STATE AND PARAMETER ESTIMATION ARCHITECTURE FOR QUAD-ROTOR TAIL-SITTER VTOL UAV

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Abstract - In this paper, we present a novel architecture for state and parameter estimation of a quad-rotor tail-sitter VTOL UAV. The proposed approach utilizes multiplier matrices, data-driven concurrent learning, and an adaptive observer to improve the control and navigation of tail-sitter VTOL UAVs. Under certain excitation conditions, the parameter estimation error is guaranteed to converge to a given neighborhood of the origin.

Keywords - State estimation, parameter estimation, quad-rotor tail-sitter VTOL UAV, Extended Luenberger Nonlinear Observers

I. INTRODUCTION

Unmanned aerial vehicle (UAV) technology known as vertical take-off and landing (VTOL) is expanding quickly due to its capacity to take off and land in confined locations. The tail-sitter is the most efficient type of VTOL UAV. Beyond the efficiency provided, there are still certain obstacles to be addressed, such as the difficulty of fusing the capacity to fly horizontally like a fixed-wing aircraft with the ability to hover like a helicopter [1]. The convergence properties of the expanded Luenberger state observers can be used to generate precise state estimates for parameter estimation, even when partial state measurements are available [2]. Recent research focuses on the development of adaptive observers capable of simultaneously estimating the state and parameters of nonlinear systems using methods of persistent excitation (PE) and finite excitation [3]. This research aims to allow the measurement of all state variables [4]–[5], [6]. Most methods are limited to a specific class of nonlinear systems and are based on assumptions that may be difficult to meet in practice, such as strict PE conditions [4]–[5], [6]. The methods described in [4] and [5] are effective but limited to the dynamic systems of the Brunovsky canonical form. This paper presents a combination of two approaches to estimate the state and parameters of Affine Nonlinear Systems:The matrix multiplier approach to design a Luenberger observer which guarantees the asymptotic convergence of the state estimation errors, and Concurrent learning (CL) uses recorded data to estimate the system parameters with high accuracy see [7]. We applied to quadrotor tail-sitter VTOL UAV. This work providespractical perspectives to have Adaptive Control of quadrotor Tail-sitter VTOL UAV in actual settings, paving the way for new advancements in the field of autonomous aerial systems. The rest of the article is structured as follows: Section 2 presents design of state observer; Section 3 presents design of parameter estimator, and Sections 4 presents experimental results and finally, concludes the paper.

II. DESIGN OF STATE OBSERVER

Consider A Nonlinear Dynamical System Of The Form [11]:

$$\dot{x} = Y(x)\theta + g(x)u, \quad y = Cx, \qquad (1)$$

The creation of a state observer that uses an extended Luenberger observer to produce estimates of x is presented in this section.

To simplify the observer design, the nonlinear dynamics given in (1) can be written as [11]:

$$\dot{x} = Ax + F_\theta(x,\theta) + G_u(x,u), \quad y = Cx, \qquad (2)$$

Where $A = (K_{y_1} + K_{g_1})$, $F_\theta(x,\theta) = -K_{y_1}x + Y(x)\theta$

And $G_u(x,u) = -K_{g_1}x + \sum_{i=1}^{N} g_i(x)(u)_i$.

The estimation error dynamics is given by:

$$\dot{\tilde{x}} = (A - LC)\tilde{x} + F_\theta(x,\hat{\theta}) + G_u(x,u) - F_\theta[\hat{x} + l_1(y - C\hat{x}),\hat{\theta}] - G_u[\hat{x} + l_2(y - C\hat{x}),u] + F_\theta(x,\tilde{\theta}), \qquad (3)$$

Where $F_\theta(x,\tilde{\theta}) := F_\theta(x,\theta) - F_\theta(x,\hat{\theta})$.

