2020 IEEE International Conference on Robotics and Automation (ICRA)
31 May - 31 August, 2020. Paris, France

Iterative Learning based feedforward control for Transition of a Biplane-Quadrotor Tailsitter UAS

Nidhish Raj, Ashutosh Simha, Mangal Kothari, Abhishek and Ravi N. Banavar

Abstract— **This paper provides a real time on-board algorithm for a biplane-quadrotor to iteratively learn a forward transition maneuver via repeated flight trials. The maneuver is controlled by regulating the pitch angle and propeller thrust according to feedforward control laws that are parameterized by polynomials. Based on a nominal model with simplified aerodynamics, the optimal coefficients of the polynomials are chosen through simulation such that the maneuver is completed with specified terminal conditions on altitude and air speed. In order to compensate for modeling errors, repeated flight trials are performed by updating the feedforward control paramters according to an iterative learning algorithm until the maneuver is perfected. A geometric attitude controller, valid for all flight modes is employed in order to track the pitch angle according to the feedforward law. Further, a high-fidelity thrust model of the propeller for varying advance-ratio and orientation angle is obtained from wind tunnel data which is captured using a neural network model. This facilitates accurate application of feedforward thrust for varying flow conditions during transition. Experimental flight trials are performed to demonstrate the robustness and rapid convergence of the proposed learning algorithm.**

Index Terms— **VTOL UAS, transition maneuver, iterative learning**

I. Introduction

The technological revolution in the area of Unmanned Aerial Systems (UAS) has opened up new avenues for the application of small UAS. Among the myriad of applications, precision delivery of package containing small consumer goods or life saving drugs or blood to its destination is fast capturing attention. This requires the UAS to precisely hover at low altitude and fly long distances efficiently. Conventional UAS solutions such as fixed wing and quadrotors and helicopters, fail to meet these requirements. This has motivated researchers to design hybrid vertical take-off and landing (VTOL) UAS, such as tilt-rotors, tilt-wings, compound helicopters and tailsitter configurations [1]. These hybrid designs are capable of precise and agile hovering as well as efficient high speed forward flight like an airplane. The transition from hover to forward flight and from forward flight to hover remains a challenging task that governs the success of these hybrid UAS.

Automatic control design for performing seamless transition maneuvers of hybrid vehicles is indeed a formidable challenge because during the maneuver, the UAS operates in a wide aerodynamic regime including stall. Conventional feedback control methods such as regulating the pitch angle and net thrust according to a commanded acceleration are not applicable. This is because the aerodynamic lift and drag forces are complicated functions of the pitch angle and airspeed, and therefore feedback laws can not be explicitly computed in a closed form. Moreover, even if one could afford sophisticated on-board computational capability, the numerically computed feedback requires a high fidelity aerodynamic model in order to be practically applicable. Some approaches to the transition control problem can be found in literature as follows. In [2], [3], [4], [5], an optimal maneuver is designed by dynamically varying the angle of attack of the wing, or the propeller axis, or regulating control surfaces such as slats or flaps, and in [6], [7], [8], the optimal transition problem has been solved in simulation. A tailsitter with no additional moving parts is considered in [9], [10], [11], [12], and the transition maneuver has been performed based on high-fidelity aerodynamic models, via optimal feedforward control. A feedback control solution is proposed in [13], where the nonlinear equation governing the pitch angle and net thrust for achieving a desired acceleration has been numerically solved on-board, after obtaining accurate aerodynamic models. A recent work [14] has applied iterative learning for performing Pugachev's Cobra maneuver with a quadrotor tailsitter. This uses the technique described in [15] which results in solving a convex optimization problem.

In the above literature, the optimal feedforward control trajectory depends heavily on the accuracy of the aerodynamic model and parameters such as lift and drag coefficients of the vehicle. Since the vehicle undergoes high angle of attack flight at low Reynolds number and due to the complex geometry of a biplane, the aerodynamic parameters commonly available for airfoils are not accurate enough, and thus need to be determined from wind tunnel data or high fidelity computational fluid dynamics simulations. Both of the above methods are expensive and time consuming. In order to address this issue, an alternative approach is to employ iterative learning techniques ([16], [17], [18], [15]). Here, for a predefined maneuver, an optimally parameterized feedforward control trajectory is first computed based on a nominal aerodynamic model. Then, the trajectory parameters are iteratively updated through repeated experimental flight trials using the on-board computer, until the maneuver is perfected. This approach appreciably compensates modeling errors, and moreover can be easily implemented on-board in real-time due to its computational simplicity.

