



Pilot Adaptation to Changing Dynamics and Adaptive Control

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Also involved:

- **Irene Gregory**
NASA Langley Research Center
 - Controls
- **Chris Hartman**
ATK at NASA Langley Research Center
 - System identification techniques
- **Thanks to Ron Hess for his helpful discussions**

Humans and Adaptive Controllers

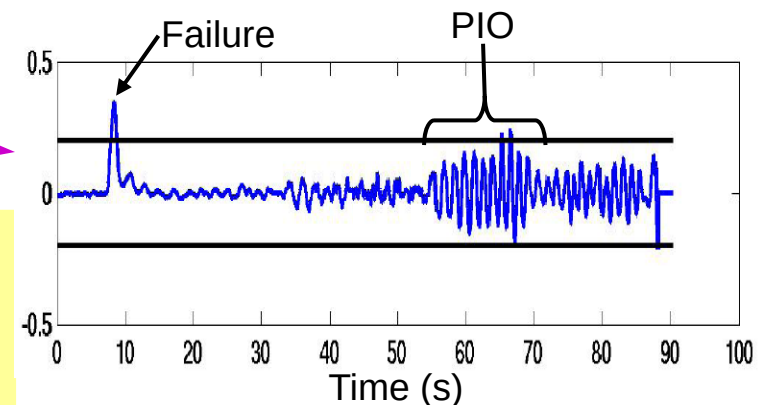


- Humans affect the attitude of the vehicle
- Humans adapt to conditions
 - Cessna 182 $\rightarrow C_{l_p} = -0.487$
 - B747-200 $\rightarrow C_{l_p} = -0.502$
 - F-4 $\rightarrow C_{l_p} = -0.272$

Recent experiences of pilot-in-the-loop with adaptive controller exhibit unpredicted interactions

- Navy F-18
- Dryden IFCS F-15

- Could be due to:
 - (1) Interaction of pilot & controller
 - (2) Pilot not knowing what controller is doing



J. Bosworth & P. Williams-Hayes, 2007

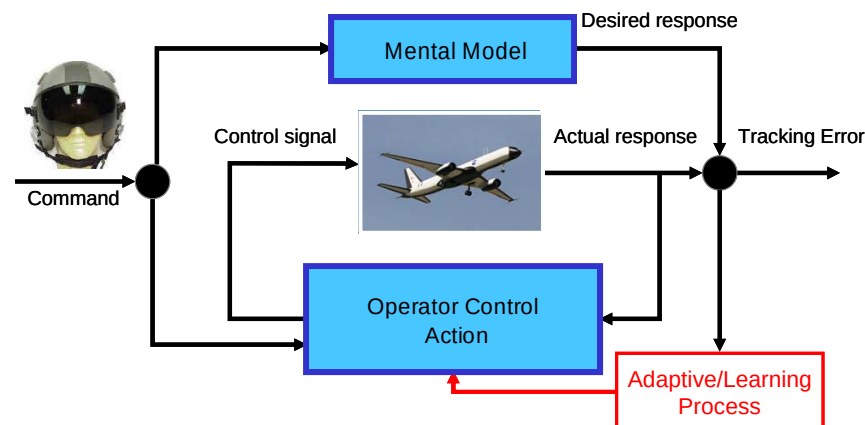


Humans as Adaptive Controller

- Consider the operator as part of the control system
 - Another entity that may affect the attitude of the vehicle
 - » Interaction between human and adaptive controller
 - Mathematically analyze the problem



Model Human as Adaptive Controller → Analyze problem as interaction between 2 adaptive elements

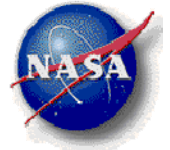




Overall Objectives

- **Can we build a mathematical expression that would reflect adaptive nature of the pilot response to aircraft under anomaly that would allow us to formally analyze pilot in the loop dynamics**
- **Determine how manual control affects an adaptive flight controller design requirements → Does this impose any additional control requirements**
- **Determine informational displays about aircraft flight dynamic changes for pilots**
- **Determine the function allocation between adaptive autopilot and pilot during failures / upset conditions**

Research Objectives



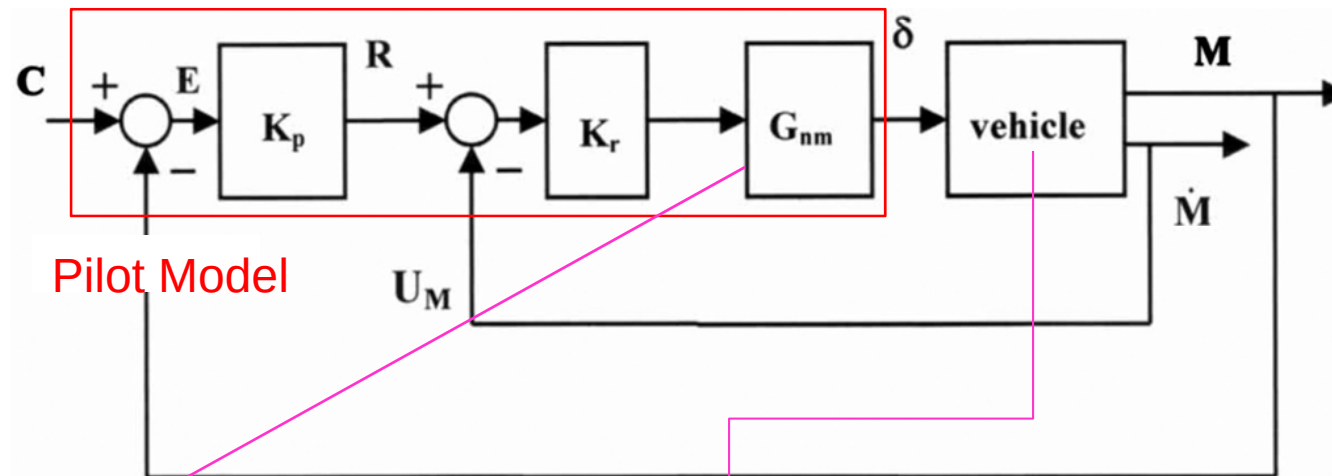
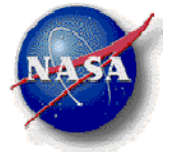
- 1. Determine if system identification techniques can be applied to mathematically model an adapting human pilot**
 - Does pilot model structure remains constant under adaptation?
- 2. Apply system identification techniques to human tracking for various aircraft models to determine how the pilot model changes with aircraft dynamics**
 - Static pilot model
- 3. Apply system identification techniques to human tracking while continuously changing the aircraft model to determine if real-time system identification will be needed for the pilot**
 - Dynamic pilot model



