, February 2025, pp. 41~51, p-ISSN 2685-2381, e-ISSN 2715-2626
http://dx.doi.org/10.28989/avitec.v7i1.2743

Implementation of Kalman Filter on PID Based Quadcopter for Controlling Pitch Angle

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Article Info

Article history:
Submitted December 30, 2024
Accepted February 4, 2025
Published February 10, 2025

Keywords:
Quadcopter;
PID;
Kalman Filter

ABSTRACT

Improving quadcopter control systems poses significant challenges in unmanned flight technology development. Key issues include the intricate nature of PID and Kalman filter parameter settings, necessitating profound knowledge of system dynamics and sensor properties. Furthermore, successfully integrating the Kalman Filter with PID control demands meticulous coordination to optimize state estimation precision and system responsiveness. This research emphasizes the incorporation of the Kalman filter into PID-based control for quadcopter pitch angle regulation. The Proportional-Integral-Derivative (PID) approach governs pitch angle, augmented by the Kalman Filter, to enhance estimation accuracy and mitigate sensor uncertainty. Optimal outcomes during system response testing were achieved with parameters of *Kp* at 2.95, *Ki* at 0.23, and *Kd* at 0.02, resulting in superior oscillatory response, including a 9-degree overshoot, a 5-second rise time, a 15-second settling time, and a 0.15-degree steady-state error, showcasing effective regulation of the quadcopter pitch angle. A concurrent observation during testing indicated that including the Kalman filter led to a significantly reduced overshoot compared to tests without it; conversely, the settling time experienced considerable acceleration, while measurement accuracy in the steady-state condition improved by 50%.

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1. INTRODUCTION

As time progresses, it is inextricably linked to advancements in technology. A notable advancement in this domain is the “Unmanned Aerial Vehicle (UAV).” UAVs manifest in various configurations, including rotary wing, fixed wing, ducted fan, and flapping wing designs. Quadcopters are crafted for unmanned operations, either remotely piloted or functioning autonomously via autopilot systems. Currently, UAV technology serves significant functions for both civilian applications and military use [1]. The blades spinning create upward force, allowing the plane to rise, lower, and shift sideways. These aircraft can either maintain a stationary position or exhibit high agility in flight. The primary advantage of rotary-wing aircraft lies in their capability for vertical takeoff and landing. Control of quadcopters is facilitated through a flight controller equipped with specialized algorithms and sensors. Two operational modes characterize quadcopters: manual mode, which is managed through a remote control, and autonomous mode, governed by pre-programmed instructions without the need for remote intervention [2]. The quadcopter's mechanical structure is relatively simple because it lacks additional drives to perform a variety of motions such as roll, which is a tilting movement from side to side, pitch, which is an up and down movement, and yaw, which is a sideways movement. Given the simplicity of mechanical design, totals have significantly influenced the control that size exerted on it. In this case, the motion's stability will be impacted if one of the rotors experiences a different thrust force. Therefore, in order ensure its stability, the quadcopter also needs an appropriate control system.

By implementing Proportional-Integral-Derivative (PID) control in quadcopters is a pivotal aspect of modern drone technology, enhancing stability, responsiveness, and overall flight performance. PID controllers are widely utilized in various engineering fields because they effectively manage dynamic systems. In the context of quadcopters [3], these controllers play a critical role in maintaining desired flight attitudes, such as pitch, roll, and yaw, by continuously adjusting motor outputs based on real-time sensor feedback [4]. As quadcopters evolve, integrating machine learning techniques alongside traditional PID control presents an exciting frontier for enhancing flight performance. This hybrid approach augments the precision of trajectory tracking and enables quadcopters to navigate better complex environments, such as urban landscapes, where obstacles may arise unexpectedly [5][6] . Implementing PID control on a quadcopter involves establishing a mathematical model of its dynamics using the Newton-Euler formulation. This model is the foundation for applying the PID control strategy, which regulates the quadcopter's pitch, roll, and yaw to maintain its desired flight trajectory. Simulation tests conducted in MATLAB/Simulink demonstrate the PID controller's effectiveness in ensuring rapid response times and precise attitude regulation, enhancing the quadcopter's stability against external disturbances [7].

