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Wind Compensation in Drones using PID Control Enhanced by Extended Kalman Filtering

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Abstract

Several sectors, including relief, precision farming, logistics, and security, have started using drones. Their performance is often impacted by external factors, and among these, winds are the most impactful as they negatively affect aerodynamic efficiency, flight stability, and trajectory accuracy. Although H-infinity controllers could address the problem as a solution for disturbances, the amount of computation is large and therefore cannot fit into light-weight platforms such as drones that need lean and fast processing in real time. We propose a lightweight control scheme consisting of an Extended Kalman Filter (EKF) and a PID controller to address wind disturbance compensation. The drone dynamics are nonlinear; the EKF acts as a refining mechanism that improves input from noisy IMU/GPS sensors while also modeling wind forces as a state variable for real-time estimation of disturbances. This estimation is then fed in a feedforward manner into the controller that proactively rejects wind disturbances before they reach flight level. Simulated investigations on a 1.5 kg quadrotor subjected to sinusoidal and random wind disturbances have shown that PID+EKF has reduced the root-mean-square trajectory error by about 45% compared to that with the PID controller alone and has also reduced the velocity settling time to almost half of that with the PID controller.

Keywords: Wind Disturbance Compensation, PID Controller, Extended Kalman Filter, Flight Stability, Disturbance Rejection, Outdoor Flight Conditions.

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1. Introduction

The use of unmanned aerial vehicles (UAVs) or drones today is impressive, ranging from surveillance, precision agriculture, and infrastructure inspections to logistics. UAVs also play an important role in disaster response. A drone can operate in areas that are impossible for humans to reach or are harder to access, executing autonomous tasks while simultaneously gathering real-time data. Although used for many promising purposes, particularly in wind conditions, the adverse effects of the environment have posed a major limitation to the efficiency of drones, especially those used outdoors. Wind is a major source of instability in flight operations, especially when it is strong and winds change very suddenly. This instability causes the drone to veer off its intended path, drifting away from its target trajectory. As a result, the drone has to expend extra power to maintain its course, which leads to a definite loss of efficiency and power. It should be considered to implement controls that are effective in real time to counter environmental disturbances, especially in such conditions. As referenced in the literature, the rejection of disturbances using Model Predictive Control (MPC) and H-infinity methods is known to be very computationally expensive. These methods are known to be complementary in terms of parameter tuning requirements, which means that implementing any type of control on these lightweight and resource-constrained drones is not feasible for real-time execution on lightweight aerial platforms. Sometimes, due to their energy inefficiency, ease of implementation, or primarily because of ease of use, PID controllers are and have been used. However, the classic PID controller is inadequate for modern UAV applications, which require greater precision and adaptability to rapidly changing conditions noticeable by noise-laden sensors and turbulent winds. To address such problems, the current study proposes a modern hybrid control system consisting of PID and an Extended Kalman Filter (EKF) with feed-forward compensation. In this research, where the EKF is not a general state estimator, it plays a significant role in enhancing the PID. By considering the wind disturbances in the state vector, the EKF provides estimates of position, velocity, and attitude with a degree of refinement, even in the presence of noisy IMU/GPS measurements. Such estimates reduce overshoot and increase PID response time to external disturbances. With the EKF, feedback becomes reliable, and the control system improves significantly. The feed-forward system would utilize either real-time data or estimations of wind forces to preemptively counteract disturbances, reducing the need for feedback and enabling the UAV to respond to turbulence more efficiently and swiftly. The result of the PID calculations is to arrive at control inputs that are sharper and more stable. Such inputs, when refined through an EKF, hold the drone steady on its path even through strong gusts of wind, as demonstrated in [4][6][7]. The contribution of this paper is the design, implementation, and simulation of the PID-EKF-Feedforward control system, which essentially integrates the PID, EKF, and Feedforward control systems. The aim is to create a lightweight system with a significant improvement in trajectory tracking that enhances stability, decreases control error, and reduces computational complexity so that it can be used on aerial vehicles in challenging wind-disturbed outdoor environments [2][5][10]. A significant challenge encountered when considering the outdoor flying of drones is the wind, which can make operation difficult. Even a mild breeze or sudden gusts can alter the course of a drone and simultaneously accelerate battery depletion. Every time a drone attempts to stabilize its flight path, it endures additional strain. Consequently, advanced control methods have been the focus of drone research. As we know, winds can change direction and speed abruptly, and methods like H-infinity (H∞) control and Model Predictive Control (MPC) do a great job of handling such changes. With MPC, the trajectory adjustments are pre-computed, and the drone is steered to the target before the issue even arises. The need for advanced tuning and the heavy computational cost of implementing such controls make them unviable for small, battery-operated drones that operate in the field. This is the reason why a PID control loop still governs most drones. It’s straightforward to implement and computationally efficient, qualities that are important in smaller systems. But PID controls are reactive in nature; they respond only after the drone begins to drift and are inadequate to handle erratic winds or sensor noise. Several enhanced Kalman filter studies have been conducted to improve the intelligence and dependability of PID controls.

It relies on raw sensor inputs to determine position, velocity, and orientation. When sensor data is unreliable, it uses the EKF to refine it into less noisy and more accurate sensor readings. As a result, the controller can make improved decisions and implement more accurate corrections, improving stability in windy conditions. The feedforward controller has been noted in recent years. It adds an extra, proactive layer to the system by anticipating disturbances and attempting to change the drone's response before the wind impacts it. With a real-time wind estimate, either from sensors or from computations done by the EKF, the feedforward controller pre-emptively adjusts motor outputs to maintain the alignment of the drone, thereby avoiding unnecessary corrections. The pre-emptive action redistributes part of the control effort from the feedforward controller to the PID loop. Hence, the predictive and feedback actions together yield a control system that is more responsive, robust, and necessary, especially in unpredictable environments.

