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THESIS

ADAPTIVE CONTROL FOR FIXED WING AIRCRAFT

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ADAPTIVE CONTROL FOR FIXED WING AIRCRAFT

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ABSTRACT

The field of adaptive control offers techniques for increasing performance and robustness in numerous settings and applications. Adaptive control is different than traditional feedback in that it offers a mechanism for adjusting the controller's parameters to reduce plant uncertainty. Traditional feedback control utilizes parameters, which are specified by the engineer to optimize an ideal use case, which often times requires extensive tuning and testing. Adaptive controllers adjust their control parameters using various intelligent mechanisms designed to increase robustness to plant variation or unanticipated disturbances. Adaptive control has many applications in the aerospace domain to include control strategies when aerodynamic coefficients are unknown or are non-constant, actuator failure, airframe damage, etc. This research evaluates fixed wing UAS controller performance and robustness using the \mathcal{L}_1 adaptive control architecture.

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List of Acronyms and Abbreviations

DoD	Department of Defense
NPS	Naval Postgraduate School
USN	U.S. Navy
APM	ArduPilotMega / Multi-Platform Autopilot
CG	Center of Gravity
FIR	Finite Impulse Response
IIR	Infinite Impulse Response
IMU	inertial measurement unit
LTI	Linear Time Invariant
MAV	Mirco Aerial Vehcile
MEMS	Microelectromechanical Systems
MIMO	Multiple Input Multiple Output
MRAC	Model Reference Adaptive Control
NED	North East Down
PCHIP	Piecewise Cubic Hermite Interpolating Polynomial
PID	Proportional Integral Differential
PWM	Pulse Width Modulation
RC	Remote Controlled
SISO	Single Input Single Output

TF	Transfer Function
UAS	unmanned aerial system
ZOH	zero order hold

Executive Summary

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CHAPTER 1:

Introduction and History

1.1 Problem Statement

The unmanned aerial system (UAS) has evolved tremendously over the past decade. Miniature autopilots have gotten smaller and cheaper with more sensitive and redundant sensor packages largely due to the cellular phone industry accelerating Microelectromechanical Systems (MEMS) technology. The ability to manufacture these autonomous systems at fractions of the cost enables the advancement in multiple cooperative UAV applications including swarming capability. This ability to mass-produce large quantities of UAS's poses an interesting challenge. Even though the price has gone down and the performance has gone up, there still exists a significant amount of man-hours dedicated to sensor calibration and autopilot control law configuration and tuning for best achievable performance.. Tuning the six to ten conventional Proportional Integral Differential (PID) controllers for one airframe is not an insignificant task. Imagine a swarming systems often use the same airframes potentially assembled by the same manufacturer and all aircraft still require a tedious quality assurance check. Physical aspects of the airframes such as Center of Gravity (CG), control surface deflection/calibration/speed, airframe alignment, etc. all can drastically vary within the same delivered batch of airframes. It should also be considered that most of these miniature UAS's experience hard landings, crashes, and/or damage in transportation, which all can effect aerodynamic handling qualities. In summary, conventional control laws require a moderate to high level of expertise and require significant man-hours to tune properly for every airframe even if identical.

UAS avionics have drastically improved over the past decade, but the fundamental control law algorithms have not changed. The PID architecture found it's origin in automatic ship steering applications in 1922 [1]. Conventional control law architectures for UAS's predominately still use PID controllers. Conventional control law architectures for UAS's predominately still use PID controllers. Their architecture offers a well understood and predictable behavior and for this reason is well suited for the aviation application. The detriment of PID control is that it application is mostly constrained by the use on a linear

plant and most aerospace applications are non-linear and time varying. An aircraft's control authority that increases proportionally to dynamic pressure is one example of aerodynamic non-linear control behavior. In this case, the PID controller's robustness to changes in velocity and/or density altitude is not guaranteed and for most aircraft has to be delicately handled with lookup tables produced from hours of flight test.

1.2 Adaptive Control History

Adaptive control saw its early debut in the NASA North American X-15 hypersonic rocket-powered X-plane experimental aircraft. The X-15's performance envelope exceeded mach 6.0 and 300,000 feet [2]. Engineers realized early on that the linear controllers performed well only at one dynamic pressure, but nowhere near the entire flight envelope. Scheduling the controller gains with respect to dynamic pressure (gain scheduling) was one method used to help ensure robustness; the method is still wide spread in commercial aviation due to its robustness but requires a lot of effort to 'explore' the entire flight envelope. This was when the initial benefits of adaptive control were becoming realized.

The X-15 program started in 1959 and continued to 1968 flying nearly 200 successful flights. It was considered one of NASA's most successful programs. The benefit of adaptive control to the X-15 was that the adaptive controller was supposed to adjust the gain parameters online automatically. If the controller was self tuning, it could potentially offer increased performance while reducing complexity. The Honeywell MH-96 adaptive controller was implemented in the X-15-3 as a fly-by-wire controller designed to adaptively adjust the damping in pitch and roll with respect to a desired model response. The goal was to achieve consistent aircraft response regardless of dynamic pressure and other variables. During test flights of the MH-96 adaptive control, increased performance was observed especially in the dynamic phases of reentry over that of the linear fixed gain damping system [3]. These early breakthroughs in adaptive control proved the benefits could be viable aerospace solutions. However, on November 15, 1967 there was a fatal accident caused by the adaptive controller. The adaptive controller created an out of control flight situation resulting in dynamic pressures exceeding the structural limits and subsequent breakup of the airframe at 65,000 feet.

The turbulent start of adaptive control as implemented on the X-15 program was largely

due to the early naive understanding of robustness. Contemporary robust adaptive control strive to encapsulate these deficiencies of robustness in studies and proofs using Lyapunov stability analysis. In addition to the developments of rigorous stability tools, a number of unique techniques have also been implemented to further increase controller robustness although. One such technique utilizes dead band limits on the model adaptation process to avoid system/measurement noise from causing the un-learning of the states [4]. The \mathcal{L}_1 adaptive control algorithm utilizes a technique which seeks to decouple the adaptation rate from robustness by 'low pass filtering' the contribution of the fast estimator under the premise that estimating the entire frequency spectrum is overly ambitious and should be limited to the bandwidth of the actuator. Many advances have been made in the adaptive control field over the past few decades and this research sets out to evaluate a small subset of these techniques in the unforgiving aerospace environment.

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CHAPTER 2: Background and Literature Review

2.1 Preliminaries and Notation

This thesis uses the following notation, nomenclature, and fundamental equations of motion for fixed wing rigid body aerodynamics.

2.1.1 Kinematics and Dynamics

The following is the nomenclature that will be used to describe the kinematic equations. Euler angles for pitch (θ), roll (ϕ), and yaw (ψ) will have the units of radians. The following Figure 2.1 illustrates the North East Down (NED) reference frame definitions used for body rotational rates about the x axis (p), y axis (q), and the z axis (r) as well as the body velocities in the x axis (u), y axis (v), and the z axis (w).

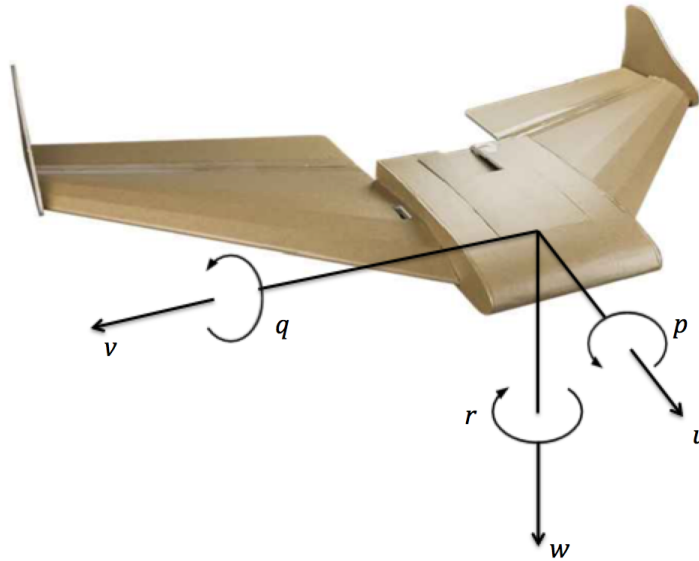


Figure 2.1. Reference frame - body rates and velocities

The primary goal of this research is to implement an algorithm which controls fixed wing attitude. Therefore, the focus of the following kinematic and dynamics equations will

primarily focus on deriving only rotational motion from first principles.

Newton's second law as it pertains to rotational motion can be stated as

$$\tau = J \frac{d\omega}{dt_i} \quad (2.1)$$

where τ is the torques applied to the body, J is the moment of inertia, and $\frac{d\omega}{dt_i}$ is the angular acceleration of the body with respect to the inertial frame.