PID method optimization is frequently combined with other superior methods, nevertheless the Kalman filter method can be used to optimize sensor output and allow for better control estimation. The Kalman filter is a powerful mathematical tool widely used in various applications to estimate the state of a dynamic system from noisy measurements. In the context of quadcopters, implementing a Kalman filter plays a crucial role in enhancing state estimation accuracy, which is vital for stable flight control and navigation [8]. The implementation process typically involves two main steps: prediction and update. In the prediction step, the filter uses the system's mathematical model to estimate the current state based on the previous state and control inputs. The update step incorporates new measurements to correct the predicted state, thus refining the estimate. This iterative process allows the Kalman filter to adapt to changing conditions and improve accuracy [9]. As a result, the Kalman filter has become an essential tool in various applications, including robotics, aerospace, and autonomous vehicles, where precise navigation and control are crucial for optimal performance. Implementing a Kalman filter for controlling the pitch angle of a quadcopter involves integrating sensor data to achieve accurate attitude estimation, which is crucial for stable flight control. The Kalman filter, particularly the Extended Kalman Filter (EKF), is widely used in this context due to its ability to handle the nonlinear dynamics of quadcopters. The EKF fuses data from gyroscopes and accelerometers to estimate the pitch angle, compensating for the drift in gyroscope data and the limitations of accelerometer data under dynamic conditions [10][11]. The fusion of these sensor inputs through the Kalman filter enhances the accuracy of the pitch angle estimation, achieving measurement accuracies as high as 98.91% for pitch angles [10]. The EKF's effectiveness in estimating attitude information has been validated through simulations and real-time experiments, demonstrating its capability to improve flight performance and reliability, especially in autonomous navigation tasks such as waypoint navigation and handling wind disturbances [12].

Besides Kalman filter, adaptive Kalman filters have been proposed to enhance pitch angle estimation by adjusting the filter's measurement covariance matrix in response to varying dynamic conditions, thus improving robustness against external acceleration [13]. Implementing the Kalman filter on low-cost microcontrollers has also been explored, showing that proper tuning of noise parameters can provide stable and accurate pitch angle estimates in real-time applications [14]. Overall, the Kalman filter, particularly in its extended and adaptive forms, is a critical component in the control systems of quadcopters, enabling precise pitch angle control and contributing to the overall stability and performance of the UAV [15][16].

The implementation of a Kalman filter on a PID-based quadcopter for controlling the pitch angle involves integrating the Kalman filter to enhance the accuracy and stability of the PID control system by mitigating sensor noise and improving state estimation. The Kalman filter is particularly effective in processing the noisy output from sensors like gyroscopes and accelerometers, which are crucial for maintaining the quadcopter's balance and stability during flight. For instance, the Kalman filter is used to refine the gyroscope data, which is often affected by vibrations during flight, thereby providing a more accurate input for the PID controller to manage the pitch and roll angles effectively [17]. The combination of a Kalman filter with a PID controller has been shown to improve the dynamic performance of UAVs, offering advantages such as better stability, anti-disturbance capabilities, and real-time control, which are essential for precise pitch angle control [18]. Moreover, the Kalman filter's ability to estimate the UAV's attitude accurately by integrating gyro and accelerometer data helps in reducing drift and compensating for external accelerations, thus enhancing the control precision of the pitch angle [13]. The integration of the Kalman filter before the PID controller, as demonstrated in the Qball-X4 quad-rotor UAV, ensures the validity of the control system by estimating the target trajectory and addressing system errors and data delays [19]. Additionally, the adaptive Kalman filter can further optimize the PID gains, improving the system's robustness against noise and enhancing the overall control performance[20]. This integrated approach not only improves the quadcopter's stability and responsiveness but also ensures minimal overshoot and precise control, fulfilling the requirements for effective pitch angle management in UAVs. Overall, the integration of Kalman filtering with PID control in quadcopters results in a robust system capable of maintaining stable flight and precise pitch angle control.

Based on the problems above, a control with good and strong performance in various operating conditions is needed, and can minimize rise time, reduce errors, and reduce overshot or undershot. In this study, the first step is to design a quadcopter control system to obtain pitch values using PID (Proportional Integral

Derivative) on the microcontroller used. The next stage is to verify the system testing to achieve the level of success of the designed control system. The Testing and Analysis study aims to test and analyze the control system whether the Kalman filter can improve the response and stability of PID control by providing a more accurate state estimate. With this research, it is hoped that the method will be able to read the pitch value using the Kalman filter.

