PILOTING CHANGES TO CHANGING AIRCRAFT DYNAMICS: WHAT DO PILOTS NEED TO KNOW?

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Abstract

An experiment was conducted to quantify the effects of changing dynamics on a subject's ability to track a signal in order to eventually model a pilot adapting to changing aircraft dynamics. The data will be used to identify primary aircraft dynamics variables that influence changes in pilot's response and produce a simplified pilot model that incorporates this relationship. Each run incorporated a different set of second-order aircraft dynamics representing short period transfer function pitch attitude response: damping ratio, frequency, gain, zero location, and time delay. The subject's ability to conduct the tracking task was the greatest source of root mean square error tracking variability. As for the aircraft dynamics, the factors that affected the subjects' ability to conduct the tracking were the time delay, frequency, and zero location. In addition to creating a simplified pilot model, the results of the experiment can be utilized in an advisory capacity. A situation awareness/prediction aid based on the pilot behavior and aircraft dynamics may help tailor pilot's inputs more quickly so that PIO or an upset condition can be avoided.

Introduction

Significant research has been conducted to model or identify the pilot, as a way to quantify handling qualities or to better understand the behavior of a human pilot in controlling a vehicle [1-7]. Our research is investigating new analytical methods to model the pilot's changing behavior over short time periods in response to changing aircraft dynamics.

A model that captures the pilot's adaptability to changing aircraft dynamics without *a priori* knowledge of these changes is the long-term objective of this research. Availability of such an analytical model would have impact in a number of different areas; among these are decision aids for the pilot, function allocation between the pilot and automation especially during changes in effective dynamics, and potential requirements for adaptive control law design. The research presented here builds on past work to provide tools to analyze and solve this type of modeling problem.

Method

An experiment was conducted to quantify the effects of changing dynamics on a subject's ability to track a signal in order to eventually model a pilot adapting to changing aircraft dynamics. This paper documents the development of a database that will be used for this work. The experiment evaluated primary aircraft dynamics variables that influence changes in pilot's response and produce a simplified pilot model that incorporates this relationship.

The experiment, conducted to identify the pilot-dynamic variable relationship, required each subject to track as closely as possible a pitch attitude signal. The input for the tracking task was designed to contain a variety of frequencies in the frequency range associated with human pilot inputs, namely 0.1 to 10 rad/sec. Each run incorporated a different set of second-order aircraft dynamics representing short period transfer function pitch attitude response. This response was then displayed to the pilot as the aircraft response.

Independent Variables

The following independent variables were controlled during each data run.

Pitch Dynamics

This experiment looked at short period dynamics, which affect flying qualities the most. Therefore, longitudinal dynamics were controlled while lateral/directional and thrust values were held constant at a heading of 40 deg and a speed of 300 kts. The altitude at the beginning of each data run was 10,000 ft. The aircraft short-period pitch attitude transfer function was:

$$\frac{\theta}{\delta}(s) = \frac{K\left(s + L_{\alpha}\right)}{s\left[\left(s/\omega\right)^{2} + 2\varsigma\left(s/\omega\right) + 1\right]} e^{-\tau s} \qquad (1)$$

where θ is pitch attitude and δ is pilot stick. The damping ratio (ς) was 0.4, 0.7, or 1. The short period frequency (ω) was 0.5 Hz, 1 Hz, or 1.5 Hz. Gain (K) was 1, 2, or 3. Zero location (L_α) was 0.5, 1, or 1.5. Lastly, time delay τ was 0 ms, 75 ms, or 150 ms.

Tracking Signal

The maneuver was designed as a 30 sec longitudinal tracking task. The tracking command input contained a range of frequencies and amplitudes to excite an appropriate dynamic range.

The longitudinal tracking task was designed to contain a variety of discrete frequencies in the frequency range associated with human pilot inputs, namely 0.1 to 10 rad/sec. The input design method is described in detail by Klein and Morelli [8, 9]. The result was the equivalent of a frequency sweep input, but used many sinusoidal components with discrete frequencies applied simultaneously, instead of a single sinusoid with frequency increasing monotonically in time.

Figure 1 shows an example tracking task. The sum-of-sines task was generated as:

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

where *u(t)* is the pitch attitude tracking command (deg), the discrete frequencies $2\pi k/T$ were chosen to span the frequency range of 0.1 to 10 rad/sec, the phase angles (ϕ_k) were random, and the amplitudes (A_k) were chosen to customize the power spectrum of the multi-sine input. In this application, the phase angles were chosen at random to emulate a random sinusoidal input. The frequency indices (k) were chosen at irregular intervals, which also helps to emulate a random sinusoidal input.

Subjects

Four pilots participated as subjects. The average age was 50 (standard deviation of 3.6) years old. The average years flying was 20.5±12 and the average number of flight hours was 3312±4483 hrs. Subject 2 had the least number of flight hours (<600 hrs) and years flying (≈ 6) whereas the next closest subject had just about 1000 flight hours and approximately 15 years of flying experience. Subject 4 had the most

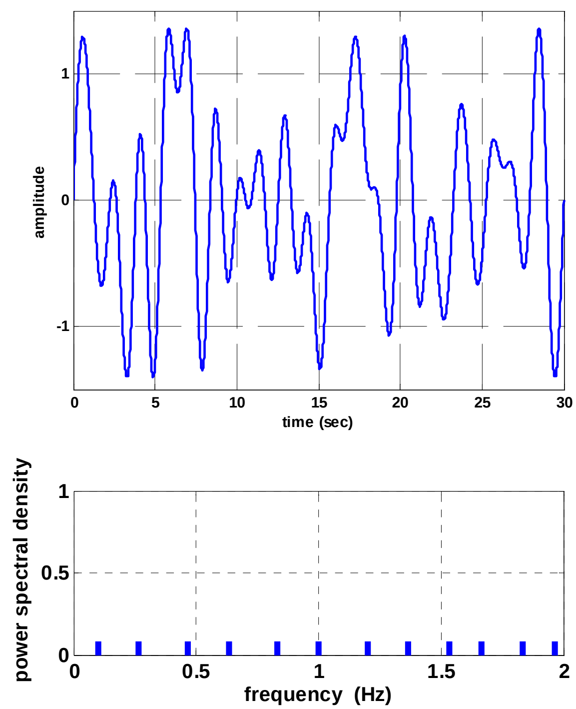

Figure 1. Longitudinal Input Signal

number of flight hours (>10,000 hrs) and the most years flying (> 30 years) while the next nearest subject had just under 2000 flight hours.