Equation 2.1 can be rewritten in the body reference frame as follows:

$$\tau^b = J\dot{\omega}_{b/i}^b + \omega_{b/i}^b \times (J\omega_{b/i}^b) \quad (2.2)$$

The expression $\dot{\omega}_{b/i}^b$ is the angular acceleration in the body frame as viewed in the body frame:

$$\dot{\omega}_{b/i}^b = \begin{pmatrix} \dot{p} \\ \dot{q} \\ \dot{r} \end{pmatrix} \quad (2.3)$$

The equation can then be rewritten with respect to $\dot{\omega}_{b/i}^b$:

$$\dot{\omega}_{b/i}^b = J^{-1} \left[-\omega_{b/i}^b \times (J\omega_{b/i}^b) + \tau^b \right] \quad (2.4)$$

J can be defined as the inertia matrix as follows

$$J = \begin{pmatrix} J_x & -J_{xy} & -J_{xz} \\ -J_{xy} & J_y & -J_{yz} \\ -J_{xz} & -J_{yz} & J_z \end{pmatrix} \quad (2.5)$$

The moments of inertia, or the diagonal terms, must be non-zero. The products of inertia, or

the off-diagonal terms, are terms which describe the coupling between axis. For a traditional fixed wing aircraft, the natural symmetry will simplify the inertia matrix in the off-diagonal terms as follows:

$$J = \begin{pmatrix} J_x & 0 & -J_{xz} \\ 0 & J_y & 0 \\ -J_{xz} & 0 & J_z \end{pmatrix} \quad (2.6)$$

The inverse of J can be found to be

$$J^{-1} = \begin{pmatrix} \frac{J_z}{\Gamma} & 0 & \frac{J_{xz}}{\Gamma} \\ 0 & \frac{1}{J_y} & 0 \\ \frac{J_{xz}}{\Gamma} & 0 & \frac{J_x}{\Gamma} \end{pmatrix} \quad (2.7)$$

where,

$$\Gamma = J_x J_z - J_{xz}^2 \quad (2.8)$$

Aircraft nomenclature for torques are defined $\tau \triangleq (l, m, n)^T$ and therefore the combined equations derived from first principles take the form:

$$\begin{aligned}
\begin{pmatrix} \dot{p} \\ \dot{q} \\ \dot{r} \end{pmatrix} &= \begin{pmatrix} \frac{J_z}{\Gamma} & 0 & \frac{J_{xz}}{\Gamma} \\ 0 & \frac{1}{J_y} & 0 \\ \frac{J_{xz}}{\Gamma} & 0 & \frac{J_x}{\Gamma} \end{pmatrix} \left[\begin{pmatrix} 0 & r & -q \\ -r & 0 & p \\ q & -p & 0 \end{pmatrix} \begin{pmatrix} J_x & 0 & -J_{xz} \\ 0 & J_y & 0 \\ -J_{xz} & 0 & J_z \end{pmatrix} \begin{pmatrix} p \\ q \\ r \end{pmatrix} + \begin{pmatrix} l \\ m \\ n \end{pmatrix} \right] \\
&= \begin{pmatrix} \frac{J_z}{\Gamma} & 0 & \frac{J_{xz}}{\Gamma} \\ 0 & \frac{1}{J_y} & 0 \\ \frac{J_{xz}}{\Gamma} & 0 & \frac{J_x}{\Gamma} \end{pmatrix} \left[\begin{pmatrix} J_{xz}pq + (J_y - J_z)qr \\ J_{xz}(r^2 - p^2) + (J_z - J_x)pr \\ (J_x - J_y)pq - J_{xz}qr \end{pmatrix} + \begin{pmatrix} l \\ m \\ n \end{pmatrix} \right] \\
&= \begin{pmatrix} \Gamma_1 pq - \Gamma_2 qr + \Gamma_3 l + \Gamma_4 n \\ \Gamma_5 pr - \Gamma_6(p^2 - r^2) + \frac{1}{J_y}m \\ \Gamma_7 pq - \Gamma_1 qr + \Gamma_4 l + \Gamma_8 n \end{pmatrix}
\end{aligned} \tag{2.9}$$

where,

$$\begin{aligned}
\Gamma_1 &= \frac{J_{xz}(J_x - J_y + J_z)}{\Gamma} \\
\Gamma_2 &= \frac{J_z(J_z - J_y) + J_{xz}^2}{\Gamma} \\
\Gamma_3 &= \frac{J_z}{\Gamma} \\
\Gamma_4 &= \frac{J_{xz}}{\Gamma} \\
\Gamma_5 &= \frac{J_z - J_x}{J_y} \\
\Gamma_6 &= \frac{J_{xz}}{J_y} \\
\Gamma_7 &= \frac{J_x(J_x - J_y) + J_{xz}^2}{\Gamma} \\
\Gamma_8 &= \frac{J_x}{\Gamma}
\end{aligned} \tag{2.10}$$

Replacing the torques $(l, m, n)^T$ with the aerodynamics which generates them results in the following substitutions.

The body rates of a fixed wing airframe take the form [5]:

$$\begin{aligned}
\dot{p} &= \Gamma_1 pq - \Gamma_2 qr + \frac{1}{2} \rho V_a^2 S b \left[C_{p_0} + C_{p_\beta} \beta + C_{p_p} \frac{bp}{2V_a} + C_{p_r} \frac{br}{2V_a} + C_{p_{\delta_a}} \delta_a + C_{p_{\delta_r}} \delta_r \right] \\
\dot{q} &= \Gamma_5 pr - \Gamma_6 (p^2 - r^2) + \frac{\rho V_a^2 S c}{2J_y} \left[C_{m_0} + C_{m_\alpha} \alpha + C_{m_q} \frac{cq}{2V_a} + C_{m_{\delta_e}} \delta_e \right] \\
\dot{r} &= \Gamma_7 pq - \Gamma_1 qr + \frac{1}{2} \rho V_a^2 S b \left[C_{r_0} + C_{r_\beta} \beta + C_{r_p} \frac{bp}{2V_a} + C_{r_r} \frac{br}{2V_a} + C_{r_{\delta_a}} \delta_a + C_{r_{\delta_r}} \delta_r \right]
\end{aligned} \tag{2.11}$$

These equations are highly non-linear with numerous coupled responses as factors of multiple aerodynamic coefficients. For this research, the model will be simplified by assuming each axis is not mass coupled or aerodynamically coupled. This model takes the form:

$$\begin{aligned}
\hat{p} &= A_p \hat{p} + b_p (\hat{\omega}_p \delta_a + \hat{\theta}_p \hat{p} + \hat{\sigma}_p) \\
\hat{q} &= A_q \hat{q} + b_q (\hat{\omega}_q \delta_e + \hat{\theta}_q \hat{q} + \hat{\sigma}_q) \\
\hat{r} &= A_r \hat{r} + b_r (\hat{\omega}_r \delta_r + \hat{\theta}_r \hat{r} + \hat{\sigma}_r)
\end{aligned} \tag{2.12}$$

where,

- $\hat{\omega}$ - estimated input gain coefficient
- $\hat{\theta}$ - estimated constant state coefficient
- $\hat{\sigma}$ - estimated disturbance estimate

2.1.2 Transfer Functions

This research utilizes Transfer Function (TF) representation of aircraft flight dynamics that is typical of Linear Time Invariant (LTI) systems. A transfer function is a very effective approach to describe the relationship between inputs and outputs of LTI systems. Both analytically and numerically, the TF approach has significant benefits in continuous and discrete time domains as its construct is based on well-developed properties and primitives of polynomials. These polynomial representation of various aerodynamic, flight dynamics, and control properties of aircraft are well-developed. What is unknown or partially known a priori, are the numerical values of coefficients for those polynomials, therefore the tools

from the areas of online estimation such as regression are utilized to solve for them.

Transfer functions take the form:

$$H(s) = \frac{Y(s)}{X(s)} \quad (2.13)$$

where:

$Y(s)$ is the Laplace transform of the output

$X(s)$ is the Laplace transform of the input

Standard physics models of first and second order form are well understood and seen in many model derivations. The first order model takes the form:

$$H(s) = \frac{k_{dc}}{\tau s + 1} \quad (2.14)$$

where:

k_{dc} is the DC gain

τ is the system time constant (time in seconds to reach 63% of steady state)

Similarly the standard form for a second order system takes the form:

$$H(s) = \frac{\omega_0^2}{s^2 + 2\zeta\omega_0 s + \omega_0^2} \quad (2.15)$$

where:

ω_0 is the system natural frequency in radians per second

ζ is the system damping ratio

The modeling of a system can also be converted to a system of first order differential equations also known as state space modeling. The following nomenclature will be used to illustrate the modeling of first order systems where \dot{x} is the time derivative of the state, A is

the Hurwitz matrix, B is the input matrix, and u is the input vector.

$$\dot{x}(t) = Ax(t) + Bu(t) \quad (2.16)$$

2.2 Classical Feedback vs Adaptive Control

Control of a system can be broken into two required elements. There is the requirement to control the system from:

1. disturbances which affect the controlled states
2. disturbances which affect the performance of the system as a whole

Classical feedback control seeks to solve the first type of disturbance. This form of control is meticulously tuned to achieve the desired overshoot and settling time for example. The important assumption that is made by classical feedback controllers is that the underlying plant/system performance is not changing. For example the cruise control that maintains a vehicles speed assumes that the available horse power of the car is fixed. This is a fairly good assumption as the horsepower with respect to rpm available at sea level and at 5,000 feet for an internal combustion engine is constant enough that a fixed gain feedback controller would perform well at maintaining the speed of the vehicle in both environments. In the case of an airplane, the dynamic pressure is proportional to velocity squared and can drastically change the performance of the aircraft. In this case, the constant system performance assumption can cause a fixed gain classical feedback controller to go unstable at higher dynamic pressures (higher airspeeds). Conversely, adaptive controllers assume that the system performance is unknown and is likely to vary with time. Adaptive control seeks to ensure a systems performance in terms of characteristics like damping ratio and settling time are kept constant regardless of a plant dynamics that may be unknown and time varying. For both classical and adaptive control there exists some form of error which drives the controller. In the case of classical feedback, the error is calculated between the command and the feedback state of the plant. In adaptive control (in general), the error is calculated between the outputs of the desired reference model and real plant's measured performance.