Nidhish Raj, Abhishek, and Mangal Kothari are with the Department of Aerospace Engineering, Indian Institute of Technology Kanpur, India. Emails: {nraj,abhish,mangal}@iitk.ac.in. Ravi N Banavar is with the Systems and Control Group, Indian Institute of Technology Bombay, Mumbai, India. Email: ravi.banavar@gmail.com. Ashutosh Simha is a researcher at the Institute of Cybernetics, Tallinn University of Technology, Estonia. Email: ashutosh.iisc@gmail.com

978-1-7281-7395-5/20/$31.00 ©2020 IEEE

A. Contribution

The main contribution of this paper is to perform an autonomous forward transition of the biplane-quadrotor using iterative learning. A 2D model (corresponding to longitudinal dynamics) of the vehicle is used wherein the thrust and pitch angle of the vehicle are assumed to be control inputs for transition. Both control inputs are parameterized as polynomials, and the iterative learning algorithm (based on [16]) is employed in determining the optimal parameters of the feedforward trajectory through repeated experiments, such that the maneuver is completed with minimal terminal state errors. This relieves the controller designer from determining the accurate aerodynamic parameters through extensive testing. As the propeller disk moves through the air in a wide range of advance-ratios and angles of attack, the static thrust model typically used for quadrotor is no longer valid. In order to apply the desired feedforward thrust accurately throughout the operating range of the vehicle, the thrust model of the motor-propeller combination is completely characterized in the wind tunnel and a simple neural network based data fitting is done. This relaxes the requirement on the learning algorithm to capture the high non-linearity associated with the thrust model. Additionally, in order to perform manual flights at pitch angles ranging from quadrotor hover condition to forward flight mode of biplane, 312 Euler angles are used to specify the desired attitude. This avoids the singularity present in the commonly used 321 Euler angles. A rotation matrix based attitude controller is used to track the desired rotation angles, thereby achieving the demanded feedforward pitch control as well as restricting the dynamics to the vertical plane.

II. Vehicle Dynamics

A. Vehicle Description

The biplane quadrotor configuration consists of a quadrotor with two wings attached to it as shown in Fig. 1. The vehicle takes off in the quadrotor hover mode and the entire body gradually tilts forward about body frame Y_b-axis to enter into fixed-wing cruise flight mode. As shown in Fig. 1, the motors of the quadrotor are tilted inward by 10 degree to improve the yaw control authority in hover (which corresponds to roll control in cruise flight mode) [10]. There is greater disturbance and damping about the roll axis (Z_b-axis) in the fixed wing mode due to the wing aerodynamics. In order to reject the disturbance and augment the control authority of motors about the Z_b-axis, the front wing is provided with ailerons.

NACA 0015 airfoil is chosen for designing the wings to facilitate low speed flying as it is a thick airfoil and offers high lift at low angle of attack. The choice of symmetric airfoil is dictated by the fact that the movement of center of pressure for a symmetric airfoil is minimal, even for large variation in angle of attack. This ensures that the airfoil pitching moment remains low and vary in a consistent manner. The GPS is mounted on a tilting mechanism to get continuous signal throughout the transition. The wing separation is kept more than 1.5 times the chord to minimize interference between the wings [10]. The vehicle geometric parameters are given in Table I.

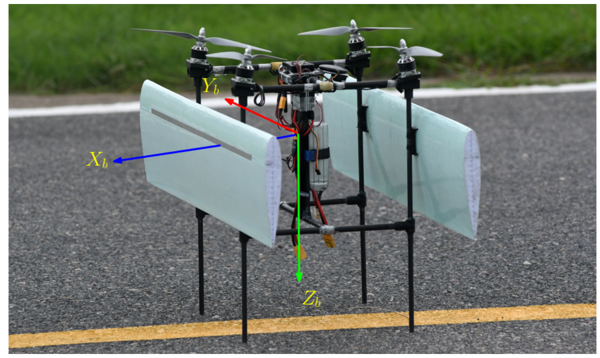


Fig. 1: Biplane quadrotor with body frame axes

Parameter	Values
Wingspan	1 m
Wing chord	0.22 m
Mass	2.72 kg
Motor separation	0.34 m
Wing separation	0.36 m

TABLE I: Biplane Quad geometric parameters

B. Equations of Motion

The equations of motion of the vehicle are given by

$$\begin{aligned} \dot{R} &= R\hat{\omega}, \\ I\dot{\omega} + \omega \times I\omega &= M, \end{aligned} \tag{1}$$

$$m\ddot{X} = F_A + Re_3 f_T + mge_3, \tag{2}$$

where $R \in SO(3)$ is the rotation matrix which transforms vectors from the body fixed frame of reference, (O_b, X_b, Y_b, Z_b), to the spatial frame of reference, (O_e, X_e, Y_e, Z_e), $M = [M_x, M_y, M_z]$ is the external moment acting on the vehicle, I is the body moment of inertia tensor, $\omega = [\omega_x, \omega_y, \omega_z]$ is the angular velocity of the body frame and $e_3 = [0, 0, 1]^T$. The hat map, $\hat{\cdot}$, is such that $\hat{a}b = a \times b$. F_A is the sum of aerodynamic forces, lift f_L and drag f_D, and f_T is the propeller thrust.

