An Intelligent Multi-Vehicle Drone Testbed for Space Systems and Remote Sensing Verification

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Abstract

This paper presents an easily accessible intelligent multi-vehicle drone testbed, which will enable the development, validation, and qualification of new drone or satellite control hardware and algorithms without the need for costly launches, microgravity emulators or the need to obtain airspace permission to fly outside.

The drone testbed consists of several copter-style drones and gimbals below each to allow six-axis control. The dynamics of the drones are identified intelligently with minimal measuring using artificial intelligence.

By programming drones with a nested feed-forward control loop, a simulated dynamic environment is achieved, which will provide sufficient abstraction needed for independent spacecraft or drone control. Using this architecture, any type of dynamics can be emulated, including different gravity levels or air viscosities. For multi-spacecraft control investigations in Earth orbit, multiple vehicles and Clohessy Wiltshire equations can be used to represent the relative motion of one spacecraft with respect to another in neighboring orbits, which is difficult to replicate on Earth. This testbed will enable rapid development and verification of remote sensing technologies to be deployed on either drones or spacecraft.

Keywords: drone, quadrotor, quadcopter, hexacopter artificial intelligence, PSO, system identification, space simulation, microgravity, aerodynamics, control

Introduction

Using new technologies for the space industry has always been a challenging and expensive task because of the number of qualification tests needed. As a result, there has always been some resistance against implementing novel methods and technologies in the space industry. This has resulted in a considerable time lag between the latest science and technology advancements and what is used in the space industry, which, besides making the industry prohibitively expensive and therefore inaccessible, has caused several challenges in the space industry to remain unaddressed. These challenges include the potential instability of control algorithms in emergency situations when inputs to system or system variables are out of range, potentially resulting in irrecoverable disasters such as a crash landing and total or partial mission failure. Another challenge arises when using traditional control and estimation algorithms with fixed parameters, resulting in non-optimized operations, particularly when the system's dynamics change over time either due to normal aging or from systems failures. Further, the inability of traditional control algorithms to adapt to and predict dynamic changes, leads mission designers to spend excessive amounts of time (and money) trying to predict and simulate, all possible combinations of failures and changes to the system over its entire lifetime in an attempt to verify that a single (or a collection of) fixed-parameter controllers can be suitable for the entire space mission.

This research will develop automated drone system identification and auto code generation technologies that support an easily accessible multi-vehicle drone testbed, which enables rapid development, validation, and qualification of novel drone or satellite control algorithms, control hardware, and remote sensing technologies to be deployed on either drones or spacecraft. The drone testbed will consist of several copter-style drones and gimbals below each to allow six-axis control. The environment consists of Vicon motion capture cameras and computer interfaces, which allow measuring, testing, and data analysis capabilities. When completed, the drone testbed will facilitate advanced navigation and controls research by emulating a multitude of dynamic environments.

Using this testbed, we will be able to test and qualify new technologies in a hardware-in-the-loop environment, and so we can reach a technology readiness level of 7. This will eliminate the need for costly launches, microgravity emulators or the need to obtain airspace permission to fly drones outside, and as a result, will drastically decrease the costs and time spent on readiness proofs. As you see in Figure 1, technology readiness level is a requirement by NASA which demonstrates the amount of proves and tests that new technology has passed, which indicates how it is ready to be used in space.