Let the parameter estimation error is defined $\tilde{\theta} := \theta - \hat{\theta}$. To facilitate the design of the state observer, the following assumption is made about the set Θ, which contains θ. The observer error dynamics in (3) can then be expressed as˙:

$$\dot{\tilde{x}} = (A - LC)\tilde{x} + \emptyset_y(t,\tilde{x},\tilde{\theta}) + \emptyset_g(t,\tilde{x}) + F_\theta(x,\tilde{\theta}), \quad (4)$$

According to the differential mean value theorem (DMVT) the difference functions$\emptyset_y$ and $\emptyset_g$ are guaranteed to be bounded, which can be expressed in their quadratic forms as:

$$\begin{bmatrix}\tilde{x}\\ \emptyset_y\end{bmatrix}^T\begin{bmatrix}I_n - l_1C & 0\\ 0 & I_n\end{bmatrix}^T M_y\begin{bmatrix}I_n - l_1C & 0\\ 0 & I_n\end{bmatrix}\begin{bmatrix}\tilde{x}\\ \emptyset_y\end{bmatrix} \le 0, \qquad (5)$$

And

$$\begin{bmatrix}\tilde{x}\\ \emptyset_g\end{bmatrix}^T\begin{bmatrix}I_n - l_2C & 0\\ 0 & I_n\end{bmatrix}^T M_g\begin{bmatrix}I_n - l_2C & 0\\ 0 & I_n\end{bmatrix}\begin{bmatrix}\tilde{x}\\ \emptyset_g\end{bmatrix} \le 0, \qquad (6)$$

With their corresponding multiplier matrices designed as:

$$M_y = \begin{bmatrix}0 & \frac{-K^T{}_{y_2} - K^T{}_{y_1}}{2}\\ \frac{-K_{y_2} - K_{y_1}}{2} & I_n\end{bmatrix}, \qquad (7)$$

$$M_g = \begin{bmatrix}0 & \frac{-K^T{}_{g_2} - K^T{}_{g_1}}{2}\\ \frac{-K_{g_2} - K_{g_1}}{2} & I_n\end{bmatrix}, \qquad (8)$$

A Lyapunov-based analysis that uses the above inequalities to establish bounddness of the state estimation error for all $t \in R \ge 0$.

-Analysis of State Observer: The following Theorem establishes local uniform ultimatebounddness of the state estimation errors.

Theorem 1: Provided Assumption 1 and 2 hold, there exists a constant symmetric positive definite matrix P, and three observer gains, l_1, l_2 and L, that satisfy the matrix inequality:

$$\begin{bmatrix}\begin{pmatrix}(A-LC)^TP\\ +P(A-LC)\end{pmatrix} + 2\alpha P & P-(I-l_1C)^T(M_y)_{22} & P-(I-l_2C)^T(M_g)_{22}\\ P-(M_y)_{21}(I-l_1C) & -(M_y)_{22} & 0\\ P-(M_g)_{21}(I-l_2C) & 0 & -(M_g)_{22}\end{bmatrix} < 0, \qquad (9)$$

Then observer error in (3) is locally uniformly ultimately bounded.
Proof: Consider the continuously differentiable candidateLyapunov function, $W: D \to R$ defined as:

$$W(\tilde{x}) := \tilde{x}^T P\tilde{x}, \qquad (10)$$

Which satisfies $\lambda_{min}(P)\|\tilde{x}\|^2 \le W(\tilde{x}) \le \lambda_{max}(P)\|\tilde{x}\|^2$. since P is a constant symmetric positive definite matrix, both eigenvalues are positive. On the set D, the orbital derivative of the Lyapunov function along the trajectories of (3) can be expressed as:

$$\dot{W}(\tilde{x},t) := \begin{bmatrix}\tilde{x}\\ \emptyset_f\\ \emptyset_g\end{bmatrix}^T\begin{bmatrix}(A-LC)^TP + P(A-LC) & P & P\\ P & 0 & 0\\ P & 0 & 0\end{bmatrix} + \tilde{x}^T P F_\theta(x,\tilde{\theta}) + F_\theta(x,\tilde{\theta})P\tilde{x}, \qquad (11)$$

Provided the matrix inequalities in (9) is satisfied for some constant $\alpha \in R_+$,

$$\dot{W}(\tilde{x},t) \le -2\alpha W(\tilde{x}) + 2\lambda_{max}(P)\bar{F}_{\tilde{\theta}}\|\tilde{x}\|, \qquad (12)$$

Forall$\tilde{x} \in D$, where $\max_{x\in C}\|F_\theta(x,\tilde{\theta})\| \le \bar{F}_{\tilde{\theta}}$for some