Aerodynamic Model

The aerodynamic model given here is detailed in [9]. The total lift is given by the sum of lift generated by area of wing under the influence of propwash, S_w, and the area outside propwash, S_{nw},

$$f_L = \frac{1}{2}\rho V^2 S C_L(\alpha, Re) = \frac{1}{2}\rho V^2 S_{nw} C_{Lnw} + \frac{1}{2}\rho V^2 S_w C_{Lw}. \tag{3}$$

Similarly the drag is given by

$$f_D = \frac{1}{2}\rho V^2 S C_D(\alpha, Re) = \frac{1}{2}\rho V^2 S_{nw} C_{Dnw} + \frac{1}{2}\rho V^2 S_w C_{Dw}. \tag{4}$$

Here C_L and C_D are the equivalent lift and drag coefficients of the entire vehicle. For the purpose of determining optimal thrust and pitch inputs for level forward transition, we use a simple lift and drag model proposed in [19]

$$
\begin{aligned}
C_L(\alpha) &= b_1 \sin(2\alpha) \\
C_D(\alpha) &= b_2 + 2b_1 \sin^2(\alpha),
\end{aligned} \tag{5}
$$

where the constants b_1, b_2 are determined from flight data.

Thrust Model

The thrust model conventionally used for quadrotors is based on blade element momentum theory for hover condition and is given by

$$T_{prop} = \rho \pi R_{prop}^4 C_T \Omega_{prop}^2.$$

This relation is a good approximation for quadrotor mode flight as there is no significant axial inflow and as a result the coefficient of thrust C_T is constant with propeller angular speed Ω_{prop}. This model is not appropriate for propellers which enter into high speed edgewise and axial flight as C_T varies significantly with axial speed, propeller orientation with flow, and Ω_{prop}. Therefore, the thrust is obtained from wind tunnel data for the given motor-propeller combination. The data is collected for airspeed varying from 0 to 16 m/s and shaft angle (α_s) ranging from 0 to 90 deg in steps of 22.5 deg at the National Wind Tunnel Facility of IIT Kanpur (See Fig. 2).

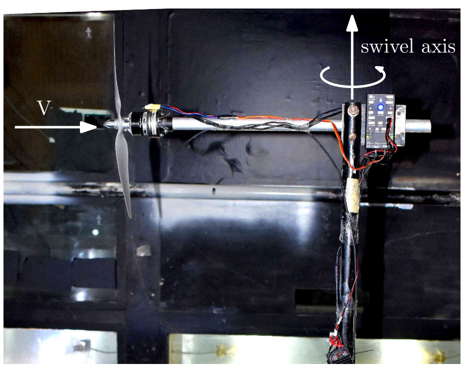
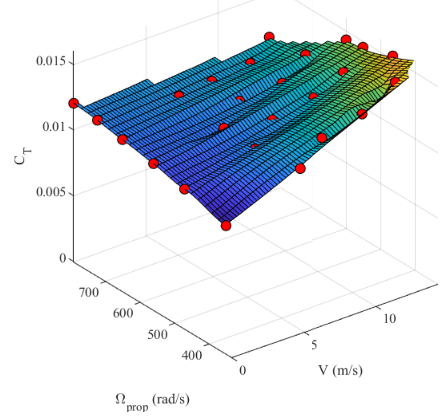


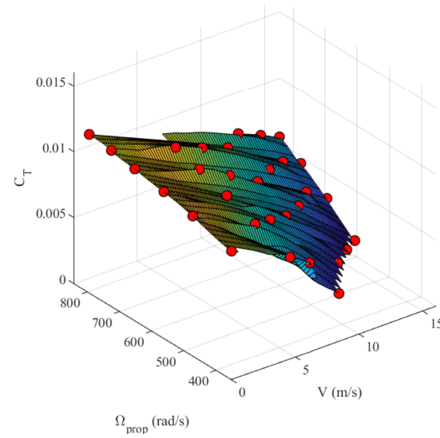
Fig. 2: Thrust measurement setup in windtunnel.

The wind tunnel data depicting variation of thrust with various flow conditions corresponding to shaft angle of $\alpha_s = 0$ and $\alpha_s = 67.5$ deg is shown in Fig. 3. The following observations can be made from Fig. 3:

1) C_T does not vary significantly when the shaft angle is close to zero. This is the typical quadrotor flight regime. As the propeller shaft is inclined further towards the flow, there is a significant reduction in C_T with forward speed.
2) C_T is no longer a constant, but varies with forward speed and propeller rpm. For a given rpm, no thrust is produced beyond a certain forward speed. This is critical for the biplane quadrotor as the attitude controller might become ineffective at higher speeds of fixed wing mode. This warrants a separate control allocation scheme dependent on α_s and V for the attitude controller.