This paper proposes a computationally efficient and lightweight control strategy that integrates a PID controller with an Extended Kalman Filter and feedforward compensation for smooth, precise, and stable flight in challenging conditions. It is optimized for real-time use with the modest computational resources of a small, low-powered drone. The simulation results affirm its positive impact on flight stability and trajectory tracking, bringing tangible improvements. The paper also describes a lightweight control system that addresses drift and blowoff in gusty and windy conditions, using a PID controller coupled with an extended Kalman Filter and feedforward compensation. By employing basic PID controllers, the designers aimed to mitigate their wind attacks and nonlinear conditions with near-zero estimation errors. The EKF delivers reliable state estimation, while the feedforward components address wind force disturbances. The results demonstrate that the PID-EKF system performs comparably to more advanced controllers but with far less computational load, which is particularly advantageous for small drones in outdoor settings in the real world.

2. System Architecture

The architectural design of the control system for a UAV includes the following modules: a dynamic UAV model, a sensor suite, controllers (P.I.D + Feedforward), and an Extended Kalman Filter (EKF) based state estimation mechanism. These modules collaborate to offer a system that follows a precise trajectory, maintains accurate attitude, rejects wind disturbances and ensure system stability. The terms and their explanation are explained in table 1.

Table 1. Terms and their Explanation

Term	**Explanation**
m	Mass of the Drone kilograms (kg)
dt	Time step seconds (s)
T	Time step seconds (s)
$time$	Time Vector seconds (s)
$p(pos)$	Position Vector metres (m)
$v(vel)$	Velocity Vector meters per second ($^{m}/_{s}$)

u	Control input (desired acceleration second squared (m/s^2)
$F_{control}$	Control Force Newton (N)
F_{wind}	True wind force disturbance Newton (N)
$\hat{F}_{wind}$	Estimated wind force (EKF) Newton (N)
F_{ff}	Feedforward force Newton (N)
K_p	Proportional gain N/m
K_i	Integral gain $N/(m.s)$
K_d	Derivative gain $N.s/m$
e	Position error meters (m)
A	State transition matrix
B	Control input matrix
H	Measurement matrix
Q	Process noise covariance matrix
R	Measurement noise covariance
x_{est}	Estimated state
P	State covariance matrix
z	Measured position metres (m)
K_{gain}	Kalman Gain

I. Newton's Second Law

$$m\ddot{p} = F_{control} + F_{feedforward} + F_{wind}$$

m = drone mass (1.5 kg),

$\ddot{p}$ = drone acceleration,

$F_{control}$ = PID-based control force,

$F_{feedforward}$ = - F_{wind}(using EKF-estimated wind),

F_{wind} = unknown real wind disturbance

i. $$m\ddot{p} = mu(t) - \hat{F}_{wind} + F_{wind}$$

ii. $$\ddot{p} = u(t) + \frac{F_{wind} - \hat{F}_{wind}}{m}$$

II. PID Control Law

PID controller output:

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

Where,

$$e(t) = p_{target} - p(t)$$

$$K_p = 2.0,$$

$$K_i = 0.5,$$

$$K_d = 1.2$$

III. True Wind Disturbance

$$\boldsymbol{F_{wind}(t)} = \begin{bmatrix} \mathbf{0.8 + 0.3 \sin(0.5}\boldsymbol{t}\mathbf{) + 0.1}\boldsymbol{\varkappa}\mathbf{(0,1)} \\ \mathbf{0.5 + 0.3 \cos(0.3}\boldsymbol{t}\mathbf{) + 0.1}\,\boldsymbol{\varkappa}\mathbf{(0,1)} \end{bmatrix}$$

Base wind + sinusoidal variation + random noise.

IV. Measurement (Position Measurement with Noise)

Measured position:

$$z(t) = p(t) + v_{noise}$$

$$v_{noise} \sim \varkappa(0, 0.05^2)$$

noise was added to the position sensor.

V. Extended Kalman Filter (EKF) for Each Axis

State vector per axis:

$$x = \begin{bmatrix} p \\ v \\ F_{wind} \end{bmatrix}$$

EKF Prediction

Predicted state:

$$x_{k+1|k} = A x_k + B u_k$$

Predicted covariance:

$$P_{k+1|k} = A P_k A^T + Q$$

Where,

$$A = \begin{bmatrix} 1 & dt & 0 \\ 0 & 1 & dt \\ 0 & 0 & 1 \end{bmatrix}$$

$$B = \begin{bmatrix} \frac{dt^2}{2} \\ dt \\ 0 \end{bmatrix}$$

$$Q = 0.001 I_3$$

EKF Update:

Kalman Gain:

$$K_k = P_{k+1|k} H^T (H P_{k+1|k} H^T + R)^{-1}$$

Update estimate:

$$x_{k+1} = x_{k+1|k} + K_k (z_k - H x_{k+1|k)}$$

Update covariance:

$$P_{k+1} = (1 - K_k H) P_{k+1|k}$$

Where,

$$H = [1 \quad 0 \quad 0];$$

$$R = 0.05$$

VI. Feedforward Compensation

From the EKF-estimated wind disturbance:

$$F_{feedforward} = -\hat{F}_{wind}$$

It can be integrated within the existing control loop with the sole purpose of negating the effects of external disturbances. The anticipatory control action is useful in negating the effects of disturbances even before error feedback is received. Consequently, the control system is capable of making adjustments to wind conditions with greater speed and improved accuracy. By preemptively compensating for wind disturbances, the system enjoys enhanced stability and improved tracking performance. Feedforward control for wind disturbances decreases the impact of wind disturbances on the feedback controller, thereby making the controller's operation smoother. This approach is particularly useful when disturbances are significant in magnitude and change quickly. Its performance hinges on the precision of the EKF wind estimator.