$\bar{F}_{\tilde{\theta}} \in R_+$. Hence, the orbital derivative is bounded along the trajectories of (4) as:

$$\dot{W}(\tilde{x},t) \le -\alpha W(\tilde{x}), \forall \tilde{x} \in D, \|\tilde{x}\| \ge \xi > 0, \qquad (13)$$

Where $\xi = \frac{2\lambda_{max}(P)\bar{F}_{\tilde{\theta}}}{\alpha\lambda_{min}(P)}$. Invoking [13, Thereom 4.18], the state estimation error is locally uniformly ultimately bounded. The matrix P and the observer gains L, l_1 and l_2 can be obtained by solving the LMI:

$$\begin{bmatrix} \begin{pmatrix} A^T P + PA \\ -C^T R^T - RC \end{pmatrix} + 2\alpha P & P - (I - l_1 C)^T (M_y)_{22} & P - (I - l_2 C)^T (M_g)_{22} \\ P - (M_y)_{21}(I - l_1 C) & -(M_y)_{22} & 0 \\ P - (M_g)_{21}(I - l_2 C) & 0 & -(M_g)_{22} \end{bmatrix} < 0, \quad (11)$$

For P, R, l_1 and l_2.

III. DESIGN OF PARAMETER ESTIMATOR

The parameter estimator to be designed in this sectionrelies the difference between the state estimates at time t and time (t – ς), where ς∈ R+ denotes the time delay, can be expressed as an affine function of the parameters θ and a residual that reduces with reducing state estimation errors as described in the following Lemma.

Lemma 1: If x, x̃∈C and if Assumption 1 holds for all $\varsigma \geq 0$ and for all $t \geq \varsigma$, the state estimates satisfy:

$$\hat{x}(t) - \hat{x}(t - \varsigma) = \hat{y}(t)\theta + \hat{G}_u(t) + E(t),$$

Where $\hat{y}(t) := \int_{t-\varsigma}^{t} Y(\hat{x}(\tau))d\tau, \hat{G}_u(t) := \int_{t-\varsigma}^{t} g(\hat{x}(\tau))u(\tau)d\tau,$

And $E(t) = O(\sup_{\sigma\in[t-\varsigma,\ t]}\|\tilde{x}(\sigma)\|)$.

Proof: Integrating the dynamics in (1) yields. Lemma 1 implies that the parameter estimation error at any time t can be expressed as: $\hat{y}(t)\tilde{\theta}(t) = \hat{x}(t) - \hat{x}(t - \varsigma) - \hat{G}_u(t) - \hat{y}(t)\tilde{\theta}(t) - E(t),$

Witch motivates the update law:

$$\dot{\hat{\theta}} = \begin{cases} k_\theta \Gamma_\emptyset\ , & \text{if } \hat{\theta}^T\hat{\theta} < \bar{\theta}^2 \text{ or} \\ & \text{if } \hat{\theta}^T\hat{\theta} = \bar{\theta}^2 \text{ and } (k_\theta\Gamma_\emptyset)^T\hat{\theta} \leq 0 \\ I_p - \dfrac{T\hat{\theta}\hat{\theta}^T}{\hat{\theta}^T T\hat{\theta}}\ , & \text{otherwise} \end{cases} \quad (14)$$

Where

$\emptyset(t) := \sum_{i=1}^{N}\left(\frac{\hat{y}(t_i)}{1+k\|\hat{y}(t_i)\|^2}\right)^T(\hat{x}(t_i) - \hat{x}(t_i - \varsigma) - \hat{G}_u(t_i) - \hat{y}(t_i)\hat{\theta})$, $k\epsilon R_{>0}$, the normalization is gain, and $k_\theta \epsilon R_{>0}$ is the CL gain. The matrix $\Gamma\epsilon R^{pxp}$ is the least-squares gain matrix updated as:

$$\dot{\Gamma} = \begin{cases} \beta_1\Gamma - k_\theta\Gamma\dfrac{\hat{y}(t_i)^T\hat{y}(t_i)}{1 + k\|\hat{y}(t_i)\|^2}\Gamma, & \text{if}\hat{\theta}^T\hat{\theta} < \bar{\theta}^2\text{or} \\ & \text{if}\hat{\theta}^T\hat{\theta} = \bar{\theta}^2\text{and}(k_\theta\Gamma_\emptyset)^T\hat{\theta} \leq 0 \\ 0\ , & \text{otherwise} \end{cases} \quad (15)$$