Dependent Variables

During each of the 35 data runs, subjects tracked the pitch command input signal as closely as possible for 30 sec. After each run, subjects then completed a Cooper-Harper (CH) rating scale.

RMS Error

Root Mean Square (RMS) error was calculated by taking the current pitch attitude of the aircraft and subtracting the desired pitch attitude of the aircraft. This was calculated in deg.

CH Rating

At the end of each data run, subjects gave a modified CH rating [10, 11]. An electronic format of the CH rating process was used which enforced the structure of the CH logic decision path, starting at the bottom (“Is it controllable?”) format (Fig. 2), and progressing accordingly until a final rating is given [12]. The pitch attitude command signal (u) drove the flight director symbol on the Attitude Direction Indicator (ADI) shown in Figure 3. Zero tracking error was defined by the airplane symbol nudged

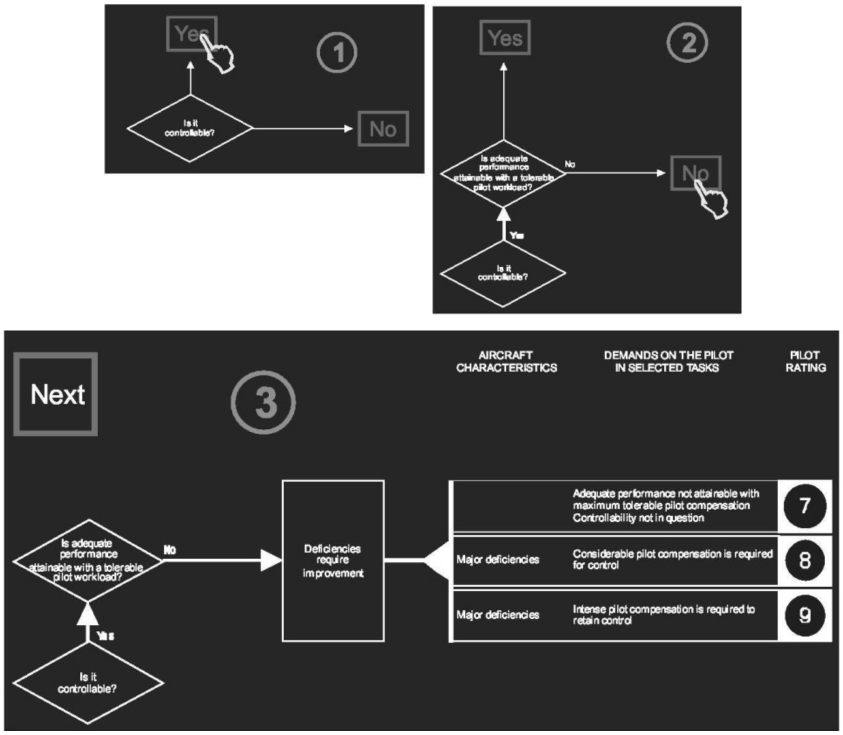

Figure 2. Cooper-Harper Controllability Scale Format

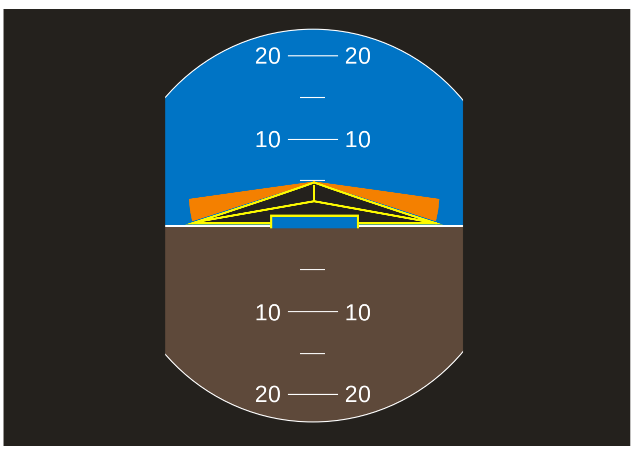

Figure 3. CH Optimal Rating Performance

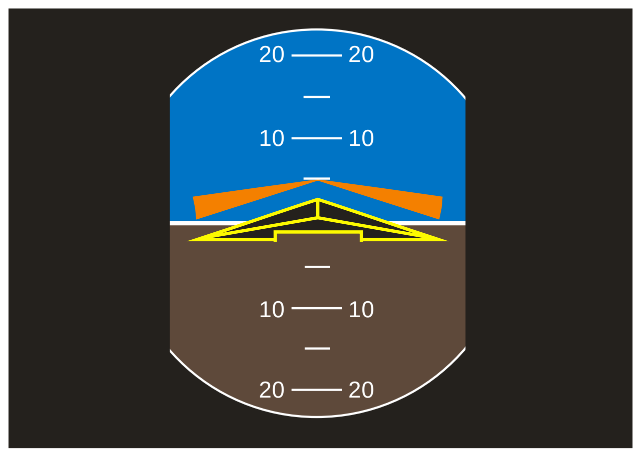

Figure 4. CH Desired Rating Performance

under the flight director (Fig. 3). Desired performance was defined as being within 2.5 degrees, which was half the width of the airplane symbol wings, of the flight director (Fig. 4). Adequate performance was defined as being within 5 degrees of the flight director which was the width of the airplane symbol wings (Fig. 5).

Procedure

After arrival, subjects were briefed on the experiment, task, and displays using still pictures.