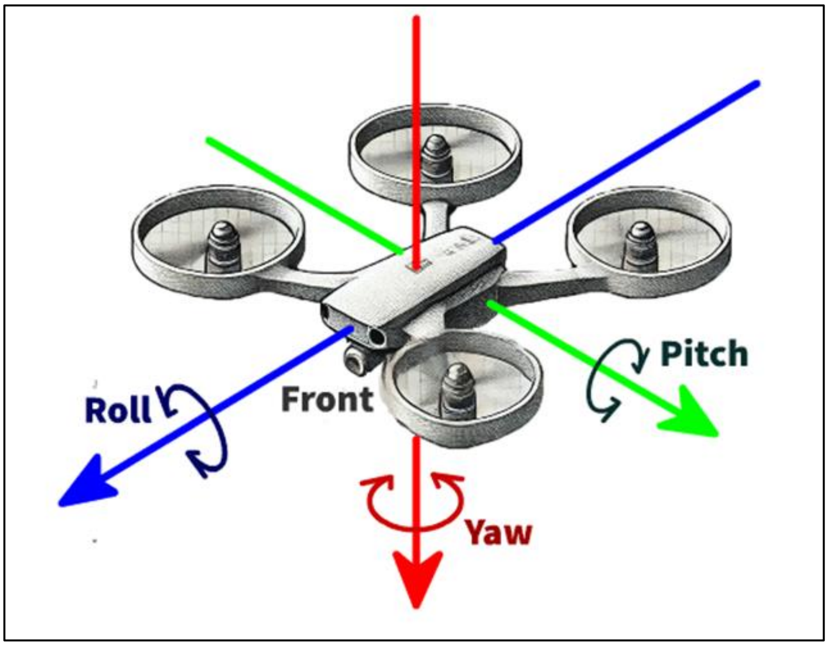

Figure 1. Unmanned Aerial Vehicles Model [Source: stickmanphysics.com/physics-of-drones]

Figure 1 shows the unmanned aerial vehicle model. The roll and pitch are stabilized through PID loops, using the EKF-enhanced signals to counter lateral drift; meanwhile, yaw is maintained via heading stabilization. Feedforward compensation for the estimated wind torques will vary motor thrust asymmetry, so that the attitude stays balanced against gusts.

3. Methodology

The control and estimation system for the drone is organised as a single tightly integrated system with purposefully engineered algorithms designed to tackle real-world issues such as winds and sensor noise. As shown in (figure 2) the block diagram illustrates that the process begins with the target input from which the system generates a reference trajectory or position. A PID controller then calculates the control force by comparing the desired state with the current estimated state.