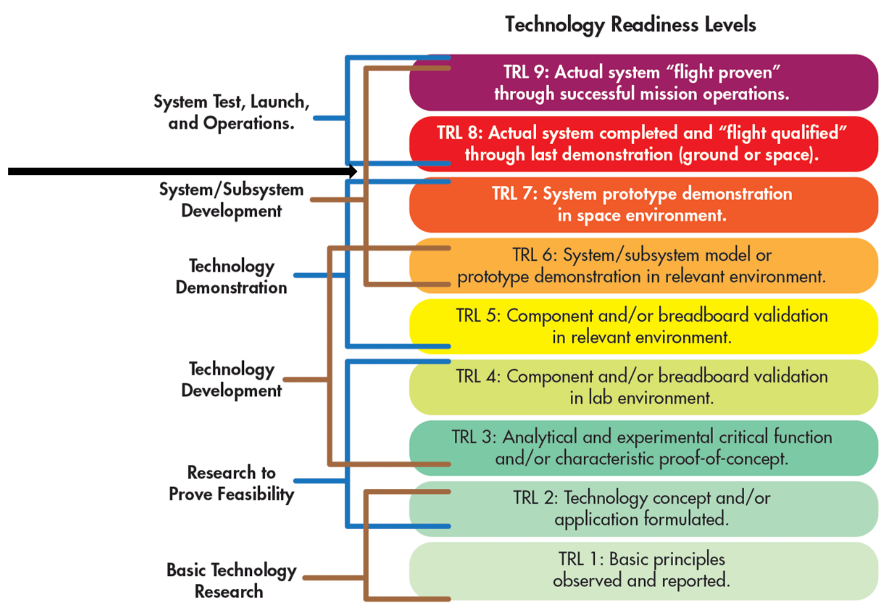

Figure 1 Technology Readiness Level

Background

A key challenge with creating a drone-based testbed is modeling the drone dynamics so that appropriate compensation can be done. The following describes the state of drone modeling in the recent research literature.

Shukla discusses in [1], [2], and [3] that "approximations used in helicopter rotor theories are primarily based on the assumption that very high Re flows act mostly like inviscid and irrotational flows everywhere except in small regions containing high vorticity. Thin boundary layers and strong, tightly concentrated tip vortices, and thin vortex-sheet wakes are assumed in calculations that use the Blade Element, Prescribed Wake and Free Wake methods. Outside these thin regions of vorticity, the flow is presumed to be inviscid and irrotational and hence amenable to potential flow methods." As a result, helicopter rotor theories based on the high Reynolds number assumptions cannot be expected to give reliable predictions for most UAVs, and at a low Re, the effects of viscosity become more comparable to inertial effects.

As discussed in [4], researchers tried to develop and improve drone models in three sections: thrust force, drag force, and moment models.

To improve the thrust forces model, research mostly have used the helicopter momentum theory and blade element theory or their combination as discussed by Johnson in [5] and [6] in addition to experimental results or by considering other effects. Most of the models do not account for variations in rotor performance with the velocity and incidence angle of airflow relative to the rotor disk and are only appropriate for modeling flight near hover [7]. Hoffmann in [8] and [9] seeks to address the issues that arise when deviating significantly from the hover flight regime by considering moments and trusts that caused by effects of vehicular velocity, the angle of attack, and airframe design, and he tries to elaborate on the cause of thrust variation during translational flight. Perozzi [10], [11] presented a quadrotor model using a combination of momentum and blade element theory and also by considering wind effect. In [12], [13], and [14] similar approaches using combined theories were used to enhance thrust model.

To improve drag forces model, one can consider three main sources of drag including:

- Blade flapping effect [8], [15], [16], [17], [18],
- Lift which generates drag and hub forces [19], [13], [20], [17],
- Airframe drag [12].

To improve moments model, one can consider many sources of moments including:

- Additional pitching moment due to the translational velocities [21]
- Damping effects moment [18]
- Blade stiffness moment [22]
- Drag forces moment [18]
- Pitching moment generated by airframe itself [7].

To get a more accurate model, one should also consider airframe rotor–rotor and airframe–rotor interaction effects as they are suspected to greatly influence the aerodynamic forces and moments. In [7] Foster divided the forces and moments into propulsion, airframe, and interaction units, and in [23] Kaya used the test data for showing the effect of interactions between rotors. Some theoretical models considering these effects were developed in [24] and [25].

Sun in [4] and [26] aims to further reveal the effect of the interactions from flight data and establishing accurate force and moment models taking account of these effects using a gray box, and in [26] identifies the forces and moments occurring during high-speed flight as a function of states and rotor speeds.