Where $\beta_1 \epsilon\ R > 0$ is a constant adaptation gain. The update law relies on the time delay ς, and a history stackH. The history stack represents a set of piecewise constant functions that can be expressed as:

$$\hat{X} := \begin{bmatrix} \hat{x}(t_1) - \hat{x}(t_1 - \varsigma) \\ \vdots \\ \hat{x}(t_N) - \hat{x}(t_N - \varsigma) \end{bmatrix}, \hat{Y} = \begin{bmatrix} \hat{y}(t_1) \\ \vdots \\ \hat{y}(t_N) \end{bmatrix}, \hat{G}_u := \begin{bmatrix} \hat{G}_u(t_1) \\ \vdots \\ \hat{G}_u(t_N) \end{bmatrix}, \quad (16)$$

Where $\hat{X}\epsilon\ R^{nN}, \hat{Y}\epsilon\ R^{nNxp}$, and $\hat{G}_u \epsilon R^{nN}$. Using Lemma 1, the parameter estimation error dynamics can be expressed as:

$$\dot{\tilde{\theta}} = -k_\theta\Gamma\sum_{i=1}^{N}\frac{\hat{y}(t_i)^T\hat{y}(t_i)}{1 + k\|\hat{y}(t_i)\|^2}\tilde{\theta} - k_\theta\Gamma\sum_{i=1}^{N}\frac{\hat{y}(t_i)^T E(t_i)}{1 + k\|\hat{y}(t_i)\|^2}, \quad (17)$$

It is clear from (17) that for the parameter estimation error to be bounded, the matrix $\sum_{i=1}^{N}\frac{\hat{y}(t_i)^T\hat{y}(t_i)}{1+k\|\hat{y}(t_i)\|^2}$ needs to be positive definite, which can be ensured if the trajectories are sufficiently informative and the data$(\hat{x}(t_1) -$

$\hat{x}(t_1 - \varsigma)$, $\hat{y}(t_i), \widehat{G}_{u_i})_{i=1}^{N}$ stored in the history stack H are recorded carefully. Architecture (The algorithm) presented in Algorithm1 [7].

The availability of accurate state estimates is required for precise parameter estimation. However, the initial history stack, recorded during transients, may contain inaccurate data, requiring a purge of the history stack once more accurate state estimates become available. In such cases, newer state estimates are preferred, subject to the conditions of Theorem 1.

A greedy purging algorithm based on dwell time is employed to ensure estimator stability while utilizing newer data. This architecture (algorithm) uses two history stacks: a main stack denoted as H and a transient stack labeled G. The transient stack is filled until a sufficient dwell time T has elapsed. Then, the main stack is purged, and the transient stack is copied into the main stack. This approach enables the use of newer, more accurate data while maintaining estimator stability.

Algorithm 1 Algorithm for Adaptive History Stack Observer. At each time instance t, τ_1 stores the last time an event occurred, τ_2 stores the last time instance $\mathcal{H}$ was purged, λ stores the highest minimum eigenvalue encountered so far, $\mathcal{T}$ denotes the dwell time, λ^* denotes some user selected eigenvalue threshold, t^* denotes some user selected sampling rate and $\xi \in (0, 1]$ is a threshold for purging.