2. RESEARCH METHODS

2.1 Proportional Integral Derivative (PID)

The Proportional-Integral-Derivative Proper tuning can significantly enhance system performance, ensuring quick response times and minimal steady-state error while avoiding excessive oscillations or instability. PID method is a widely used control algorithm in industrial automation and systems engineering. It combines three fundamental control actions: proportional control, which adjusts the output based on the current error; integral control, which accumulates past errors to eliminate steady-state offset; and derivative control, which predicts future errors based on the rate of change [21]. Effective tuning of these parameters is crucial, as it directly influences the responsiveness and stability of the control system, ultimately leading to improved operational efficiency and reliability. The proper balance of these control actions allows for a tailored response to varying system dynamics, making PID controllers versatile and applicable across a wide range of industries, from manufacturing to robotics. The ability to fine-tune these controllers is essential for optimizing performance, as different applications may require distinct settings to achieve the desired level of precision and responsiveness. Achieving this fine-tuning often involves iterative testing and adjustments, where engineers must carefully analyze system behavior to determine the optimal gains for proportional, integral, and derivative components. This process not only enhances the system's performance but also ensures that it can adapt to changing conditions and maintain stability under various operational scenarios. The PID control system is a controller to determine the precision of an instrumentation system with the characteristics of feedback on the system. The PID control system consists of three control methods, namely P (Proportional), I (Integral), D (Derivative) control, each of which has advantages and disadvantages. In its implementation, each method can work alone or combined. With the appropriate *Kp, Ki* and *Kd* parameters, the system will have a very fast response in reaching its set point, eliminating offsets, accelerating conditions and eliminating steady state errors. PID controller is a controller that is used to determine the precision of an instrumentation system with the characteristics of feedback on the system. The PID control components consist of three types, namely Proportional, Integrative and Derivative. The elements of the P, I and D controllers aim to accelerate the reaction of a system, eliminate offsets and produce large initial changes.

a. Proportional controller (P): The proportional controller produces an output that is proportional to the size of the input. Simply put, it can be said that the output of the proportional controller is the multiplication of the proportional constant with its input.
b. Integral controller (I): The integral controller functions to produce a system response that has a zero steady state error (Error Steady State = 0). If a plant does not have an integrator element, the proportional controller will not be able to guarantee its system output with a zero Error Steady State.
c. Derivative controller (D): The output of a differential controller has properties similar to a derivative operation. Sudden changes in the controller input will result in very large and rapid changes. When the input does not change, the controller output also does not change and vice versa.

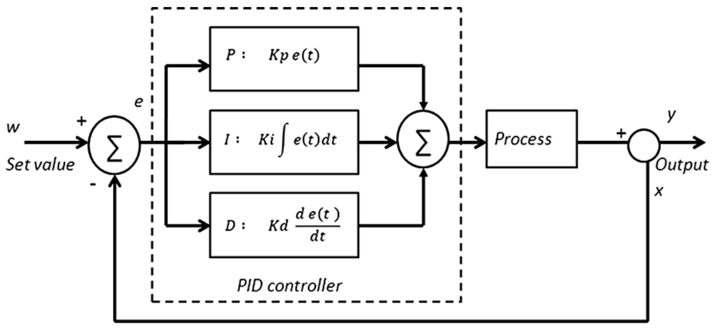


Figure 1. Diagram block of PID controller [22]

The PID controller output is the sum of the outputs of the proportional controller, integral controller and differential controller. The characteristics of the PID controller are greatly influenced by the large contribution of the three parameters P, I and D. Adjusting the constants *Kp*, *Ki*, and *Kd* will result in the prominence of the properties of each element. One or two of the three constants can be set more prominently than the other. Together, these three components allow PID controllers to achieve a balance between responsiveness and stability, making them suitable for a wide range of applications, from temperature control to robotic systems. The tuning of the PID parameters is crucial for optimizing performance and achieving desired control characteristics[23]. Proper tuning can be achieved through various methods, including trial and error, Ziegler-Nichols, or software-based optimization techniques, each offering unique advantages depending on the specific application and system dynamics.

2.2 Kalman Filter

The Kalman filter is a powerful mathematical tool used for estimating the state of a dynamic system from a series of noisy measurements. Developed by Rudolf E. Kalman in the 1960s, this recursive algorithm provides an efficient means to predict and update the state of a system over time, making it particularly valuable in fields such as control systems, robotics, navigation, and signal processing. Its ability to minimize the mean of the squared errors in predictions allows for improved accuracy and reliability, which is crucial in applications where precision is paramount. This adaptability and robustness make the Kalman filter an essential component in various technologies, including autonomous vehicles, aerospace systems, and financial modeling, where real-time data integration is critical for optimal performance[15]. It has two main stages:

a. Prediction: In this stage, the Kalman filter uses a known model of the system to predict the state of the system at a later time based on previous estimates. This involves forward projection of the system state and uncertainty which have two predictions:
   1) Status Prediction

$$\hat{x} = F \times x(t-1) + B \times u(t) \quad (1)$$

with:
- $\hat{x}$: the estimated status of the variable at time t.
- F : the transition matrix that describes the evolution of the system from one time to the next
- $x(t-1)$: the status of the variable at the previous time.
- B : the control matrix that relates the influence of the control input to changes in the status of the variable.
- $u(t)$: the control input at time t.