Research Objectives

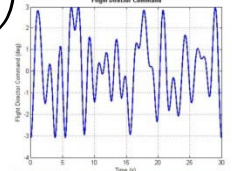
4. Identify what model structure best represents an adaptive pilot
 1. Hess's simplified pursuit model structure
 2. Non-parametric model - frequency response, Volterra series
 3. Identify parametric model structure and parameters from the data
- Helps answer first **Overall Research Objectives**
 - Can we build a mathematical expression that would reflect adaptive nature of the pilot response for aircraft under anomaly that would allow us to formally analyze pilot in the loop dynamics

Experimental Setup



$$G_{nm} = \frac{10^2}{s^2 + 2(0.707)10s + 10^2}$$

$$C \triangleq u = \sum_{k \in \{1, 2, \dots, M\}} A_k \sin\left(\frac{2\pi kt}{T} + \varphi_k\right)$$



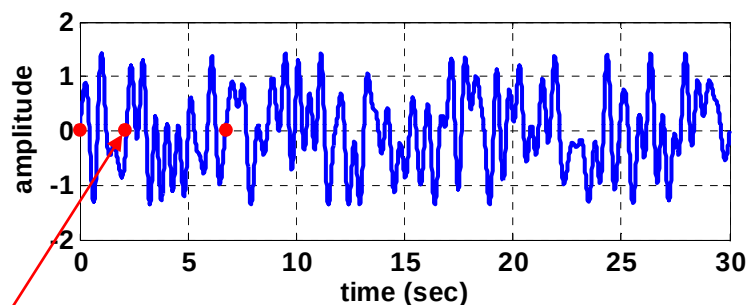
$$\frac{M}{\delta} \triangleq \frac{\theta}{\delta} = \frac{K(1/T_{\theta_2} s + 1)}{s \left[(s/\omega)^2 + 2\zeta(s/\omega) + 1 \right]} e^{-s\tau}$$



Experimental Setup – Tracking Task

- Longitudinal tracking task

- 30 sec
- Subject shown commanded position and error from commanded position → pursuit tracking task



13 Discrete Freq → [0.1, 10] rad/sec

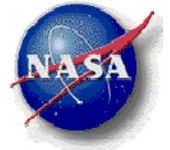
$$u = \sum_{k \in \{1, 2, \dots, M\}} A_k \sin\left(\frac{2\pi kt}{T} + \phi_k\right)$$

Phase angles → random

Amplitude → customize the power spectrum

- Multi-sine – sum of sinusoids with different frequencies
- Start time within the period varied but was always when amplitude = 0

Experimental Setup – Independent Variables



- **Closed-loop longitudinal short-period dynamics**

- Short-period dynamics are most important for flying qualities

- $$\frac{\theta}{\delta} = \frac{K \left(\frac{1}{T_{\theta_2}} s + 1 \right)}{s \left[\left(\frac{s}{\omega} \right)^2 + 2\zeta \left(\frac{s}{\omega} \right) + 1 \right]} e^{-s\tau}$$