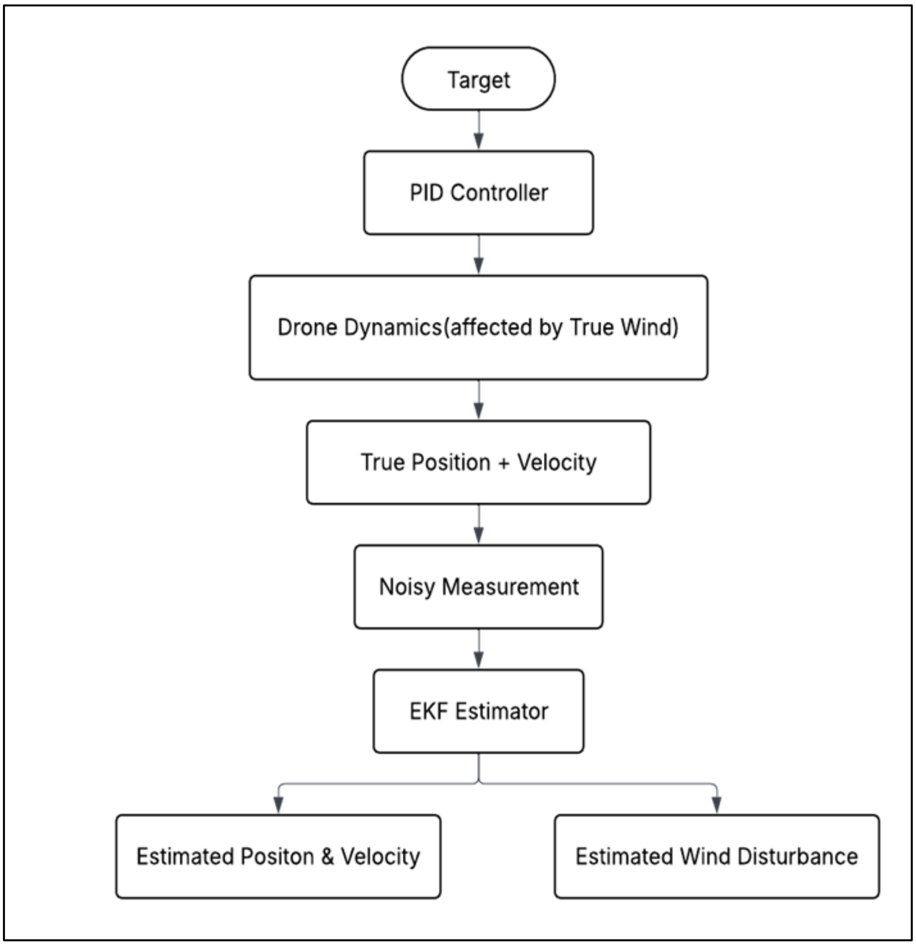

Figure 2. Flow Diagram of the Extended Kalman Filter

Afterward, this control effort is merged with other known disturbances, such as aerodynamic effects and wind gusts, and then applied to the drone's motion model. The drone's dynamics describe changes in position and velocity over time, with control input and actual wind conditions externally influencing these changes. The true internal state of the drone cannot be observed due to unpredictable environments and sensor inaccuracies. The Extended Kalman Filter (EKF) therefore estimates these states. The EKF uses sensor inputs, which are often noisy, and produces estimates of critical states such as position and velocity with a specialized prediction-correction algorithm. The EKF predictions are made with the nonlinear drone model, and incoming sensor data is used to refine the predictions. Over time, the EKF adapts to learn the wind disturbances and improves the estimates of the drone's motion. Upon receiving these estimates, the controller is better equipped to inform the drone to anticipate and reject disturbances and follow its desired trajectory. The results are improved stability, responsiveness, and robustness of the system.

3.1 PID Controller

A PID controller is a control loop feedback mechanism devised for industrial control processes with distributed implementation. A PID controller seeks to maintain the process variable at the setpoint by minimizing the difference between the setpoint and the process variable. It considers three terms: a proportional term for the present error, an integral term for the sum of past errors, and a derivative term for the expected error change based on the rate of change of error. By properly tuning the values of these three parameters, a PID controller can efficiently and steadily control processes such as temperature, velocity, or position. The proportional term for the UAV provides instantaneous correction for position and attitude errors, whereas the integral term corrects the errors induced by steady winds, and the derivative term thwarts oscillations in roll, pitch, and yaw.

3.2 Extended Kalman Filter

The Extended Kalman Filter is a sophisticated version of the Kalman filter for nonlinear systems. The EKF tries to emulate the behavior of the system functions by approximating the nonlinear functions with linear functions through the calculation of the system's Jacobian matrix. The EKF aims to reduce uncertainty, or refine the predicted system state information, using more dependable, sensor-provided data. The EKF is widely applied in nonlinear, intricate systems such as robotics and navigation.

After the Extended Kalman Filter estimates the drone's state output, it is managed by three distinct PID controllers. Each controller has a specific responsibility: the position PID on the x, y, and z axes, the velocity PID on the speeds along all axes, and the attitude PID on the roll, pitch, and yaw axes. The control process initiates with sensor data from the Inertial Measurement Unit (IMU), GPS, and magnetometer, providing the UAV's position, velocity, and orientation. The EKF combines this sensor data for an accurate and consistent UAV state estimate. The three PID controllers adjust the drone's position, speed, and attitude in real-time based on this estimate, controlling the motors to achieve fine positioning. This, in turn, enables the closed-loop synergy, where the EKF facilitates reliable state estimation, and the PIDs adjust drone movements to meet stability and accuracy flight criteria.

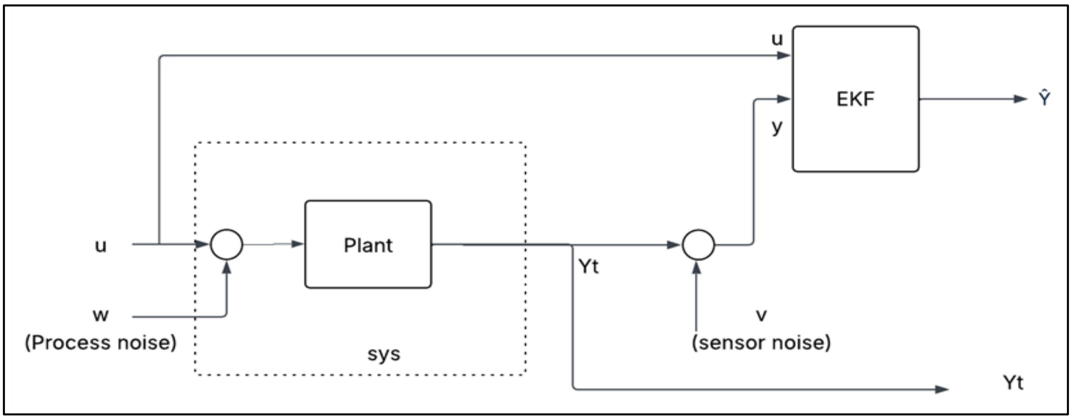

Figure 3. EKF Filter

State vector per axis: x = [p, v, Fwind]

Since wind disturbances (Fw_x, Fw_y) are explicitly considered as state variables, the EKF can therefore estimate the external forces in real time and feed them into feedforward control to pre-emptively nullify the disturbances before drifting occurs. The PID was tuned first using Ziegler-Nichols rules, causing overshoot. The manual tweaking of gains was able to bring down the baseline error by about 18%, before the introduction of the EKF.