Figure 2.2 outlines the decision making process a controls engineer makes when deciding

the type of controller needed for a given circumstance.

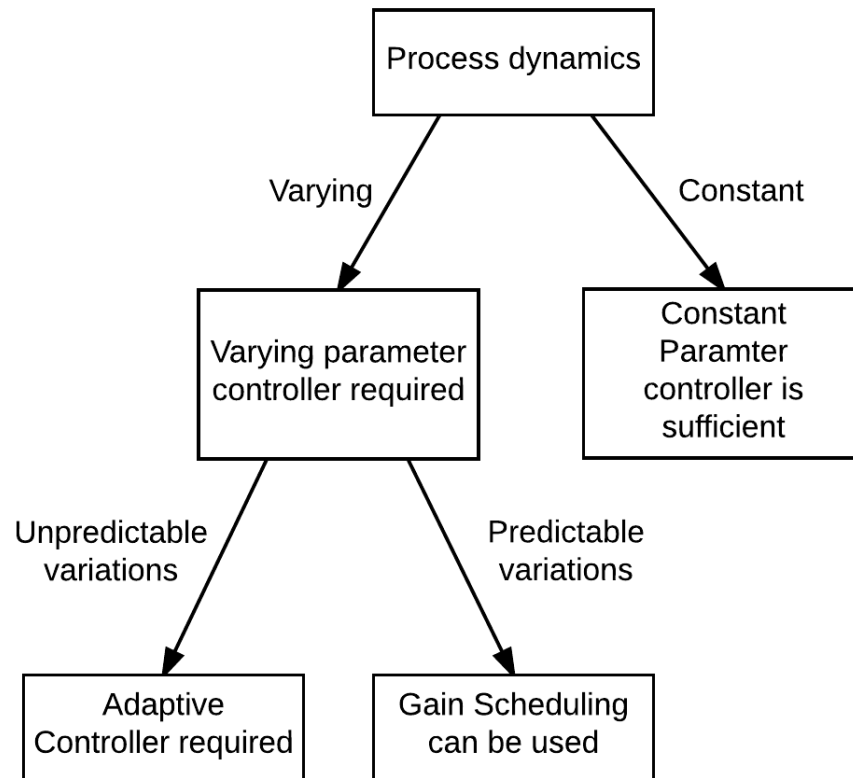


Figure 2.2. Determine if adaptive control should be used

2.3 Model Reference Adaptive Control

Model Reference Adaptive Control (MRAC) establishes the foundation for most of modern robust adaptive control. Its structure is intuitive in nature and seeks to define a system's response to a command signal with a reference model. Unlike traditional feedback where the error signal is generated with respect to state error, MRAC attempts to achieve a system response with respect to some reference model performance. MRAC assumes there is some nominal response of the system which can be characterized with a model of unknown parameters. The error between the model response and the system response generates the error for an 'adjustment mechanism' to learn the unknown model parameters.

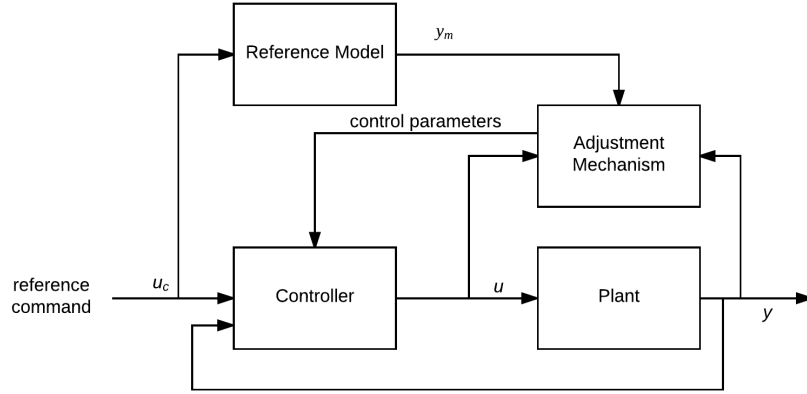


Figure 2.3. Traditional MRAC architecture

Figure 2.3 illustrates a topology where a traditional feedback controller is established as an inner loop and the 'Reference Model' and 'Adjustment Mechanism' is established as an outer loop. The outer loop attempts to minimize the error between the reference model output and the plant output. Using this error to learn the system parameters can be done utilizing one of two methods; gradient decent or stability theory.

2.3.1 MIT Rule - Gradient Decent

One of the first approaches to MRAC controllers was implemented at the Instrument Labs at MIT (now known as Draper Labs). The gradient decent based method was called the 'MIT Rule' for this reason [6]. This method attempts to learn some unknown parameter by descending the gradient of the error between the reference model and the plant output.

Given the simple first order system $G(s)$:

$$G(s) = k_{dc} \frac{1}{s + 1} \quad (2.17)$$

where k_{dc} is some unknown feedforward gain. In the case of the MIT rule, k_{dc} is the parameter to be learned and is defined as θ . The first step in the MIT rule is to establish a cost (or loss) function. One example of a cost function $J(\theta)$ is:

$$J(\theta) = \frac{1}{2} e^2 \quad (2.18)$$

$$e = y - y_m \quad (2.19)$$

where e is error, y is the plant output, and y_m is the model output.

In order for the cost function to be minimized, the negative gradient of the cost function is calculated and used to correct the a priori estimate. This method takes the following form where γ is the adaptation gain:

$$\frac{d\theta}{dt} = -\gamma \frac{\partial J}{\partial \theta} = -\gamma e \frac{\partial e}{\partial \theta} \quad (2.20)$$

The stability of this method is very system dependent and heavily relies on trial and error to ensure the adaptation gain (γ) is not too high. This usually requires low adaptation rates for most systems and may not produce adequate results. It should also be noted that this method presupposes there is adequate persistence of excitation. Without a frequency rich error signal being generated by adequate persistence of excitation, the model will fail to adapt. This method also offers no guarantees that the learned parameters are actually the correct values.

2.3.2 Lyapunov Stability Criteria

Aerospace controllers tend to use linear controllers for their simplicity and well understood robustness characteristics. This is despite the fact that the applications of these linear controllers are applied to a non-linear dynamical system such as attitude control with varying dynamic pressure. Adaptive Controllers are non-linear and may offer performance benefits to non-linear systems as seen in aforementioned aerospace applications. However, non-linear controller's robustness properties need to be evaluated. The Lyapunov stability criteria offers methods of evaluating these controller's boundedness and robustness behavior.

Aleksandr Lyapunov was a Russian mathematician who's work was published in 1892 [7] concerning the behavior of non-linear systems close to equilibrium without having to rigorously find the unique solutions to difficult differential equations used to model the system. His work was largely overlooked until the Cold War when aerospace solutions required a more rigorous approach to analyzing non-linear control robustness. Modern non-linear control engineers extensively utilize Lyapunov's techniques to design and evaluate

non-linear controllers.

Lyapunov Stability Definitions

Lyapunov's methods attempt to evaluate autonomous nonlinear dynamical systems within the bounds of three classifications. In this case the autonomous system is defined as definable set of ordinary differential equations which are not explicitly dependent upon the independent variable. These classifications can be used to define a nonlinear system as Lyapunov stable, asymptotically stable, or exponentially stable.

Given the following autonomous nonlinear dynamical system:

$$\dot{x}(t) = f(x(t)), \quad x(0) = x_0 \quad (2.21)$$

where f has equilibrium at x_e :

$$f(x_e) = 0 \quad (2.22)$$

then the equilibrium is said to be:

1. Lyapunov Stable

for every $\epsilon > 0$ there exists a $\delta > 0$ such that, if $\|x(0) - x_e\| < \delta$, then for every $t \geq 0$ we have $\|x(t) - x_e\| < \epsilon$

2. Asymptotically Stable

if the system is Lyapunov stable and there exists a $\delta > 0$ such that if $\|x(0) - x_e\| < \delta$, then $\lim_{t \rightarrow \infty} \|x(t) - x_e\| = 0$

3. Exponentially Stable

if the system is asymptotically stable and there exists $\alpha > 0, \beta > 0, \delta > 0$ such that if $\|x(0) - x_e\| < \delta$, then $\|x(t) - x_e\| \leq \alpha \|x(0) - x_e\| e^{-\beta t}$, for all $t \geq 0$

Being Lyapunov stable infers that if a system is near equilibrium then it will indefinitely remain near equilibrium. If the system is found to be asymptotically stable then it eventually will achieve equilibrium as $t \rightarrow \infty$ and being exponentially stable implies it reaches equilibrium even faster.