   2) Covariant Prediction

$$P(t) = F \times P(t-1) \times F^T + Q \quad (2)$$

with:
- $P(t)$: the estimated covariance matrix at time t.
- Q : the process noise covariance matrix representing the uncertainty in the dynamic model.

b. Correction (Correction Process): At this stage, the Kalman filter updates the prediction based on the measurement data received at the next time. This is done by comparing the actual measurements with the predictions and calculating the extent to which these measurements affect the estimation of the system state and uncertainty which have three parameters:
   1) Kalman gain

$$K(t) = P(t) \times H^T \times (H \times P(t) \times H^T + R)^{-1} \quad (3)$$

   2) Status correction

$$\hat{x} = \hat{x} + K(t) \times y(t) \quad (4)$$

   3) Covariant correction

$$P(t) = (I - K(t) \times H) \times P(t) \quad (5)$$

with:
- $K(t)$: Kalman gain, determines how much we trust the actual measurement compared to the prediction.
- R : the measurement noise covariance matrix that represents the uncertainty in the measurement.
- I : the identity matrix

The Kalman filter is particularly effective in scenarios where measurements are corrupted by noise, as it systematically reduces the impact of this noise on the state estimates. Its recursive nature allows it to process measurements sequentially, making it suitable for real-time applications. The main advantage of the Kalman filter is its ability to combine information from the system model and measurement data to produce better estimates than either one separately. It is also able to cope with noise or uncertainty in the measurement data, which is often a problem in real-world applications. The Kalman filter has evolved over the years, leading to various extensions and adaptations, including the Extended Kalman Filter (EKF) for non-linear systems and the Unscented Kalman Filter (UKF) for more complex scenarios. These advancements have broadened the applicability of the Kalman filter across diverse fields, from aerospace engineering to finance, where accurate state estimation is critical for performance and decision-making [24].

2.3 System Design

The hardware design of this quadcopter uses the (X) model. The front and rear brushless motors rotate clockwise, while the right and left rotate counterclockwise. The hardware used in this study is an electronic system, namely the Teensy Microcontroller, Brushless Motor, Electronic Speed Controller (ESC). The electronic design in this system refers to its control, namely four brushless motors which function as quadcopter drivers. Based on the electronic system scheme in Figure 2, the ESC functions as a speed controller for the brushless motor controller based on the output provided. The components needed to design a quadcopter PID controller are (1) four brushless motors; (2) electronic speed controller (ESC); (3) four propellers; (4) frame; (5) teensy microcontroller; (6) Universal Battery Eliminated Circuit (UBEC); (7) Battery; (8) inertial measurement unit (IMU) sensor. In general, these components consist of three parts, namely the controlled part, the sensor and the controller part as shown in Figure 1. The controlled part consists of the motor, ESC, and propeller. The frame is the quadcopter frame where the motor, ESC and propeller are installed as the propeller driver to produce lift. The Inertial Measurement Unit (IMU) sensor consists of an accelerometer and gyroscope sensor to determine the position and path traveled by the quadcopter. This PID controller is then programmed into the microcontroller to regulate the roll and pitch angle movements when given a push so that it matches the given reference.

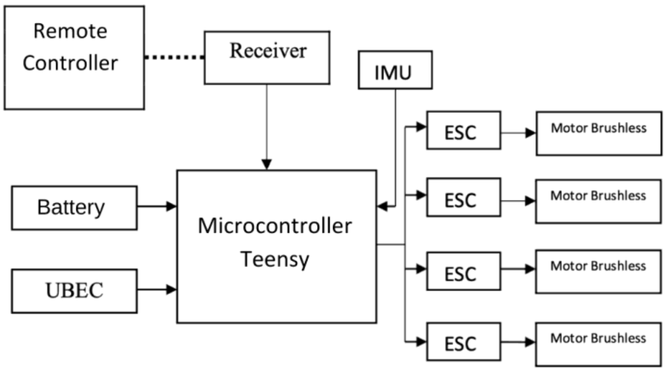


Figure 2. Hardware Diagram Design

The system input device consists of a teensy microcontroller that is tasked with reading the IMU (Inertial Measurement Unit) sensor, namely the accelerometer, gyroscope, and magnetometer to detect the tilt position of the quadcopter. The teensy microcontroller as an embedded system device is embedded with a PID control method to input IMU sensor data and provide pulse width modulation (PWM) data to the actuator as an output device, where the values of *Kp*, *Ki*, and *Kd* were previously determined from a series of static tests on the quadcopter, with the initial values obtained through trial and error. The values of the covariance matrix for the prediction covariance (Q) and correction covariance (R) are 0.01 and 10, respectively.