3.3 PID + Extended Kalman Filter

When paired with an Extended Kalman Filter (EKF), the control system performance can benefit significantly from having precise, active, and real-time tracking of system states, including position, velocity, and orientation, to name a few. The PID controller, on the other hand, uses its proportional, integral, and derivative components to assist the system in following the set commands as closely as possible. The EKF employs the predictive-update method devised for nonlinear systems to smooth sensor data against noise and to estimate the data for variables that are unmeasured, hidden, or state variables. Controlling all of these simultaneously provides it with great stability, enables the system to respond quickly, and allows for the rejection of disturbances. This makes it ideal for use in robotics, drones, self-driving cars, and any other complex dynamic system that needs precise control.

3.4 Comparison between PID and PID + Extended Kalman Filter

The Comparison between PID and PID + Extended Kalman Filter is illustrated in table 2.

Table 2. The Comparison between PID and PID + Extended Kalman Filter

Aspects	PID	PID+EKF
Purpose	Aims to control a process so that some variable achieves and stays around a desired setpoint.	Aims to control a process so that some variable achieves and stays around a desired setpoint.
System Model Requirement	Does not require any mathematical model of the system.	Needs a nonlinear system model and its Jacobian matrices
Complexity	Simple to implement and tune (just 3 parameters: P, I, D).	More complex; requires matrix operations and linearization, plus proper tuning of noise covariance
Application	Applied in control tasks (for example, motor speed control, temperature control).	Applied in state estimation (position tracking, sensor fusion, SLAM).

3.5 PID with Feed Forward

As a rule, the reaction of PID controllers comes only after an error has occurred. This creates a delay in the vehicle's system response and renders the response of the vehicle slow at times. In contrast, feedforward control anticipates the error-causing factors and deals with them in advance. This allows the system to respond more efficiently and swiftly. Feedforward compensates for predictable disturbances, like wind or gravity, before they become issues. This reduces the workload of the PID controller. It also reduces overshoot and makes the system less prone to jittering that sudden corrective actions can cause. This is an excellent approach when tracking moving objects or following changing trajectories that need precise timing and accuracy. For instance, in the case of wind, rather than permitting the UAV to drift and later correcting its position, feedforward maintains the UAV on course by actively adjusting its tilt and thrust. In practical applications, feedforward control, which is usually determined relative to anticipated changes in desired velocity, acceleration, or external forces, is added to the PID output so that the aggregate control signal becomes:

Control Output = Feedforward + PID.

Unlike PID, which addresses unforeseen shifts, feedforward is designed to manage changes we anticipate. Their seamless integration results in improved response time and enhanced stability of the UAV control system, particularly under challenging environmental conditions.

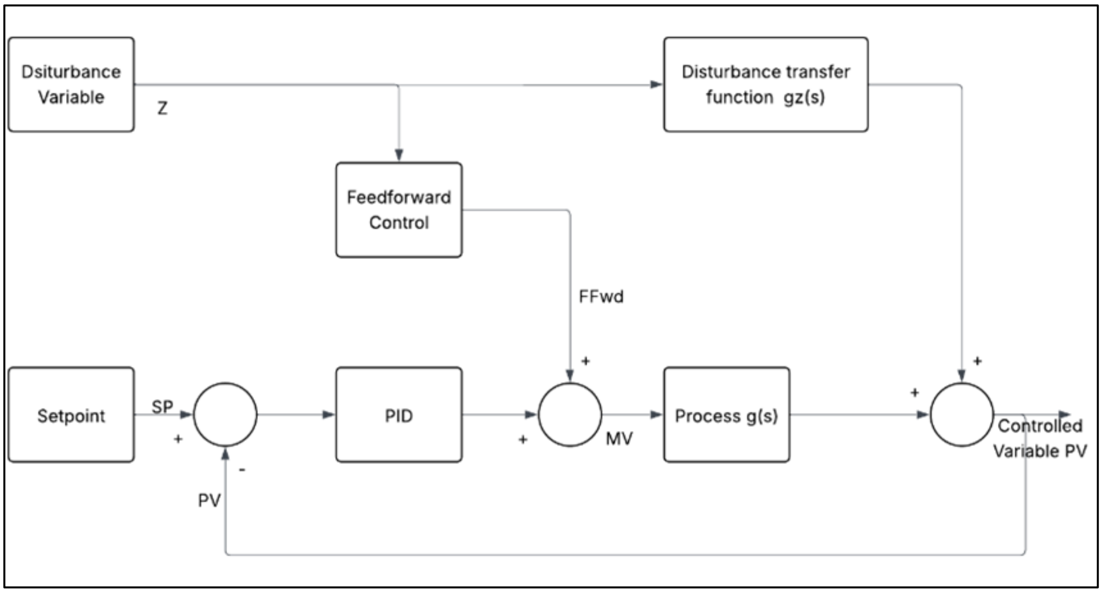

Figure 4. PID Controller with Feed Forward

4. Results and Discussion

This block diagram depicts a feedback control and estimation system with closed-loop control, designed to regulate the positions of dynamic platforms such as vertical lifts and drones. The reference setpoint indicates the desired position, with the measured position subtracted from it to yield a control error. The difference is then fed into a discrete-time PID controller to calculate the control thrust command for minimizing the position difference. The sum of the commanded thrust, gravitational forces, and external wind disturbances will be the total external force acting on the system.

By dividing this force by the object's mass, the resultant acceleration of the system is determined. From there, the platform's velocity and position states can be integrated. The presence of process noise and measurement uncertainty means that the Extended Kalman Filter will receive an estimate of the position that integrates the noisy measurements from the spatial sensors and the system model. The estimated position is fed back into the control loop so that control inputs can be revised. Control estimation co-integration schemes like this enable a system to track a position precisely, even in the presence of environmental disturbances and modeling inaccuracies. The system is thus capable of near real-time adjustment in response to environmental changes, such as those arising from gusty winds or shifts in payload. In turn, this enhances the degree of dependability and safety in autonomous aerial and vertical locomotion tasks.