Require: $t_f \in \mathbb{R}_{>t_0}$, $t^* \in \mathbb{R}_+$, $\mathcal{T} \in \mathbb{R}_{>0}$, $\lambda^* \geq 0$
$\mathcal{Y} \leftarrow 0$, $\mathcal{G} \leftarrow 0$, $\mathcal{G}_u \leftarrow 0$, $\tau_1 \leftarrow 0$, $\tau_2 \leftarrow 0$ ▷ Global variables
$\lambda \leftarrow \min(\text{eig}(\mathcal{G}^\top \mathcal{G}))$, $t_0 \leftarrow 0$, $\hat{x}_0 \leftarrow \hat{x}(t_0)$, $\hat{\theta}_0 = \hat{\theta}(t_0)$
while $t_0 < t_f$ **do**
  integrate DDEs in (21), (22) and (24) over $[t_0, t_f]$
  if $(t - \tau_1) \geq t^*$ **then**
    if $t \geq \varsigma$ **then**
      stop integration, an event has occurred
      $j \leftarrow \text{argmax}_{i=1:N}\{\min\{\text{eig}(\mathcal{G}^\top\mathcal{G} - \hat{\mathcal{Y}}_i^\top\hat{\mathcal{Y}}_i + \hat{\mathcal{Y}}^\top\hat{\mathcal{Y}})\}\}$
      if $\max_{i=1:N}\{\min\{\text{eig}(\mathcal{G}^\top\mathcal{G} - \hat{\mathcal{Y}}_i^\top\hat{\mathcal{Y}}_i + \hat{\mathcal{Y}}^\top\hat{\mathcal{Y}})\}\} - \lambda \geq \lambda^*$ **then**
        $\lambda \leftarrow \max_{i=1:N}\{\min\{\text{eig}(\mathcal{G}^\top\mathcal{G} - \hat{\mathcal{Y}}_i^\top\hat{\mathcal{Y}}_i + \hat{\mathcal{Y}}^\top\hat{\mathcal{Y}})\}\}$
        $\{\mathcal{Y}_i\}_{i=(j-1)}^{n_j} \leftarrow \hat{\mathcal{Y}}(t)$
        $\{\mathcal{G}_{u_i}\}_{i=(j-1)}^{n_j} \leftarrow \hat{G}_u(t)$
        $\{\mathcal{X}_i\}_{i=(j-1)}^{n_j} \leftarrow \hat{x}(t) - \hat{x}(t - \varsigma)$
        if $\mathcal{G}$ is not full **then**
          add the data points to $\mathcal{G}$
        else
          add the data points to $\mathcal{G}$ if (26) holds
        end if
        if $\min(\text{eig}(\mathcal{G}^\top\mathcal{G})) \geq \xi\lambda$ **then**
          if $(t - \tau_2) \geq \mathcal{T}(t)$ **then**
            $\mathcal{H} \leftarrow \mathcal{G}$, $\mathcal{G} \leftarrow 0$, and $\tau_2 \leftarrow t$
            if $\lambda < \min(\text{eig}(\mathcal{G}^\top\mathcal{G}))$ **then**
              $\lambda \leftarrow \min(\text{eig}(\mathcal{G}^\top\mathcal{G}))$
            end if
          end if
          $t_0 \leftarrow t$, $x_0 \leftarrow x(t)$, $\hat{\theta}_0 \leftarrow \hat{\theta}(t)$
          $I_{Y,0} \leftarrow I_Y(t)$, $I_{g_u,0} \leftarrow I_{g_u}(t)$
        end if
      end if
    else
      no event, keep on integrating the DDEs
    end if
    $\tau_1 \leftarrow t$ ▷ Set this even if a new event is not detected
  end if
  no event, keep on integrating the DDEs
end while

-Analysis of Parameter Estimator: in order to rigorously analyze the convergence properties of the parameter estimation error, a precise definition of "Finitely Informative" and "Persistently Informative" data in the history stack [12]. The dynamics of the parameter estimation error in (17) and (15) can be expressed as:

$$\dot{\tilde{\theta}} = -k_\theta \Gamma \Psi_s \tilde{\theta} - k_\theta \Gamma Q_s \text{ and } \dot{\Gamma} = \beta_1 \Gamma - k_\theta \Gamma \Psi_s \Gamma \quad (18)$$

Respectively, it is important to note that the functions Ψ_s and Q_s are piece-wise continuous. Thus, the trajectories of (18) are defined in the sense of Caratheodory [5]. Using arguments similar to [4, Theorem 1], provided the conditions of Theorem 1 are satisfied, and the states and state estimation errors remain within the compact sets C and D, respectively, over the time interval I_{s-1} in which the history stack was recorded, then using the error bound developed in Lemma 1 the error terms can be bounded as:

$$\|E_{si}\| \leq L_e \bar{e}_s, \forall i \in \{1, \cdots, N\}, \forall \tilde{x} \epsilon D, \quad (19)$$

Where $\bar{e}_s := \sup_{t \in I_{s-1}} \|\tilde{x}\|$ and $L_e \in R_+$ is a constant.