Lyapunov's Second Method

Lyapunov's second proposed method is also known as Lyapunov stability criteria. This method offers a less tenuous method for evaluating mathematically non-ideal systems. Lyapunov analysis of the linearized system around equilibrium can be cumbersome in the case where equilibrium is at the origin or the eigenvalues are purely imaginary. In this case, the solutions can rapidly depart to infinity or approach zero with little perturbation to the eigenvalues. Lyapunov's second method offers an alternative approach for classifying a systems stability using a concept that is similar to how energy is defined in classical dynamics.

Conceptually, Lyapunov's second method can be compared to evaluating the energy of a vibrating spring mass system. The energy of the unforced spring mass system will dissipate energy due to friction and or damping etc. This trend of energy leaving the system towards some 'attractor' is evidence of the system's stability characteristics and identifies that there will be some stable end state. Like wise, Lyapunov's second method characterizes this with the use of a Lyapunov candidate function $V(x)$. It is important to note that Lyapunov realized that the candidate function can be any function so as long as one candidate function is found in agreement with the stability criteria. It is then said to be Lyapunov stable if any candidate equation is found and meets the stability criteria. This means that it is only incumbent upon the engineer to find one candidate equation to meet the criteria. This can be an iterative process of trying multiple energy like equations. A common approach is to model the Lyapunov candidate equation as kinetic energy ($\frac{1}{2}u^2$). Lyapunov realized that characterizing the energy of a nonlinear system could be almost impossible for some cases, but this approach could prove stability without the rigorous knowledge of the true system's energy.

Lyapunov's second method defines a system as Lyapunov Stable for a system $\dot{x} = f(x)$ having an equilibrium point at $x = 0$ where the Lyapunov candidate function $V(x) : \mathbb{R}^n \rightarrow \mathbb{R}$ such that:

- $V(x) = 0$ if and only if $x = 0$
- $V(x) > 0$ if and only if $x \neq 0$
- $\dot{V}(x) = \frac{d}{dt}V(x) = \sum_{i=1}^n \frac{\partial V}{\partial x_i} f_i(x) \leq 0$, for all values of $x \neq 0$

if $\dot{V}(x) < 0$ for $x \neq 0$ then system is asymptotically stable.

To determine if the system is globally stable, it is additionally required to prove the condition of radial unboundedness.

2.4 Least Squares Adaptive Control

Least squares Adaptive control offers a reasonably promising approach to adaptive control. Its based on the idea that the parameter estimate can be refined using recorded model measurements and minimizing the least squared error of a cost function similar to the MIT Rule. Successful flight test have been flown using a batched least squares estimator for increasing fault tolerance in small unmanned systems [8]. An unknown state parameter vector can be defined as θ . It was assumed that the dominating dynamics were a gain and bias for each control channel that were both scaled by airspeed.

$$\theta = \begin{bmatrix} \theta_{q,\delta elev} \\ \theta_{q,bias} \\ \theta_{p,\delta ail} \\ \theta_{p,bias} \end{bmatrix} \quad (2.23)$$

The system output equation can be modeled as:

$$y = \theta w \quad (2.24)$$

where w is a vector of inputs signals and:

$$y = \begin{bmatrix} q, pitchrate \\ p, rollrate \end{bmatrix} \quad (2.25)$$

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CHAPTER 3:

\mathcal{L}_1 Adaptive Control Derivation

Introduction here!!!

3.1 \mathcal{L}_1 Adaptive Control

The \mathcal{L}_1 adaptive controller is an evolution of the concepts implemented by MRAC. They are similar approaches designed to model a LTI system with unknown constant parameters. These parameters are adjusted to achieve the desired outcome of the error between the actual plant (system) and the referenced system model (state predictor) to asymptotically approach zero. Adaptive control attempts to estimate the plant's unknown parameters in situ. Parameter estimation is done using either direct or indirect architectures. The indirect architecture attempts to estimate the system's parameters, which could be considered similar to system identification. Alternately the easier to implement direct architecture estimates the controller parameters explicitly. These architectures can be seen below in Figures 3.1 and 3.2.

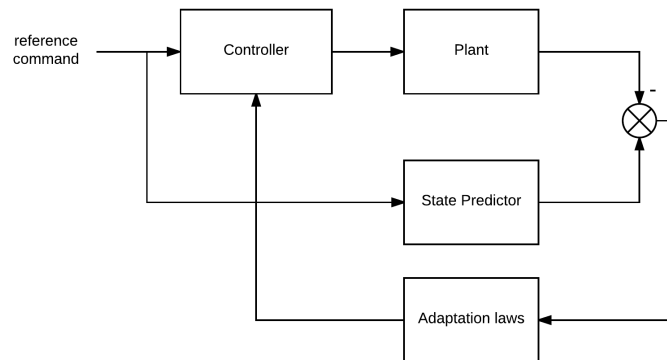


Figure 3.1. Direct MRAC architecture

The \mathcal{L}_1 adaptive control algorithm asserts that trying to estimate the plant uncertainties outside of the control actuators' bandwidth is overly ambitious. The system's actuator bandwidth and the slow dynamics of the plant are most commonly the system's limiting factors, and the estimator's robustness/stability could be in question if un-modeled high

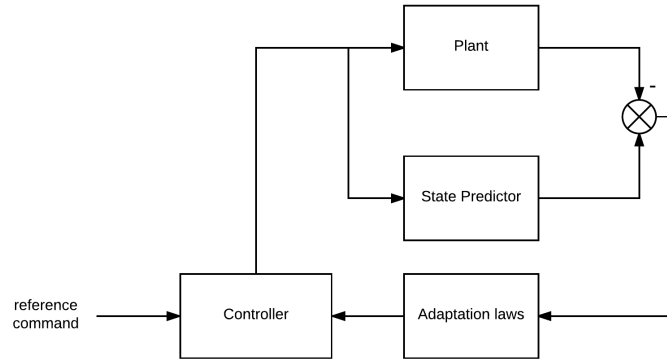


Figure 3.2. Indirect MRAC architecture

frequency content exists in the plant. The \mathcal{L}_1 adaptive control constrains the objective function by using a low-pass filter (first or second order) to band the frequency response in order to meet robustness specifications. This low-pass filter should be tuned to a frequency response commensurate with the actuator's frequency response. When looking at examples of where to place the low-pass filter in the direct and indirect architectures, it becomes clear that the indirect architecture is the only candidate. Figures 3.3 and 3.4 illustrate the placement of the low-pass filter and its implication on the closed loop model.

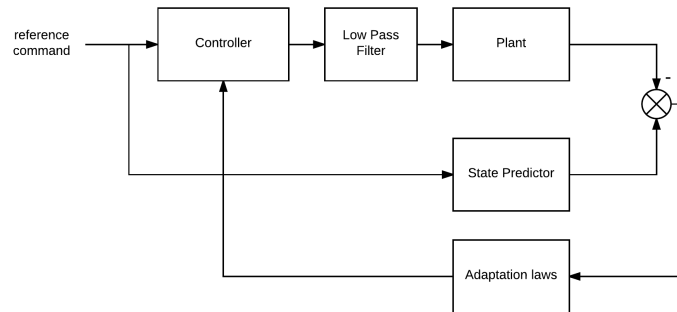


Figure 3.3. Direct MRAC architecture with low-pass filter

It can be seen that the low-pass filter in the direct architecture inherently changes the structure of the model with the cascading of the low-pass filter and plant block diagrams. This change mathematically is not mirrored in the state predictor and therefore is not subtractable. However, in the indirect case, the structure of the model is kept intact and the low-pass filter is applied to both the plant and the state predictor. This ensures that the

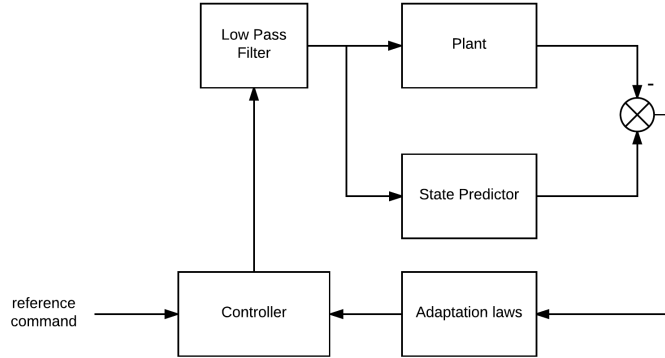


Figure 3.4. Indirect MRAC architecture with low-pass filter

low-pass filter is subtractable when calculating the error state and the model's structure is kept intact.

In the primary literature for this research [9], the author often refers to the state predictor as the reference model or companion model for the direct and indirect architectures respectively. The reference model (direct architecture) intuitively maps the desired model response to the error feedback. In the indirect architecture case, the error state is a result of the companion model plus the low-pass filter. This subtle distinction is necessary because it must be accounted for when tuning the companion model with the included low-pass filter.

Many slight variations of the \mathcal{L}_1 adaptive architectures have been derived for various use cases [9]. Some of the following forms were studied for viability in the fixed wing UAS use case:

- Single Input Single Output (SISO) with constant but unknown state parameters
- SISO with time variant and/or nonlinear unknown state parameters
- Multiple Input Multiple Output (MIMO) with constant but unknown state parameters
- MIMO with time variant and/or nonlinear unknown state parameters

MIMO control algorithms would potentially afford the controller more ability to cope with system coupling if present. A fixed wing UAS would exhibit coupled behavior due to the coupling present in the aerodynamics but was not chosen due to the added architectural complexity. Unknown state parameters that are assumed to be constant or time invariant are considered matched uncertainty. Unknown state parameters that are non-constant (time

variant) and/or exhibit non-linear behavior are considered unmatched uncertainty. The unmatched uncertainty architecture offers a more appealing solution for fixed wing use cases (asymmetric actuator failure, aerodynamic coefficients scaled by dynamic pressure, etc.), but adds a significant amount of complexity to the architecture. In summary, the SISO architecture with matched uncertainty was chosen for this research.