Next, subjects were introduced to the simulator using a 20-minute familiarization run. The familiarization run had a 5 min periodic longitudinal tracking signal similar to the data runs. For both the familiarization run and for the data runs, the flight director had an amplitude of no more than ±5 degrees. During the familiarization run, the subject was also able to free fly the simulation. The pitch attitude response transfer function (see Eq. 1) had the baseline characteristics of: $\zeta = 0.4$, $\omega = 0.5$ Hz, $\tau = 0$ ms, $L_\alpha = 1.5$, and $K = 3$. Subjects were allowed to fly

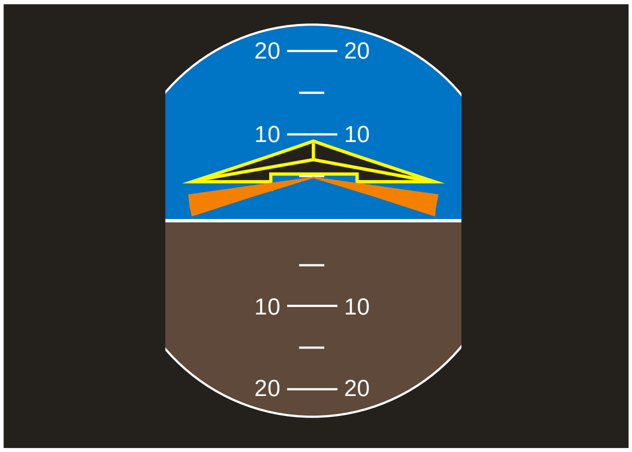

Figure 5. CH Adequate Rating Performance

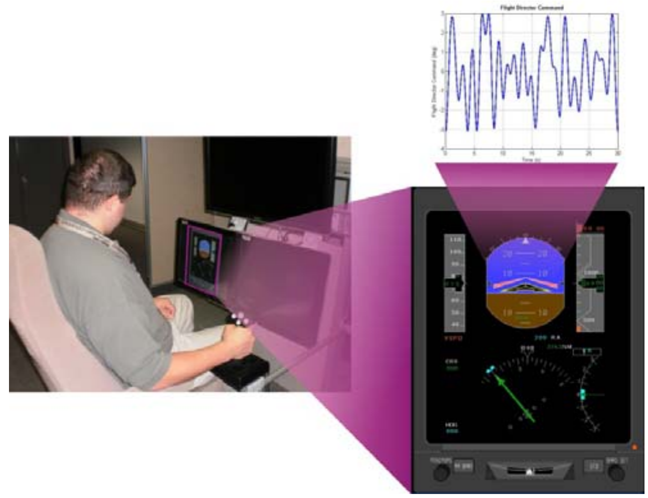

Figure 6. Simulator Setup

the familiarization run until they were comfortable with the simulation dynamics.

After the subject was comfortable with the sidestick and the task, each subject completed 35 data runs. During each data run, straight and level flight was established for 2 sec before the tracking task initiated. After the 30 sec tracking task, straight and level flight was reestablished for 2 sec. Therefore, each run lasted a total of 34 sec. At the end of the runs, subjects gave a CH rating.

The simulation was implemented in Matlab/Simulink® 2009b. The simulator setup is shown in Figure 6 and the general simulation diagram is shown in Figure 7.

Results

Analyses were done using SPSS™ v16. Significance was set at a p-value ≤ 0.05.

Subject Effects on RMS Error

Individual subjects tracking variability had the greatest effect on RMS error ($F_{(3,201)}$=11.418, p≤0.01). These data are shown in Figure 8 as the mean RMS error for each subject collapsed across all aircraft dynamics variations with deviation bars, indicating 1 unit of computed standard error (SE) from the mean. A closer look at the data indicated that the subject with the larger RMS error had less flight hours (Subject 2 flight hours < 600) as compared to the other subjects who had more flight hours and a smaller RMS error.

Aircraft Dynamic Effects on RMS Error

Tables 1 and 2 detail how the aircraft dynamics affected the RMS error. As seen in Table 1, all individual aircraft dynamics significantly affected the RMS error. The most significant effects were the time delay, frequency, and zero location as indicated by η^2 (Table 1).

Time Delay Effects on RMS Error

For the 150 ms time delay, subjects' RMS error was significantly larger than for the 0 and 75 ms time delay (Fig. 9). This increase in RMS error was also reflected by the subjects' CH rating. As can be seen in Figure 10, as the time delay increased, the vehicle moved towards more Level 2 and 3 handling qualities.