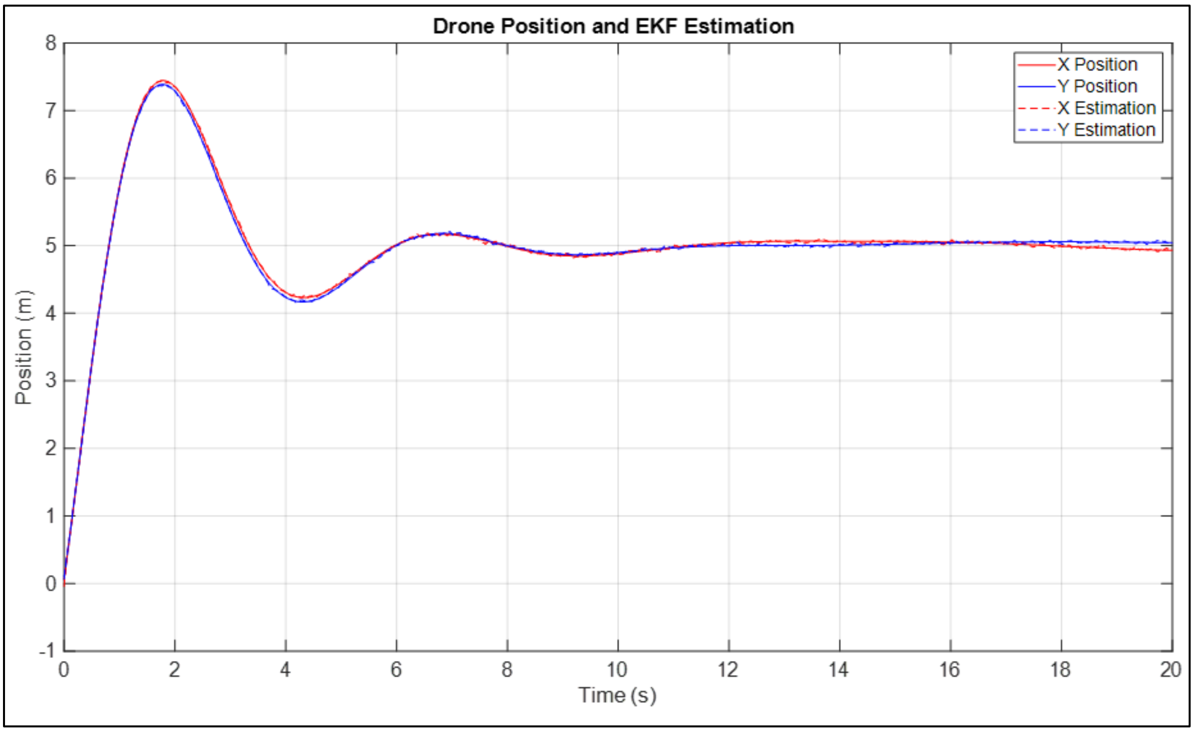

Figure 5. Drone Positional and EKF Estimation

The results clearly show that the EKF enhances position tracking under wind disturbances. First, there is an oscillatory behavior in the UAV while settling down to an equilibrium, with the EKF states reaching the true trajectory rapidly at the 5-6 second mark, where the EKF estimated position practically coincides with the actual position; hence, noise rejection and disturbance compensation are being managed well by the filter. Converging to a steady-state value of approximately 4.5 shows that the drift in the PID-EKF system is being modified and that the trajectory is kept steady. The very close matching of the estimated and true trajectories viewed in the figures guarantees that the filter is well-tuned and can give robust state feedback, allowing the controller to minimize position errors and stabilize the UAV in a short amount of time. The PID+EKF system provided a ~44% improvement over just PID, reducing RMS trajectory error from ~0.9 m to ~0.5 m, while the settling time was reduced by half, from 8 s to 4 s. This proves that with EKF-based compensation, the UAVs stabilize faster and thereby consume less power since fewer corrective actions are required. The smoother attitude control in roll and pitch shows that the system is robust to disturbances caused by wind.