Several other researchers have studied parameter identification:

Nonami [27] developed a helicopter model and measured some of its parameters, and for the rest of the parameters, he did manual tweaking until when the model and real experiment result and performance matched each other. Bresciani [28] studied the calculation and measurement of different parameters of a quadrotor model. Elsamanty in [29] describes a methodology to identify all of the parameters of a quadrotor system including the structure parameters and rotor assembly parameters, and three simple test rigs are built and used to identify the relationship between the motor input Pulse Width Modulation (PWM) signal and the angular velocity, the thrust force, and the drag moment of the rotors. In [30], Derafa develops a drone model and considers different effects such as aerodynamic friction and gyroscopic effects, and then uses system identification to estimate parameters. In [31], Stanculeanu uses a new approach in the identification of the quadrotor dynamic model using a black box and tries to address problems that arise in identifying the closed-loop behavior. Stanculeanu also offers a technical solution for overcoming the correlation between the input noise present in the output. In [32] and [33], Abas identifies an unknown parameter of the quadrotor using a state estimation method with the implementation of an Unscented Kalman Filter (UKF). Beard in [34] discusses different sensor measurement equations and state estimation using a Kalman filter for a quadrotor drone. In [35], Sa describes system identification, estimation, and control of translational motion and the heading angle for a cost-effective open-source quadcopter. In [36], Rich presents a comprehensive model considering different aerodynamic effects and finds different parameters using system identification. In [37] Chovancová presents three drone models including the nonlinear model, a model described in quaternions, and a near-hover model, and investigate the parameters that both can be calculated or experimentally identified such as arm length, total mass of the quadrotor, inertia matrix, friction coefficients, thrust coefficient, and drag coefficient. Also, he describes that experimental identification of an actuator is usually required. Zhang in [38] gives a tutorial of the platform configuration, methodology of modeling, comprehensive nonlinear model, the aerodynamic effects, and model identification for a quadrotor. Bisheban in [39] presents a computational framework to identify the effects of wind on the dynamics of a quadrotor. In [40], Filatov is concerned with the thrust generation subsystem for small quadrotors and identifying its parameters using a black box.

In [41], Angarita presents an initial analysis of methods used to generate and evaluate a range of model structures that best define a generic quadrotor. In [42] Lyu estimates the parameters of the thrust, drag force, torque, rolling moment and pitching moment are through Kalman filter. Global positioning system and inertial sensors are used as measurements. In [43] Sung does system identification of the 3DR X8+ aircraft via frequency-domain system identification techniques. In [44], the aerial manipulator model is first derived analytically using the Newton-Euler formulation for the quadrotor and Recursive Newton-Euler formulation for the manipulator. The simulation data is then used for system identification of the aerial manipulator. AutoRegressive with exogenous inputs (ARX) models are obtained from the system identification for linear accelerations and yaw angular acceleration. For linear acceleration and pitch and roll angular accelerations, Auto-Regressive Moving Average with exogenous inputs (ARMAX) models are identified. Yang in [45] develops an aerodynamic parameter estimation method and an adaptive attitude control method based on a Linear Active Disturbance Rejection Controller (LADRC). Cunningham in [46] states that past research involving the system identification of a multirotor vehicle generally produces only a closed-loop model because the identification of the open-loop unstable dynamics of a multirotor is considered as impractical, and he uses time-domain equation-error and frequency domain output-error techniques to estimate an open-loop model of a multirotor vehicle. Wang in [47] presents a Lyapunov-MARI (Model Reference Adaptive Identification) algorithm, which only needs the UAV and some common sensors to realize the parameter identification. Firstly, he determines specific parameters which are not easy to be measured in the quad-rotor UAV model. These parameters mainly include the three-axis moments of inertia, the rotors lift coefficient, and drag coefficient. Then, for the moments of inertia, the traditional period measurement method of the Rope Suspension Approach is improved. For the lift and drag coefficients, the Lyapunov-MARI algorithm is proposed for the parameter identification. The result shows that the flight state calculated by the identified parameters are compatible with the actual flight data. Mohajerin in [48], proposes a hybrid model with two configurations predicting the system state over many future steps using only the input by combining deep recurrent neural networks with a quadrotor motion model.

In this research, we will also consider Hexacopter modeling. In [49] and [50] Alaimo talks about modeling of hexacopter using quaternions.