The SISO controller with matched uncertainty was chosen to control pitch rate (q) and roll rate (p) of the aircraft using two separate but parallel controllers. This meant that the controller could be generalized to a first principles physical point mass model similar to derivations found in rigid body equations of motion. In this implementation of the \mathcal{L}_1 adaptive controller, the desired state x to be controlled was an individual body rate (e.g., q , p).

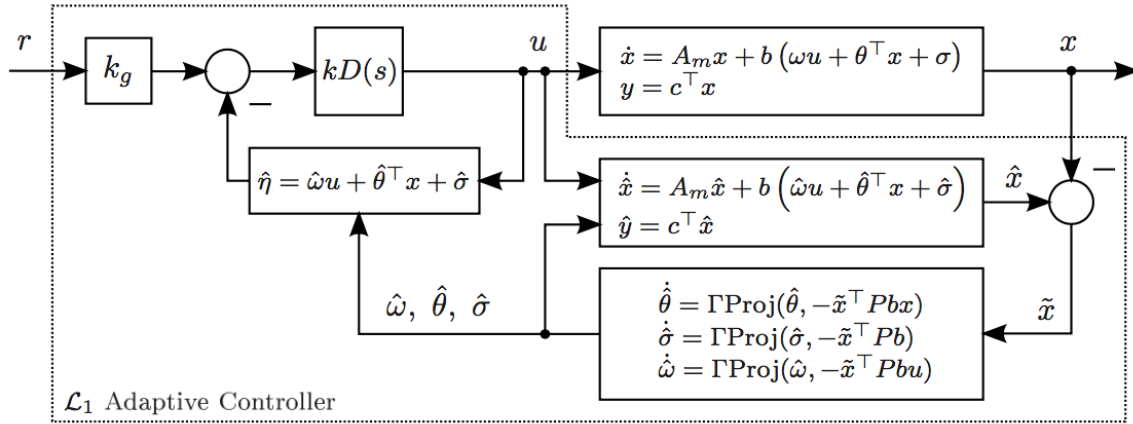


Figure 3.5. \mathcal{L}_1 Architecture with Matched Uncertainty Block Diagram [9]

As seen in Figure 3.5, the generalized \mathcal{L}_1 architecture in block diagram form and the following elements can be identified:

- k_g - feed forward input gain
- $kD(s)$ - user described filter (second order low pass plus integrator)
- $\hat{\eta}$ - \mathcal{L}_1 controller state
- \dot{x} - first order differential equation of state model
- \hat{x} - state estimate
- \tilde{x} - state error
- u - reference objective

A_m - Hurwitz matrix
 b - input matrix
 $\hat{\omega}$ - unknown input gain coefficient
 $\hat{\theta}$ - unknown constant state coefficient
 $\hat{\sigma}$ - unknown disturbance estimate
 Γ - adaptation gain
 Pb - solution to the Lyapunov stability criterion

It should also be noted that the architecture presented in Figure 3.5 includes the use of a projection operator. The parameters for $\hat{\omega}$, $\hat{\theta}$, and $\hat{\sigma}$ are all projection based adaptation laws. This simply ensures that the adaptation stays bounded around the feasible region of parameter space. The Lyapunov stability proofs for this architecture rely on this method to guarantee stability [9]. More discussion on the specific application of this operator can be found in Appendix [???].

One of the main benefits of using the SISO architecture is that the solution to the Lyapunov stability criterion (Pb) used in the projection based adaptation laws is greatly simplified.

In this case, Pb reduces to:

$$Pb = \frac{1}{2\omega_n} \quad (3.1)$$

where ω_n is the natural frequency in rad/s for the first order companion model in discrete recursive form assuming DC gain of 1.

3.2 \mathcal{L}_1 Discrete Time Implementation

Implementing any algorithm on actual autopilot hardware will inevitably force some if not all parts of the algorithm to be discretized. Autopilots like the Pixhawk operate at some scheduled loop rate for executing the litany of subprograms that measure sensors, calculate navigation commands, and many more. In the case of the Pixhawk autopilot, you can run the main loop up to 400 Hz. At 400 Hz, there is a significant insurance that the vehicle's full frequency domain of importance will be achievable. However, the ArduPilotMega / Multi-Platform Autopilot (APM) flight stack records all logged parameters also at this loop rate and can create log files larger than are reasonably desired. There are a myriad of

other reasons why the engineer would not want to run at high loop rates, but successful flight at the lowest (default of 50Hz) is desired if adequate performance of the adaptive control can be achieved. Failures in early adaptive control were largely impart due to a very naive understanding of robustness. Brian Anderson concludes that "it is clear that the identification time scale needs to be faster than the plant variation time scale, else identification cannot keep up" [10].

3.2.1 Digital Bi-Quad Filter

The L1 adaptive control algorithm utilizes two specific elements that will require careful discretization; the companion model and the low pass filter. The digital bi-quad filter offers a very versatile and straight forward method for accurately implementing the companion model and the low pass filter discretely using it's recursive nature. It is a second order filter which uses a Finite Impulse Response (FIR) front end and an Infinite Impulse Response (IIR) back end requiring 4 total memory blocks. This topology allows the designer to create numerous types of filters (low pass, high pass, bandpass, etc) simply by choosing appropriate coefficients. If a first order filter is needed then the two higher order FIR/IIR terms can be set to zero. Figure 3.6 illustrates this filter's topology where the FIR structure is the left two memory blocks and the IIR structure is the right two memory blocks.

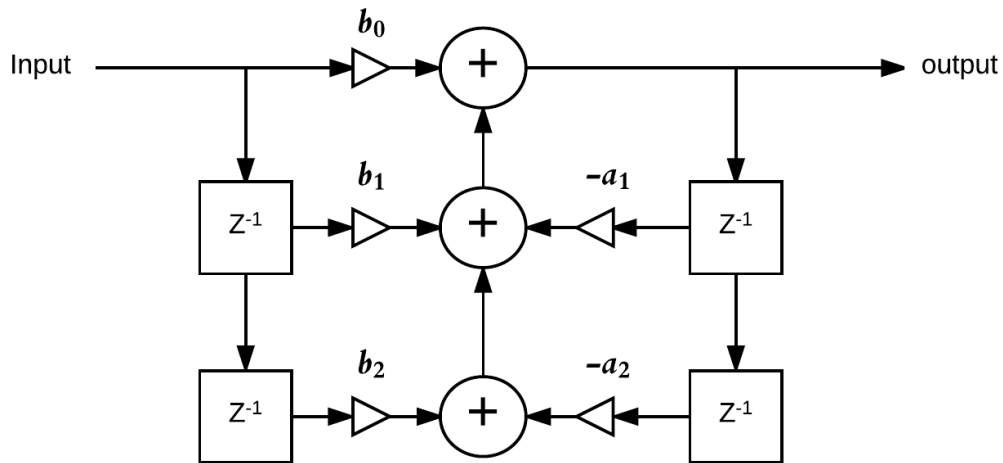


Figure 3.6. Digital Bi-quad Filter Architecture

To determine the structure of the coefficients, a bi-linear Z transform is used to convert a desired S-domain (continuous time domain) filter/model into the Z-domain (discrete time domain).

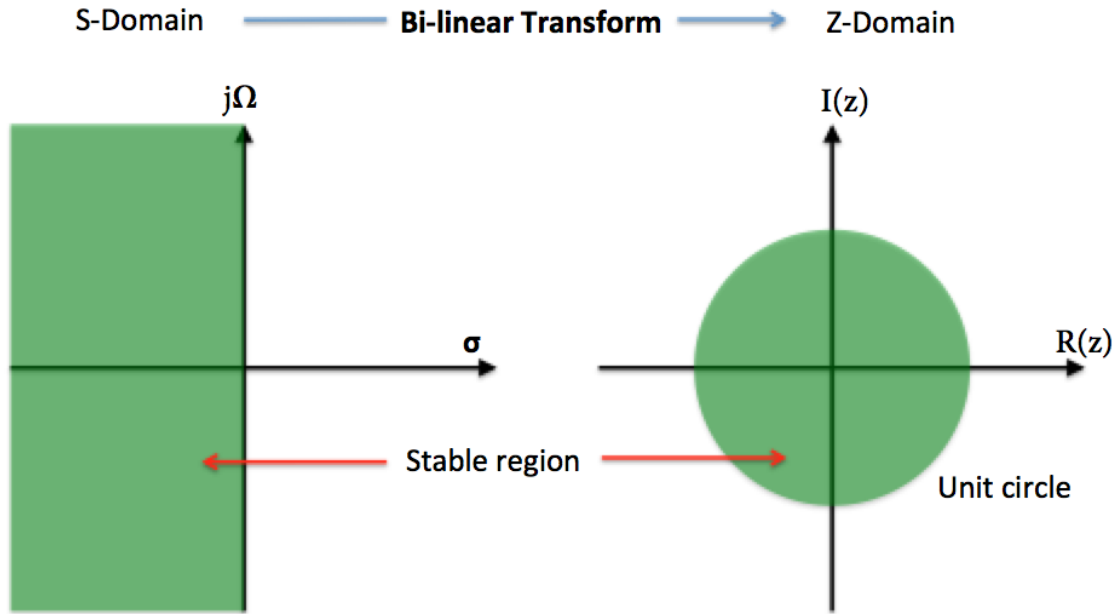


Figure 3.7. Bi-linear Transform

This derivation can be seen below for the second order low pass model:

$$H(s) = \frac{1}{s^2 + \frac{s}{Q} + 1} \quad (3.2)$$

where the bi-linear transform converts s to z via:

$$s = \left(\frac{1}{K} \right) \left(\frac{z - 1}{z + 1} \right) \quad (3.3)$$

K is the 'pre-warping' factor which accounts for the transition of the vertical s -plane into the circular z -plane as seen in figure 3.7.