Theorem 2: If the state and parameters of the system in (1) are estimated using state and parameter estimators that satisfy the conditions of Theorem 1 and Assumption 3, the signal ($\hat{x}$, u) is FI, H is populated using Architecture (Algorithm1) [5], and if the excitation lasts long enough for two purging events (i.e. H_3 is full rank), then the trajectories of the parameter estimation error are ultimately bounded.

Proof: Consider the candidate Lyapunovfunction V:

$\Theta \times R \geq 0 \rightarrow R$ defined as:

$$V(\tilde{\theta}, t) := \frac{1}{2}\tilde{\theta}^T \Gamma^{-1}(t)\tilde{\theta}, \quad (20)$$

The candidate Lyapunov function satisfies the following inequality:

$$\frac{1}{2\bar{\Gamma}}\|\tilde{\theta}\|^2 \leq V(\tilde{\theta}, t) \leq \frac{1}{2\underline{\Gamma}}\|\tilde{\theta}\|^2, \quad \forall t \epsilon R_{\geq 0}, \quad (21)$$

Using the completion of squares, the orbital derivative is then bounded for all $\forall t \epsilon R_{\geq 0}$ as:

$$\dot{V}_s(\tilde{\theta}, t) \leq -\frac{1}{4}\underline{a}\|\tilde{\theta}\|^2, \quad \forall \|\tilde{\theta}\| \geq \varrho(\|u\|), \quad (22)$$

Where $\varrho(\|u\|) := \sqrt{\frac{\bar{\Gamma}}{\underline{\Gamma}}(\frac{4k_\theta}{\underline{a}})}\|u\|^2$ and $:= \sqrt{\bar{Q}_s}$. Hence, the conditions of [13, Theorem 4.19] are satisfied, and it can be concluded that (18) is input-to-state stable with state $\tilde{\theta}$ and input μ. If Architecture (Algorithm 1) is implemented and if the signal ($\hat{x}$, u) is FI, then there exists a time instance T_s, such that for all $t \geq T_s$, the history stack remains unchanged. And as a result, using [13, Exercise 4.58], and an ultimate bound on $\tilde{\theta}$ can be estimated as:

$$\limsup_{t \to \infty} \|\tilde{\theta}(t)\| \leq \bar{\theta}(T_s) := \sqrt{\frac{\bar{\Gamma}}{\underline{\Gamma}}\left(\frac{4k_\theta \bar{Q}(T_s)}{\underline{a}}\right)} \quad (23)$$

Where $Q(T_s)$ denotes a bound on residual error term Q_s, in the history stack H for all $t \geq T_s$. The

parameter estimation error can be reduced by reducing the estimation errors corresponding to the state estimates stored in the history stack, which reducesQ_s. The projection algorithm and Theorem 1 imply the boundedness of all signals in the closed loop for all t. Furthermore, Theorem 1 implies that given any $\varepsilon \in R_+$ the gain α can be selected large enough to ensure that $\tilde{x}$ has reached the ultimate bound before $t = T_1$ and that the ultimate bound is smaller than ε so that $\bar{e}_2 \leq \varepsilon$. Since the history stack H_3, which is active over the interval I_3, is recorded during the intervalI_2, the bounds in (19) can be used to show

$\bar{Q}_3 = \frac{NL_e\bar{e}_2}{2\sqrt{k}} \leq \frac{NL_e\bar{e}_2}{2\sqrt{k}}\varepsilon$. As such, if $(\hat{x}, u)$ is FI with the excitation lasting long enough so thatH_3 is full rank, then (23) implies that:

$$\limsup_{t\to\infty}\|\tilde{\theta}(t)\| \leq \sqrt{\frac{\bar{\Gamma}}{k\underline{\Gamma}}}\left(\frac{2k_\theta NL_e}{\underline{a}}\right)\varepsilon$$

IV. EXPERIMENTAL RESULTS

This section presents the quad-rotor tail-sitter VTOL UAV system and the obtained experimental results. A mathematical model of quad-rotor tail-sitter VTOL UAV is developed using the Newtonian or Lagrangian approach. For u, v and where the X, Y, and Z directional body-axis velocities, p, q, and r as the angular velocities, the flight dynamics and the quad-rotor tail-sitter VTOL UAVs is considered a quad-rotor for analysis purposes, and The dynamical equations for quad-rotor mode in the hybrid frame see [10].