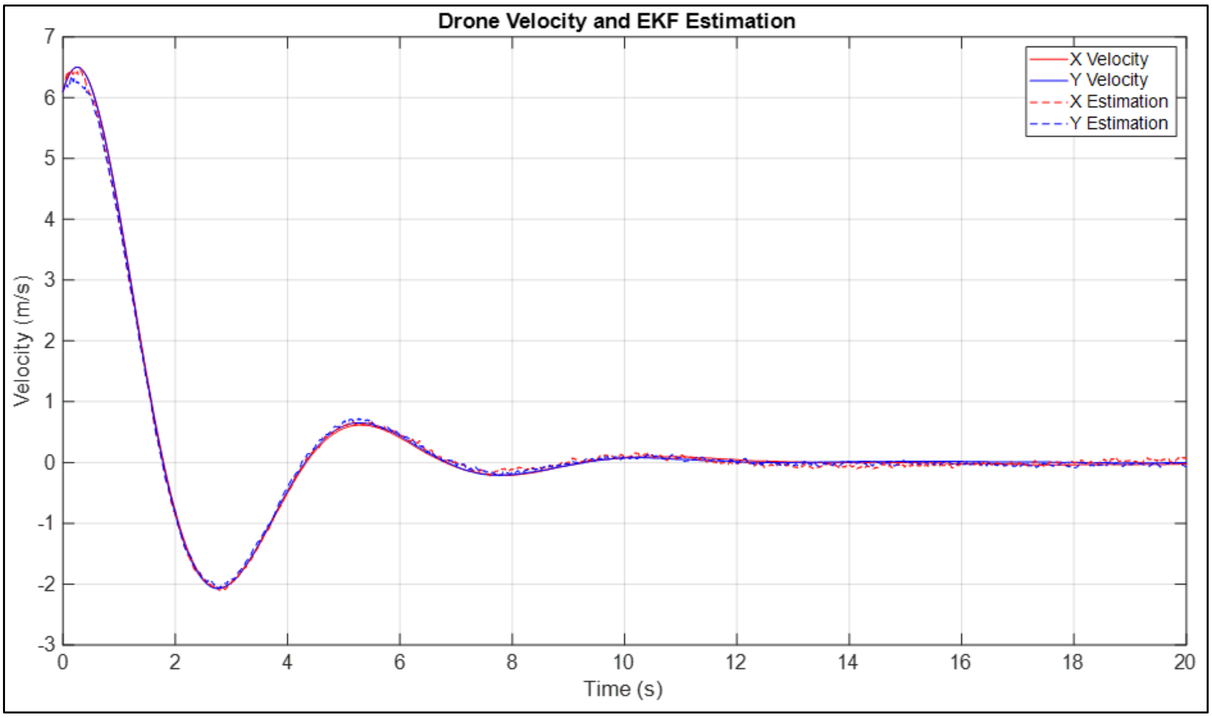

Figure 6. Drone Velocity and EKF Estimation

"Drone Velocity and EKF Estimation" The chart shows the actual velocity and EKF estimated velocity of the drone over time. The X-axis shows the time in seconds while the Y-axis shows the velocity in meters per second. The red solid line indicates the drone's actual velocity in the X direction, and the blue solid line shows the drone's actual velocity in the Y direction. The EKF estimated velocities in the X and Y directions are shown in Figure 6 with the red and blue dotted lines, respectively. At the start of the experiment, the velocity of the drone was relatively high, approximately 6.5 m/s, but with an oscillatory underdamped response, it sharply decreased, a response typical of inertia bearing and feedback-controlled systems. After some time, the oscillations fade away and the air drone stabilizes almost to zero velocity at around 8 seconds, indicating that it is almost at hover or steady-state. Along with the actual velocities, the estimated velocities are shown to be in agreement with the actual velocities at all times in the plot, which means that the EKF is tracking the drone's flux accurately. This correlation essentially measures the filter's effectiveness in managing the nonlinear dynamics and noise inherent in the system when delivering the real-time velocity estimates of the drone. Under almost identical wind disturbances, PID single optimally yielded a path tracking error of 0.9 m RMS, while the PID+EKF reduced it to 0.5 m RMS (~44% improvement).