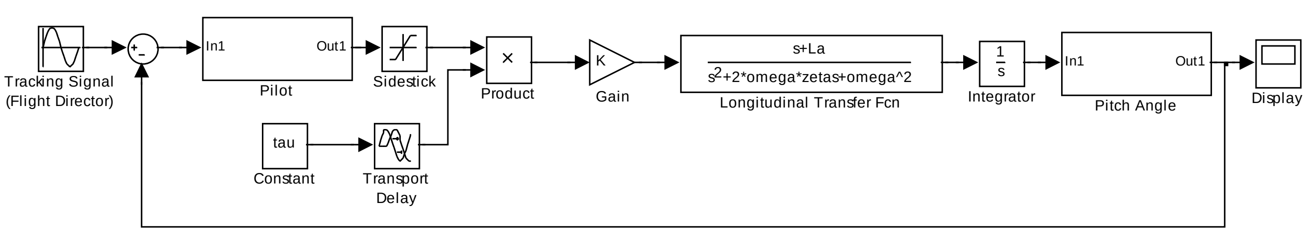

Figure 7. Block Diagram of the Simulation

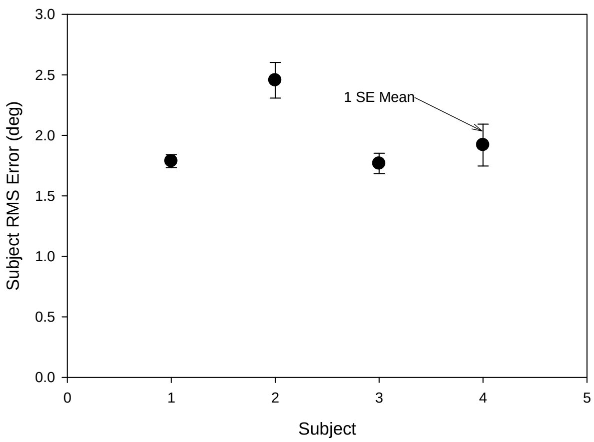

Figure 8. RMS Error by Subject

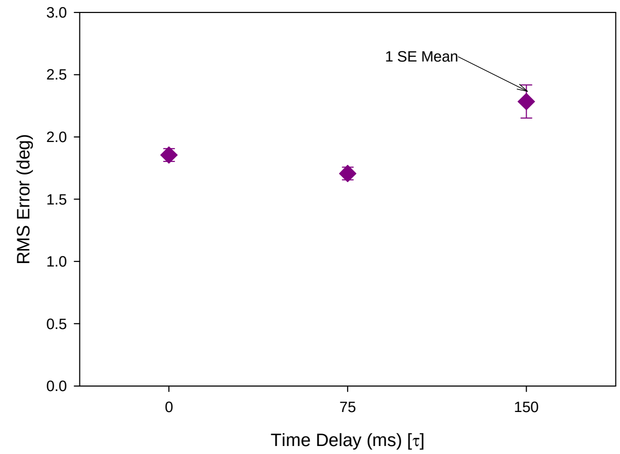

Figure 9. RMS Error by Time Delay

Table 1. Effects of Dynamics on RMS Error

Aircraft Dynamic	$F_{(1,207)}$	p	η^2
Gain [K]	9.64	≤0.01	0.023
Zero Location [L_α]	26.12	≤0.01	0.063
Damping Ratio [ζ]	6.95	≤0.01	0.017
Frequency [ω]	58.20	≤0.01	0.141
Time Delay [τ]	14.99	≤0.01	0.036

Table 2. RMS Error by Aircraft Dynamics

Aircraft Dynamic		Mean RMS Error (deg)	SE
Gain [K]	1	1.86	0.04
	2	1.75	0.05
	3	2.40	0.17
Zero Location [L_α]	0.5	1.74	0.35
	1.0	1.75	0.38
	1.5	2.28	1.21
Damping Ratio [ζ]	0.4	2.19	0.12
	0.7	1.70	0.05
	1.0	1.90	0.05
Frequency (Hz) [ω]	0.5	2.46	1.22
	1.0	1.70	0.32
	1.5	1.64	0.24
Time Delay (ms) [τ]	0	1.85	0.05
	75	1.70	0.05
	150	2.28	0.13

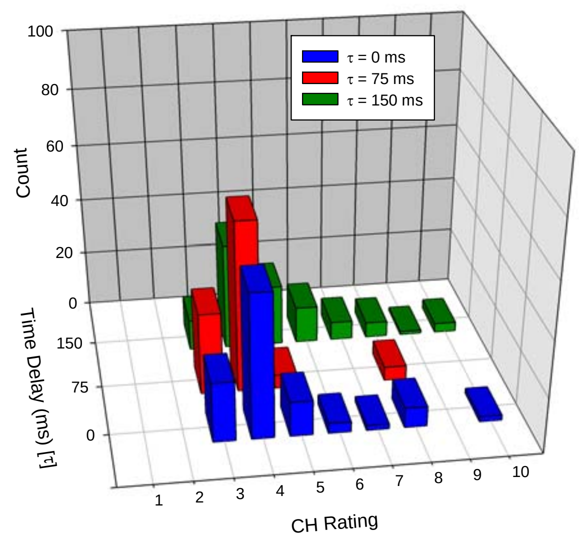

Figure 10. CH Rating Count by Time Delay

Frequency Effects on RMS Error

The RMS error for the frequency increased as the speed of the system response decreased down to 0.5 Hz (Fig. 11) which was different from the 1.0 and 1.5 Hz frequencies. As with the time delay, subjects' CH ratings also indicated this increase in RMS error (Fig. 12). The handling qualities shifted to Level 2 and 3 as the frequency decreased.