Methods Overview

While it is clear that we need to consider an accurate math model in order to enhance testbed performance and control accuracy, no one to date has developed a cohesive model, and then utilized it for controlling or identifying the dynamics of a drone. Given the recent attempts for identifying an accurate rotorcraft model by considering the aerodynamic effects to their full extent, it stands to reason that considering these effects in design and control will enhance the performance, particularly when paired with modern machine learning methods. Finally, this research program will evaluate the utility of these models. In the following sections, I outline my research plan.

The first phase of this research is to determine the drone dynamics intelligently with minimal measuring using system identification techniques for the drone. Specific tests will be designed to collect the data, which is the task of measuring the inputs and outputs of the actual drone. In parallel, a drone model will be developed in MATLAB and the same inputs will be applied to the model and the resultant model outputs will be measured.

The system identifier estimates drone model parameters based on the error between the model outputs and drone output, and the algorithm tries to minimize this error. Artificial Intelligence

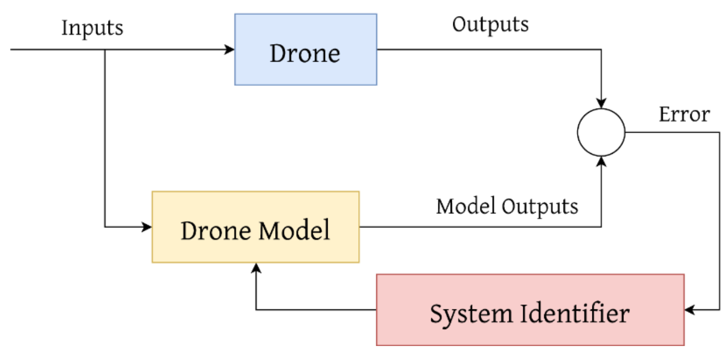

Figure 2 System Identification

methods (*e.g.,* metaheuristic algorithms) and conventional methods [51] will be used to estimate the parameters. For verification of system identification performance, the drone model parameters will be measured manually and will be compared to the estimates. See Figure 2.

Metaheuristic algorithms can also be used to estimate the parameters by rewriting the system identification problem as an optimization method. After the structure of the drone model is developed, these algorithms are used to find the optimized parameters that make the error between the real experiment measurements and model output minimized. Particle swarm optimization (PSO) is one of the metaheuristic algorithms which will be used for finding the optimal parameters based on a defined competence function. Firstly, the algorithm initializes the population (candidate answers in the answer plane). Then, the cost function is calculated for each of the population and then based on a defined rule the position of the population is updated until an optimal point is found. In [52], Lui uses a closed-loop multi-variable extremum seeking algorithm for a nonlinear quadrotor helicopter parameter identification with two groups of input data, and as the gradients of the performance parameters are obtained by step response experiments, the whole system searches along the negative gradient of the cost function until the reference trajectory or point is derived.

As discussed, a MATLAB model will be developed to simulate the drone model. All the operations of system identification will be done on this model, and in addition to system identification, this simulator will also be used for exploring the implementation of new control algorithms for the drone.

The sensors that are used to measure states and their derivatives for system identification include Vicon cameras, accelerometers, gyroscopes, magnetometers, and as a result these parameters are considered known: position, Euler angles or quaternions, translational velocities, angular velocities, control inputs, acceleration, motor speed, etc. The system identifier will estimate systems constants (*e.g.,* motor properties), and parameters of the drone model (*e.g.,* constants in the state-space model).

After doing the system identification, the drone testbed will be developed. A block diagram similar to Figure 3 will be used as the programming structure of the drones and gimbals to set the testbed up.