- **Damping ratio (ζ)**

- 0.7 – nominal
- 0.4 & 1.0

- **Frequency (ω)**

- 1 Hz – nominal
- 0.5 Hz & 1.5 Hz

- **Time delay (τ)**

- 75 ms – nominal
- 0 ms & 150 ms

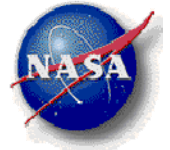
- **Zero Location ($1/T_{\theta_2}$)**

- 1.0 – nominal
- 0.5 & 1.5

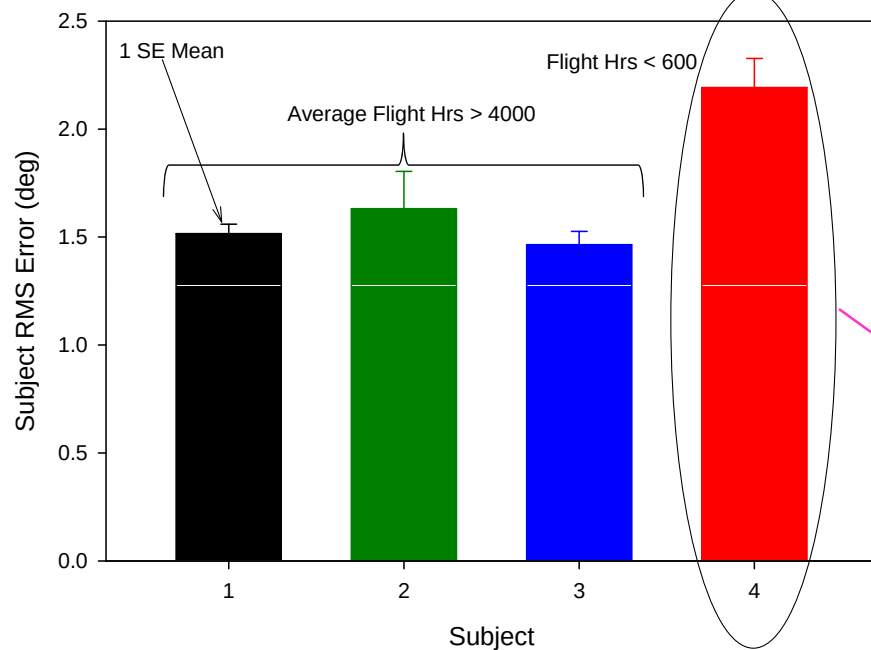
- **Gain (K)**

- 2.0 – nominal
- 1.0 & 3.0

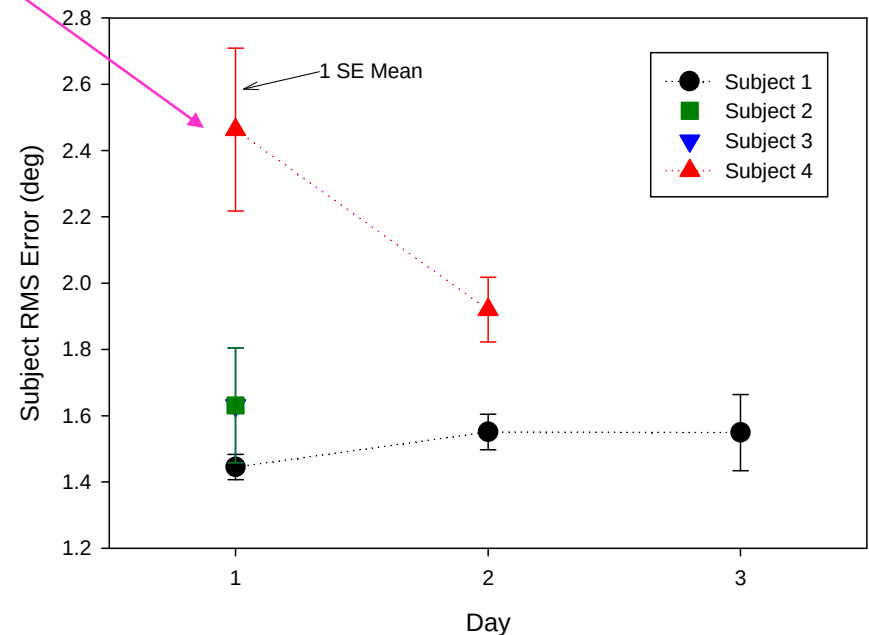
Between Subject Tracking Ability



- **Varies by subject based more on experience**
 - Strong learning effect for inexperienced subject



Note: SE Mean = Standard Error of the Mean





Between Subject Tracking Differences

- When closely following a high frequency signal, tracking ability may vary only slightly between pilots as experience increases → May not need to take into consideration individual differences in developing a mathematical model of an adapting human pilot

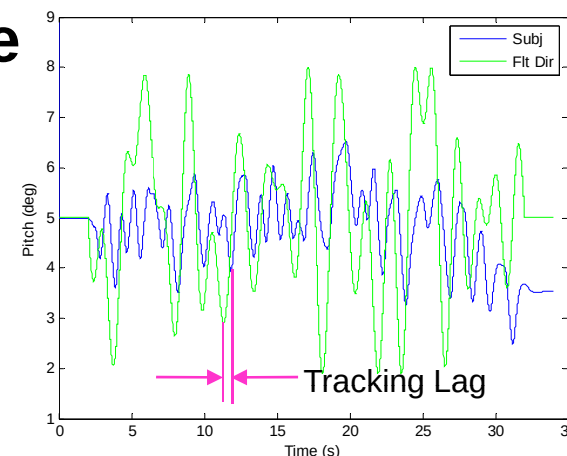
BUT

- Tracking styles were similar among 4 subjects
 - Tracking task was not fully representative of typical aircraft attitude flying tasks
 - » Turbulence mitigation
 - Need to look for:
 - (1) “smooth” and “abrupt” controllers
 - (2) “maintain zero error” and “maintain error within x ” controllers
- Differences may be more noticeable in a more realistic flying task



Subject Tracking Lag on Tracking Flt Dir

- **Tracking Lag = subject peak time – corresponding tracking signal peak time**



- **Too small a subject pool to determine if there is a statistical dependence on subject**

Subject	Tracking Lag Mean (s)	Tracking Lag SE Mean
1	0.435	0.018
2	0.380	0.011
3	0.387	0.025
4	0.440	0.017