where ωT is:

$$\omega T = 2\pi \left(\frac{F_c}{F_s} \right) \quad (3.4)$$

$$\begin{aligned} K &= \tan \left(\frac{\omega T}{2} \right) \\ &= \tan \left(\pi \frac{F_c}{F_s} \right) \end{aligned} \quad (3.5)$$

F_c is the desired corner frequency of the filter and F_s is the sampling rate (or loop rate of the autopilot). This 'pre-warping' is critical to ensure that the continuous time cutoff frequency desired is correctly established in the discrete implementation. It is the engineer's discretion if pre-warping is required for the appropriate application, but the general guidance is to pre-warp the Z-domain coefficients if the desired cut-off frequency is close to Nyquist. It was chosen for this application to always pre-warp the coefficients even though the error is small for corner frequencies which are fairly distant from Nyquist. This was chosen simply because calculating the $\tan()$ function real time on the CPU adds negligible computational strain but offers ease of tuning for the engineer.

Applying the bi-linear transform to the continuous time second order low pass filter results in:

$$H(z) = \frac{1}{\left[\left(\frac{1}{K} \right) \left(\frac{z-1}{z+1} \right) \right]^2 + \frac{\left(\frac{1}{K} \right) \left(\frac{z-1}{z+1} \right)}{Q} + 1} \quad (3.6)$$

The desired form is:

$$H(z) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{a_0 + a_1 z^{-1} + a_2 z^{-2}} \quad (3.7)$$

Reducing equation 3.6 to match the form in equation 3.7 results in the following coefficients:

$$\begin{aligned}
a_0 &= 1 \\
a_1 &= \frac{2(K^2 - 1)}{K^2 + \frac{K}{Q} + 1} \\
a_2 &= \frac{K^2 - \frac{K}{Q} + 1}{K^2 + \frac{K}{Q} + 1} \\
b_0 &= \frac{K^2}{K^2 + \frac{K}{Q} + 1} \\
b_1 &= 2b_0 \\
b_2 &= b_0
\end{aligned} \tag{3.8}$$

The bandwidth of the filter Q can be set by the engineer. For example, if the pass-band of the filter is desired to be flat (Butterworth) then Q can be set equal to $\frac{1}{\sqrt{2}}$. For this research the following C++ code segments were used to explicitly calculate the bi-quad low-pass filter implementation:

```

void DigitalBiquadFilter<T>::compute_params(float sample_freq ,
float cutoff_freq , biquad_params &ret) {
    ret.cutoff_freq = cutoff_freq;
    ret.sample_freq = sample_freq;

    float fr = sample_freq / cutoff_freq;
    float K = tanf(M_PI / fr); //Pre-Warp calculation
    float c = 1.0f + 2.0f * cosf(M_PI / 4.0f) * K + K * K;

    ret.b0 = K * K / c;
    ret.b1 = 2.0f * ret.b0;
    ret.b2 = ret.b0;
    ret.a1 = 2.0f * (K * K - 1.0f) / c;
    ret.a2 = (1.0f - 2.0f * cosf(M_PI / 4.0f) * K + K * K) / c;
}

```

```

T DigitalBiquadFilter<T>::apply(const T &sample ,
const struct biquad_params &params) {

```

```

    T delay_element_0 = sample - _delay_element_1 * params.a1
      - _delay_element_2 * params.a2;

    T output = delay_element_0 * params.b0
      + _delay_element_1 * params.b1
      + _delay_element_2 * params.b2;

    _delay_element_2 = _delay_element_1;
    _delay_element_1 = delay_element_0;

    return output;
}

```

This implementation can be used as the \mathcal{L}_1 low-pass filter and as the companion model. It can be seen in the above code segment that K , the pre-warp factor, is explicitly calculated every iteration.

3.2.2 Simplified Bi-quad First Order Model

In the case of the companion model, a first order response may be desired. As described in equations 2.14 and 2.16, the discrete first order model can be derived from a simplified Bi-quad as seen below in figure 3.8. It can be seen that on the first two coefficients of the FIR filter are kept from this topology.

The first order model can be specified by either its time constant (time in seconds to reach 63% of steady state) or its -3dB corner frequency. The system takes the form as seen in equation 3.9 when defined by its corner frequency.

$$H(s) = \frac{\omega_n}{s + \omega_n} \quad (3.9)$$

therefore the explicit calculation of the Bi-quad coefficients in this case becomes:

$$\begin{aligned} a_1 &= e^{\left(\frac{-\omega_n}{F_s}\right)} \\ b_0 &= 1 - a_1 \end{aligned} \quad (3.10)$$

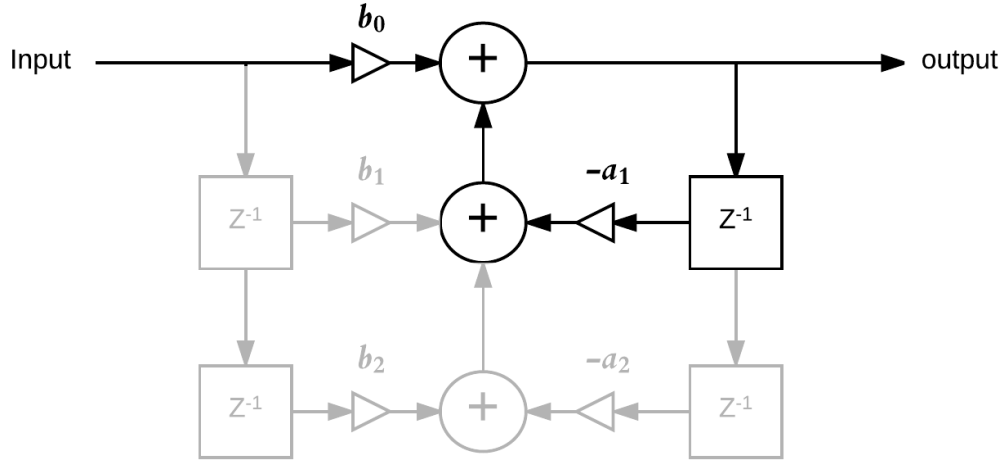


Figure 3.8. Digital Bi-quad Simplified First Order Low-pass Filter

where ω_n is the -3dB corner frequency in radians per second and F_s is the sampling frequency in Hz.

Therefore the discrete recursive form of the first order model becomes:

$$y_{i+1} = a_1 y_{i-1} + b_0 y_i \quad (3.11)$$

Another form commonly seen in software form which is designed to optimize for speed takes the form:

```
float b_0=exp(-f_c / f_s);
float out+=(in-out)*b_0;
```

3.2.3 Euler vs Trapezoid Rule

The model estimate as well as the parameter estimates for the \mathcal{L}_1 algorithm are both numerically estimated using discrete integration. The Euler method is a numerical procedure for solving ordinary differential equations. The Euler method as applied to discrete integration, is the fundamental method for recursively integrating a digital signal. The algorithm takes the form:

where h is the uniform step size,

$$y_{i+1} = y_i + hf(t_i, y_i) \quad (3.12)$$

The recursive trapezoidal method (Heun's method) takes the form:

$$\begin{aligned} \tilde{y}_{i+1} &= y_i + hf(t_i, y_i) \\ y_{i+1} &= y_i + \frac{h}{2}[f(t_i, y_i) + f(t_{i+1}, \tilde{y}_{i+1})] \end{aligned} \quad (3.13)$$

Comparing the accuracy of the two numerical methods for discretely calculating the integral of $y = e^t$ can be seen in figure 3.9:

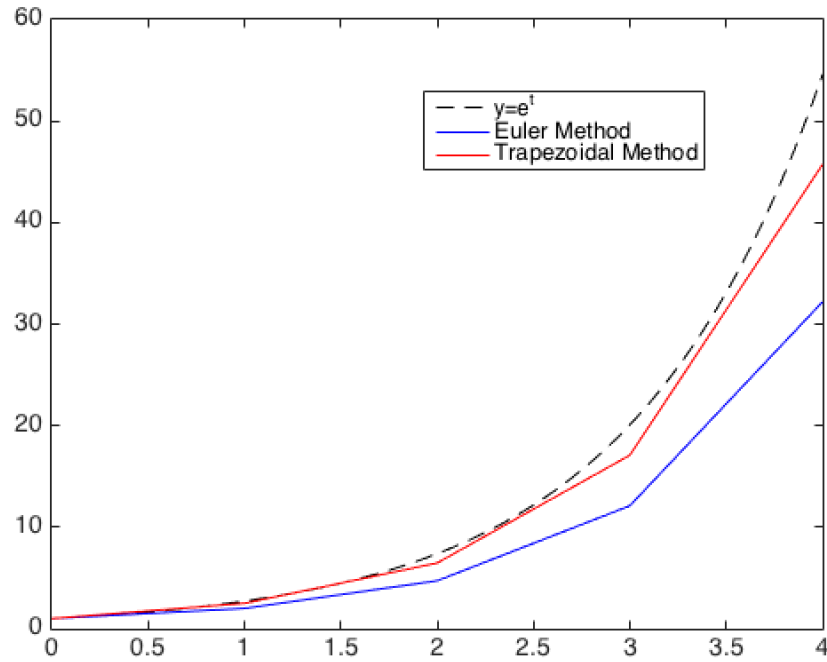


Figure 3.9. Euler vs Trapezoidal Integration error

As seen in equation 3.13, the recursive trapezoidal integration method only adds one more line of complexity to the algorithm for a significant gain in accuracy and therefore will be the chosen method applied for all discrete numerical integration in this research.