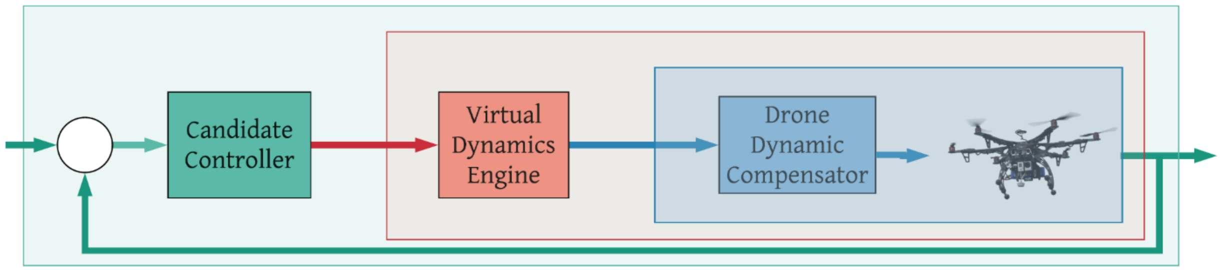

Figure 3 Drone block diagram

Firstly, using the "Drone Dynamic Compensator," we will eliminate on earth drone dynamics, which will provide sufficient abstraction needed for independent spacecraft or drone control. Its tasks include removing gravity (the drone does not fall) and eliminating friction (after an initial imposed impact force it will continue to move with a constant velocity).

Secondly, by using the "Virtual Dynamic Engine," we can emulate any type of virtual dynamics, including different gravity levels, different air viscosities, and any virtual environments like the environment of Titan, Mars, etc. These virtual dynamics can be represented by special environment forces as feed-forward control augmentations (*e.g.,* custom friction or gravity).

As an example of a "Virtual Dynamic Engine," I will simulate the environment of multi-spacecraft in Earth orbit and will investigate controlling of multiple spacecraft in this environment. Multiple vehicles Clohessy-Wiltshire equations are used. In this way, we can represent the relative motion of one spacecraft with respect to another in neighboring orbits, which is difficult to replicate on Earth. Clohessy-Wiltshire equations govern the linearized behavior of two spacecraft in nearby circular and slightly elliptical orbits.

Dynamic Model of Drone

We consider that a body-fixed frame is attached to the drone. Z-axis is considered to be perpendicular to the drone plane, and X for both + and × is shown in Figure 4.

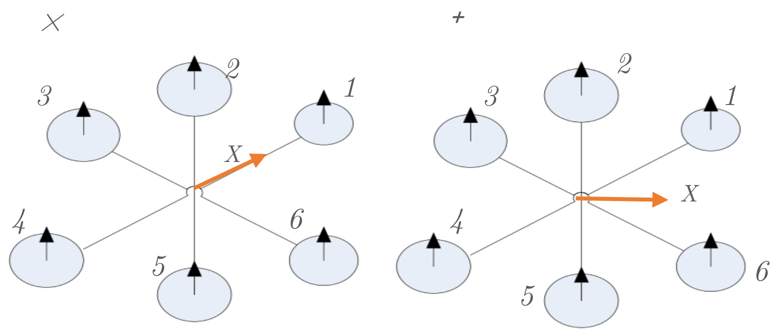

Figure 4 - Drone frame set and motor configuration

The angles between arms and X-axis for × and + configuration of motors are found from Eq. 1, $mNum$ is the total number of motors.

$$a_n = \begin{cases} -\frac{2\pi}{m\text{Num}}(n-1) & + \; configuration \\ \frac{2\pi}{mNum}(n-1) + \frac{\pi}{mNum} & X \; configuration \end{cases} \qquad \textit{Eq. 1}$$

To describe the orientation of the drone we use Euler angles ϕ, θ, and ψ, which indicate the rotation about Z, Y', and X'' respectively (sequential rotation about body-fixed axes). So, the rotation matrix for describing the attitude is calculated from Eq. 2.

$$R = R_Z R_{Y'} R_{X''} = R_\phi R_\theta R_\psi = \begin{pmatrix} c_\phi & -s_\phi & 0 \\ s_\phi & c_\phi & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} c_\theta & 0 & s_\theta \\ 0 & 1 & 0 \\ -s_\theta & 0 & c_\theta \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & c_\psi & -s_\psi \\ 0 & s_\psi & c_\psi \end{pmatrix} \rightarrow$$

$$R = \begin{pmatrix} c_\phi \, c_\theta & -c_\theta \, s_\phi & s_\theta \\ c_\psi \, s_\phi + c_\phi \, s_\psi \, s_\theta & c_\phi \, c_\psi - s_\phi \, s_\psi \, s_\theta & -c_\theta \, s_\psi \\ s_\phi \, s_\psi - c_\phi \, c_\psi \, s_\theta & c_\phi \, s_\psi + c_\psi \, s_\phi \, s_\theta & c_\psi \, c_\theta \end{pmatrix} \qquad \textit{Eq. 2}$$