(a) $\alpha_s = 0$ deg



(b) $\alpha_s = 67.5$ deg

Fig. 3: Surface fit of coefficient of thrust (C_T) measurement from wind tunnel with forward speed V, rotor rpm Ω_{prop} for various flow angles α_s. $\alpha_s = 0$ represents edgewise flow (quadrotor mode) and $\alpha_s = 90$ deg represents axial flow (fixedwing mode).

The thrust produced by the propeller is not influenced significantly by the wing since the wings are placed sufficiently below the propeller. The thrust data obtained from the wind tunnel data is approximated with a neural network to obtain the following relation which is subsequently used for realizing the feedforward thrust demanded by the iterative learning algorithm

$$
\begin{aligned}
T_{prop} &= T_{nn}(\Omega_{prop}, V, \alpha_s), \\
\Omega_{prop} &= \Omega_{nn}(T_{prop}, V, \alpha_s).
\end{aligned}
$$

The task of obtaining propeller performance data from the wind tunnel is much cheaper and simpler than a complete aerodynamic characterization of the entire biplane model in the wind tunnel.

III. Iterative Learning Based Control

We now describe an iterative algorithm for experimentally learning the forward transition maneuver similar to the one used for performing aggressive maneuvers of quadrotors in [16]. For this maneuver, the translational dynamics (2) in the vertical plane are considered, and the pitch-angle (corresponding to R) and the net rotor thrust f_T are taken as inputs. The dynamics (2) in the vertical plane can be written as

$$m\ddot{\bar{X}} \quad = \quad \bar{F}_A(\dot{\bar{X}},\theta) + \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} 0 \\ f_T \end{bmatrix} + \begin{bmatrix} 0 \\ mg \end{bmatrix}, \tag{6}$$

where $\bar{X}$ and $\bar{F}_A$ are the first two components of X and F_A acting in the vertical plane, and θ is the and pitch angle.

Transition problem: The VTOL transition problem is to maneuver the UAS within a time T, from a hover equilibrium condition i.e. $\theta = 0,\ \dot{\bar{X}} = 0$ to a cruise flight trim condition $\bar{X}_2(T) = z_f,\ \dot{\bar{X}}_2 = V_{zf},\ \dot{\bar{X}}_1 = V_{xf}, \theta(T) = \theta_f$, where the trim conditions are determined experimentally according to the vehicle specifications.

Due to the complex nature of $\bar{F}_A$, it is intractable to directly solve for θ and f_T in order to track a desired position trajectory $\bar{X}_d$. As such, one would have to solve a nonlinear system, which may not yield a closed form solution. While numerical techniques can be employed given sufficiently capable hardware, the solutions itself are heavily dependent on the accuracy of the aerodynamic model $\bar{F}_A$. In order to overcome these issues, the following simple methodology is employed.

A. Optimal Feedforward Control from Simulation

First, the feedforward control trajectories for θ and f_T are parameterized with time and coefficients as

$$\begin{aligned} \theta(t) \quad &= \quad \mathscr{P}_1(t,P) = p_{10} + p_{11}t + p_{12}t^2 + p_{13}t^3 + p_{14}t^4, \\ f_T(t) \quad &= \quad \mathscr{P}_2(t,P) = p_{20} + p_{21}t + p_{22}t^2 + p_{23}t^3 + p_{24}t^4, \end{aligned} \tag{7}$$

where $P = (p_{10},\ldots,p_{24})$ are scalar coefficients to be determined. It has been observed from manual flight data that the variation in thrust and pitch angle could be sufficiently captured with a fourth-order polynomial. Then, having fixed a transition time period T (based on initial manual experiments), initial condition $\bar{X}(0)$, initial inputs $f_T(0), \theta(0)$, and final pitch angle $\theta(T)$, the coefficients P of the feedforward polynomial inputs $\mathscr{P}_1$ and $\mathscr{P}_2$ which optimally perform the transition maneuver are obtained as the solution of a static optimization problem, as follows.

Denote $\mathscr{X}^t(P,X_0) = [\bar{X}(t)^\top, \dot{\bar{X}}^\top(t)]^\top$, where $\bar{X}(t), \dot{\bar{X}}(t)$ are the solution of (6) at time t (obtained from numerical simulation) with initial condition $\bar{X}(0) = X_0$ and control inputs θ and f_T as in (7).

