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Article

Observer-Driven LQR and FOLQR Control for Enhanced Stability of Underactuated 2-DOF Helicopter.

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Abstract: This study offers an empirical comparison of the Linear Quadratic Regulator (LQR) and Fractional Order LQR (FOLQR) controllers that were implemented on a two-degrees-of-freedom (2-DOF) Quanser Aero 2 helicopter platform. It employs both full and reduced-order observer designs to facilitate trajectory monitoring and stabilisation. The Aero 2 platform is dynamically modelled using Euler-Lagrange equations to develop a multi-input multi-output (MIMO) system. This system comprises two inputs and four state equations. In collaboration with observers, the LQR and FOLQR controllers approximate states that are not directly measurable by utilising the system model and available data. This procedure effectively overcomes the practical limitations of sensors. The enhanced performance of FOLQR in terms of tracking precision and stability has been depicted from the experimental results, showing real-time execution on the Aero 2 platform. This paper provides rigorous insights into control engineering and advanced observer-based control design for underactuated systems.

Keywords: LQR; euler-lagrange; trajectory tracking; MIMO system and observer design

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1 Introduction

In the last couple of years, there has been a tremendous increase in the usage of Unmanned Aerial Vehicles due to their versatility and multifunctionality in application areas like surveillance, search and rescue operations, and scientific research[1,2]. One of the types of unmanned aerial vehicles (UAVs), helicopters, offer unique advantages hovering to precise manoeuvres in confined spaces. Helicopter dynamics management is challenging due to its intrinsic nonlinearities and interdependent dynamics. This paper deals with the control problem of the Aero2-2 degrees of freedom (DOF) helicopter experimental apparatus. The Aero 2 represents a common platform for teaching and research in control, offering a simplified but accurate model of the real dynamics of a helicopter[3]. This work is concerned with designing and implementing feedback control algorithms that stabilize the Aero 2 and realize precise trajectory tracking. Linear quadratic regulator (LQR) control is one of the most powerful methods in which the control input is determined directly using the system's state variables. However, in most real applications, not all the state variables can be measured or obtained through sensors[4],[5]. That is where state observers come into play. Model-based state observers are estimation techniques that reconstruct the system states based on the currently available measurements and input signals. Using state observers in the control loop enables the application of LQR and Fractional Order LQR (FOLQR) in a system where it would not be directly observable otherwise. This paper will consider two types of state observers: full-order and reduced-order observers[6,7]. Full-order observers (FOO) estimate all system states in order to provide a representation of the complete system dynamics.

These observers can be computationally expensive and sensitive to model uncertainty. On the other hand, reduced-order observer (ROO) estimates only part of the states, which could reduce computational complexity and provide greater robustness to model errors[8]. However, this reduction in observer order could adversely affect estimating performance or stability margins. Full-order versus reduced-order observers present trade-offs in estimating accuracy, processing requirements, and other application-dependent robustness considerations. The research in this paper looks into different methods: linear quadratic regulator control (LQR), fractional order LQR (FOLQR), and then using FOLQR with a full-order observer and FOLQR with a reduced-order observer. It is observed that the LQR controller is mostly engineered to minimize a quadratic cost function that equilibrates control effort and state deviations[9]. Conversely, it depends on estimates of system states acquired from observers, whether full-order or reduced-order, to ascertain the control inputs. The efficacy of these four control systems is assessed based on their capacity to stabilize the Aero 2 and accurately follow planned trajectories. Experimental hardware findings are provided to evaluate the efficacy of each method under diverse operational settings and perturbations.

Fractional order Linear Quadratic Regulator (FOLQR) control presents numerous advantages over traditional LQR, particularly in systems with intricate dynamics, such as Unmanned Aerial Vehicles (UAVs). Conventional LQR systems are based on integer-order calculus, which confines the control dynamics to the integer-order nature of differential equations only[10-13]. However, fractional-order control offers better flexibility in controlling the system by allowing the system dynamics to be governed by the fractional-order differential equations. This allows finer tuning of system responses, ensuring better control of transient response, overshoot, and damping in the system. Unmanned Aerial Vehicles (UAVs) are very often confronted with dynamic instabilities due to underactuated designs and thus could greatly benefit from fractional-order control, owing to its ability to provide much smoother and more stable system responses[14-16]. In addition, the fractional order LQR enhances the robustness of systems prone to parameter uncertainty and external disturbances. Increased flexibility in adapting fractional-order parameters allows for more adaptive control techniques that could maintain stability and optimality for a wider range of operating conditions than in the traditional LQR. Enhanced robustness is essential in the case of UAV applications since environmental fluctuations greatly affect stability. FOLQR improves the control system by fine-tuning it for better management of uncertainties, hence enhancing the reliability of the system in practical applications[17].

In applications of FOLQR control, observer design becomes one of the most important choices concerning UAV system performance. Compared with a reduced-order observer, which usually guesses only a subset of the states of the system, a full-order observer design enjoys several key advantages, estimating all the states of the system. The full-order observer performs better in the context of UAV, where precise state estimation is necessary, which includes velocity, attitude, and position for reliable control. It assures that all states are reconstructed accurately. It is particularly useful in highly nonlinear or time-varying systems where either the absence of states or the estimation of states in a wrong way may result in poor control performance or instability[18-20].