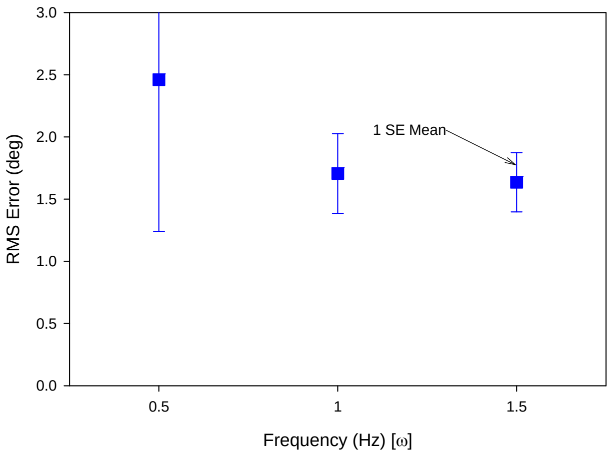

Figure 11. RMS Error by Frequency

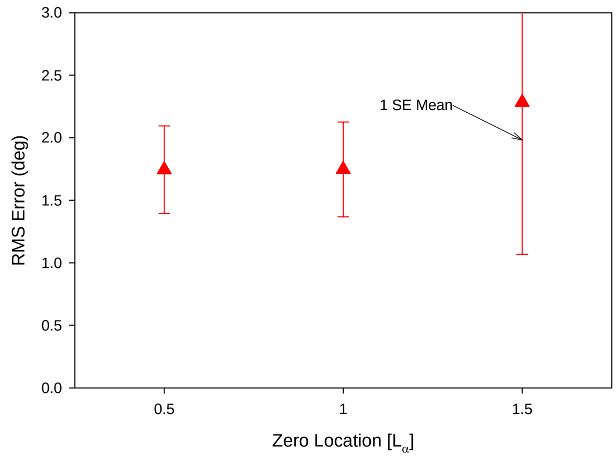

Figure 13. RMS Error by Zero Location

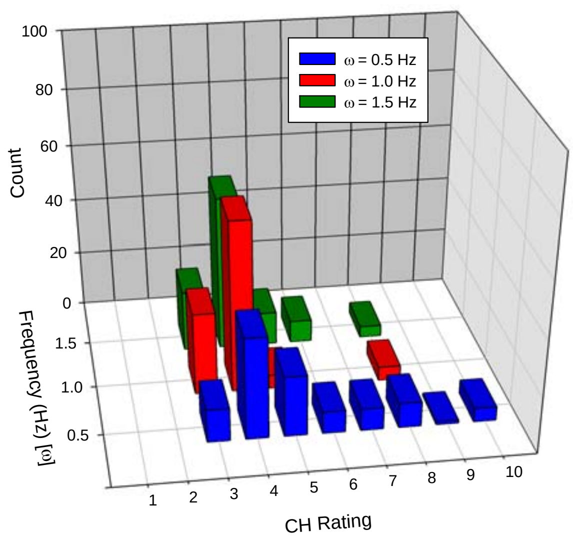

Figure 12. CH Rating Count by Frequency

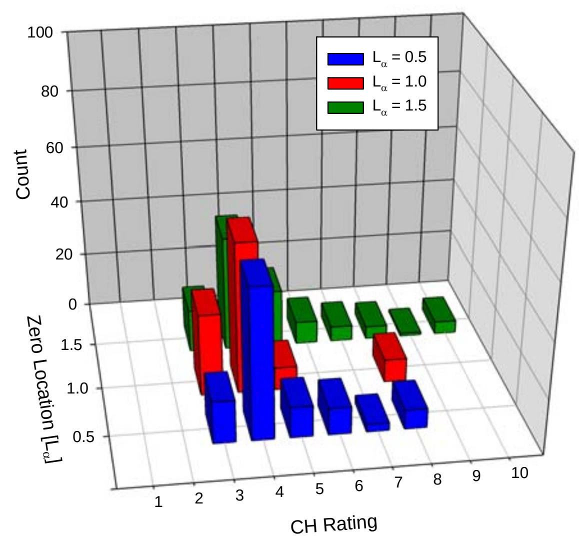

Figure 14. CH Rating Count by Zero Location

Zero Location Effects on RMS Error

Lastly, RMS error increased with a zero location further into the left half plane (Fig. 13). Once again, this increase in RMS error manifests itself in the subjects' CH ratings. As the zero location moves farther into the left-half plane, the subjects' CH rating spread increases towards Level 2 and 3 handling qualities (Fig. 14). Furthermore, this increase in RMS error was even more pronounced with a zero location further into the left half plane for lower frequencies (Fig. 15) as would be expected by the control anticipation parameter (CAP) which is proportional to $\frac{\omega^2}{L_\alpha}$ [13, 14]. In fact, the interaction between the zero location and frequency was significant ($F_{(1,207)}$=10.001, p≤0.01) and η^2 was 0.0242.

Aircraft-Pilot Coupling

When the system response was slower than the subject desired by either an increasing time delay or decreasing the frequency, especially with a corresponding zero location increase, the RMS error increased. In fact, some subjects mentioned

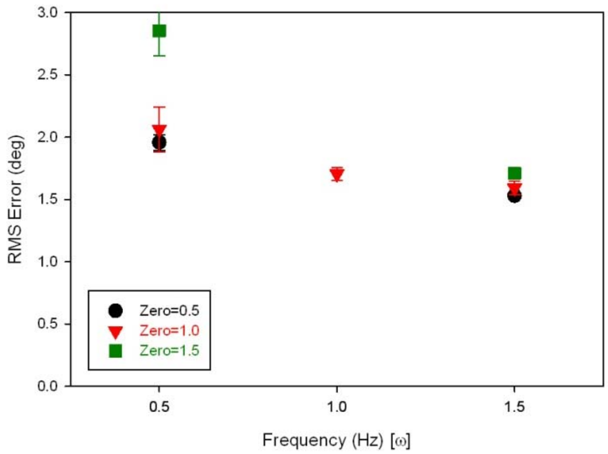

Figure 15. RMS Error by Frequency and Zero

that certain runs were "PIO prone" (Table 3). These runs had a frequency of 0.5 Hz with the zero location farther into the left half plane or a large time delay.

Table 3. PIO Comments

Time Delay (ms) [τ]	Frequency (Hz) [ω]	Zero Location [L_α]	Count of Subjects Mentioning "PIO Prone"
0	0.5	1.0	1
0	0.5	1.5	2
150	0.5	0.5	4
150	0.5	1.5	6

Moreover, subjects' CH ratings became more diverse towards higher CH ratings as more subjects mentioned "PIO Prone" (Fig. 16).

Pilot Modeling Considerations

Using System Identification to Determine Hess Simplified Pursuit Model Gain Parameters

The Hess simplified pursuit pilot model includes two gains, K_p and K_r and a fixed neuromuscular model to represent a pilot's response to a vehicle [15, 16]. K_r is the gain that results in a minimum damping ratio of 0.15 and K_p is the gain that provides the desired open-loop crossover frequency consistent with the classical McRuer cross-over model [6, 7]. The pilot-vehicle model is shown in Figure 17 where the vehicle is represent by Equation 1 and G_{nm}, the neuromuscular model, is