Define the terminal error cost function $\Phi : \mathbb{R}^8 \to \mathbb{R}^3$ as

$$\Phi(P) = \begin{bmatrix} \mathscr{X}_2^T(P,X_0) - z_f \\ \mathscr{X}_3^T(P,X_0) - V_{xf} \\ \mathscr{X}_4^T(P,X_0) - V_{zf} \end{bmatrix}. \tag{8}$$

Then, an optimal parameter set P^0 is obtained as the solution to

$$\begin{aligned} &\min_{P\in S} ||\Phi(P)||, \\ \text{such that} \quad &\mathscr{P}_2(0,P) = f_0, \\ &\mathscr{P}_1(0,P) = \theta_0, \\ &\mathscr{P}_1(T,P) = \theta_f \end{aligned} \tag{9}$$

Here, S is an admissible set of parameters determined based on actuator limitations, and X_0, f_0, θ_0 are the initial state, thrust and pitch angle corresponding to the hover equilibrium respectively.

B. Experimentally Updating Feedforward Parameters using Iterative Learning

If the aerodynamic model were accurately known, then the parameter set P^0 obtained as described above through simulations would indeed generate feedforward inputs which achieve a perfect transition maneuver. However, due to modeling inaccuracies, the parameter set needs to be experimentally updated until the maneuver is perfected. For this we adopt the iterative learning algorithm proposed in [16] wherein, first an experimental flight trial is performed using feedforward control with initial parameter P^0, and subsequently the parameter is updated and flight trials are repeated with the updated feedforward input, until the maneuver is achieved with minimal terminal error.

1) **Offline computation (One-time):**
   - Using numerical differentiation, compute
   $$J = \left.\frac{\partial \Phi}{\partial P}\right|_{P=P^0}, \tag{10}$$
   where P^0 is obtained from (**??**) and Φ is obtained from (8) using numerical simulations.
   - Compute C as the *right inverse* of J, assuming that it exists. This is guaranteed as long as there are sufficient number of parameters in P such that the error $\Phi(P)$ can be arbitrarily, locally modified.
2) **Online experimental update:**
   - Let $\bar{\mathscr{X}}^t(P^i,X_0)$ denote the experimentally obtained final state of (6), from initial (hover) condition X_0 and feedforward control $\theta(t) = \mathscr{P}_1(t,P^i)$, $f_T(t) = \mathscr{P}_2(t,P^i)$, and $\bar{\Phi}(P^i)$ the corresponding terminal error as in (8).
   - The parameter set is updated after each flight trial via a gradient descent scheme
   $$P^{i+1} = P^i - \gamma_i C\bar{\Phi}(P^i), \tag{11}$$
   where $\gamma^i \in (0,1)$.

Assuming first order dynamics of $\bar{\Phi}$, it can be shown (see [16]) that the terminal error dynamics are obtained as

$$\bar{\Phi}(P^{i+1}) = (1-\gamma^i)\bar{\Phi}(P^i),\ P^0 = P^0, \tag{12}$$

which converges to 0, with experimental optimal parameters P^*. Note that γ_i can be varied such that the jump in parameter decreases in the iterations.

C. Feedback Control for Transition

During the transition maneuver, the vehicle is maintained in a plane using the lateral directional controller given by (13). It is a PD controller on the cross track error which specifies the desired lateral acceleration which in turn sets the desired roll angle. The desired yaw angle is set such that the side-slip is maintained zero.

$$\begin{aligned} a_{lat} &= -k_{\chi p}P_\chi - k_{\chi d}\dot{P}_\chi, \\ \phi_d &= \tan^{-1}\left(\frac{a_{lat}}{g}\right), \\ \psi_d &= \tan^{-1}\left(\frac{v_y}{v_x}\right), \end{aligned} \tag{13}$$

where a_{lat} is the desired lateral acceleration, P_χ is the cross track error, and ϕ_d and ψ_d are respectively the desired roll and yaw angles.

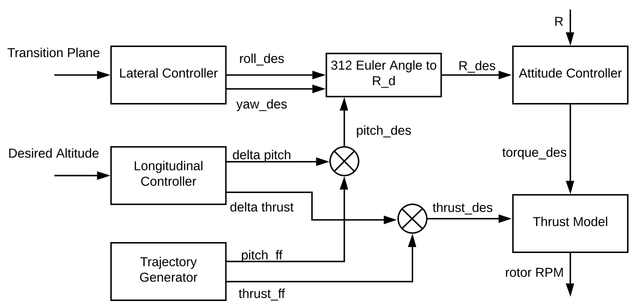


Fig. 4: Block diagram of the transition controller.