Furthermore, a full-order observer in combination with FOLQR drastically enhances the system's robustness and fault tolerance. In unmanned aerial vehicle applications, the failure or disturbance of any sensor can cause the loss of a partial amount of information on the states, which cannot be handled effectively with reduced-order observers[21,22]. By contrast, the full-order observer can compensate for such deficiency through an expanded estimation of internal system dynamics, guaranteeing seamless continuity of optimal control. The effect will then be enhanced trajectory tracking and disturbance rejection due to increased control performance, which is generally a highly required feature for all high-precision tasks involved in unmanned aerial vehicle operations such as autonomous navigation or aerial surveillance[23-25]. This research work has two primary contributions:

• Initially, it thoroughly compares the four control systems for the Aero 2 system, emphasizing their strengths and weaknesses.

• Secondly, it illustrates the effective execution of these control strategies on an experimental platform, demonstrating their capability to handle practical challenges such as sensor noise, model uncertainties, and disturbances in real-time applications.

Moreover, the entire research article has been divided into five sections such that the introduction and background related to the topic can be studied in section 1. Section 2 shares the full description of the system and its modelling. One may find the observer details integrated with proposed control schemes in Section 3 whereas Section 4 presents real runtime implemented on Quanser Aero2 along with technical analysis. Last but not the least one may find the conclusion of this research work in section 5. The entire organization flow is illustrated in Figure 1 as well.

2 System Modelling

The Advance Unmanned Aerial System Lab at the Interdisciplinary Research Centre for Aviation and Space Exploration, King Fahd University of Petroleum and Minerals (KFUPM), Saudi Arabia, currently utilizes the

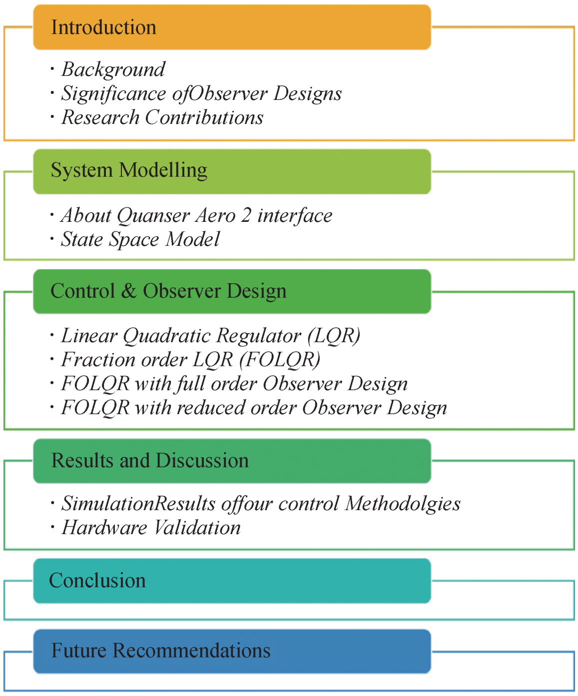

Fig.1 Organization of this proposed research work

Aero 2 control system from Quanser. This arrangement is illustrated in Figure 2. It is a dual-rotor laboratory device for research on flight control. The system can be configured in a helicopter-like arrangement, featuring a horizontally positioned primary thruster and a vertically orientated tail thruster, both driven by two DC motors.

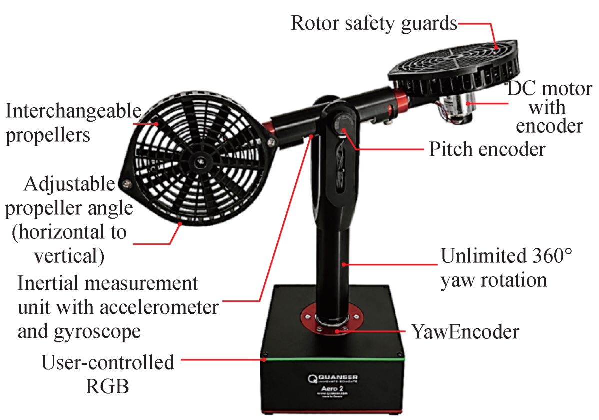

Fig.2 Aero 2 Helicopter Physical System (Quanser)

The system comprises a compact base unit with an integrated amplifier with current-sensing functionalities and an embedded data acquisition device for measurement collection. The versatile QFLEX 2 interface panel provides connectivity choices for devices including personal computers, embedded computers, and microcontrollers[10]. The system employs four high-resolution optical encoders in conjunction with an Inertial Measurement Unit (IMU) for accurate attitude measurement and control in the pitch and yaw axes. Significantly, slip ring wiring enables unfettered, continuous 360-degree yaw rotation. Upon receiving a voltage V_p, the pitch motor generates a force from the front rotor that acts perpendicularly on the body, directed away from the pitch axis (along the x-axis). The torque generated by the spinning of the front propeller blade also induces a torque at the yaw-axis due to aerodynamic drag along the z-axis. Consequently, conventional helicopters are equipped with a tail rotor to counteract the torque generated by the large main rotor around the yaw axis. Like the front motor, the rear motor generates a force that influences the body away from the yaw axis. The equations of motion for the Aero 2 are derived from the free body diagram (Fig. 3) concerning the horizontal axis as follows[10]:

