# Flight Test Instrumentation System for Small UAS System Identification

*Han-Hsun Lu*

*Joshua Harris*

*Vinicius Goecks*

*Ezekiel Bowden*

*John Valasek*

*Texas A&M University*

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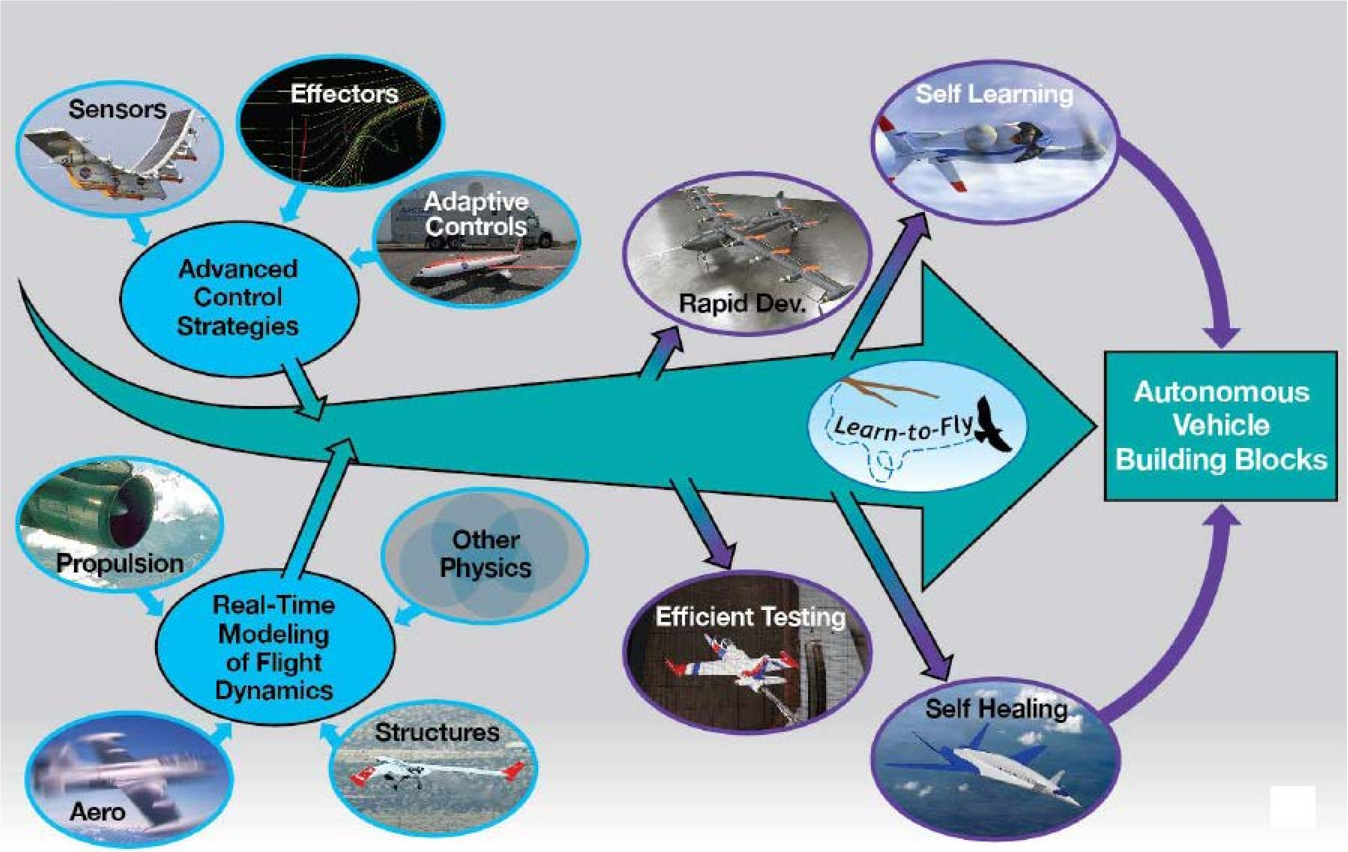
# Outline

- **Motivation**
- **System Identification**
  - Observer Kalman-filter IDentification (OKID)
- **Flight Instrumentation**
  - Developmental Flight Test Instrumentation (DFTI)
- **Flight test results**
- **Conclusions**
- **Future work**

# Motivation - I
# NASA Learn-To-Fly

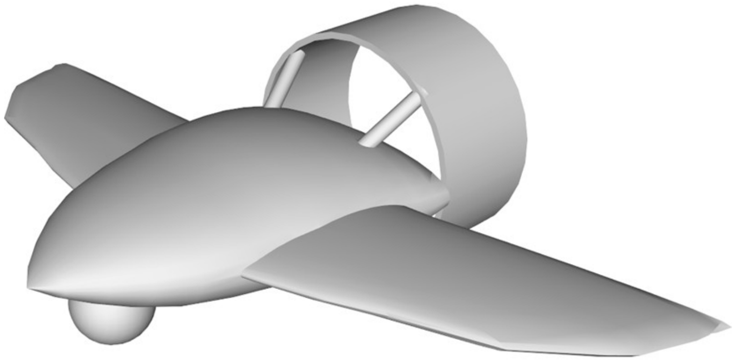
- **Real-Time System Identification and adaptive control**
  - **Approaching Self-Learning and Autonomously-Adapting Vehicles**

- Morelli, Eugene A. "Real-Time Global Nonlinear Aerodynamic Modeling for Learn-To-Fly."(2016).