The longitudinal controller is responsible for maintaining the altitude during the transition. In the helicopter mode, the altitude is controlled by varying the thrust command whereas in the cruise flight mode it is actuated by changing the pitch angle (indirectly the angle-of-attack) of the vehicle. Therefore during the transition from hover to forward flight mode, the control input for the longitudinal controller is weighed based to the flight regime determined by the current pitch angle of the vehicle. The weighing parameters were determined based on experimental flight data. The control block diagram used for the transition maneuver is given in Fig 4. Here, pitch_ff and thrust_ff terms are the pitch and thrust feedforward components determined by the learning algorithm.

IV. Attitude Controller

In this section we develop a robust attitude controller for the biplane quadrotor which tracks the feedforward pitch angle $\theta_d = \mathscr{P}(t, P^i)$ in each iteration, as well as ψ_d, ϕ_d as defined in (13) in order to restrict the UAS dynamics to the vertical plane. First, a singularity free expression for the desired rotation matrix is obtained using 312 Euler angles which is uniformally valid for both the quadrotor mode and fixedwing mode and the intermediate transition region. This is important as the conventionally used 321 Euler angle has a singularity at pitch angle of ±90 degree, which is an operating point of the vehicle. The 312 sequence suffers from singularity at roll angles of ±90 degree, but this is a far away configuration for the normal operation of the vehicle. Another advantage of 312 sequence is that for a given pitch angle, a change in roll command rotates the vehicle about a horizontal axis, thus maintaining the angle of attack. This facilitates an easy manual control of the vehicle during transition and fixed wing mode unlike the 321 Euler sequence which introduces side slip with a variation in roll angle.

The desired Euler angles (ϕ_d, ψ_d) are obtained from (13) and θ_d is obtained as $\mathscr{P}_1(t, P^i)$ for each iteration, and the corresponding rotation matrix R_d is obtained from the 312 Euler angle representation. The desired angular velocity is obtained as $\omega_d = R_d^T \dot{R}_d$.

A geometric attitude controller is designed with a cascaded structure, with the inner loop being angular rate and outer loop defined on attitude. Note that though the desired attitude is parameterized, the actual attitude of the UAS is intrinsically defined on $SO(3)$, thereby avoiding singularities in the system state. The error function on $SO(3)$ used to define the controller is

$$\psi(R_e) = \frac{1}{2} tr(I - R_e) \tag{14}$$

where $R_e = R_d^T R$. Its time derivative $\dot{\psi} = e_R^T e_\omega$, where $e_R = (R_e - R_e^T)^\vee / 2$, and $e_\omega = \omega - R_e^T \omega_d$. $\dot{\psi}$ can be made negative, $\dot{\psi} = -k_R \|e_R\|^2$, by choosing ω to track

$$\omega_D = -k_R e_R + R_e^T \omega_d. \tag{15}$$

Defining $\omega_e = \omega - \omega_D$, the inner loop angular rate controller is a PID on ω_e given by

$$M = k_P \omega_e + k_D \dot{\omega}_e + k_I \int \omega_e. \tag{16}$$

The stability of the attitude controller can be derived on similar lines as in [20], [21]. Note that the above controller is second order in angular rate which makes the attitude controller third order. It is experimentally observed that this control structure is more robust for quadrotor than the more prevalent second order controller found in the literature, especially with regard to handling steady state error. This is particularly important in case of biplane quadrotor as the vehicle undergoes rapid transition maneuvers with large aerodynamic disturbance moments.

V. Experimental Flight

The iterative learning algorithm is applied on the biplane tailsitter depicted in Fig. 1 and described in Sec. II-A. The vehicle is instrumented with a Pixhawk autopilot running the PX4 flight stack. The autopilot consists of a 3-axis inertial measurement unit, 3-axis magnetometer, a barometer and a GPS. We use the stock EKF based state estimator for obtaining the full state of the vehicle from the sensor data. The guidance and control algorithms are implemented as separate modules and runs independently based on the assigned priority.

The initial set of parameters for the thrust and pitch angle profiles for forward transition are determined from simulation after solving (9). The corresponding Jacobian J and correction matrix C are also determined based on numerical simulation. The initial thrust is constrained to be the hover thrust ($f_T(T) = 26.73$N), the terminal desired speed and pitch angle are set to be the cruise flight condition ($V_{xf} = 14$m/s $V_{zf} = 0$, $\theta_f = 80$ deg). Multiple flight trials are performed to check the convergence properties of the iterative learning algorithm (**video: https://youtu.be/0cXGagMbBtg**). It is observed from the flight trials that the output error converges to satisfactory levels in five to six iterations as shown in Fig. 5.