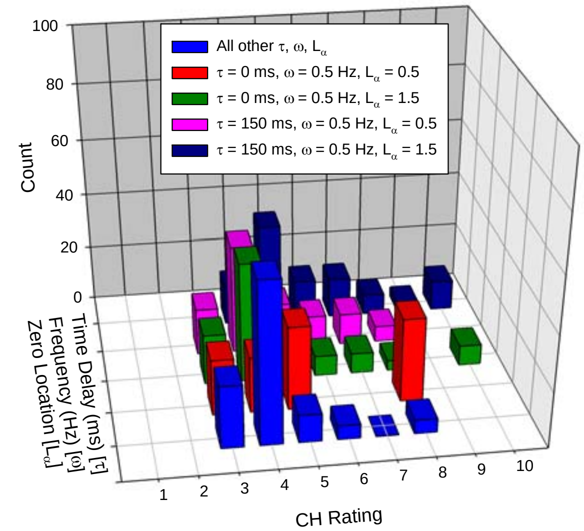

Figure 16. CH Rating Count for PIO Conditions

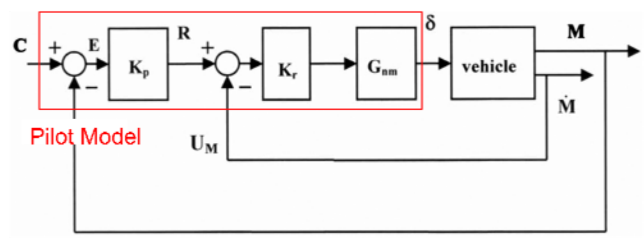

Figure 17. Hess Simplified Pursuit Model

$$G_{nm} = \frac{10^2}{s^2 + 2(0.707)10s + 10^2} \qquad (3)$$

For the purposes of this experiment, input C is commanded pitch attitude u, the output M is aircraft pitch attitude θ and $\dot{M}$ is pitch rate q. The above model does not include a time delay. For this analysis, the time delay was incorporated into the Hess simplified pursuit model with a sixth order Padé approximation.

System identification techniques were used to calculate these gains [9] from the recorded data runs. The K_p and K_r gains vary slightly by pilot and are dependent on the scenarios which had varying system dynamics ($f(K, L_\alpha, \varsigma, \omega, \tau)$) (Figs. 18 and 19). The dependency on the subject may be due to learning affects or piloting styles.

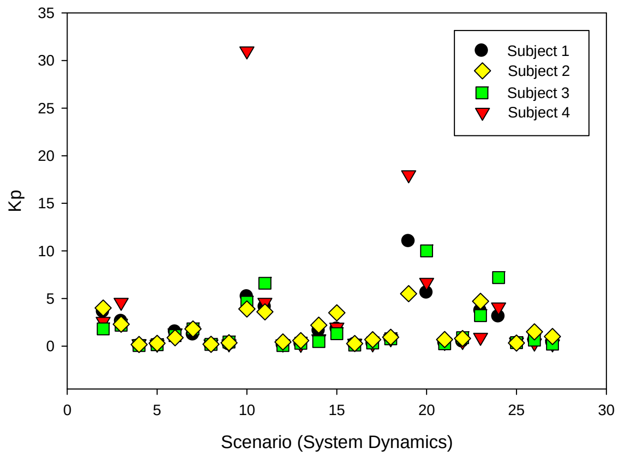

Figure 18. Effects of Scenario and Subject on Kp

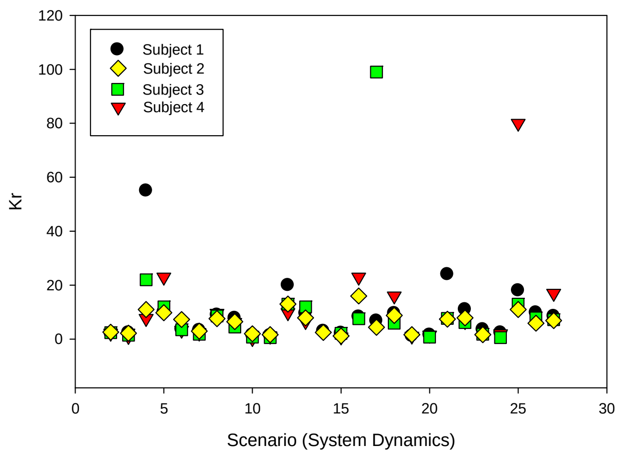

Figure 19. Effects of Scenario and Subject on Kr

Furthermore, within a given subject and constant system dynamics, the calculated K_p and K_r values using system identification techniques varied by run (Table 4). The values typically settled around an average but there were some outliers. Therefore, the need for real-time system identification is apparent especially if the aircraft dynamics change.

Lastly, the Hess simplified pursuit model was shown to generally emulate the recorded pilot behavior when using the K_p and K_r values calculated using system identification (Fig. 20 where K=2, L_α=1, ζ=0.7, ω=1 Hz, τ=75 ms). However, the Hess model does not reproduce the higher frequency responses very well.

As expected, these results indicate that the model changes in pilot control behavior due to the values of K_p and K_r vary with the aircraft dynamics. The dependence of the pilot model on aircraft dynamics prompts consideration of other techniques that could sudden changes in aircraft dynamics in real-time. The technique considered has been successful in dealing with the changes in aircraft dynamics from the flight control perspective. The ultimate goal is to develop an algorithm that would capture pilot behavior changes due to aircraft dynamic changes without *a priori* knowledge of how

Table 4. Repetition Effects on Kp and Kr

Repetition (K=2, L_α=1, ζ=0.7, ω=1 Hz, τ=75 ms)	Calculated Kp Using System Identification	Calculated Kr Using System Identification
1	0.55	9.20
2	0.51	6.80
3	0.77	8.06
4	0.87	6.46
5	0.89	5.95
6	1.11	7.59
7	0.68	6.56
8	0.89	8.86
9	0.85	7.61
10	0.78	5.99
11	1.05	7.34
12	0.66	8.43
13 (outlier)	0.06	35.69
Average±StDev (for Repetitions 1-12)	0.80±0.18	7.40±1.09

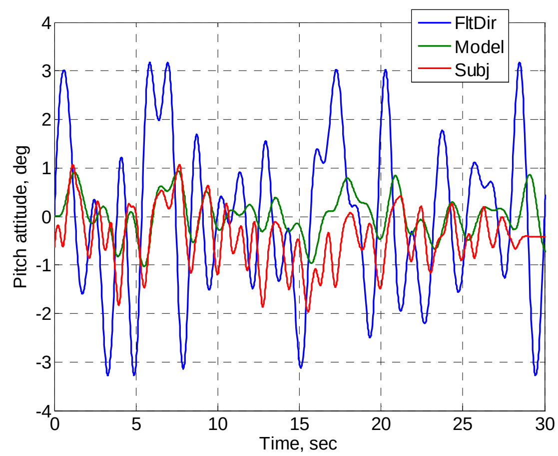

Figure 20. Model vs. Subject Tracking

these dynamic changes occur. The approach outlined herein is only an initial step.