3. RESULTS AND DISCUSSION

3.1 System Testing

The testing is done to determine the performance level of the system. Testing is done to find out whether the planned system can work well. from each component that is tested can work well or there is an error. For receiver testing to the remote control, the microcontroller pins are connected to the designed PCB board, the result is that the remote control can control the direction and determine the movement according to the pilot's wishes. ESC operation connected to the microcontroller when flying manually will be controlled by the remote control (RC) connected or connected to the receiver and regulates the motor rotation speed through the ESC. In this process, the remote as a signal sender to the receiver to be able to rotate the brushless motor connected to the ESC requires routine calibration so that each motor is in line with the remote control so that it gets the desired rotation results. Then the combination of four (4) ESCs that regulate the brushless motor on the PCB board that can be seen in Figure 3.

The calibration process of the brushless motor and ESC rotation in aligning the rotation at the output value of the remote control using the receiver. The calibration process is fairly easy by connecting the input cable on the ESC to the receiver then raising the throttle lever on the remote control then connecting the battery as a voltage source, a few moments after the battery is installed the brushless motor will sound several times then lower the throttle lever and wait until the brushless motor is connected then the calibration process is complete.

Figure 3. ESC and brushless motor calibration process

Several stages are carried out before the sensor is used on the vehicle being created, one of which is to recalibrate the MPU6050 sensor to obtain the desired tilt angle by the sensor user. After the offsets value is obtained, then that value will be entered into the Arduino program to get the desired tilt angle by the author. Several processes are carried out when calibrating or finding the offsets value on the MPU6050 sensor. After a series of processes are carried out, the calibration of the MPU6050 sensor is completed. Then the output results are compared with the comparative measuring instrument to obtain results that are in accordance with what is expected.

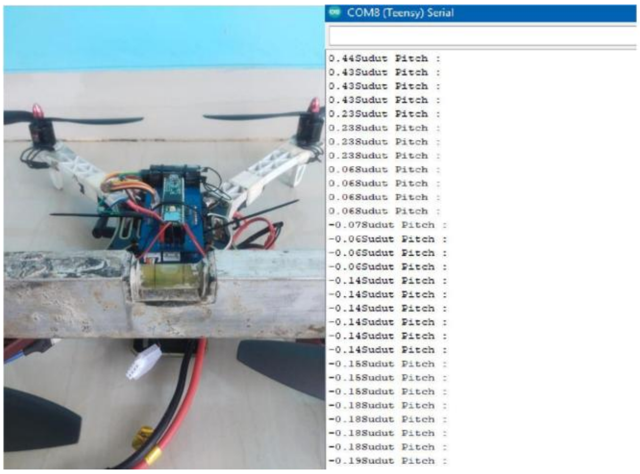


Figure 4. The testing of MPU6050 sensor against a measuring instrument

According to Figure 4, the figure showing the output of the MPU6050 with a set point of 0° tilt angle and on the comparator measuring instrument can be seen the air bubble is right in the middle of the comparator measuring instrument.

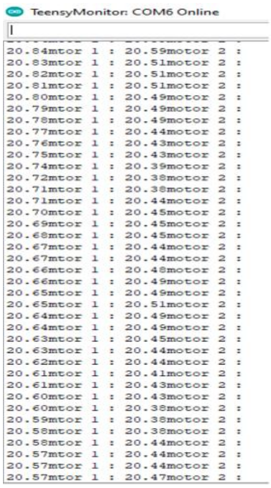


Figure 5. Teensy microcontroller testing of Kalman filter values (left) and PID values (right)

After the initial system experiment was completed, the next experiment was to test the ability of the Kalman filter method to improve the stability value before being combined with the PID method. The test was carried out at an angle of 20º as seen in Figure 5. After conducting the experiment at an angle of 20º, the results were obtained using the Kalman filter (left) and using PID (right). The value using the Kalman filter took 10 seconds to get the same value as the PID value. A similar thing also happened in the experiment at an angle of 40º. At the value using the Kalman filter, it took 20 seconds to get the same value as the PID value.

3.2 Results

The test results of the PID value tuning were conducted by trial and error. The data collection process used a rope tied to both ends of the quadcopter body and provided input on the P (Proportional), I (integral), and D (Derivative) values that were combined with each other. The testing was carried out to find the best system response produced by the quadcopter vehicle. When conducting the test, the quadcopter vehicle will be tied to the quadcopter frame body using a rope that can be seen in Figure 5.