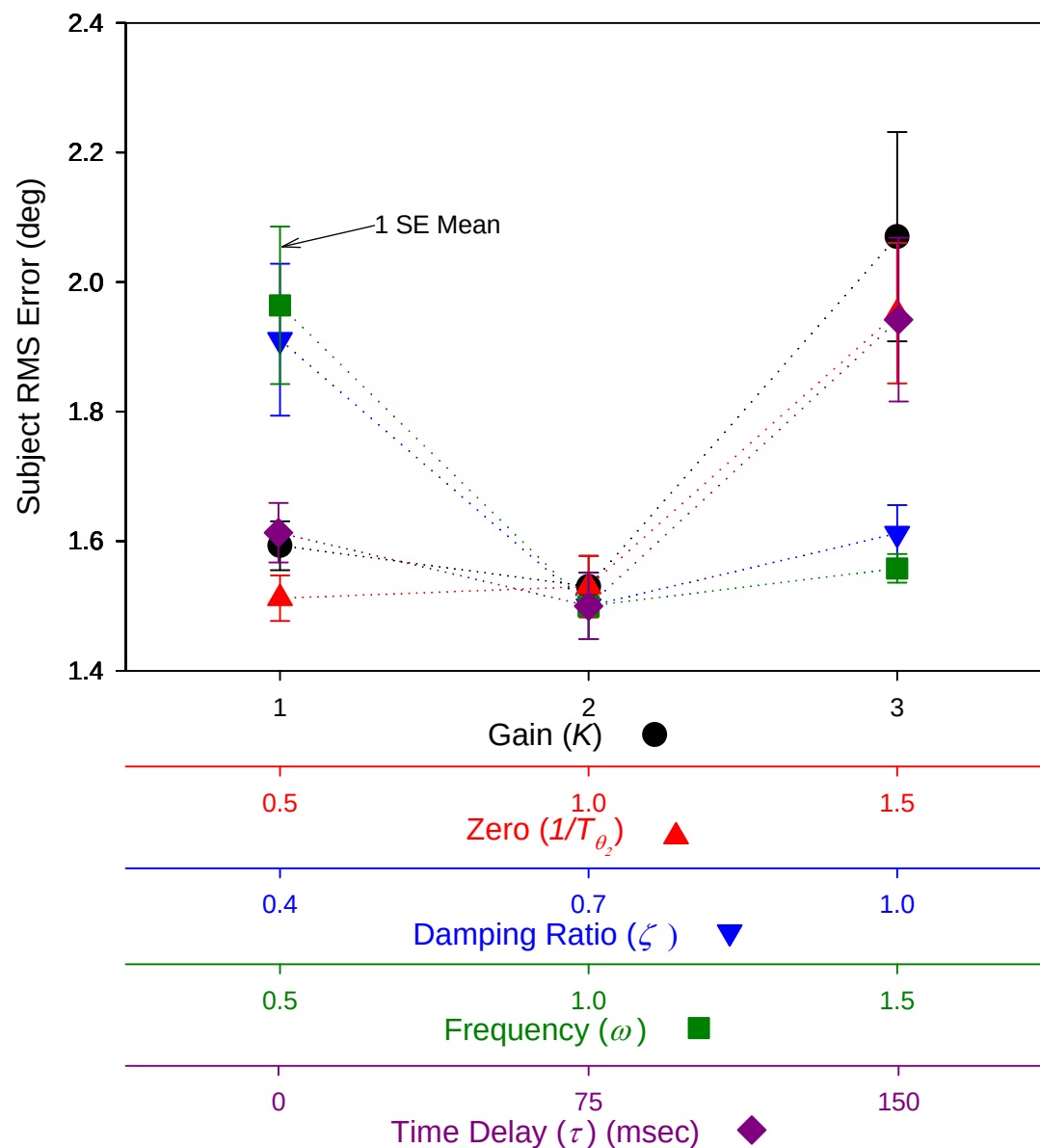
Note: SE Mean = Standard Error of the Mean

- **Subject time differences may be attributable to piloting styles**

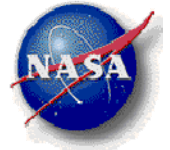
Vehicle Dynamics Effects on Tracking

- **Consistent subject behavior with system dynamics**

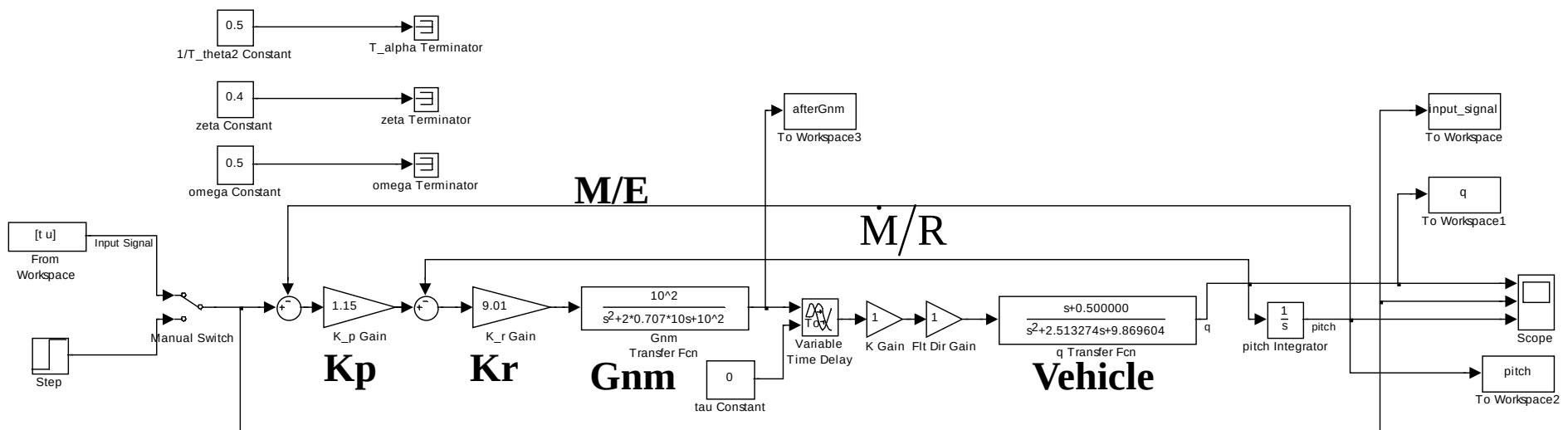
- Minimize time delay
- Desired range for K , $1/T_{\theta_2}$, ζ , and ω