Estimating Pilot Response with a Simple Gradient Descent Estimator

A number of different pilot models with a specific structure have been proposed in literature [4-7, 16]; however, all of these depend on *a priori* knowledge of aircraft dynamic changes to alter the pilot behavior model. The proposed approach is to assume the pilot can be represented by a system in the linear parameterization form:

$$y(t) = \Theta^T \Phi\left(x(t)\right) + \varepsilon(t) \quad (4)$$

where $y(t) \in \mathbb{R}^m$, $x(t) \in \mathbb{R}^n$ are the system output and input signals, the $(N \times m)$ – matrix $\Theta \in \mathbb{R}^{Nxm}$ contains the unknown parameters to be estimated, $\Phi(x(t)) \in \mathbb{R}^N$ (called the "regressor") represents the N – dimensional vector of chosen basis functions, and $\varepsilon(t) \in \mathbb{R}^m$ denotes the non-parametric uncertainties in the system (such as noise, modeling errors, *etc.*). Note that in the equation above both $y(t)$ and $\Phi\left(x(t)\right)$ are known quantities. This implies that (4) is simply a system of linear equations in terms of the unknown Θ which at time t is estimated by $\hat{\Theta}(t)$. Then based on the latter, one can predict the value of the system output:

$$\hat{y}(t) = \hat{\Theta}^T \Phi(x(t)) \quad (5)$$

where $\hat{y}(t)$ is called the predicted output at time *t*.

Consider a simple gradient estimator to update the predictor output $\hat{y}(t)$. The basic idea in the gradient-based estimation is to update the estimated parameters $\hat{\Theta}(t)$ in such a way that the prediction error $e_y = y(t) - \hat{y}(t)$ is reduced. The online implementation of the Gradient Estimator is of the form:

$$\dot{\hat{\Theta}}(t) = -\Gamma \Phi(x(t))\left(\hat{y}(t) - y(t)\right) \quad (6)$$

where $\Gamma = \Gamma^T > 0$ is a symmetric positive definite matrix called the estimation gain [17].

For pilot model identification, $x(t)$ is the pitch attitude commanded by the flight director while $y(t)$ is the aircraft pitch attitude response to the pilot stick command as the pilot attempts to follow the flight director. The update law for the estimates of the unknown parameters (6) is a function of the tracking error and a regressor chosen *a priori*. The only assumption about the structure of the pilot model made in this formulation is that it can be represented as linear parameterization.

A sample result for the predicted pilot output using the gradient estimator is given in Figure 21. As can be seen in Figure 21, this initial estimate (ThetaHat_Pilot) follows the pilot's response (Theta_Pilot) fairly well. Furthermore, this method does appear to pick up more of the pilot's high frequency responses.

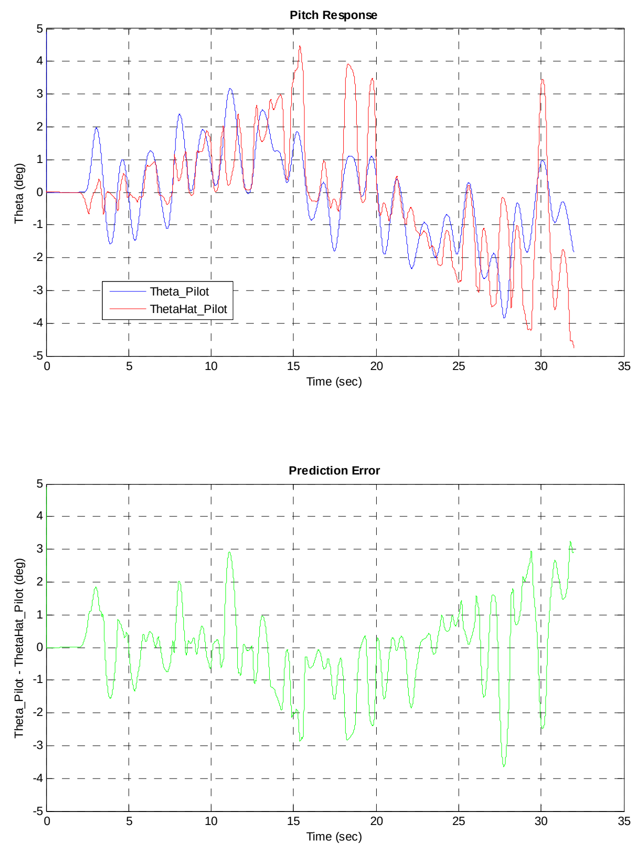

Figure 21. Pilot and Estimator Pitch Response

The parameters of the gradient estimator appear to remain fairly constant from subject to subject with the same pitch dynamics (Fig. 22). However, when the pitch dynamics change within a subject, the current combination of the basis functions $\Phi\left(x(t)\right)$, which are held constant across all subjects and all dynamics, and the gradient estimator parameter