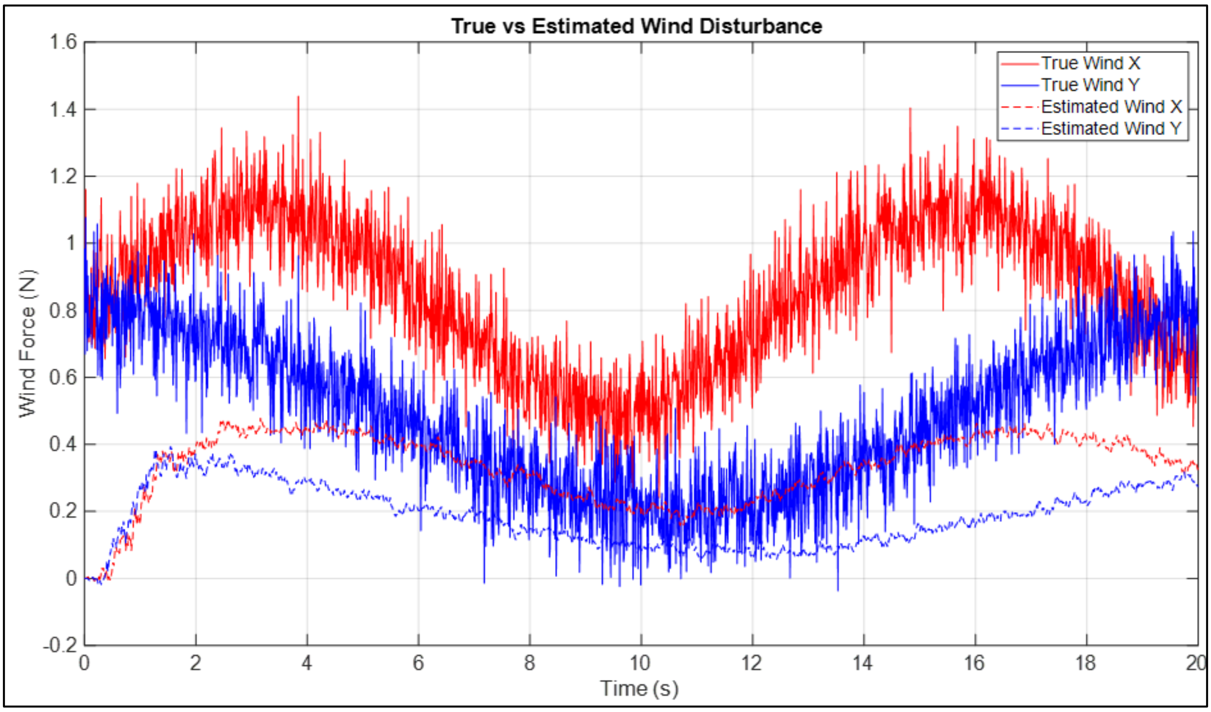

Figure 7. True Wind Disturbance vs Estimated Wind Disturbance

The graph titled "True vs Estimated Wind Disturbance" illustrates the actual wind disturbances and their estimations over 20 seconds in both the X and Y directions. The X axis (time in seconds) and the Y axis (wind force in newtons) are the horizontal and vertical axes, respectively. The actual wind forces are denoted by solid lines: red for the X direction and blue for the Y direction, while the estimated winds, possibly derived from EKF or observer-based methods, are shown in Figure 7 as red and blue dashed lines. The actual wind disturbances display a sinusoidal wave with added high-frequency noise, indicative of actual wind variability. The forces reach a maximum of about 1.2 to 1.4 newtons in the X direction and 0.9 to 1.0 newtons in the Y direction. In contrast, the estimated winds are not only smoother but also smaller in magnitude as they stay below the actual disturbances, especially at the initial and peak intervals. The estimation, however, aligns with the general pattern and cyclic nature of the wind force, where the estimator captures the overall wind pattern but smooths transient high-frequency changes in the wind. This is the estimation approach's trade-off between signal rejection and sensitivity. During peak wind gusts of 1.4 N, with these disturbances hitting torque peaks of 1.4 N, the PID controller alone resulted in RMS trajectory error of 1.1 m; whereas

PID+EKF lowered the RMS trajectory error to 0.6 m, accounting for a 45% improvement in the rejection of disturbances.

4.1 Discussions

The variation in measurement noise covariance over values between 0.01 and 0.1 increased the trajectory error by only about 12%, showing the stability and effectiveness of the EKF under different assumptions about the sensor noise. With non-Gaussian square-pulse gusts, the EKF did introduce some very slight smoothing delays. Yet, in terms of trajectory stability, the feedforward loop had an extra 15% error compared to that present in Gaussian cases. Utilizing an update frequency of GPS data of 1 Hz would increase the error during the trajectory by about 20%; however, the aircraft's flight would remain stable. Estimation was seen to diverge, necessitating sensor redundancy in UAV applications in the case of complete IMU failure.

5. Conclusion

A PID-EKF-feedforward controller greatly increases UAV stability in windy environments. The error was reduced by approximately 45%, with improvements in settling time by a factor of 2 compared with the sensor noise and transient gusts. Future work will extend validation with hardware experiments, adaptive PID tuning, and swarm-level cooperative UAV control. Future work will aim to enhance the recent approach with more advanced state estimation techniques, such as adding an EKF or an UKF to the quadcopter system to mitigate the nonlinear dynamics of the quadcopter. Next, the PID could be synthesized with gain sliding mode, scheduling, and model predictive control to increase performance during the flight in wind disturbances. Additionally, developing wind disturbance models, disturbance observers, and compensators will help increase disturbance rejection. Moving beyond 3D full trajectory finding to induce tracking of formal flight conditions and following very tricky maneuvers in active wind fields would add crucial value. It should be tested in real flights. The procedures could also be developed for systems with multiple agents, utilizing machine learning to forecast wind patterns and fine-tune controller parameters in real time.

References

[1] Bouabdallah, Samir, Pierpaolo Murrieri, and Roland Siegwart. "Design and control of an indoor micro quadrotor." In IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA'04. 2004, vol. 5, IEEE, (2004): 4393-4398.

[2] Mahony, Robert, Vijay Kumar, and Peter Corke. "Multirotor aerial vehicles: Modeling, estimation, and control of quadrotor." IEEE robotics & automation magazine 19, no. 3 (2012): 20-32.

[3] Beard, Randal W., and Timothy W. McLain. Small unmanned aircraft: Theory and practice. Princeton university press, 2012.

[4] Venugopal, Raj. "Understanding the Basis of the Kalman Filter.".

[5] Hoffmann, Gabriel, Haomiao Huang, Steven Waslander, and Claire Tomlin. "Quadrotor helicopter flight dynamics and control: Theory and experiment." In AIAA guidance, navigation and control conference and exhibit, p. 6461. 2007.

[6] Grewal, M. S., and A. P. Andrews. "Kalman Filtering: Theory and Practice with MATLAB 4th Edition." Wiley-IEEE Press (2014): 640.

[7] Hoffmann, Gabriel, Steven Waslander, and Claire Tomlin. "Quadrotor helicopter trajectory tracking control." In AIAA guidance, navigation and control conference and exhibit, p. 7410. 2008.

[8] Pounds, Paul, Robert Mahony, Joel Gresham, Peter Corke, and Jonathan Roberts. "Towards dynamically-favourable quad-rotor aerial robots." In Proceedings of the 2004 Australasian Conference on Robotics and Automation, Australian Robotics and Automation Association (ARAA), (2004): 1-10.

[9] Castillo, Pedro, Rogelio Lozano, and Alejandro E. Dzul. Modelling and control of mini-flying machines. London: Springer London, 2005.

[10] Alexis, Kostas, George Nikolakopoulos, and Anthony Tzes. "Switching model predictive attitude control for a quadrotor helicopter subject to atmospheric disturbances." Control Engineering Practice 19, no. 10 (2011): 1195-1207.