CHAPTER 4:

Design of Experimental Platform

4.1 Autopilot

4.2 Simulation

4.3 Airframe

The aircraft used for this research was the Flitetest Spear [?]. The Spear airframe was chosen for its endurance capability of greater than 45 minutes of flight time and its large capacity fuselage. The flying-wing architecture keeps the actuation requirement to a minimum of two servos by utilizing an elevon configuration.



Figure 4.1. Spear Airframe

The large blunt nose provides adequate space for two 2,200 mAh (12.6volts) lithium polymer batteries wired in parallel. The remaining cargo space was used for accommodating the Pixhawk autopilot.

This plane was constructed out of craft foam board. The plans were downloaded from flitetest.com [?] and converted to CorelDraw vector files for use in a laser cutter. These files were then cut out of four sheets of foam board using the laser cutter. The wing halves were joined with standard box tape and hot-glue. This provided a cheap and rapid construction process which was achievable under four hours of build time.



Figure 4.2. Spear Cargo Capacity

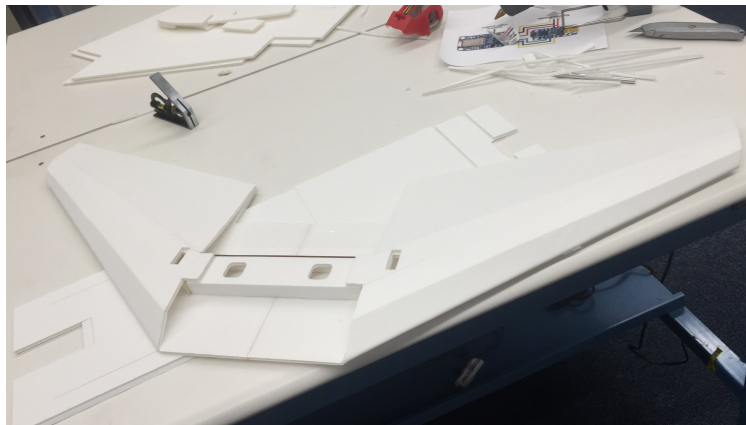


Figure 4.3. Spear Build Process

The aircraft specifications are as follows:

- Weight without battery: 1.45 lbs (658 g)
- Center of gravity: 3 – 3.5" (76 – 89 mm) in front of firewall
- Control surface throws: 16° deflection – Expo 30%
- Wingspan: 41 inches (1041 mm)
- Recommended motor: 425 sized 1200 kv minimum
- Recommended prop: 9 x 4.5 CW (reverse) prop
- Recommended ESC: 30 amp minimum
- Recommended Battery: (2) 2200 mAH 12.6 volt minimum
- Recommended Servos: (2) 9 gram servos

CHAPTER 5:

Flight Testing and Performance Evaluation

5.1 Simulation Results

5.2 Flight Test Results

5.2.1 Data Collection

The Pixhawk autopilot was used to capture roll and pitch rates (\dot{p}, \dot{q}) for the test vehicle as well as the pilot's command inputs. These outputs and inputs were the essential building blocks for creating pitch rate and roll rate models for the test vehicle. The autopilot is capable of logging data at 50-400 Hz and therefore is a discrete time domain signal. This data should ultimately be manipulated into the s-domain. The mathematics for this procedure are well defined and numerous tools can be used to simplify this process.

It is crucial to ensure there is sufficient frequency content in the data recorded. Exciting multiple frequencies in the time domain ensures the regression techniques have an adequate sample space to search for polynomial coefficients. Exciting adequate frequency inputs is analogous to only sampling at one independent variable and expecting to get a regression fit from a non-changing dependent variable.

To ensure sufficient frequency content was obtained from the aircraft, a linear chirp was chosen and implemented into the Pixhawk source code as follows:

$$x(t) = \sin \left[\phi_0 + 2\pi \left(f_0 t + \frac{k}{2} t^2 \right) \right] \quad (5.1)$$

where:

ϕ_0 is the initial phase of the chirp at $t=0$ (nominally zero degrees)

f_0 is the initial frequency at $t=0$

k is the chirp rate
 t is time in seconds

An example of this formulation can be seen below:

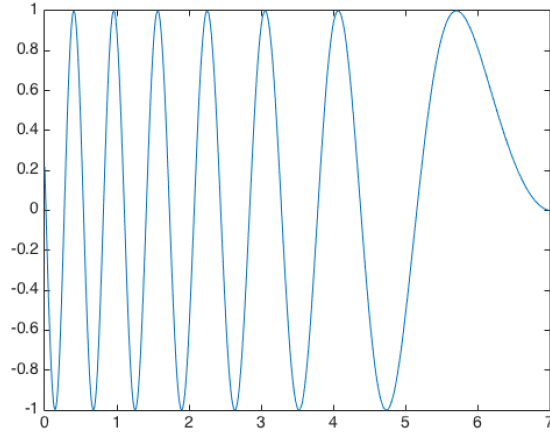


Figure 5.1. Reverse Linear Chirp Example

5.2.2 Model Regression

With the logged input and output data in discrete form, the data needs to be further shaped to properly convert to an s-domain representation. The first step is ensuring that the data is of constant sampling rate. In other words, the time between samples is uniform from sample to sample. The data provided from the Pixhawk autopilot does not have a uniform sampling rate. The sample rate is a user-defined rate (50-400Hz), but has a slight amount of jitter ($\pm 0.1\%$). Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) interpolation was used to interpolate the data into a uniform sampling rate.

After the data is shaped correctly with a uniform sample rate, the discrete data is transformed into a continuous approximation using a zero order hold (ZOH) technique. Taking the Laplace transform of the continuous input/output data will convert it into the s-domain and finally a non-linear least squares minimization algorithm can be run to find the polynomial coefficients which best fit the data.

The order of the regression (number of polynomials to estimate) is at the discretion of the engineer and their intuition of system's physical representation. Higher order models will

better fit the data, but in most cases tend to over fit the data if they cannot be justified by physical principles. Most aircraft models assume that the system is LTI and second order. These fundamental aerodynamics models divide the modeling into longitudinal and lateral dynamics. Essentially each axis of the aircraft is assigned two second order responses. Pitch, for example, has a second order response in the pitch damping mode (also known as the short period) and also has a second order response in the transition of kinetic energy to potential energy (also known as the long period or phugoid). This would imply that the collected body rate data (\dot{p}, \dot{q}) collected by the autopilot should be modeled as first order systems because body rate is the first derivative of attitude. Assuming a first order system for the collected data in this experiment keeps the originally derived physical meaning but may be insufficient upon critical analysis. Both first order and second order model were estimated for comparison sake.

Results were collected from two flight test events. The first flight test was data collected prior to implementing the chirp and the pilot attempted to increase frequency of the input signal manually. The second set of data collected was via the reverse linear chirp method previously described.

The manually piloted acquired data was expected to not have as adequate of frequency content in the signal but still provided adequate results for modeling the aircraft.

The above result demonstrates the utility of this technique even with poorly structured data from manual pilot inputs. It can be seen that the second order model starts to misrepresent the data at higher frequencies. The lower frequency validity of this model showed potential and most of the high frequency response may be able to be neglected upon further review. The following figure with the chirp results highlights the actual issue with the high-frequency modeling issues.