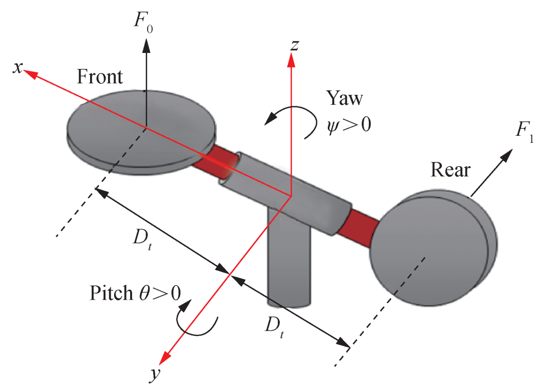

Fig.3 Aero 2-Free body Diagram (Quanser)

$$J_p\ddot{\theta}+D_p\dot{\theta}+K_{sp}\theta=\tau_p \quad (1)$$

$$J_y\ddot{\psi}+D_y\dot{\psi}=\tau_y \quad (2)$$

The pitch and yaw torque are defined as follows:

$$\tau_p=K_{pp}D_tV_p+K_{py}D_tV_y \text{ and} \quad (3)$$

$$\tau_y=K_{yp}D_tV_p+K_{yy}D_tV_y \quad (4)$$

The parameters used in the (1) and (2) are mentioned below in Table.1.

The Aero 2 User Manual[10-13] delineates several model specifications. The residual parameters are ascertained

Table 1 Parameters along with the description and values

Description of terms used	Symbol	Value
Pitch axis inertia	J_p	0.0243 Kg.m^2
Pitch axis damping	D_p	0.0021 N.m / V
Pitch axis stiffness	K_{sp}	0.0085 N-m / V
Pitch thrust gain (Front motor)	K_{pp}	0.0033 N/V
Pitch thrust gain (Rear motor)	K_{py}	0.0015 N/V
Yaw axis inertia	J_y	0.0247 Kg.m^2
Yaw axis damping	D_y	0.0020 N.m /V
Yaw thrust gain (Front motor)	K_{yp}	-0.0036 N/V
Yaw thrust gain (Rear motor)	K_{yy}	0.0062 N/V
Distance between rotor centre and pivot	D_t	0.1687 m

empirically by identification methodologies. Utilizing the state variable vector $x^T = [\theta(t), \psi(t), \dot{\theta}(t), \dot{\psi}(t),]$. Moreover, the following linear state-space model of the Aero 2 system is derived, indicating the pitch angle, yaw angle, pitch velocity, and yaw velocity, respectively:

$$\dot{x} = Ax + Bu \quad (5)$$

$$y = Cx + Du \quad (6)$$

Whereas the A, B, C and D are defined below as:

$$A = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ \frac{-K_{sp}}{J_p} & 0 & \frac{D_p}{J_p} & 0 \\ 0 & \frac{-K_{sp}}{J_y} & 0 & -\frac{D_y}{J_y} \end{bmatrix} \quad (7)$$

$$B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ D_t K_{pp}/J_p & D_t K_{py}/J_p \\ D_t K_{yp}/J_y & D_t K_{yy}/J_y \end{bmatrix} \quad (8)$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \text{ and } D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (9)$$

Equation (3) delineates a multiple-input, multiple-output (MIMO) system featuring two outputs such as $y^T = [\theta(t), \psi(t)]$ whereas the two inputs are defined as $u^T = [V_p(t), V_y(t)]$. As the system commences from a state of rest, all initial conditions are null.

3 Control and Observer design

The Linear Quadratic Regulator (LQR) is an optimum control methodology employed to formulate controllers for dynamic systems to minimize a specified cost function. In LQR framework, the system dynamics are represented by linear state-space equations, and the goal is to determine a control input that steers the system to a target state with low energy expenditure, while Optimising the trade-offs between state deviation and control effort. The LQR controller is especially effective at stabilizing systems that are intrinsically unstable or possess intricate dynamics, such as the Quanser Aero 2-DOF Helicopter platform. The controller utilizes feedback from the system's state variables to generate an optimal control rule by minimizing a quadratic cost function that penalizes state deviations and control efforts. The block Diagram for LQR is shown in the figure 4.