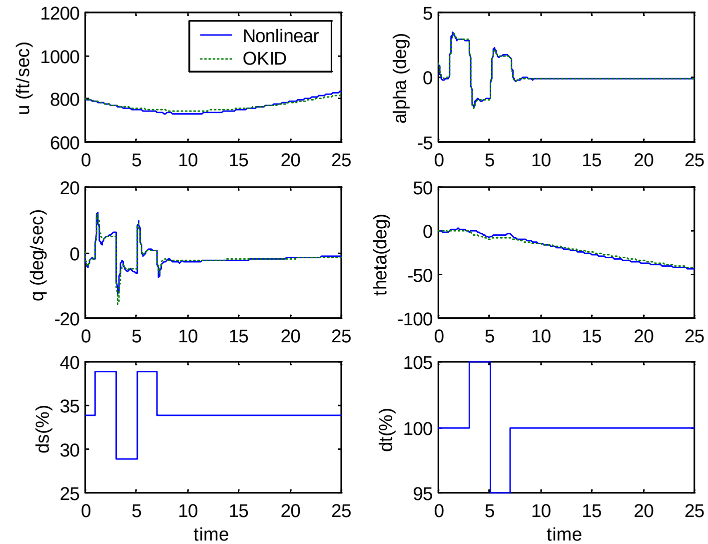
# Motivation - II

- High frequency data is needed for system identification
- Common flight controllers do not provide full aircraft states and control measurements
- Modeling and control systems are often vehicle dependent and not easily portable



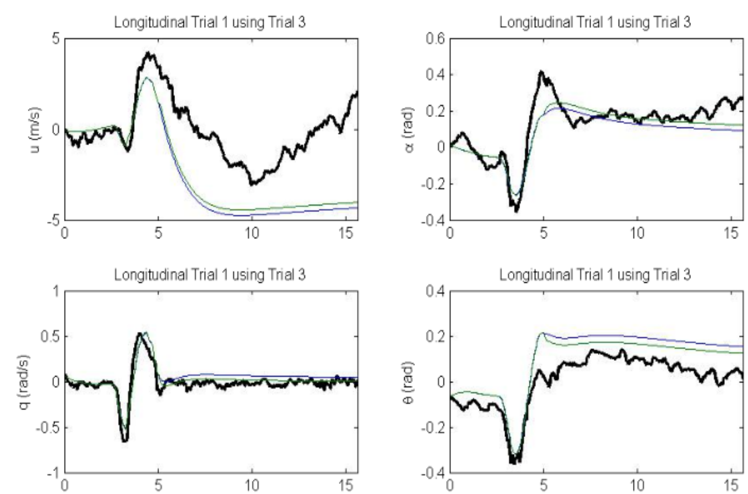
# Previous Work

- (2003) Online identification using OKID on aircrafts in nonlinear 6 DOF simulation
  - Valasek, Chen. "Observer/Kalman filter identification for online system identification of aircraft.“ *Journal of Guidance, Control, Dynamics*




- (2015) UAS flight results with 5 hole probe measurements
  - Woodbury, Arthurs, Valasek "Flight Test Results of Observer/Kalman Filter Identication of the Pegasus Unmanned Vehicle," SciTech Conf.

- (2016) Pixhawk logging states at 50 Hz
  - Arthurs, Valasek, “Precision Onboard Small Sensor System for Unmanned Air Vehicle Testing and Control,” SciTech Conf.

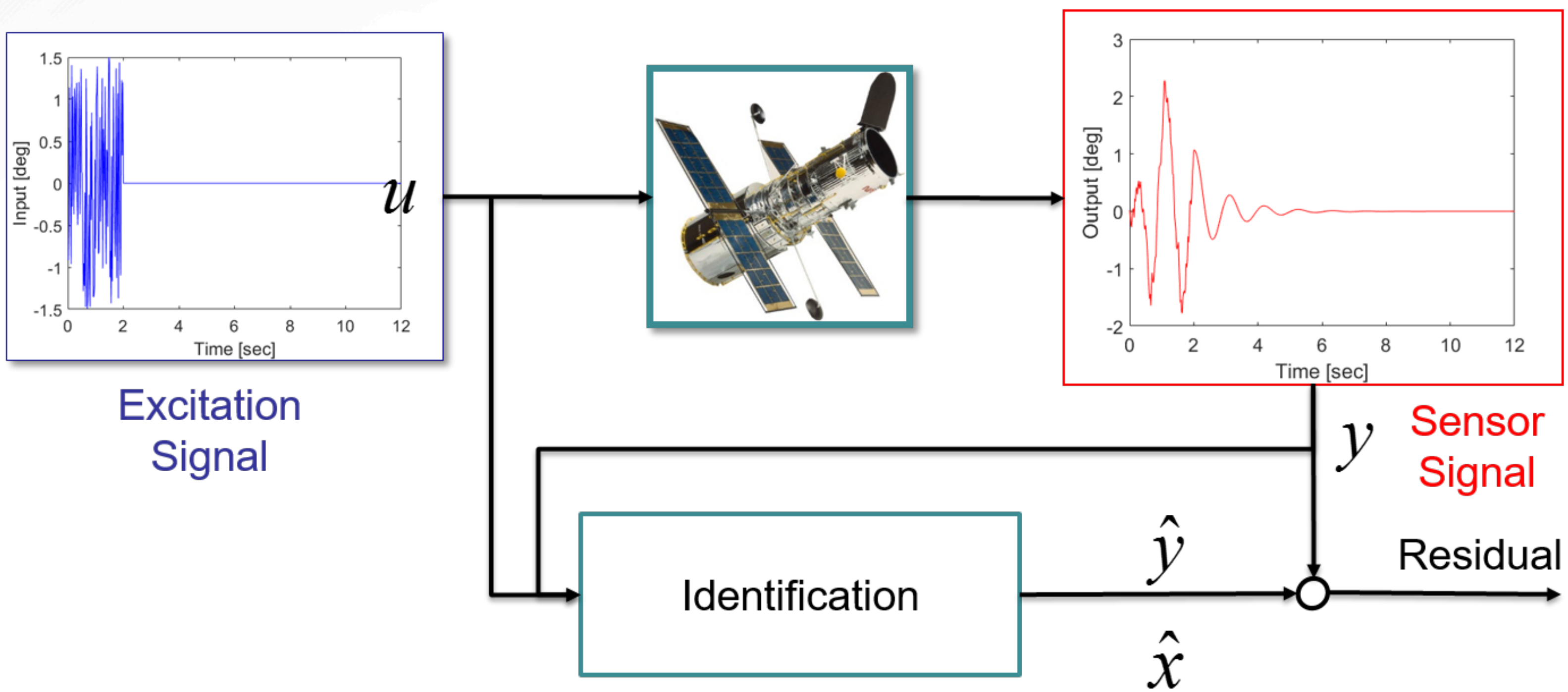


- **Objectives**
  - Develop a system with data acquisition rate of 100 Hz
  - Real time full-state measurements onboard for identification without state estimations
  - Control influence matrix represented as deflections, not PWM

- **Approach**
  1. Log aircraft states at a high rate (100 Hz)
  2. Measure control deflections
  3. Reliable excitation method capable of exciting all the dynamic modes
  4. System should be modular for extensive capabilities
  5. Easily portable between different vehicles

# Introduction-
# System Identification

- Two methods to determine models of systems from experimental data:
  - Parameter Identification
  - System Identification - OKID



# Overview of SysID – ERA/OKID

- An extended version of Ho-Kalman system realization algorithm*
- Developed at NASA Langley Research Center
- Uses input and output measurement data to form the system matrices (A,B,C,D)

* (1965) Ho, B. L. and Kalman, R. E. Effective Construction of Linear State-Variable Models From Input/Output Data.