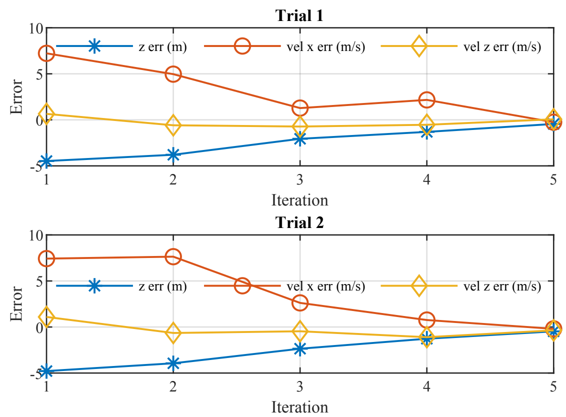


Fig. 5: Error convergence properties of the iterative learning algorithm for 2 flight trials.

The variation of thrust and pitch profiles during the iterations of flight trial 1 are given in Fig. 6. The thrust requirement below zero is constrained to zero before passing it to the neural network which determines the propeller RPM.

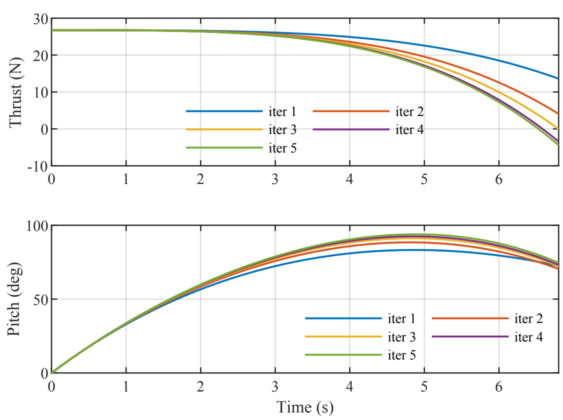


Fig. 6: Throttle and pitch command during the iterations of flight trial 1.

The maximum altitude variation is less than to 0.5 m during the transition and the forward speed attained is off by 0.5 m/s from the desired terminal speed of 14 m/s as

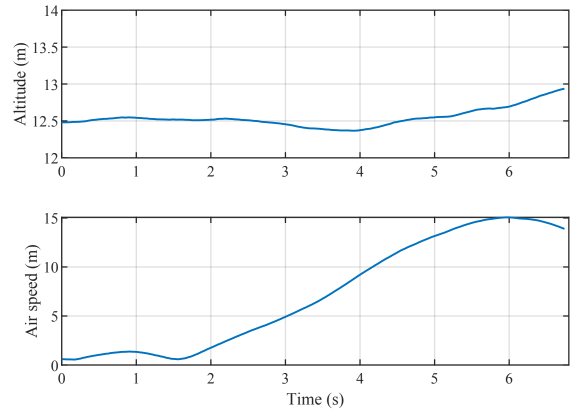


Fig. 7: Altitude and speed of the vehicle for the learned forward trajectory of iteration 5 of flight trial 1.

shown in Fig. 7. Note that the learned feed-forward thrust and pitch command is dependent upon wind conditions and therefore the feedback controller is designed to compensate for such disturbances.

VI. Conclusion and Future work

A simple on-board experimental technique for learning a forward transition maneuver of a biplane-quadrotor tailsitter UAS was proposed. A simplified nominal aerodynamic model was utilized for first numerically computing an optimally parameterized feedforward control trajectory which was subsequently refined through flight experiments in order to compensate for modeling errors. It was demonstrated over separate trials that the iterative learning algorithm enabled the UAS in perfecting the maneuver within 5 iterations, despite modeling inaccuracies. The reduced dependence on the aerodynamic model significantly minimizes the pre-flight testing and characterization effort, as well as enables operation in varying external environment. Moreover, the simplicity in implementation renders the proposed technique ideal for off-the-shelf low cost autopilot hardware. The accurate thrust model of the propeller obtained from the wind tunnel data enabled precise application of the learned feedforward thrust.

Some avenues for further research include learning back transition, cobra maneuvers, and developing a feedforward control map for varying initial conditions, learnt through multiple flight trials.

VII. Acknowledgement

A part of this work was partially supported through a project from CEFIPRA.

References

[1] Adnan S Saeed, Ahmad Bani Younes, Shafiqul Islam, Jorge Dias, Lakmal Seneviratne, and Guowei Cai. A review on the platform design, dynamic modeling and control of hybrid uavs. In *2015 International Conference on Unmanned Aircraft Systems (ICUAS)*, pages 806–815. IEEE, 2015.

[2] Burak Yuksek, Aslihan Vuruskan, Ugur Ozdemir, MA Yukselen, and Gökhan Inalhan. Transition flight modeling of a fixed-wing vtol uav. *Journal of Intelligent & Robotic Systems*, 84(1-4):83–105, 2016.

[3] Koji Muraoka, Noriaki Okada, Daisuke Kubo, and Masayuki Sato. Transition flight of quad tilt wing vtol uav. In *28th Congress of the International Council of the Aeronautical Sciences*, pages 2012–11, 2012.