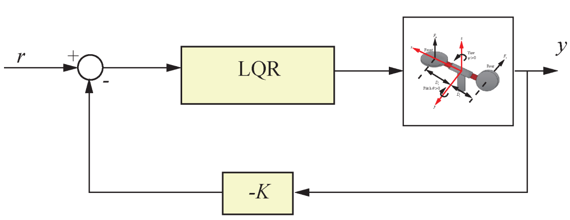

Fig.4 Simple Block Diagram for LQR Control

The LQR control is aimed to reduce quadratic cost function $J = \int_0^\infty \left(x^T(t) Q x(t) + u^T(t) R u(t) \right) dt$ whereas Q is a positive semi-definite matrix that penalizes the state error and R is a positive definite matrix that penalizes the magnitude of control input. This cost function can be turned into $J = \int_0^\infty \left(x^T Q x + u^T R u \right) dt$, thus now the Q and R will be the main matrices to decide how our proposed controller should respond to the errors in the states. Applying the solution via the Riccati equation one may get:

$$A^T P + PA - PBR^{-1} B^T P + Q = 0 \quad (10)$$

Where P is a positive definite matrix that satisfies this equation (10), results in the control input as:

$$u(t) = -Kx(t) \quad (11)$$

Where K is the feedback matrix that shares how the control inputs are applied based on the system's state. This can be calculated as $K = R^{-1} B^T P$. The Fractional Order Linear Quadratic Regulator (FOLQR) is an enhancement of the conventional LQR controller, intended for systems exhibiting fractional-order dynamics as shown in Figure 5

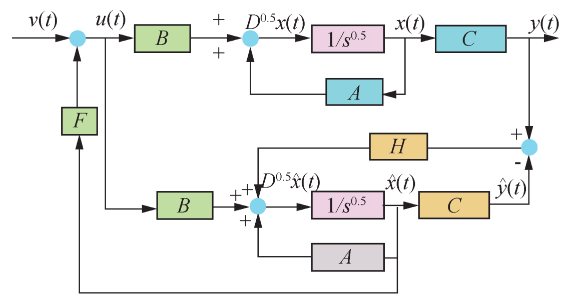

Fig.5 Block Diagram of FOLQR with Observer Design

This study employs the Caputo fractional derivative, which is extensively utilised in control applications for its capacity to integrate initial conditions similarly to integer-order systems []. The fractional-order state-space representation is articulated as:

$$D^\alpha x(t) = Ax(t) + Bu(t) \quad (12)$$

As per the similar approach followed in [14], using the laws, one may get the state equation for the augmented system which includes later the state observers as follows [15]:

$$\begin{bmatrix} D^{0.5} x(t) \\ D^{0.5} e(t) \end{bmatrix} = \begin{bmatrix} A - BF & -BF \\ 0 & A - HC \end{bmatrix} \begin{bmatrix} x(t) \\ e(t) \end{bmatrix} \quad (13)$$

The full order observer estimates the full state vector $\hat{x}(t)$ and is governed by:

$$D^\alpha \hat{x}(t) = A\hat{x}(t) + Bu(t) + L\left(y(t) - \hat{y}(y) \right) \quad (14)$$

Thus, the closed-loop system with a full order observer is described as:

$$D^\alpha \hat{x}(t) = (A - BK)\hat{x}(t) + L(C_x(t) - C\hat{x}(t)) \quad (15)$$

Moreover, a Reduced Order Observer estimates solely the unmeasured states, hence diminishing computational complexity by concentrating exclusively on a subset of the states. The reduced order observer is especially advantageous when certain states are directly measurable, necessitating only estimating a subset of the state vector. Partitioning the system, one may get:

$$x(t)=\begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} \tag{16}$$

Where $x_1(t)$ is the measurable part of the state vector and the unmeasurable part that needs to be estimated is denoted as $x_2(t)$. In this way the system matrices will be given as:

$$D^\alpha \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} u(t) \tag{17}$$

$$y(t)=C_1 x_1(t) \tag{18}$$

Thus, the reduced order observer estimates only $x_2(t)$:

$$D^\alpha \hat{x}_2(t)=A_{22}\hat{x}_2(t)+A_{21}\hat{x}_1(t)+B_2 u(t)+ L_r\big(y(t)-C_1 x_1(t)\big) \tag{19}$$

Where L_r is defined as reduced observer gain and will ensure that the estimation error $\tilde{x}_2(t)$ must converge to zero. In this way one may develop the FOLQR Control Law as:

$$u(t)=-K\begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} \tag{20}$$

Because system matrices (A and B) in the Fractional-Order LQR (FOLQR) controller are fractional-order, you need to use numbers to solve the fractional-order Riccati equation (FRE)[26]. We use the Adams-Bashforth-Moulton predictor-corrector method, a common way to solve fractional differential equations numerically, to find the state-feedback gain matrix (K) in this study[27]. We also use an iterative fractional-order version of the Kleinman method that gets closer and closer to the answer to the generalised algebraic Riccati equation (GARE) [28]. This method ensures that the computation of control gains is stable and correct, making it a good choice for real-time applications of fractional-order optimal control. The suggested mathematical approach allows underactuated UAV systems to track their paths more accurately and become more stable. Whereas the Full system with Reduced order observer FOLQR in closed-loop system dynamics will be defined as:

$$D^\alpha \hat{x}_2(t)=(A_{22}-L_r C_1)\hat{x}_2(t)+A_{21}x_1(t)+L_r C_1 x_1(t) \tag{21}$$

The Full Order Observer, in conjunction with the Fractional Order Linear Quadratic Regulator (FOLQR), is engineered to estimate all system states, rendering it appropriate for scenarios where direct measurement of each state is impractical. This method enables the control rule to employ the complete estimated state vector, guaranteeing precise control in intricate systems. Conversely, the Reduced Order Observer combined with FOLQR estimates solely the unmeasured states, hence decreasing processing demands and rendering it suitable for systems with directly measurable states. The control law in this instance is implemented based on both measured and estimated states. Both observers are effectively designed to include fractional-order dynamics, which has proved very promising results for enhancing system performance, especially when dealing with problems featuring memory effects or non-local dynamics related UAVs.