Figure 6. Top view of quadcopter testing

It can be seen in the Figure 6, that the body or frame of the quadcopter is tied using ropes on each side, this is intended so that the quadcopter can float or hover and make it easier when doing the tuning and data collection process. Then we can see from the picture below which shows the quadcopter taking pictures from the other side. The binding of the quadcopter is also done on two opposite sides (front and back) then gives space to move on the other side (right and left). This aims to provide this space so that the quadcopter can balance itself when flying.

The following are the results of several system response tests on the Proportional, Integral and Derivative values that are input into the tuning process through trial and error on the quadcopter vehicle with static testing, namely by tying parts of the quadcopter vehicle with rope media. Below are the results of the system response values from the test which can be seen in Table 1.

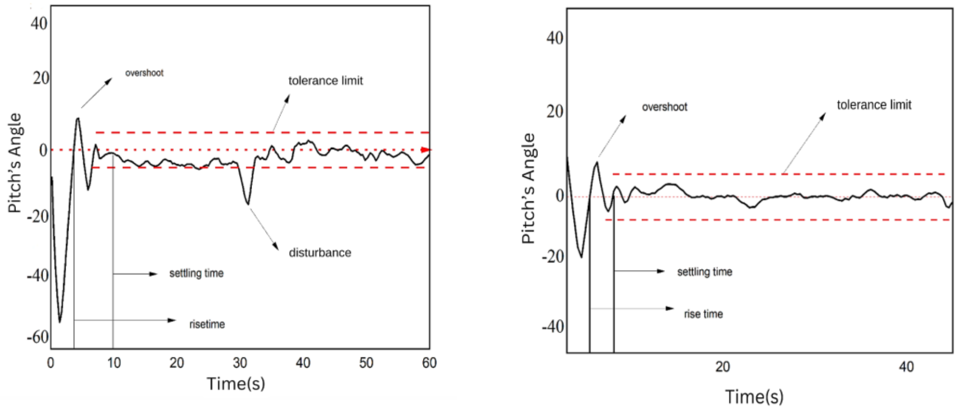
Table 1. PID values for quadcopter system response

Number of Tests	Proportional	Integral	Derivative
1st Testing	5.45	0.20	0.02
2nd Testing	2.95	0.23	0.02
3rd Testing	2.95	1.00	0.03

From Table 1, the results of the graphic analysis can be seen when data collection uses the values shown in the table. The following is a graph of the results of the tuning process carried out for each test.

3.2.1 The first testing

The first test was conducted by comparing the system response to the PID method without using a Kalman filter and the system response after adding a Kalman filter. The first test analysis graph is a graph produced during the tuning process by inputting values of *Kp*: 5.45, *Ki:* 0.20 and *Kd:* 0.02. based on the image that it affects the quadcopter's flight style when tuning is carried out. The graph of the PID system response implemented on the quadcopter can be seen in the Figure 7 (a) that there are system response results that contain many errors in the PID tuning value, the graph results of the *Kp* value above have an overshoot of 9° and a rise time of 4 seconds, a settling time of 10 seconds, and a steady state of 0.12º, from the results of the graph analysis above, it aims to see whether the results of the PID control tuning by trial and error produce similar outputs or different results after being tested.



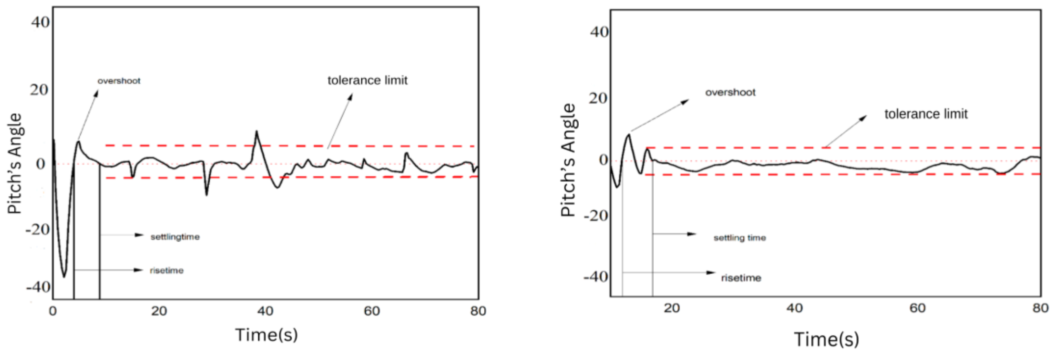
(a) (b)

Figure 7. The first testing response of (a) PID (b) Kalman filter

Observed in Figure 7 (b) it turns out that the experiment above affects the quadcopter's flight style when tuning is carried out. In the PID system response graph with the Kalman filter system implemented on the quadcopter, it can be seen in the graph that there are stable system response results due to readings or outputs that affect the offset value in the PID system response results without using the Kalman filter system, the graph results of the PID value with the Kalman Filter above have an overshoot of 7° and a rise time of 4 seconds, a settling time of 7 seconds, and a steady state of 0.06º.