[4] Adnan Maqsood and Tiauw Hiong Go. Optimization of transition maneuvers through aerodynamic vectoring. *Aerospace Science and Technology*, 23(1):363–371, 2012.

[5] Daisuke Kubo and Shinji Suzuki. Tail-sitter vertical takeoff and landing unmanned aerial vehicle: transitional flight analysis. *Journal of Aircraft*, 45(1):292–297, 2008.

[6] R Hugh Stone. Control architecture for a tail-sitter unmanned air vehicle. In *2004 5th Asian Control Conference (IEEE Cat. No. 04EX904)*, volume 2, pages 736–744. IEEE, 2004.

[7] Nathan Knoebel, Stephen Osborne, Deryl Snyder, Timothy Mclain, Randal Beard, and Andrew Eldredge. Preliminary modeling, control, and trajectory design for miniature autonomous tailsitters. In *AIAA Guidance, Navigation, and Control Conference and Exhibit*, page 6713, 2006.

[8] Roberto Naldi and Lorenzo Marconi. Optimal transition maneuvers for a class of v/stol aircraft. *Automatica*, 47(5):870–879, 2011.

[9] Swati Swarnkar, Hardik Parwana, Mangal Kothari, and Abhishek Abhishek. Biplane-quadrotor tail-sitter uav: Flight dynamics and control. *Journal of Guidance, Control, and Dynamics*, 41(5):1049–1067, 2018.

[10] Vikram Hrishikeshavan, Christopher Bogdanowicz, and Inderjit Chopra. Design, performance and testing of a quad rotor biplane micro air vehicle for multi role missions. *International Journal of Micro Air Vehicles*, 6(3):155–173, 2014.

[11] Vikram Hrishikeshavan, Dean Bawek, Omri Rand, and Inderjit Chopra. Control of a quad rotor biplane micro air vehicle in transition from hover to forward flight. In *American Helicopter Society Specialists Meeting on Unmanned Rotorcraft and Network Centric Operations*, 2013.

[12] Yeunduk Jung and David Hyunchul Shim. Development and application of controller for transition flight of tail-sitter uav. *Journal of Intelligent & Robotic Systems*, 65(1-4):137–152, 2012.

[13] Robin Ritz and Raffaello D'Andrea. A global controller for flying wing tailsitter vehicles. In *2017 IEEE international conference on robotics and automation (ICRA)*, pages 2731–2738. IEEE, 2017.

[14] Wei Xu, Haowei Gu, and Fu Zhang. Acceleration based iterative learning control for pugachev's cobra maneuver with quadrotor tail-sitter vtol uavs. *arXiv preprint arXiv:1906.02596*, 2019.

[15] Oliver Purwin and Raffaello D'Andrea. Performing aggressive maneuvers using iterative learning control. In *2009 IEEE international conference on robotics and automation*, pages 1731–1736. IEEE, 2009.

[16] Sergei Lupashin and Raffaello D'Andrea. Adaptive fast open-loop maneuvers for quadrocopters. *Autonomous Robots*, 33(1-2):89–102, 2012.

[17] Fabian L Mueller, Angela P Schoellig, and Raffaello D'Andrea. Iterative learning of feed-forward corrections for high-performance tracking. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3276–3281. IEEE, 2012.

[18] Angela Schöllig and Raffaello D'Andrea. Optimization-based iterative learning control for trajectory tracking. In *2009 European Control Conference (ECC)*, pages 1505–1510. IEEE, 2009.

[19] Daniele Pucci, Tarek Hamel, Pascal Morin, and Claude Samson. Nonlinear control of pvtol vehicles subjected to drag and lift. In *2011 50th IEEE Conference on Decision and Control and European Control Conference*, pages 6177–6183. IEEE, 2011.

[20] DHS Maithripala and Jordan M Berg. Geometric pid control for almost-global stabilization of a quadrotor with parameter error and constant disturbances. In *ASME 2014 Dynamic Systems and Control Conference*, pages V003T48A002–V003T48A002. American Society of Mechanical Engineers, 2014.

[21] Farhad Goodarzi, Daewon Lee, and Taeyoung Lee. Geometric nonlinear pid control of a quadrotor uav on se (3). In *2013 European control conference (ECC)*, pages 3845–3850. IEEE, 2013.

[22] Michiel J Van Nieuwstadt and Richard M Murray. Rapid hover-to-forward-flight transitions for a thrust-vectored aircraft. *Journal of Guidance, Control, and Dynamics*, 21(1):93–100, 1998.

[23] Atsushi Oosedo, Satoko Abiko, Atsushi Konno, and Masaru Uchiyama. Optimal transition from hovering to level-flight of a quadrotor tail-sitter uav. *Autonomous Robots*, 41(5):1143–1159, 2017.