Conventional LQR works very effectively on systems such as the Aero2 by Quanser, though its shortfalls can affect performance in most complex applications found in reality. One major limitation involves the assumptions LQR makes in having a completely measurable state vector. For most systems in practice that have either unmeasured or inaccessible states-for instance, in the case of the Aero2 platform-this may be quite an unrealistic assumption. Moreover, LQR relies on integer-order dynamics, which might be inadequate in capturing the memory effects and non-local behaviour inherent in systems such as UAVs or helicopters, thus yielding poor control efficacy. The identified deficiencies impose the necessity of using sophisticated control techniques such as the Fractional Order Linear Quadratic Regulator, incorporating fractional-order dynamics that enhance the system's responsiveness and stability. First, using FOLQR with a full-order observer allows the estimation of all system states enhancing overall control accuracy. Finally, FOLQR implements a reduced order observer architecture for computational efficiency that estimates only the unmeasured states while directly using the measured ones. The approach balances precision and efficiency in implementing the control method, overcoming the LQR constraints to ensure a resilient and flexible solution for the Aero2 system.

4 Results & Discussion

This section presents the hardware implementation of Fractional Order LQR (FOLQR), followed by FOLQR with both full and reduced order observers, on the Quanser Aero 2 helicopter, and compares the results. The initial circumstances are defined as null, with x_0 equal to 0. The experimental outcomes utilising square input waves for pitch and yaw angles are illustrated in Fig. 6 and Fig. 7, while the control inputs are detailed in Fig. 8 and Fig. 9. To get the best tracking accuracy and control effort for the Fractional-Order LQR (FOLQR) controller, the weighting matrices (Q and R) were chosen using an empirical tuning method:

$$Q=\begin{bmatrix} 5 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, R=\begin{bmatrix} 0.1 & 0 \\ 0 & 0.05 \end{bmatrix} \tag{22}$$

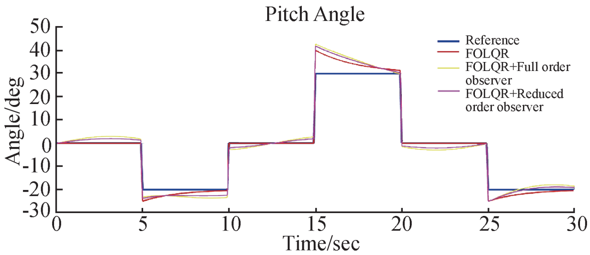

Fig.6 Pitch tracking using FOLQR, FOLQR with full order observer and reduced order observer design

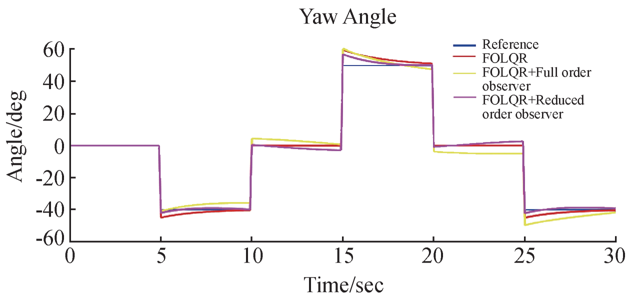

Fig.7 Yaw tracking using FOLQR, FOLQR with full order observer and reduced order observer design

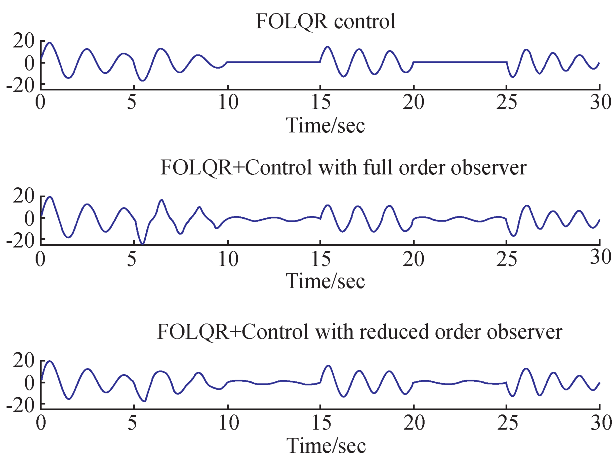

Fig.8 Motor Input (Pitch)

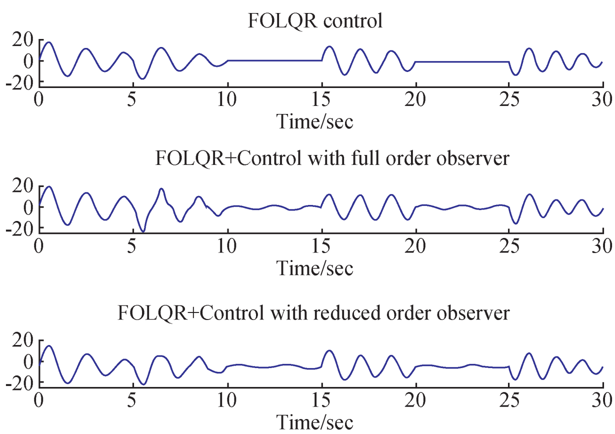

Fig.9 Motor Input (Yaw)