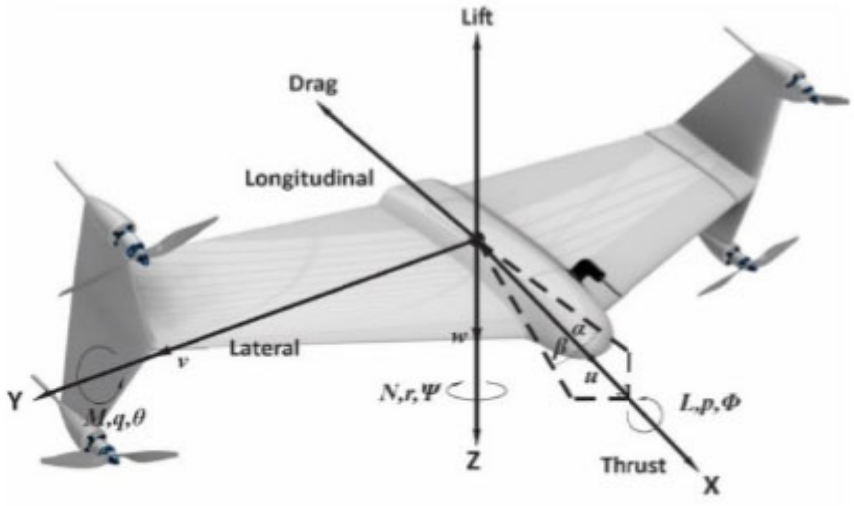


Fig.1. Aircraft forces, velocities, moments, and orientation definitions [1].

Simulation parameters are shown in Table 1:

Parameters	Value
g	9.8 m.s^{-2}
Mass(m)	1.2 kg
Lengh(l)	1m
I_{xx}, I_{yy}	7.5x10^{-3}Kg.m^2
I_{zz}	1.3x10^{-3}Kg.m^2
I_r	7.5x10^{-5}Kg.m^2
Dragcoefficient(d)	7.5x10^{-7}
Liftcoefficient(b)	7.5x10^{-3}

TABLE I. SIMULATIONPARAMETERS

-Sensor data from the quad-rotor tail-sitter VTOL UAV used for state and parameter estimation:
1-The estimation process involves: Multiplier matrices for efficient calculations,
2- Data-driven learning for adaptation,
3-Adaptive observer for real-time state estimation.

-Estimated states and parameters are used by the control and navigation algorithm.

-The algorithm calculates control signals for the actuators.
-These signals influence the quad-rotor's movement, leading to improved control and navigation.

We use Matlab/Simulink for our simulations. Taking into account outside disruptions throughout the takeoff, hovering, and landing phases,

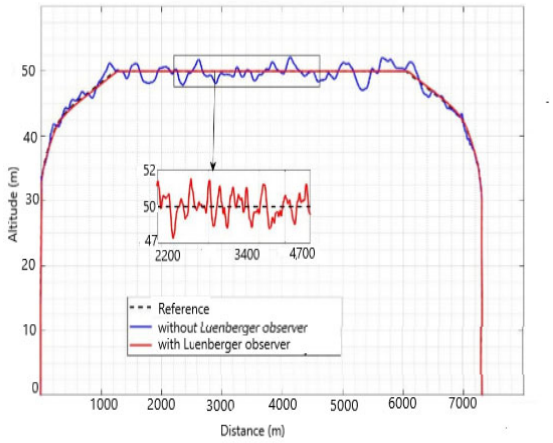


Fig.2.Trajectory tracking comparison for a tail-sitter VTOL UAV performing flight with vertical takeoff, hovering, Level flight, and vertical landing, under wind disturbance.