3.2.2 The second testing

The second test was conducted by comparing the system response to the PID method without using the Kalman filter system and the system response after adding the Kalman filter system with the respective PID parameter tuning values of *Kp*: 2.95, *Ki:* 0.23, and *Kd*, 0.02. In can be observed in Figure 8 that the experiment has an effect on the quadcopter's flight style when tuning is carried out. The graph of the PID system response that shown in Figure 8 (a), there are system response results that contain many errors in the PID tuning value, the graph results of the PID value above have an overshoot of 6° and a rise time of 4 seconds, a settling time of 9 seconds, and a steady state of 1.3º. From the results of the graph analysis above, it aims to see whether the results of the PID control tuning by trial and error produce similar output or different results after being tested.



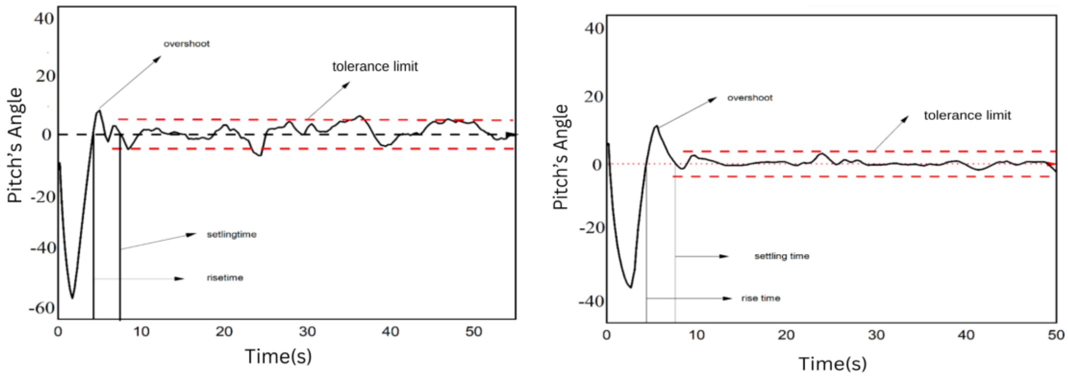
(a) (b)

Figure 8. The second testing response of (a) PID (b) Kalman filter

Based on Figure 8 (b) states that the experiment has an effect on the quadcopter's flight style when tuning is carried out, there is a stable system response result due to the reading or output that affects the offset value on the PID system response output without using the Kalman filter system, the graphic results of the PID value with the Kalman Filter have an overshoot of 9° and a rise time of 5 seconds, a settling time of 15 seconds, and a steady state of 0.15º.

3.2.3 The third testing

The third test was conducted by comparing the system response to the PID method without using the Kalman filter system and the system response after adding the Kalman filter system with the respective PID parameter tuning of *Kp:* 2.95, *Ki*: 1.00, and *Kd*: 0.03. If observed in Figure 9, the experiment has an effect on the quadcopter's flight style when tuning is carried out. In Figure 9 (a) the PID system response graph implemented on the quadcopter, it can be observed that there are system response results that contain many errors in the PID tuning value, the graph results from the *Kp* value above have an overshoot of 8° and a risetime of 4 seconds, settling time for 8 seconds and a steady state of 0.12º.



(a) (b)

Figure 9. The third testing response of (a) PID (b) Kalman filter

In figure 9 (b) it can be observed that the experiment has an effect on the quadcopter's flight style when tuning is carried out. the graph is the response of the PID system with the Kalman filter system implemented on the quadcopter, it can be seen in the graph that there are stable system response results because the reading or output affects the offset value on the PID system response without using the Kalman filter system, the graph results of the PID value with the Kalman Filter above have an overshoot of 13° and a rise time of 4 seconds, a settling time of 8 seconds, and a steady state of 0.07º.