Theoretical Calculation of Kp & Kr

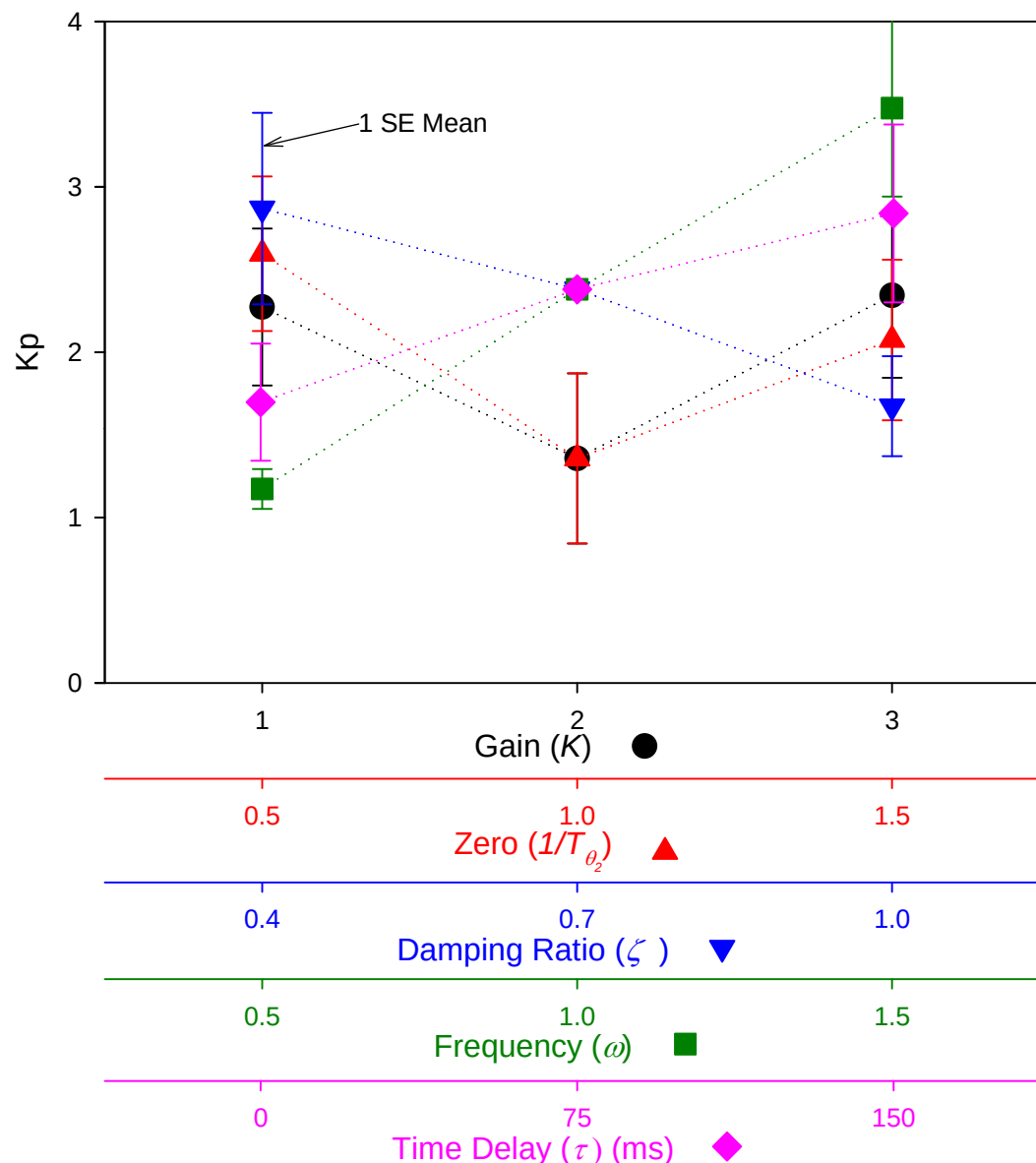


- Kr → damping ratio of most lightly damped mode of $\dot{M}/R = 0.15$
- Crossover frequency = 0.5
- Kp → gain needed to have M/E at crossover frequency
- τ incorporated using a Pade approximation