# Observer/Kalman Filter Identification

- Non-parametric identification from input/output measurements

- Assume linear, discrete-time plant:

$$x_{k+1} = Ax_k + Bu_k$$
$$y_k = Cx_k + Du_k$$

- Introduce observer G: $x_{k+1} = (A+GC)x_k + (B+GD)u_k - Gy_k = \bar{A}x_k + \bar{B}v_k$

$$v_k = \begin{bmatrix} u_k \\ y_k \end{bmatrix}$$

- Rewriting and solving for $y_k$: $y_k = C\left( A^k x_0 + \sum_{i=0}^{k-1} \left( A^{k-i-1} B u_i \right) \right) + Du_k$

*Juang, J.-N., Applied System Identification, Prentice Hall, 1994, pp. 131-199

# Observer/Kalman Filter Identification

- Observer Markov Parameters:

$$\bar{Y}_0 = D$$
$$\bar{Y}_k = C\bar{A}^{p-1}\bar{B}$$
$$= \left[ C(A+GC)^{k-1}(B+GD) \quad -C(A+GC)^{k-1}G \right]$$
$$= \left[ \bar{Y}_k^{(1)} \quad -\bar{Y}_k^{(2)} \right]$$

- System Markov Parameters:

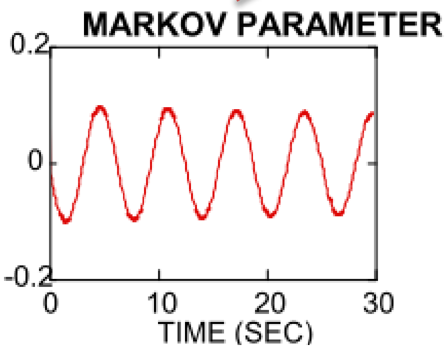
$$Y_k = \bar{Y}_k^{(1)} + \sum_{i=1}^{k} \bar{Y}_i^{(2)} Y_{k-1},\; k = 1, \ldots, p$$
$$Y_k = \sum_{i=1}^{k} \bar{Y}_i^{(2)} Y_{k-1},\; k = p+1, \ldots, \infty$$
$$D = Y_0 = \bar{Y}_0$$

# ERA/OKID

- **Hankel Matrix**

$$H(0) = \begin{bmatrix} Y_1 & Y_2 & \cdots & Y_\beta \\ Y_2 & Y_3 & \cdots & Y_{\beta+1} \\ \vdots & \vdots & \ddots & \vdots \\ Y_\alpha & Y_{\alpha+1} & \cdots & Y_{\alpha+\beta-1} \end{bmatrix} = \begin{bmatrix} CB & CAB & \cdots & CA^{\beta-1}B \\ CAB & CA^2B & \cdots & CA^\beta B \\ \vdots & \vdots & \ddots & \vdots \\ CA^{\alpha-1}B & CA^\alpha B & \cdots & CA^{\alpha+\beta-2}B \end{bmatrix}$$

$$= \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{\alpha-1} \end{bmatrix} \begin{bmatrix} B & AB & \cdots & A^{\beta-1}B \end{bmatrix}$$



# ERA/OKID

$$H(0)=\left[P\Sigma^{1/2}\right]\left[\Sigma^{1/2}Q^{T}\right]$$

- Perform SVD on Hankel Matrix
  - Identified output matrix C

$$\begin{bmatrix} C \\ CA \\ \vdots \\ CA^{\alpha-1} \end{bmatrix}=\left[P\Sigma^{1/2}\right]$$

  - Identified of input matrix B

$$\begin{bmatrix} B & AB & \cdots & A^{\beta-1}B \end{bmatrix}=\left[\Sigma^{1/2}Q^{T}\right]$$

  - Identified A matrix

$$H(0)=\left[P\Sigma^{1/2}\right]\left[\Sigma^{1/2}Q^{T}\right]$$

$$H(1)=\left[P\Sigma^{1/2}\right]A\left[\Sigma^{1/2}Q^{T}\right]$$

$$A=\left[\Sigma^{-1/2}P^{T}\right]H(1)\left[Q\Sigma^{-1/2}\right]$$

# Mode Selection

- Quality indexes including
  - Modal Controllability Index $MCI = 100 \cdot \; |B_{\mathrm{m}}| \max |B_{\mathrm{m}}|$
  - Modal Observability Index $MOI = 100 \cdot \; |C_{\mathrm{m}}| \max |C_{\mathrm{m}}|$
  - Mode Singular Values

$$MSV = 100 \cdot \frac{\dfrac{\sqrt{|B_{\mathrm{m}}| \cdot |C_{\mathrm{m}}|}}{|1 - |\zeta||}}{\max \dfrac{\sqrt{|B_{\mathrm{m}}| \cdot |C_{\mathrm{m}}|}}{|1 - |\zeta||}}$$

System state-space models acquired
Verify through quality indexes

Pappa, Richard S et. all. "Consistent-mode indicator for the eigensystem realization algorithm." (1993)