Taking the time derivative of the rotation matrix from Eq. 2, we obtain Eq. 3.

$$\frac{dR}{dt} = \begin{pmatrix} -c_\theta \dot\phi s_\phi - c_\phi s_\theta \dot\theta & s_\phi s_\theta \dot\theta - c_\phi c_\theta \dot\phi & c_\theta \dot\theta \\ c_\phi c_\psi \dot\phi - \dot\psi s_\phi s_\psi + c_\phi c_\psi \dot\psi s_\theta + c_\phi c_\theta s_\psi \dot\theta - \dot\phi s_\phi s_\psi s_\theta & -c_\psi \dot\phi s_\phi - c_\phi \dot\psi s_\psi - c_\phi \dot\phi s_\psi s_\theta - c_\psi \dot\psi s_\phi s_\theta - c_\theta s_\phi s_\psi \dot\theta & s_\psi s_\theta \dot\theta - c_\psi c_\theta \dot\psi \\ c_\phi \dot\phi s_\psi + c_\psi \dot\psi s_\phi + c_\psi \dot\phi s_\phi s_\theta + c_\phi \dot\psi s_\psi s_\theta - c_\phi c_\psi c_\theta \dot\theta & c_\phi c_\psi \dot\psi - \dot\phi s_\phi s_\psi + c_\phi c_\psi \dot\phi s_\theta + c_\psi c_\theta s_\phi \dot\theta - \dot\psi s_\phi s_\psi s_\theta & -c_\theta \dot\psi s_\psi - c_\psi s_\theta \dot\theta \end{pmatrix} \qquad \textit{Eq. 3}$$

Angular velocity of the drone relative to an inertial frame and expressed in the body-fixed frame is $\widehat{\omega}^b = R^T \dot{R}$ [53]. By plugging the calculated elements, we get Eq. 4.

$$\widehat{\omega}^b = R^T \dot{R} = \begin{pmatrix} 0 & -\dot{\phi} - \dot{\psi}\, s_\theta & c_\phi\, \dot{\theta} - c_\theta\, \dot{\psi}\, s_\phi \\ \dot{\phi} + \dot{\psi}\, s_\theta & 0 & -s_\phi\, \dot{\theta} - c_\phi\, c_\theta\, \dot{\psi} \\ c_\theta\, \dot{\psi}\, s_\phi - c_\phi\, \dot{\theta} & s_\phi\, \dot{\theta} + c_\phi\, c_\theta\, \dot{\psi} & 0 \end{pmatrix} \qquad \text{Eq. 4}$$

So, the angular velocity vector of this skew symmetry matrix will be Eq. 5.

$$\vec{\omega}^b = \begin{bmatrix} p \\ q \\ r \end{bmatrix} = unskewsymmetric(\widehat{\omega}^b) = \begin{pmatrix} s_\phi\, \dot{\theta} + c_\phi\, c_\theta\, \dot{\psi} \\ c_\phi\, \dot{\theta} - c_\theta\, \dot{\psi}\, s_\phi \\ \dot{\phi} + \dot{\psi}\, s_\theta \end{pmatrix} \qquad \text{Eq. 5}$$

From Eq. 4 by separating the rate of Euler angles from the angular velocity vector, we get Eq. 6, in which the matrix Υ relates the time derivative of Euler angles to the angular velocity vector

$$\begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{pmatrix} 0 & s_\phi & c_\phi\, c_\theta \\ 0 & c_\phi & -c_\theta\, s_\phi \\ 1 & 0 & s_\theta \end{pmatrix} \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \rightarrow \begin{bmatrix} p \\ q \\ r \end{bmatrix} = \Upsilon \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \qquad \text{Eq. 6}$$

So, from Eq. 6, the derivative of Euler angles is found as in Eq. 7.