3.3 Discussion

After testing the system response on the quadcopter vehicle by tying it to the frame or body of the quadcopter vehicle with a rope and adding PID values when tuning by trial and error to test the system response to the quadcopter vehicle, and adding a Kalman filter system to the PID value from three tests carried out on the response of the quadcopter vehicle system. Based on the results of the system response analysis from the first test, different results were obtained from testing the PID system response with and without using a Kalman filter. There is a correction or filtering of values against the output results from the reading of the MPU6050 sensor slope value that enters the PID value. The different steady state of the two first test graph results is one of the differences that we can see clearly. From these two results it is clear that the Kalman filter system works well because there is a stable graphic oscillation indicator than without using a Kalman filter. The second test also showed the same results as the first test. Based on the results of the system response analysis from the second test, different results were obtained from the PID system response test with a Kalman filter and without a Kalman filter. There is a correction or filtering of values against the output results from the reading of the MPU6050 sensor slope value that enters the PID value. The different steady state of the two second test graph results is one of the differences that we can see clearly. From these two results, it is clear that the Kalman filter system works well because there is a stable graph oscillation indicator than without using a Kalman filter. The same thing is also found in the third test which shows the same results as the first test. Based on the results of the system response analysis from the third test, different results were obtained from the PID system response test with a Kalman filter and without using a Kalman filter. There is a correction or filtering of values against the output results from the reading of the MPU6050 sensor slope value that enters the PID value. The different steady state of the two results of the third test graph is one of the differences that we can see clearly. From these two results it is explained that the Kalman filter system works well because there is a stable graphic oscillation indicator than without using the Kalman filter. From all the test results, the following is a table of test results from the PID method without a Kalman filter and with a Kalman filter.

Table 2. Overall results of the PID system response test analysis

System response parameters	PID's test system response		
	1st Testing	2nd Testing	3rd Testing
Overshoot (º)	9	6	8
Risetime (s)	4	4	4
Settling time (s)	10	9	8
Steady state (º)	0.12	1.3	0.12

Table 3. Overall results of the analysis of the response testing of the PID Kalman filter system

System response parameters	PID-Kalman Filter Test System Response		
	1st Testing	2nd Testing	3rd Testing
Overshoot (°)	7	9	13
Risetime (s)	4	5	5
Settling time (s)	7	15	8
Steady state (°)	0.06	0.15	0.07

Based on the overall results of the system response test on the quadcopter, there is a good system response in each test, resulting in a vehicle that can maintain its flight condition and return to a stable position when disturbed by the remote control, but there is a significant oscillation of the tilt angle or flight style on the quadcopter vehicle. Contrary to the experiments described in [17], oscillatory patterns frequently arise each time the quadcopter undergoes disturbances. While specific data regarding the extent of overshoot, steady-state value, rise time, and settling time are not provided, the graphical representations clearly illustrate a comparison with the results obtained from the proposed methodology. Unlike the approach by Feng Pan, Liu, and Xue [20], a Kalman filter is employed to mitigate noise derived from the system, subsequently facilitating the optimization of the PID parameters. The Kalman filter is implemented post-takeoff and assessed for pitch and roll maneuvers during the simulation. The findings indicate that overshooting occurs during pitching, accompanied by oscillations throughout the pitch phase and during the initial roll movement.

Nevertheless, unlike pitching, no oscillatory behavior is observed during the rolling phase until the quadcopter returns to its original position. In this research, oscillations were observed; however, the steady-state values achieved were remarkably proximate to the initial values of 0.06, 0.15, and 0.07, thereby not inducing any substantial disruptions. Eventually, the addition of the Kalman filter system to the quadcopter vehicle is considered successful and can work well, especially in terms of the accuracy of the final value achieved and reducing the influence of oscillation on the final value.

4. CONCLUSION

Based on the comprehensive analysis of the results derived from the series of meticulously conducted tests, it can be definitively concluded that the Proportional-Integral-Derivative (PID) control system effectively employs a Kalman filter that has been adeptly applied to the pitch angle, which was successfully implemented and rigorously tested on a quadcopter vehicle through the innovative method of utilizing a rope medium for stabilization and control. The PID control configuration that yielded the optimal system response is characterized by the following parameter values: Proportional gain (*Kp*) of 2.95, Integral gain (*Ki*) of 0.23, and Derivative gain (*Kd*) of 0.02, which collectively resulted in achieving the most favorable oscillation response, specifically an overshoot quantified at 9 degrees, accompanied by a rise time measured at 5 seconds, a settling time that extended to 15 seconds, and a steady-state error recorded at 0.15 degrees, thus demonstrating its capability to regulate the pitch angle of the quadcopter proficiently. A parallel phenomenon was observed during the testing phase when a Kalman filter was additionally incorporated, wherein the overshoot recorded was notably lower in comparison to the trials conducted without the application of a Kalman filter; conversely, the settling time parameter exhibited a significant enhancement in its acceleration, while the steady-state value displayed a remarkable increase in measurement accuracy amounting to 50%. In further research, the X-axis (roll) and Z-axis (yaw) can be added so that the UAV can take off and can be combined with other control systems, which are expected to increase the stability of the quadcopter vehicle.

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