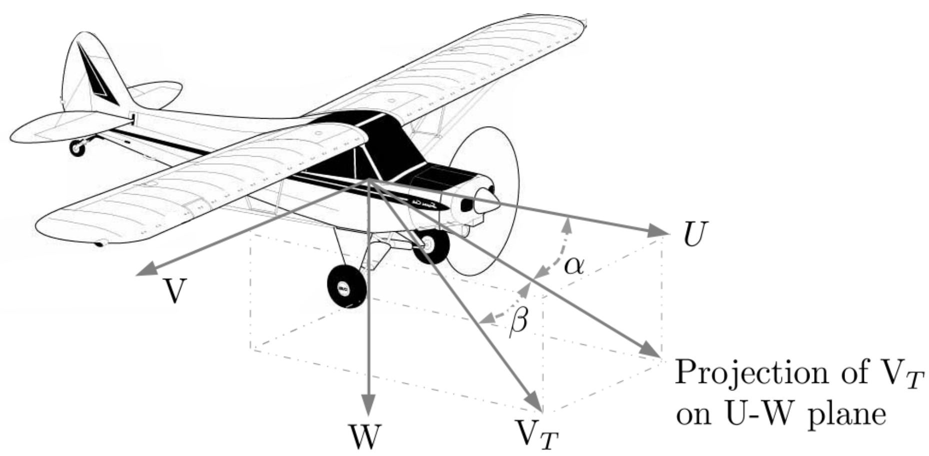
# Vehicle Description

- Measured States
  - From INS
    - GPS
    - Quaternion
    - Body Axis rates/ angles
    - Lat/ Long/ Alt
  - From Air data computer
    - True Airspeed
    - Angle of attack
    - Sideslip angle
- Measured Control
    - Aileron deflections
    - Elevator deflections
    - Rudder deflections
    - Engine RPM

| Hangar – 9 ¼ Scale PA – 18 Super Cub | |
|---|---|
| Wing Span | 8.8 ft |
| Empty Weight | 16.6 lbs |
| Loaded Weight | 25 lbs |
| Batteries | 4S 10000mAhr LiPo Battery |
| Motor | 295V E-Flite Power 110 Brushless motor |
| ESC | 85 A HV |

# Developmental Flight Test Instrumentation System (DFTI)

- Software
  - Primarily developed for use with the BeagleBone Black single-board Linux computer
  - C++11 written multithreading data logger
  - Software open sourced and available at:
  - J. Harris, V. G. Goecks, H.-H. Lu, and J. Valasek, "VSCL Developmental Flight Test Instrumentation," May 2017. [Online]. Available: https://doi.org/10.5281/zenodo.572272
  - https://github.com/tamu-vscl/dfti

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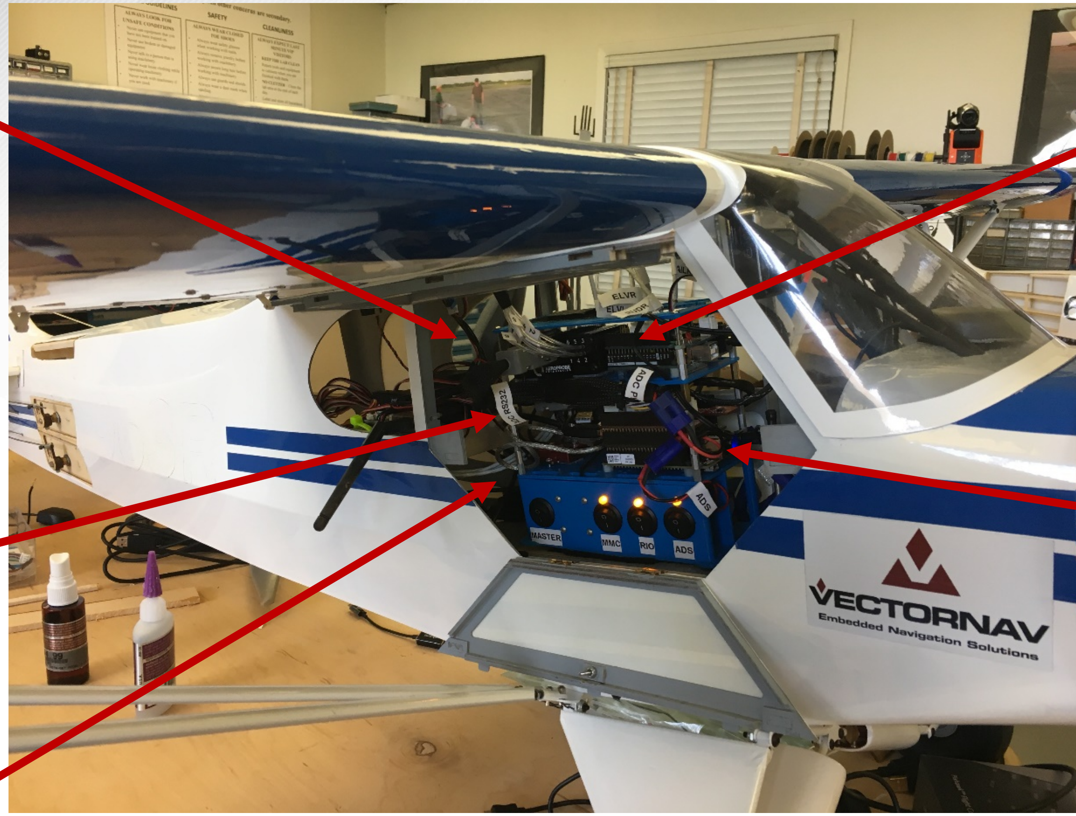
# Developmental Flight Test Instrumentation System (DFTI)