The reverse linear chirp, starting at high frequency and chirping down, clearly illustrates that this regression method has an underlying problem that was not evidently clear in the previous example. In the chirp analysis, it is clear that the high frequency modeling is in error. After reviewing this result, it was clear that the sampling rate of the input channel was aliased. The chirp response was physically observed on pre-flight, in actual flight, and in the actual body rate of the aircraft. However, the aliased input channel was arbitrarily biasing the regression result. The data was logged at 50 Hz with the assumption that 50

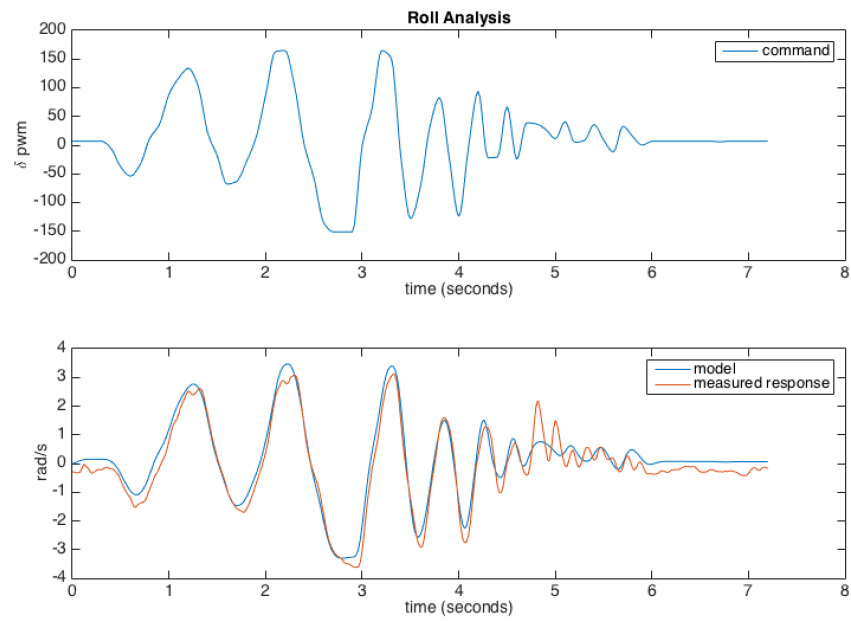


Figure 5.2. Roll Model Regression with Manual Inputs

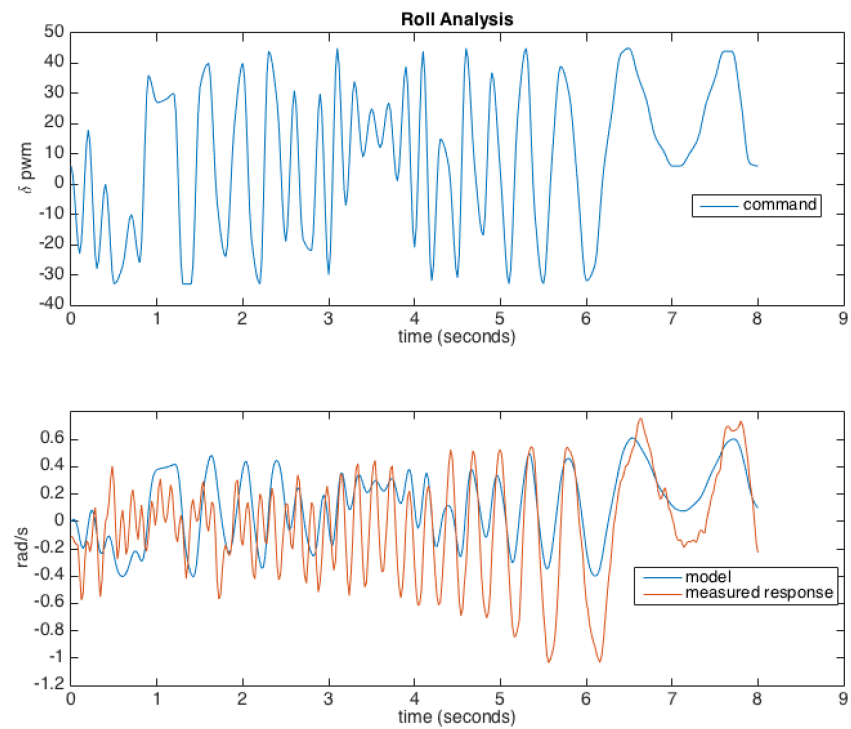


Figure 5.3. Roll Model Regression with Reverse Linear Chirp

Hz was 10 times higher than the expected natural frequency of the aircraft and at least five times higher than the Nyquist criterion. The Nyquist criterion is the theoretical minimum frequency ($2f_0$) to sample a signal and recover a given frequency. The autopilot is capable of logging data at 400Hz, but in this case, the servo output loop is still at 50Hz due to it being the hardware bandwidth limit of standard Remote Controlled (RC) servos. Some high performance servos are capable of higher input frequencies, but this still wouldn't solve the specific issue found when running this analysis. The specific aliasing issue is hardware specific to the Pixhawk 1 autopilot in how the main CPU sends servo commands to the auxiliary I/O CPU. The most recent version of firmware at the time of this test improperly logs the Pulse Width Modulation (PWM) through an aliased prone signal path. The main and I/O CPU both run at 50Hz with some appreciable clock drift. This generates a noticeable beat frequency and delay when the actual values in registry are saved for PWM values are sent back round trip to the main CPU. The implication of logging the pwm values at the very end of the digital transmission line seems valuable in principle because the values being logged are the undeniable values being sent to the actuators. However, the cost of logging these values in this manner on the the Pixhawk architecture incurs significant aliasing at almost all frequencies. Logging the commanded PWM values prior to being sent to I/O cpu solved the aliasing discrepancy and produced very frequency rich models.

The manually piloted acquired data was selected as the most viable data source for the models. There were two separate tests run on the same aircraft on the same flight and the following is the results using this regression technique to model a second order system.

$$H(s) = \frac{10.39}{s^2 + 31.26s + 504.9} \quad (5.2)$$

and

$$H(s) = \frac{10.61}{s^2 + 29.77s + 498.7} \quad (5.3)$$

Converting to standard form as described in equation 2.15:

$$H(s) = \frac{0.0206 * 22.47^2}{s^2 + 2 * 0.69 * 22.47s + 22.47^2} \quad (5.4)$$

and

$$H(s) = \frac{0.0213 * 22.33^2}{s^2 + 2 * 0.67 * 22.33s + 22.33^2} \quad (5.5)$$

It is important to note that this system identification technique run on separate sets of data has produced two models with very similar values for ω_n and ζ .

This produces the average values of:

$$\omega_n = 22.4rad/s$$

$$k = 0.0209$$

$$\zeta = 0.681$$

With the aliasing removed from the chirped input command signals the model is drastically improved and produces the following results:

$$H(s) = \frac{4.409}{s^2 + 27.11s + 430.6} \quad (5.6)$$

and

$$H(s) = \frac{3.295}{s^2 + 18.82s + 2.96.5} \quad (5.7)$$

Converting to standard form as described in equation 2.15:

$$H(s) = \frac{0.0102 * 20.75^2}{s^2 + 2 * 0.65 * 20.75s + 20.75^2} \quad (5.8)$$

and

$$H(s) = \frac{0.0111 * 17.21^2}{s^2 + 2 * 0.54 * 17.21s + 17.21^2} \quad (5.9)$$

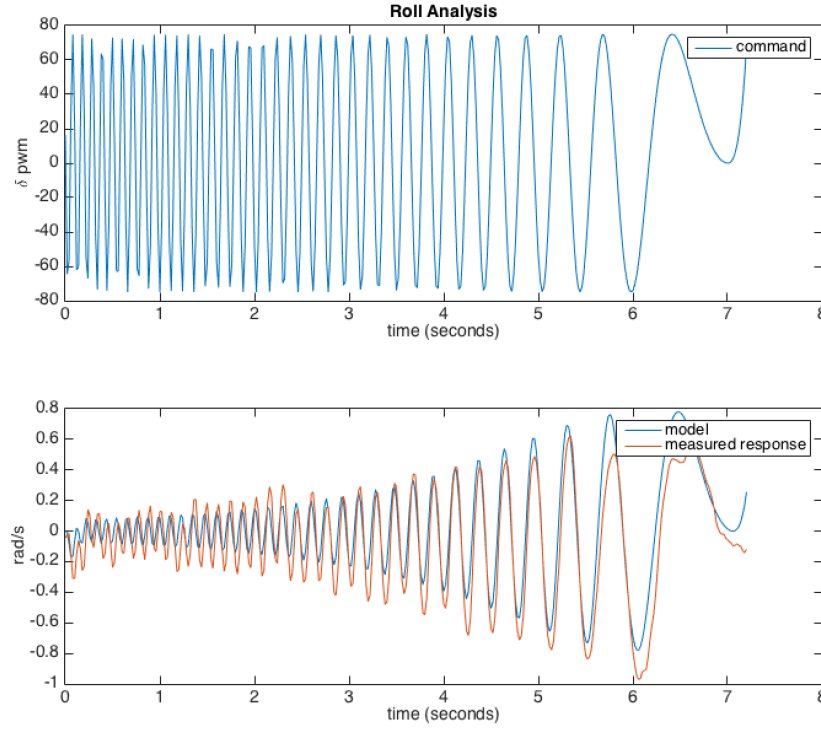


Figure 5.4. Non-Aliased Reverse Chirp model example

This produces the average values of:

$$\omega_n = 18.98 \text{ rad/s}$$

$$k = 0.010$$

$$\zeta = 0.598$$

In the author's experience, these values are reasonable values for this size and weight of airframe. This regression technique has shown potential to create realistic models from actual flight test data. The data must be properly shaped and improved models would result if the data logging rate was increased. The chirp method has the potential to increase the fidelity of the high frequency response of the aircraft if the aliasing issue can be resolved on the command input channel.

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CHAPTER 6:

Recommendation

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CHAPTER 7:

Conclusion

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