The observer gain (L) was calculated using fractional-order Kalman filtering, which made state estimates more resistant to sensor noise[29]:

$$L = \begin{bmatrix} 1.5 & 0.3 \\ 0.4 & 1.2 \\ 0.2 & 0.8 \\ 0.5 & 1.0 \end{bmatrix}$$

These parameters were implemented and tested on the 2-DOF Quanser Aero 2 helicopter, confirming the effectiveness of the proposed controller in stabilizing underactuated UAV systems[30].

$$K = \begin{bmatrix} -2.1 & 1.4 & 0.8 & -1.2 \\ 0.9 & -1.6 & 1.2 & 0.5 \end{bmatrix} \tag{23}$$

These parameters were set up and tried on the 2-DOF Quanser Aero 2 helicopter, which showed that the proposed controller works well for stabilising UAVs that aren't moving enough. The illustrated control schemes demonstrated varying efficacy for pitch and yaw. The full-order observer controller demonstrated superior performance in pitch tracking, accurately adhering to the target trajectory and conforming to ideal LQR control. This likely arises from its capacity to precisely estimate all states, essential for exact pitch control. The reduced-order observer controller attained enhanced yaw tracking. This may be due to the simplicity of yaw dynamics, necessitating fewer states for control. The reduced-order observer is adequate for yaw, whereas a full-order observer may bring superfluous complexity. The examination of motor control inputs uncovers a noteworthy finding. All methods require greater control effort equal to FOLQR. This shares that one may consider any of them but in case practical implementation where precision and efficiency really matter and are subject to real-time disturbance FOLQR with full order observer design is recommended. The reduced-order observer may incur a minor estimation error, requiring a more robust control input to attain the necessary tracking performance. The estimated states utilising both the full order observer and the reduced order observer are illustrated in Fig. 10 and Fig. 11.

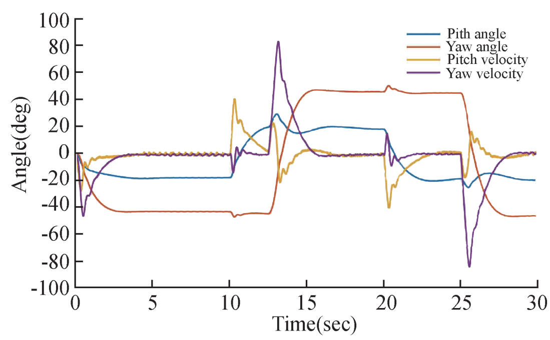

Fig.10 Estimated states using FOLQR full order observer

To assess the resilience of the proposed FOLQR with observers in the presence of unknown external disturbances, we perform stabilisation tests by

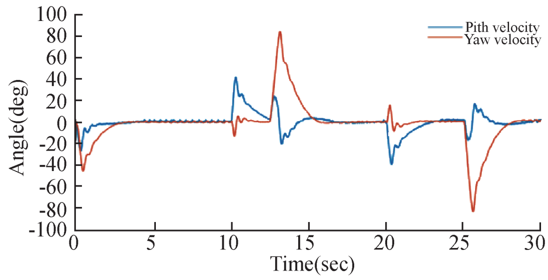

Fig.11 Estimated states using FOLQR reduced order observer

maintaining the pitch angle at 15° and the yaw angle at 30° , subsequently introducing a random disturbance manually on the Aero 2 after 15 seconds. The results obtained show that all methods attained stabilisation for pitch control; nonetheless, a continual steady-state inaccuracy persisted. The FOLQR controller mitigated this error. The FOLQR controller with a full-order observer originally exhibited oscillations, likely attributable to state estimate error. Both FOLQR with full order and reduce order observer designs effectively mitigated disturbances, underscoring the pitch's heightened sensitivity, which presumably stems from its direct influence on longitudinal motion and stability. Conversely, yaw control exhibited no steady-state inaccuracy. Moreover, both the FOLQR with full order and the reduced-order observer controller exhibited superior stabilization outcomes, even in the presence of disturbances, as compared to FOLQR standalone. Figure 12 and 13 show the pitch and Yaw stabilization respectively with and without disturbances. Moreover, analysis of the control inputs in Figures 14 and 15 indicated that LQR control minimized effort across all scenarios, both with and without disruptions, hence showing its efficacy.