$$\Upsilon^{-1} \begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \qquad \text{Eq. 7}$$

We consider x, y, z, the position of the drone, ϕ, θ, ψ, the attitude of the drone, $\dot{x}, \dot{y}, \dot{z}$, the velocity of the drone, and p, q, r, the angular velocity vector, as state vector. State vector and derivative of the state vector are shown in Eq. 8.

$$s = \begin{bmatrix} x \\ y \\ z \\ \phi \\ \theta \\ \psi \\ \dot{x} \\ \dot{y} \\ \dot{z} \\ p \\ q \\ r \end{bmatrix}, \quad \frac{ds}{dt} = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \\ \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \\ \ddot{x} \\ \ddot{y} \\ \ddot{z} \\ \dot{p} \\ \dot{q} \\ \dot{r} \end{bmatrix} \qquad \text{Eq. 8}$$

To form the state space equations, we use Newton-Euler equations of motion [27].

$$m\ddot{r} = R \,.\, F^b_{tot} - mg\hat{k} \qquad \text{Eq. 9}$$

$$I\dot{\omega}^b + \omega^b \times I\omega^b = M^b_{tot} \qquad \text{Eq. 10}$$

In Eq. 9, $r = \begin{bmatrix} x \\ y \\ z \end{bmatrix}$ is position vector, m is drone mass, F^b_{tot} is the total external forces on the drone in the body-fixed frame. In Eq. 10, I is the inertia rotation matrix in body frame, and M^b_{tot} is the total external moments on done in the body-fixed frame.

By some displacements in Eq. 9 and Eq. 10, we get the following relations

$$\ddot{r} = \frac{1}{m}\left(R \,.\, F_{tot} - mg\ \hat{k}\ \right) \qquad \textit{Eq. 11}$$

$$\dot{\omega} = I^{-1}(M_{tot} - \omega \times I\omega) \qquad \textit{Eq. 12}$$

For modeling aerodynamic forces F^b_{tot} and moments M^b_{tot} acting on the drone, a simple model including thrust force and drag moment model is considered [54].

Thrust force (F_T) is the vertical force acting on a propeller, and it is calculated from Eq. 13, in which C_{FT} is the thrust force coefficient.

$$F_T = C_{FT}\omega^2 \qquad \textit{Eq. 13}$$

The drag moment (M_D) is the moment about the rotor shaft caused by the aerodynamic drag on a propeller, and it is calculated from Eq. 14, in which C_{FT} is the thrust force coefficient.

$$M_D = C_{MD}\omega^2 \qquad \textit{Eq. 14}$$

Also, thrust forces cause some moments around roll (x) and pitch (y) directions ($M_{\text{FTx}}, M_{\text{FTy}}$). For the arm number n, the forces are

$$\begin{aligned} M_{FTx\ ,\ n} &= F_{T_n}.\,l.\,sin(a_n) \\ M_{FTy\ ,\ n} &= -F_{T_n}.\,l.\,cos(a_n) \end{aligned} \qquad \textit{Eq. 15}$$

So from Eq. 13, Eq. 14, and Eq. 15, we obtain total forces as

$$\begin{aligned} F_{tot,x} &= 0 \\ F_{tot,y} &= 0 \\ F_{tot,z} &= \sum_{1}^{n=\text{mNum}} F_{T_n} \\ M_{tot,x} &= \sum_{1}^{n=\text{mNum}} F_{T_n}.\,l.\sin(a_n) \\ M_{\ tot,y} &= \sum_{1}^{n=\text{mNum}} -F_{T_n}.\,l.\cos(a_n) \\ M_{tot,z} &= \sum_{1}^{n=\text{mNum}} M_{D_\text{n}} \end{aligned} \qquad \textit{Eq. 16}$$

Future Steps

As an ongoing research in STARLab, the University of Manitoba, based on the progress that we have made so far and by using the system identification software that we have developed, we will determine the drone parameters that affect the dynamics of the drone intelligently. For doing this we are collecting flight data in various situations and for different drones and different sets of hardware. By finding drone dynamics, we are able to control the drone behavior and implement the virtual engine that we proposed for simulating of different dynamics.

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