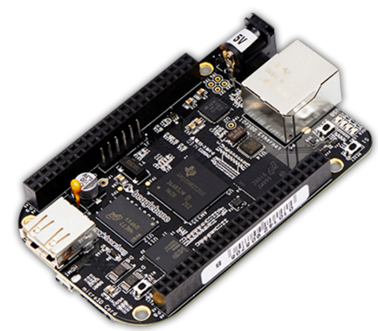
Air Data Computer

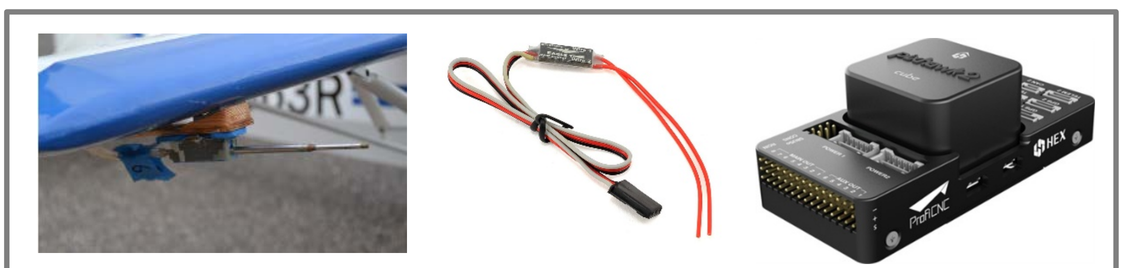

Control Surface logger

IMU

Data Processor



Power





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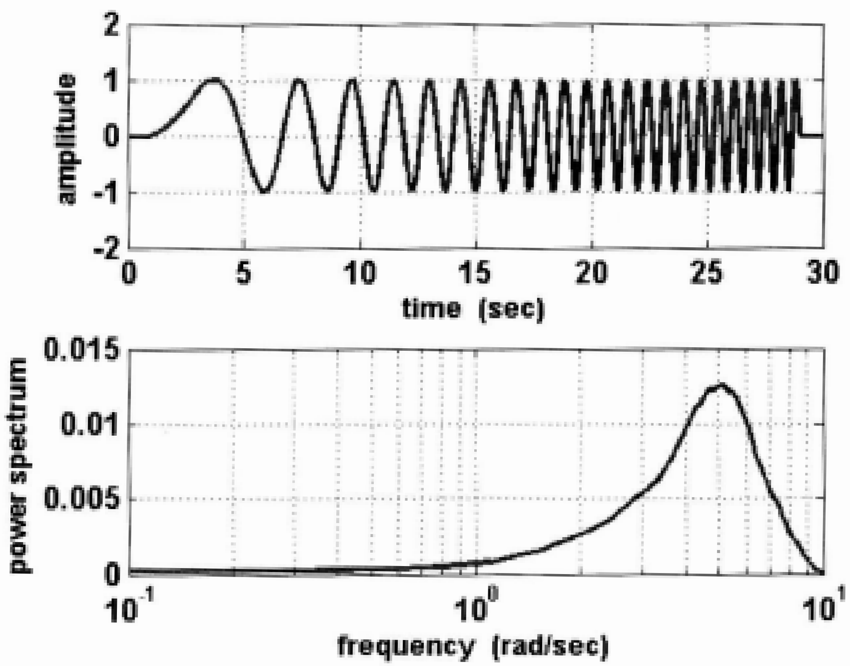
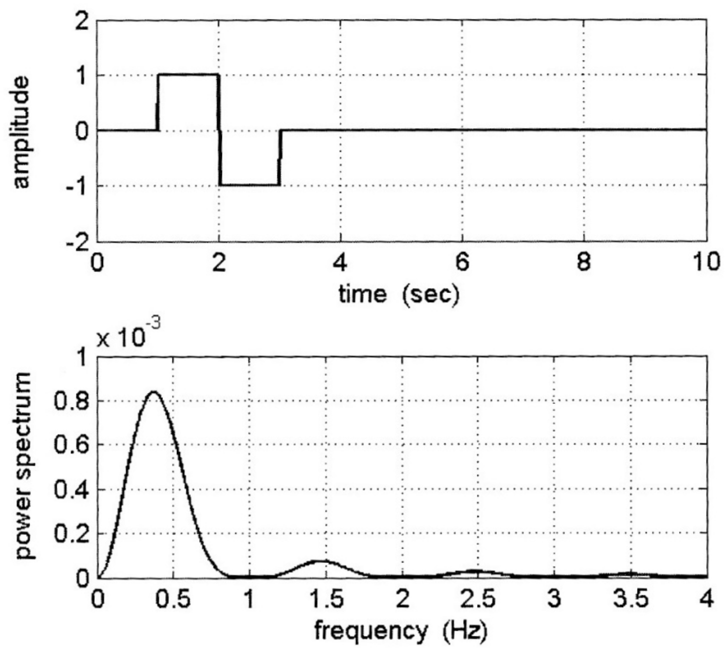
# Input Design

- **Doublets** – two sided pulses
  - amplitude chosen for good S/ N in time

- **Frequency sweep**
  – continuous sinusoid with frequency increasing

Doublets are the most practical and efficient pilot input excitation



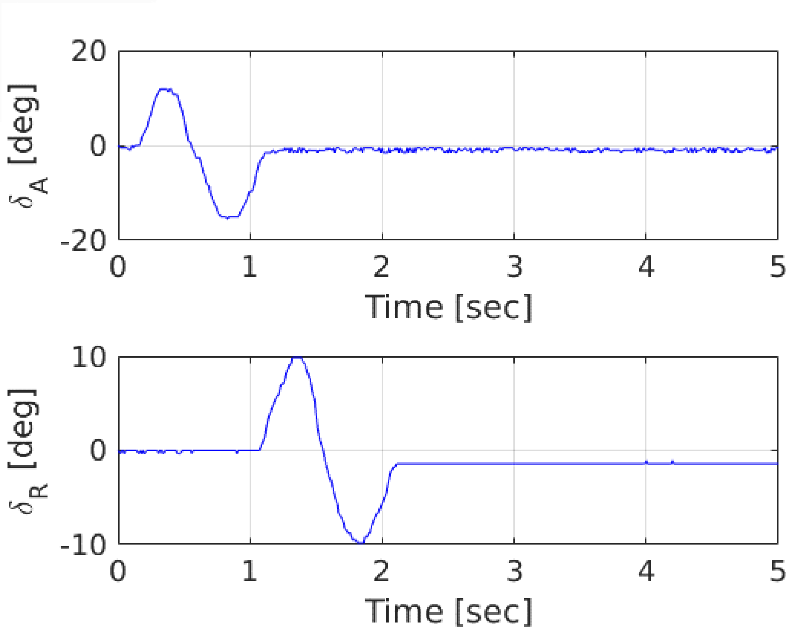
- **Motivation**
  - System Identification
  - Observer Kalman-filter Idendtification (OKID)
- **Flight Test Instrumentation**
  - Developmental Flight Test Instrumentation
- **Flight test results**
- **Conclusions and future work**