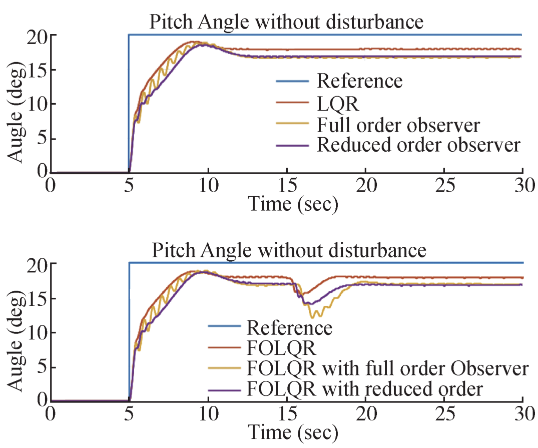

Fig.12. Pitch Stabilization with and without disturbances

Although state feedback controllers employing full-order and reduced-order observers need marginally greater control effort, especially in mitigating external disturbances, their performance remained closely aligned with the best control attained through FOLQR alone.

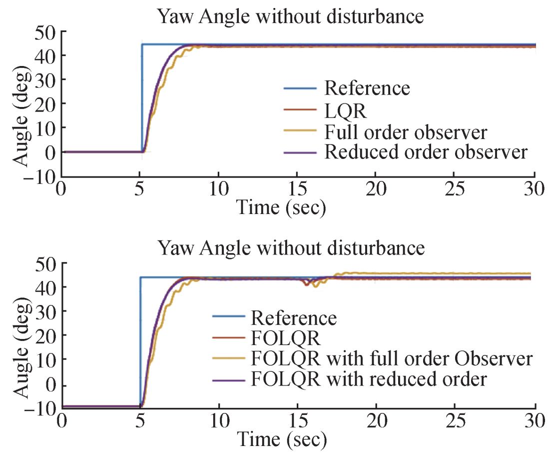

Fig.13 Yaw Stabilization with and without disturbances

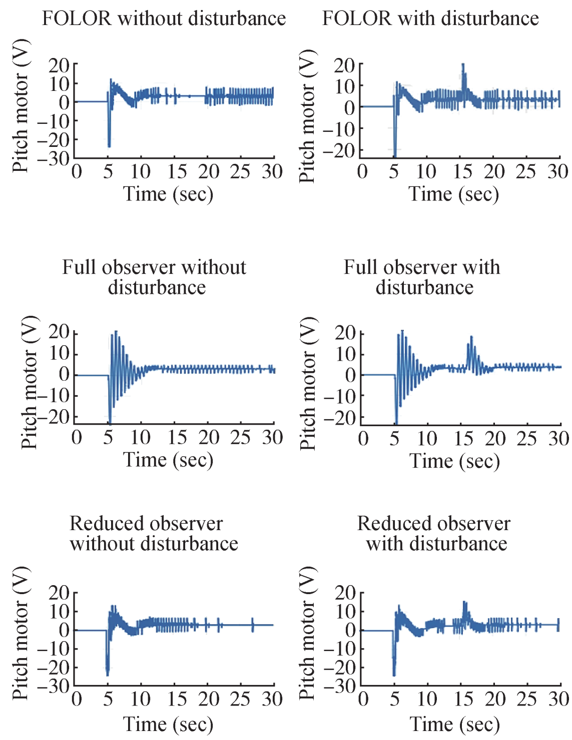

Fig.14 Response related Pitch Motor Input for Stabilization

This indicates that, even with observers, near-optimal control for both pitch and yaw axes can be attained, with all methods demonstrating heightened control effort during disturbances to preserve system stability. Regarding practical implementation, the manuscript suggests the FOLQR with full order observer design controller. This work has been conducted by utilizing the Aero 2 Equipment at Advance Un-manned Aerial Systems (AUAS) Lab at the aerospace engineering department of KFUPM as shown in Figure 16. Quanser's Aero2 experimental setup is a sophisticated platform that was built for educational and research purposes in the field of aerospace engineering and control systems interfaced with QUARC (Quanser Real-time communication) software. It was created by Quanser. This setup includes a highly realistic model of an unmanned aerial vehicle (UAV), which is outfitted with

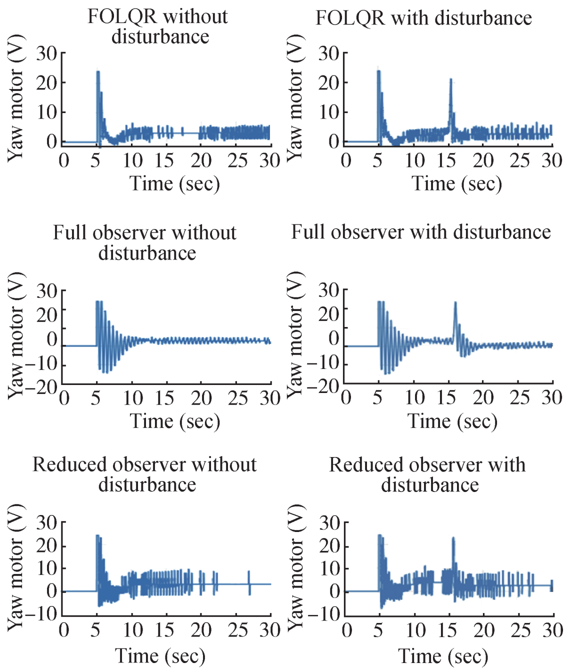

Fig.15 Response related Yaw Motor Input for Stabilization

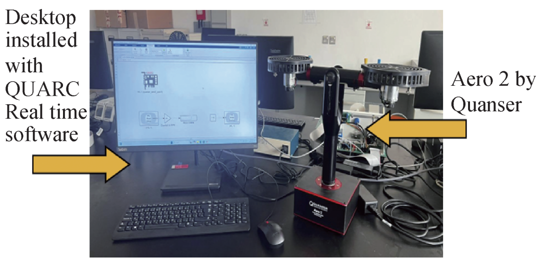

Fig.16 Aero2 Experimental Setup by Quanser (AUAS Lab of AE dept. of KFUPM)