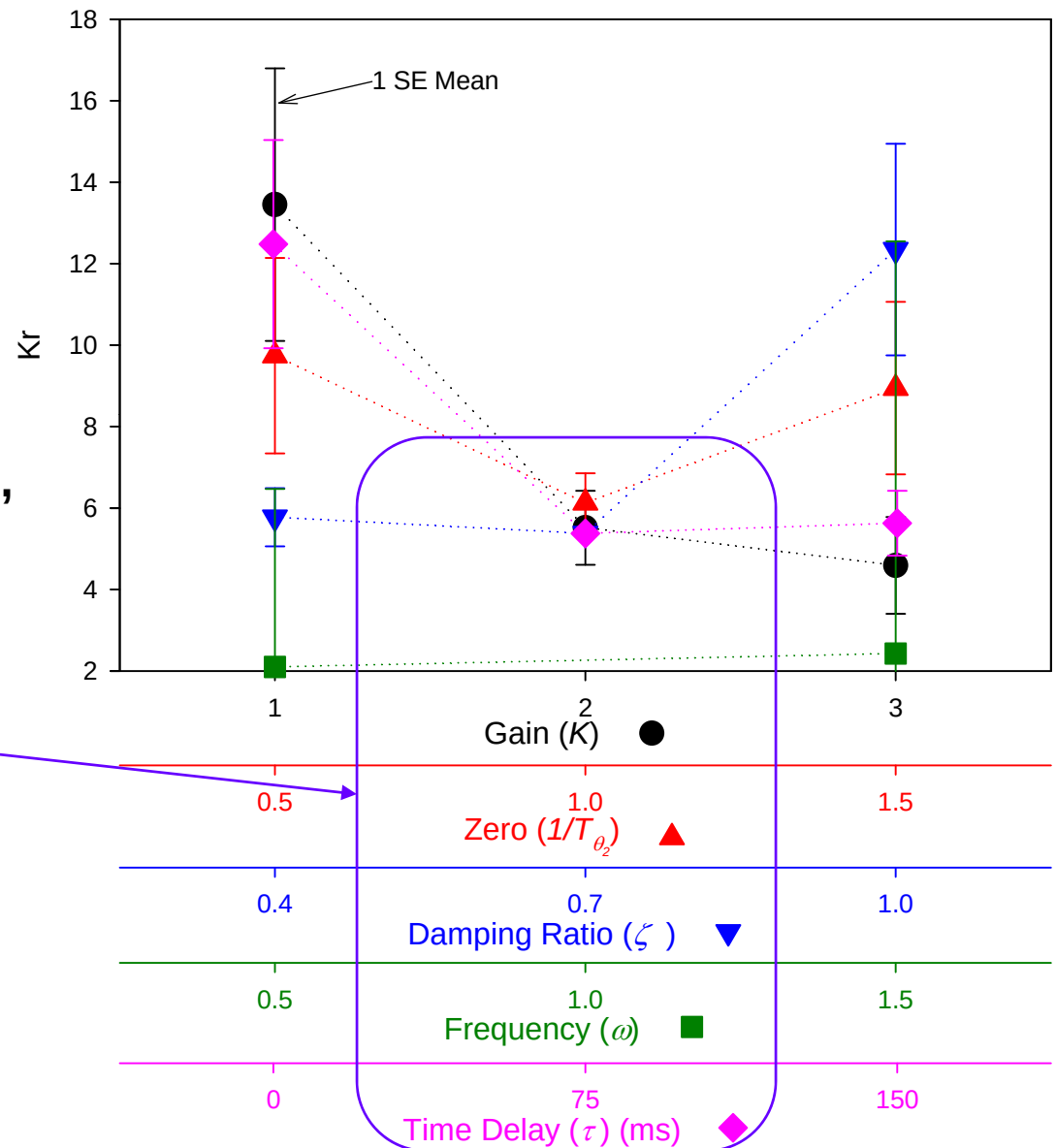
Theoretical Kp Values

- Kp as a function of system dynamics
- Error bars due to other system dynamic variables changing
 - e.g., $K=1$, $1/T_{\theta_2}=[0.5,1,1.5]$, $\zeta=[0.4,0.7,1]$, $\omega=[0.5,1,1.5]$, and $\tau=[0,75,150]$



Theoretical Kr Values

- K_p as a function of system dynamics
- Error bars due to other system dynamic variables changing
 - e.g., $K=1$, $1/T_{\theta_2}=[0.5,1,1.5]$, $\zeta=[0.4,0.7,1]$, $\omega=[0.5,1,1.5]$, and $\tau=[0,75,150]$
- Note the minimum error for a set of dynamic values $\rightarrow$ would imply the best match for Hess model