# Flight results – Lat/D

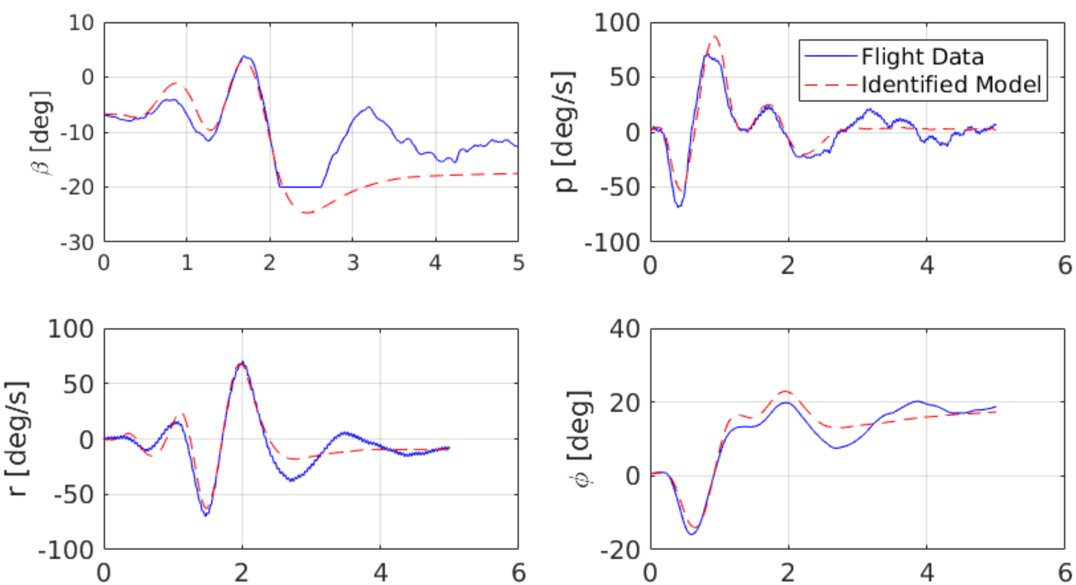
- 24th April, 2017
  - $V_{T_1} = 53$ ft/s , $\alpha_1 = 2.39^\circ$, $h_1 = 209$ ft

$$\begin{Bmatrix} \dot{\beta} \\ \dot{p} \\ \dot{r} \\ \dot{\phi} \end{Bmatrix} = \begin{bmatrix} 0.07918 & -0.1425 & -0.8387 & -0.414 \\ 4.18 & -7.098 & -3.568 & -2.693 \\ 3.444 & 4.548 & -1.98 & -0.8893 \\ -0.04679 & 0.9998 & -0.03553 & -0.02902 \end{bmatrix} \begin{Bmatrix} \beta \\ p \\ r \\ \phi \end{Bmatrix} + \begin{bmatrix} -0.002815 & 0.01296 \\ -0.666 & -0.2216 \\ 0.2464 & -0.5871 \\ -0.01386 & -0.005222 \end{bmatrix} \begin{Bmatrix} \delta_A \\ \delta_R \end{Bmatrix}$$