The graph shows the trajectory of a tail-sitter VTOL drone performing a flight with vertical takeoff, hovering, horizontal flight, and vertical landing with wind disturbance, using the new approach of online state and parameter estimation: The drone accurately follows the desired trajectory; there are no significant altitude oscillations.

Without a new approach to online state and parameter estimation, the drone would have difficulty following the desired trajectory, and its altitude would oscillate significantly.

The convergence properties of the developed method demonstrate the ultimately uniform and local character of the state estimation errors and the input-to-state stability of the parameter estimation errors under finite informative conditions.

V. CONCLUSION

We applied an architecture (algorithm1) that uses a multiplicative matrix observer design and adaptive simultaneous learning update laws to predict the state of a quad-rotor tail-sitter VTOL UAV. The algorithm works in real-time and can predict errors in parameter estimation. Moreover, under certain excitation conditions, the parameter estimation error is guaranteed to converge to a given neighborhood of the origin.

REFERENCES

[1] Tri Kuntoro Priyambodo, Abdul Mjid , Zaied Saad Salem Shouran , “Validation of Quad Tail-sitter VTOL UAV Model in Fixed Wing Mode,” Journal of Robotics and Control (JRC) Volume 4, Issue 2, March 2023.

[2] T. E. Ogri, S. M. N. Mahmud, Z. I. Bell, and R. Kamalapurkar, “Output feedback adaptive optimal control of affine nonlinear Systems with a linear measurement model,” in Proc. IEEE Conf Control Technol. Appl, 2023.

[3] G. Chowdhary, M. M¨uhlegg, J. How, and F. Holzapfel, “Concurrent learning adaptive model predictive control,” in Advances in Aerospace Guidance, Navigation and Control, Q. Chu, B. Mulder, D. Choukroun, E.-J. Van Kampen, C. de Visser, and G. Looye, Eds. Springer Berlin Heidelberg, 2013, pp. 29–47.

[4] R. Kamalapurkar, “Simultaneous state and parameter estimation for second-order nonlinear systems,” in Proc. IEEE Conf. Decis. Control, Melbourne, VIC, Australia, Dec. 2017, pp. 2164–2169.

[5] R. Kamalapurkar, “Online output-feedback parameter and state estimation for second order linear systems,” in Proc. Am. Control Conf., Seattle, WA, USA, May 2017, pp. 5672–5677.

[6] Liu, Z. Zhang, F. Liu, and M. Buss, “Adaptive Observer for a Class of Systems with Switched Unknown Parameters Using DREM,” arXiv preprint arXiv:2203.16643, 2022.

[7] Tochukwu Elijah Ogri, Zachary I. Bell, Rushikesh Kamalapurka, “State and Parameter Estimation for Affine Nonlinear Systems ,” 62nd IEEE Conference on Decision and Control (CDC). December 13-15, 2023. Marina Bay Sands, Singapore.

[8] Y. Wang, R. Rajamani, and D. M. Bevly, “Observer design for differentiable Lipschitz nonlinear systems with time-varying parameters,” in Proc. IEEE Conf. Decis. Control, 2014, pp. 145–152.

[9] Y. Huang and H. Jiang, “Neural network observer-based optimal control for unknown nonlinear systems with control constraints,” in Int. Joint Conf. Neural Netw. 2015, pp.1–7.

[10] Nihal Dalwadi, Dipankar Deb, “Disturbance Observer-Based Backstepping Control of Tail-Sitter UAVs,“ Mangal Kothari and Stepan Ozanam, Actactuators, 10,119, 2021.

[11] A. Zemouche, M. Boutayeb, and G. Bara, “Observer Design for Nonlinear Systems: An Approach Based on the Differential Mean Value Theorem.” In Proc. IEEE Conf. Decis. Control, 2005, pp. 6353–6358.

[12] R. V. Self, M. Abudia, S. M. N. Mahmud, and R. Kamalapurkar, “Model-based inverse reinforcement learning for deterministic systems,” Automatica, vol. 140, no. 110242, pp. 1–13, Jun. 2022.

[13] H. K. Khalil, Nonlinear systems, 3rd ed. Upper Saddle River, NJ: Prentice Hall,2002.

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