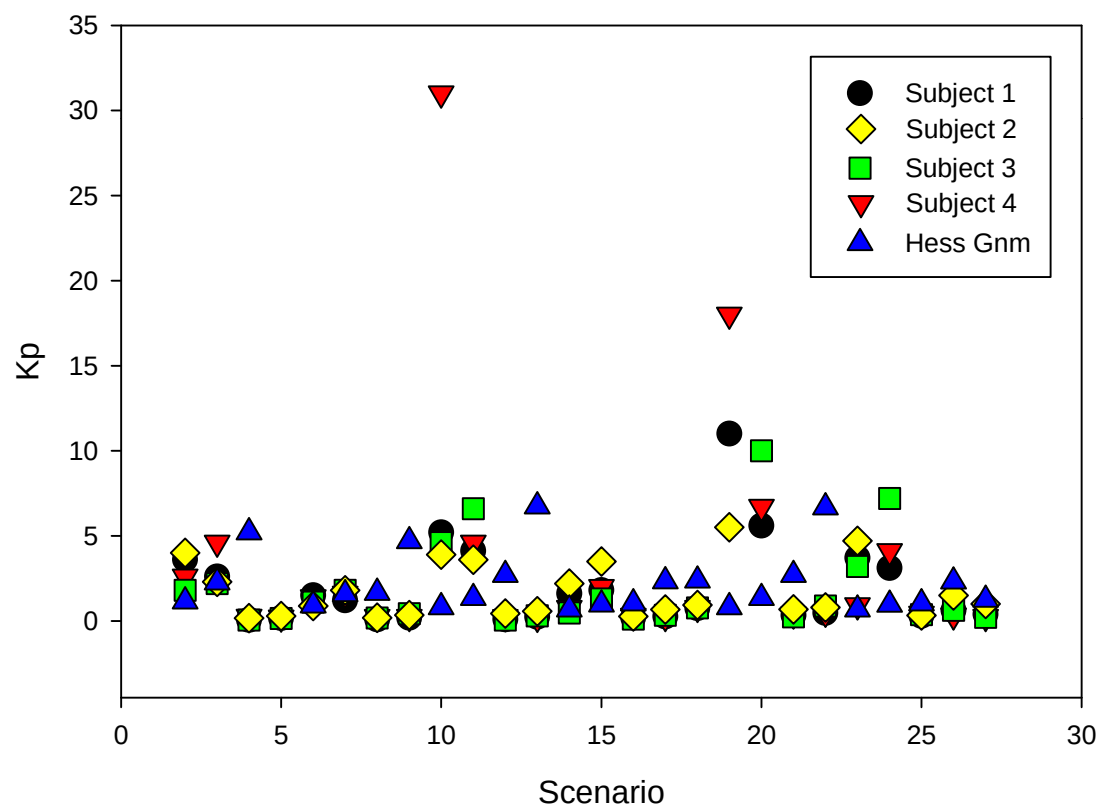
Calculated Kp & Kr Using System ID

- Used Hess simplified pursuit model as the assumed model structure for the pilot model
- Used system identification techniques on the pilot tracking data to calculate Kp and Kr
 - System ID tool developed by Gene Morelli (SIDPAC) and implemented by Chris Hartman
- Kp and Kr highly dependent on system dynamics, $f(K, 1/T_{\theta_2}, \zeta, \omega, \tau)$, or equivalent on scenarios in experimental setup
- Once data was properly set up, Kp and Kr were calculated very quickly → potential to calculate in real time



Kp Comparisons

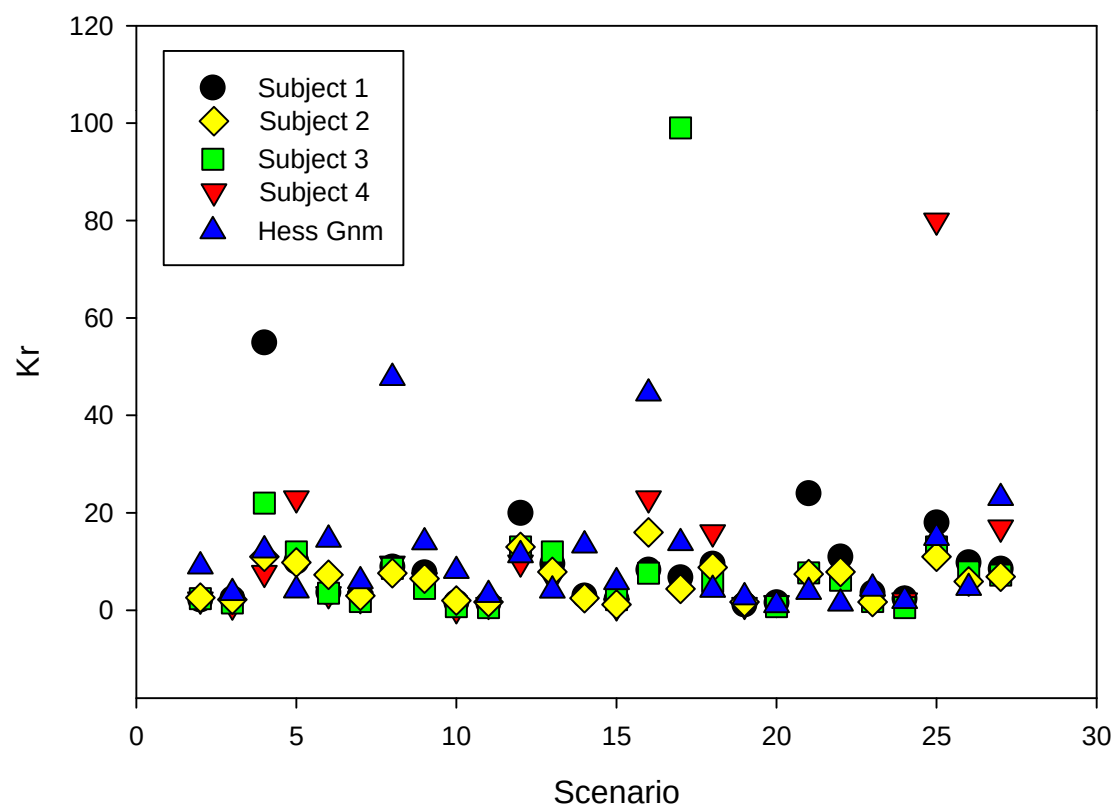
- Appears to be some dependence on subject
 - May be learning effects, piloting styles
- Scenario (values of K , $1/T_{\theta_2}$, ζ , ω , and τ) appears to affect Kp the most
- Matches between theoretical Kp ($\blacktriangle$) and Kp values calculated using system identification are dependent on a specific set of dynamics
- Subjects were not affected by day