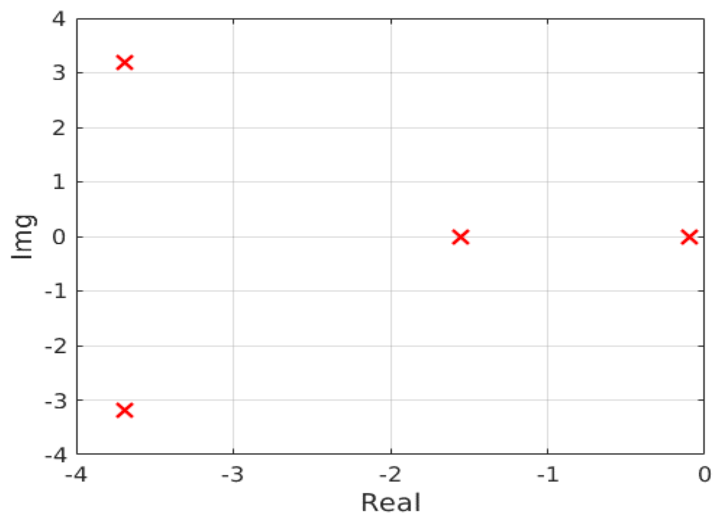
**- Excitations**




**- Response**



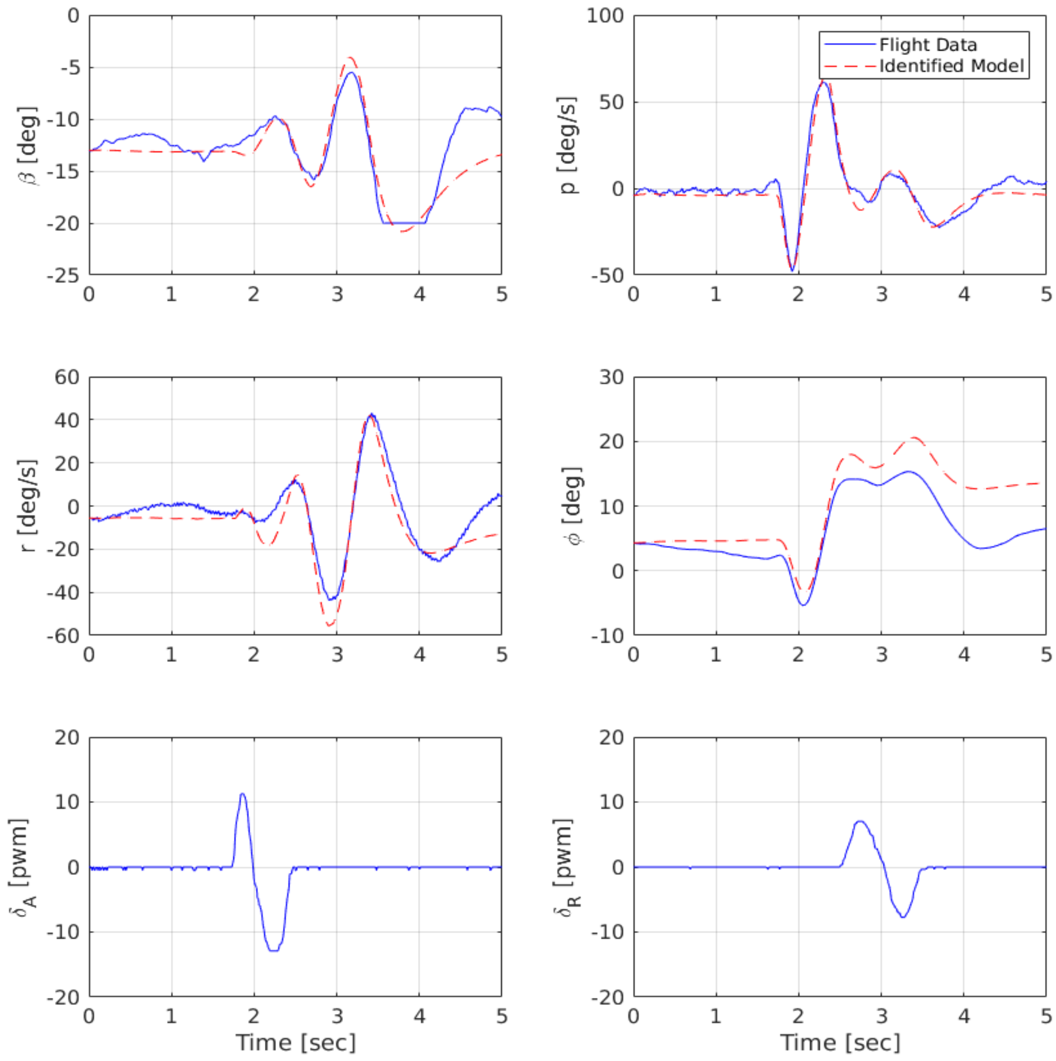
# Flight results – Lat/D




| Lateral/Directional Dynamic Modes | | | |
|---|---|---|---|
| **Mode** | Spiral | Roll | Dutch Roll |
| Eigenvalue | $-0.09$ | $-1.5492$ | $-3.619 \pm j3.1821$ |
| Damping Raio | ---------- | ---------- | 0.7575 |
| Natural Freq. (rad/s) | ---------- | ---------- | 4.88 |
| Time Const. (sec) | 11.11 | 0.65 | ---------- |
| MSV (%) | 100.0 | 66.0 | 56.5 |
| MCI (%) | 9.0 | 55.2 | 100.0 |
| MOI (%) | 86.6 | 100.0 | 95.4 |

# Lat/D Verification

- Compare identified system model with different data set
  - $V_{T_1} = 53$ ft/s , $\alpha_1 = 3.1^\circ$, $h_1 = 324$ ft

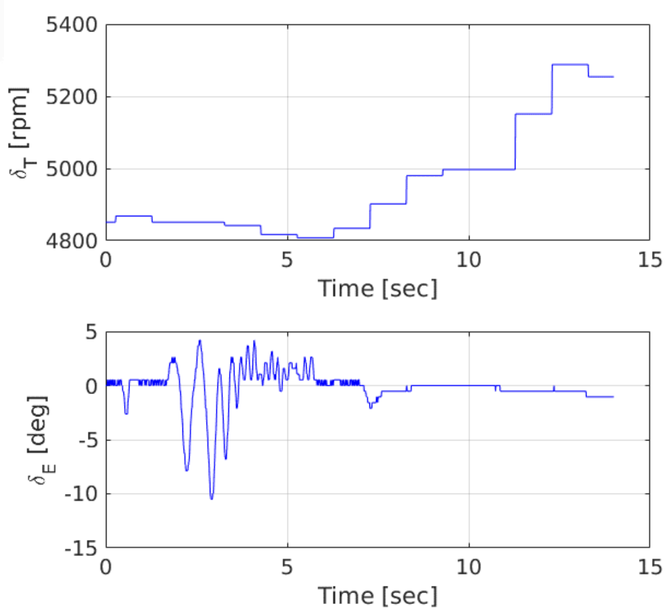


# Flight results – Long

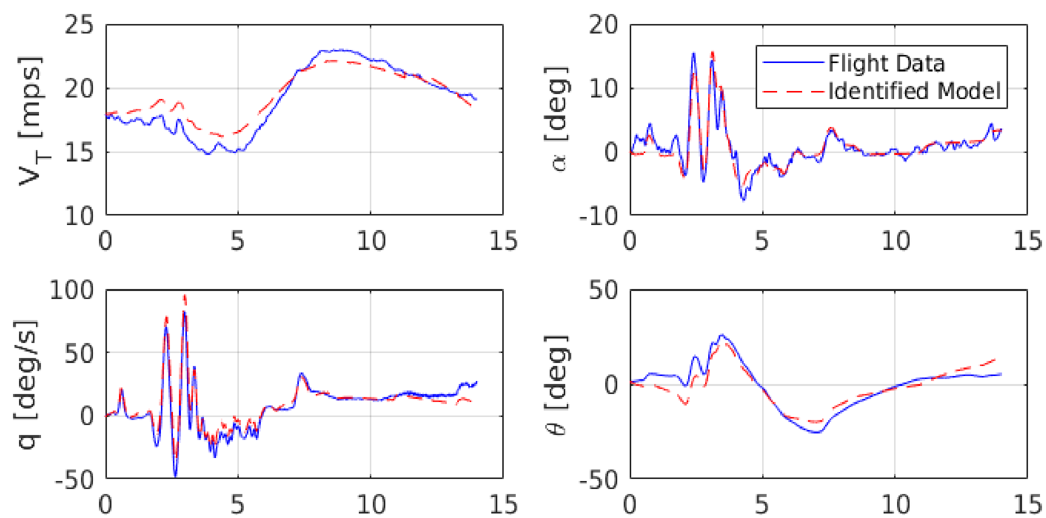
- 24th April, 2017
  - $V_{T_1} = 58$ ft/s , $\alpha_1 = 0.1^{\circ}$, $h_1 = 269$ ft

$$\begin{Bmatrix} \dot{V}_T \\ \dot{\alpha} \\ \dot{q} \\ \dot{\theta} \end{Bmatrix} = \begin{bmatrix} -0.4541 & -2.628 & 1.806 & -7.129 \\ -0.0851 & -2.468 & 1.788 & 0.1256 \\ 0.2701 & -5.163 & -7.527 & 1.255 \\ 0 & -0.2657 & 0.9126 & 0.3046 \end{bmatrix} \begin{Bmatrix} V_T \\ \alpha \\ q \\ \theta \end{Bmatrix} + \begin{bmatrix} 0 & 0.02639 \\ 0 & -0.05085 \\ -0.0002 & -1.417 \\ 0 & -0.01782 \end{bmatrix} \begin{Bmatrix} \delta_T \\ \delta_E \end{Bmatrix}$$