sophisticated sensors and actuators that simulate the flight dynamics of the actual world. The users of the Aero2 system can experiment with the various control systems such as PID, LQR and adaptive control by using hands-on experiments. One of the notable characteristics of the system is that it enables the capability to perform experiments in both the simulation and real-time context. It allows a user to design, test, and implement control algorithms effectively. Aero2 will be a very useful setup that can be used by students and researchers in order to gain deeper insight into flight control systems and dynamics.

In the 2-DOF Quanser Aero 2 helicopter platform, the experimental validation of the proposed Fractional Order LQR (FOLQR) and Observer-Based LQR techniques has confirmed their efficacy in mitigating sensor noise, model uncertainties, and external disturbances. The estimated states derived from both full-order and reduced-order observers demonstrate the controllers' proficiency in adjusting for unmeasured states, hence diminishing reliance on direct sensor measurements. The pitch and yaw stabilisation responses in both disturbed and undisturbed settings demonstrate the FOLQR controller's effectiveness in preserving trajectory accuracy despite external disturbances. The reaction of pitch and yaw motor inputs illustrates the refined control effort necessary for attaining system stability. These findings confirm that FOLQR surpasses traditional LQR, adeptly addressing real-world uncertainties and guaranteeing dependable control performance. This further substantiates the viability of executing observer-driven robust control techniques in underactuated aerial systems to improve stability and trajectory tracking precision.

5 Conclusion

This study aims to demonstrate the design and implementation of a FOLQR controller as a standalone control, followed by full and reduced order observers, and finally a comparison of these types of control techniques with one another. The assessment of the state, the enhancement of control performance, and the reduction of sensor needs are all the reasons why observers are essential in control systems. Through experimental comparisons, these controllers were evaluated about the tracking and stabilisation capabilities of the Quanser Aero 2 helicopter system. FOLQR control with full order observer design was found to be the most effective method, according to the findings of the experiments. On the other hand, FOLQR control that is standalone and uses a reduced order observer offers a valuable alternative for obtaining near ideal performance while maintaining the same level of control over the system. The benefits of this are especially significant for systems that have dynamics that are either complex or unknown. Future studies may investigate the formulation of adaptive control techniques that modify control parameters in real-time to accommodate fluctuating operating conditions and disturbances. In contrast to conventional fixed-parameter control systems, adaptive controllers can adjust their behaviour in response to alterations in the system's environment or internal dynamics, hence enhancing performance and robustness in unpredictable settings. This is particularly important for systems whose dynamics are either complicated or not well known. Future research efforts can be directed at developing adaptive control methods that adjust the control parameters online to compensate for changing operating conditions and disturbances. Unlike traditional fixed-parameter controllers, an adaptive controller can change its behaviour based on changes in the environment or internal dynamics of the system, thereby yielding improved performance and robustness under uncertain conditions. In principle, real-time adaptive tuning within either a UAV or autonomous robotic system will ensure stability and optimum performance against external disturbances initiated by wind gusts, variations in payload, or even sensor noise. Combining adaptive control with advanced approaches, such as machine learning and reinforcement learning, would significantly improve the system's ability to predict and respond to environmental changes, further enhancing its resilience within complex dynamic environments.

6 Future Recommendations

These results of the present study recommend that a search for the development of adaptive control techniques in the future be pursued. The technique is to dynamically change control parameters in real time with respect to the dynamic operating conditions and disturbances. Adaptive controllers-that is, rather than the fixed-parameter control systems normally used-may change their behavior according to changes in either the internal dynamics of the system itself or ambient variables. This, in turn, allows adaptive controllers to guarantee improved performance and robustness for situations that are difficult to foresee. This is especially important in the case of unmanned aerial vehicles and autonomous robotic systems operating under conditions wherein even slight disturbances due to wind, fluctuating payload, or sensor noise could impact system stability and performance. Adaptive control, combined with the state-of-the-art like machine learning and reinforcement learning, will further improve the system's capability to anticipate and react to changes in the ambient environment. This will be possible through a system that realizes increased resilience and stability and optimal performance in complex dynamic environments. Besides, research on reduced-order observer designs for adaptive systems may achieve a good trade-off between the computational efficiency and the precision of control for the systems whose dynamics are either not well known or very complicated. In fact, those would not only make the control systems more reliable but also extend their applications to a wide range of contemporary engineering and robotics challenges.

Author Contribution:

Ghulam E Mustafa Abro: Conceptualization; Methodology; Writing - original draft & editing.

Ayman M Abdallah: Project administration; Resources; Writing-review & editing.

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