Kr Comparisons (Similar to Kp)

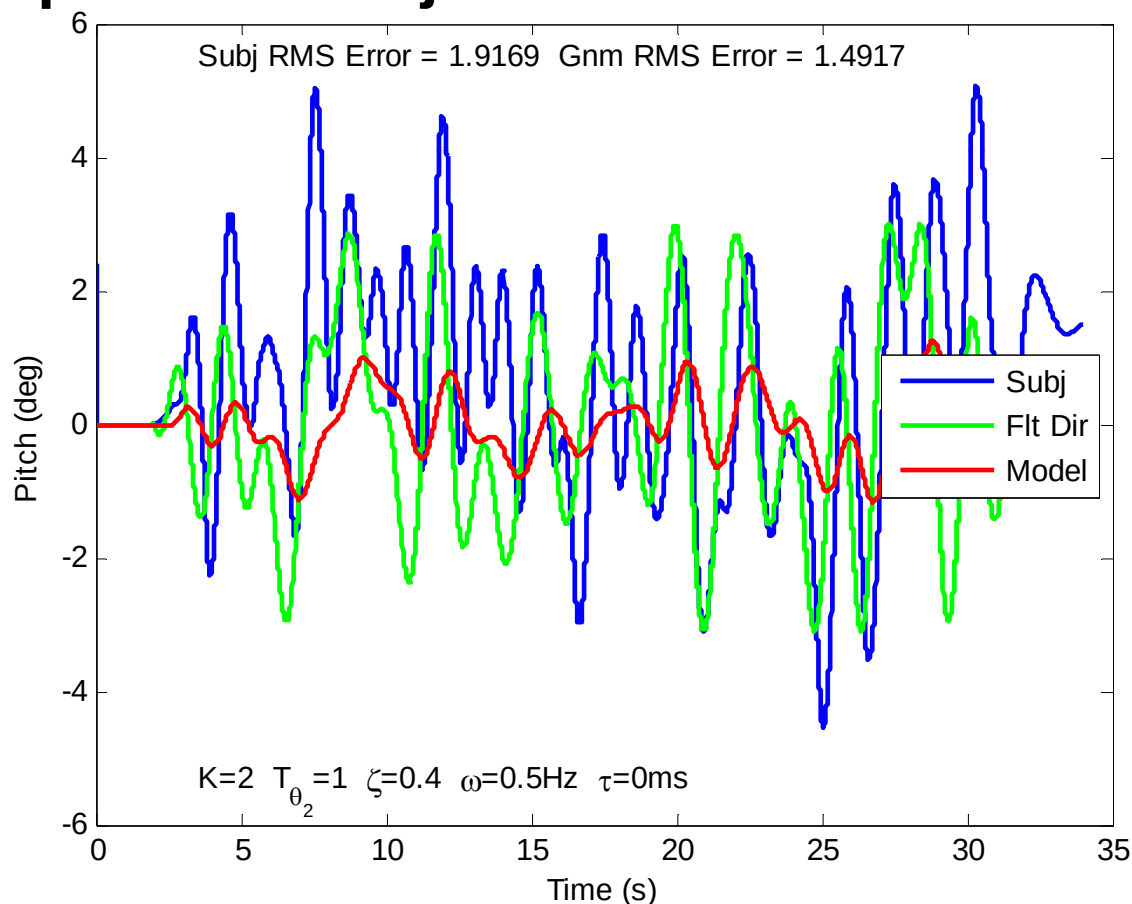
- Appears to be some dependence on subject
 - May be learning effects, piloting styles
- Scenario (values of K , $1/T_{\theta_2}$, ζ , ω , and τ) appears to affect Kr the most
- Matches between theoretical Kp (▲) and Kp values calculated using system identification are dependent on a specific set of dynamics
- Subjects were not affected by day





Subject Tracking Compared to Hess Model

- Subjects could follow higher frequencies and higher amplitudes
- Hess simplified pursuit model had lower RMS errors when compared to subjects

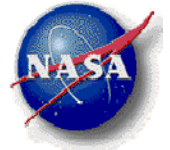




Therefore ...

- **Experience appears to affect tracking ability and tracking lag**
 - Piloting styles were similar among 4 subjects
 - » No additional feedback in tracking ability was given during the test besides current position and desired position during the scenario
 - Differences may be more noticeable in a more realistic flying task
- **Affects on calculated K_p and K_r based on subject data**
 - Vehicle dynamics affect values the most
 - Subject has some minor affects
 - Day of experiment has no effect
- **Once subject data was properly set up, K_p and K_r were calculated very quickly using system identification → implying that real time calculation is possible using the Hess simplified pursuit model as the assumed model structure for the pilot model**

Next Steps



- **Modify Hess model**

- Include higher frequencies
- Make it a bit less “accurate”
- Non-parametric model – frequency response, Volterra series
- Identify parametric model structure and parameters from the data

} Is real-time parameter estimation possible?

- **Apply system identification techniques to human tracking while continuously changing the aircraft model to determine if real-time system identification will be needed for the pilot → dynamic pilot model**

- Are pilots unique or are there groupings based on piloting styles?

- **Informational displays to show flight envelope**

- After adaptation, do pilots need to know available control authority?

» Possible information wanted by pilots:

- (1) How much can I turn
- (2) How fast can I change altitude
- (3) What are my speed limits

} From a survey