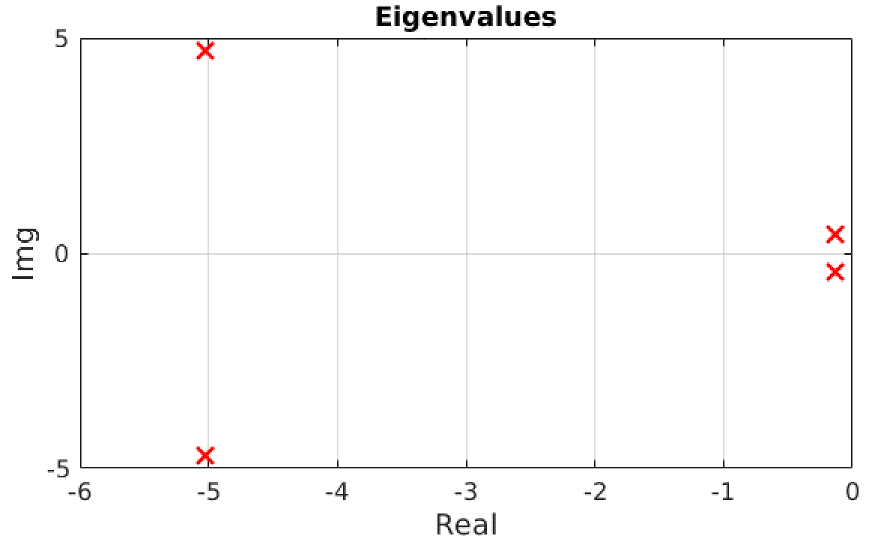
## - Excitations




## - Response



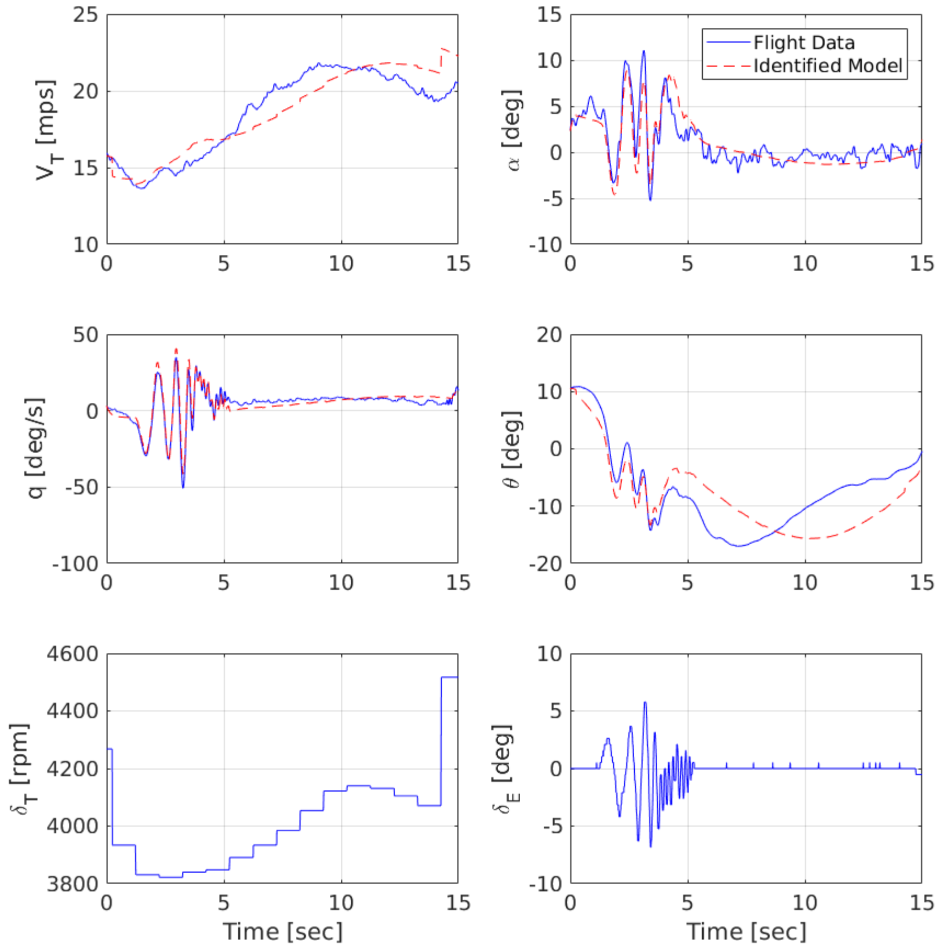
# Flight results – Long




| Longitudinal Dynamic Modes | | |
|---|---|---|
| **Mode** | Phugoid | Short Period |
| Eigenvalue | $-4.6763 \pm j4.4511$ | $-0.1328 \pm j0.4627$ |
| Damping Raio | 0.2758 | 0.7243 |
| Natural Freq. (rad/s) | 0.4838 | 6.4591 |
| MSV (%) | 100.0 | 19.0 |
| MCI (%) | 100.0 | 84.0 |
| MOI (%) | 67.8 | 100.0 |

# Longitudinal Verification

- Compare identified system model with different data set
  - $V_{T_1} = 58$ ft/s , $\alpha_1 = 0.1^{\circ}$, $h_1 = 269$ ft



# Conclusions

- System generates accurate LTI state-space models in desired form
  - Fast sampling captures all modes well and avoids aliasing
- DFTI was shown to work well for system identification
- Signal clipping was experienced in several occasions but did not impact quality of identified models
- The combined system is a promising candidate for online near real-time system identification and control design

# Future Work

- Auto-excitation to improve reliability of excitation quality
  - Doublets
  - Selected sine sweeps
  - 3-2-1-1 excitation
- Online near real-time identification with human-in-the-loop notifications of identified model quality
  - "Online Near Real-Time System Identification of a SUAS" Submitted to SciTech 2018
- Reconfigurable control
  - Model predictive control should be implemented incorporating updated model
  - Model reference adaptive control

# Questions?