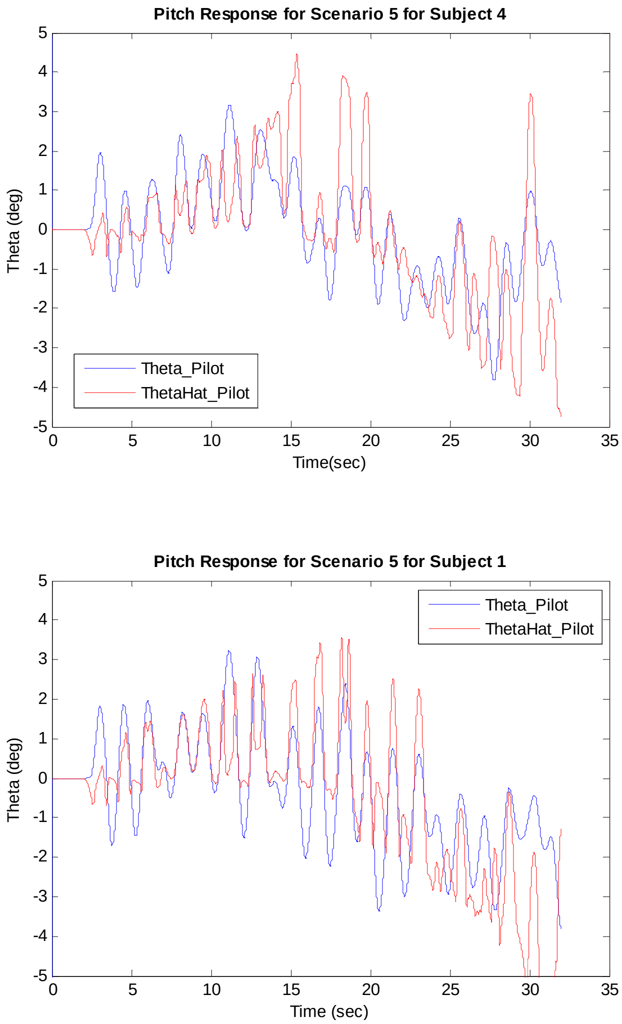

Figure 22. Pitch Response for Different Subjects

update law (6) do not do a good job of covering the range of dynamics. (Fig. 23).

It is clear from Figures 21 and 22 that while the predictor is doing an adequate job in predicting the pilot during some time intervals, *i.e.,* the predictor matches the actual pilot response, but it does a poor job in others. One issue is the estimation methodology as given by the update law (6). The simple gradient descent estimator was used as a proof of concept. Current research is looking at a variety of different approaches to find ones most suitable to predicting the pilot in this general model form.

In this more general model formulation the basis functions vector $\Phi\left(x(t)\right)$ is expected to cover the range of dynamics and differences among the pilots; the unknown parameter $\hat{\Theta}(t)$ changes in a prescribed manner to accommodate the differences between the

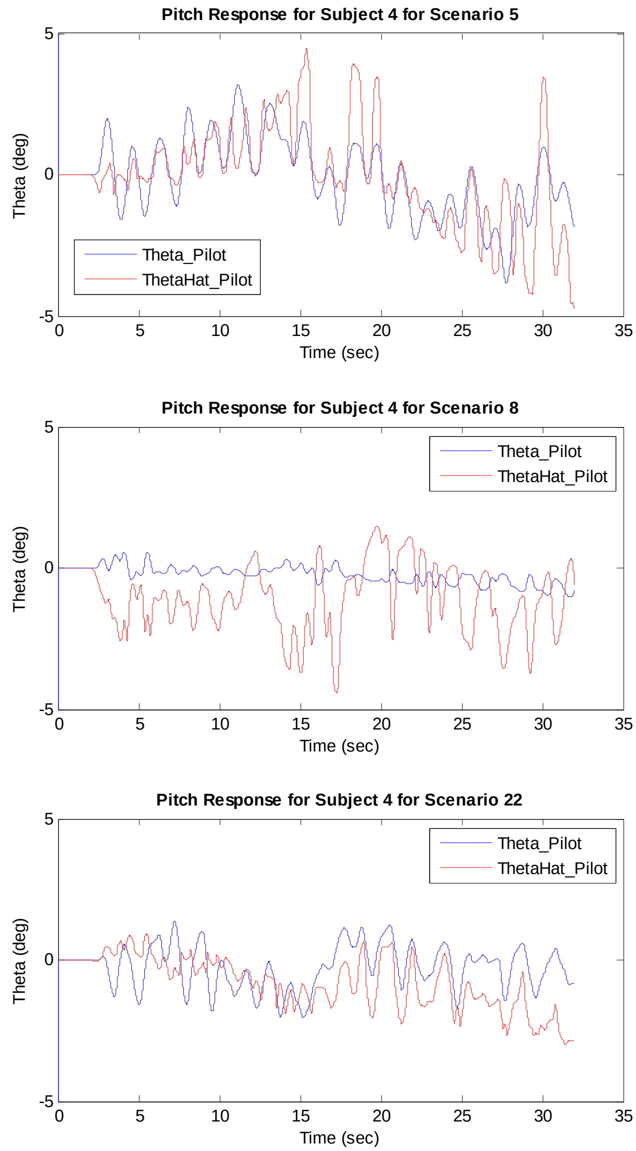

Figure 23. Pitch Response for Different Dynamics

dynamics and pilots based on a specific update law (6). This is different from a fixed structure model where parameters would change with the dynamics, e.g. the Hess model, but would have to be updated manually not based on a specific update expression.

However, it is possible the estimator's parameters $\hat{\Theta}(t)$ may need to be tuned to the current dynamics which may be estimated using real-time system identification techniques [18]. Current research is determining if this is necessary and feasible. If this is feasible, then pilot model would be build on the basis of actual aircraft dynamics. In this case, other pilot model structures [4-7, 16] might also be suitable for real-time pilot behavior prediction.

Conclusions

An experiment was conducted to quantify the effects of changing dynamics on a subject's ability to track a signal in order to eventually model an adapting pilot to changing aircraft dynamics. The research presented here attempts to identify primary aircraft dynamics variables that influence changes in pilot's response and produce a simplified pilot model that incorporates this relationship. Each run incorporated a different set of second-order aircraft dynamics representing short period transfer function pitch attitude response: damping ratio, frequency, gain, zero location, and time delay.

In the aircraft dynamics, the factors that affected the subjects' ability to track the longitudinal signal the most were the time delay, frequency, and zero location. Besides the subjects' RMS error, subjects' CH ratings also showed this effect. Furthermore, this increase in RMS error was even more pronounced when looking at the control anticipation parameter and when considering subjects' comments regarding pilot-aircraft coupling.

The Hess simplified pilot model using gains obtained from system identification techniques shows promise in predicting pilots' control behavior but further refinement on the method is needed. Under current consideration is a more general form of the pilot dynamics model borrowed from flight control application dealing with changing aircraft dynamics. Several estimation techniques are being explored to find most suitable approach to predicting the pilot without *a priori* knowledge of changed aircraft dynamics.

In addition to creating a simplified pilot model to serve as a short-term control action behavioral predictor, the results of the experiment may be utilized in an advisory capacity. Thus, if the aircraft dynamics change such that the system becomes more sluggish and unpredictable to the pilot, an increase in RMS error can be predicted. If a system does in fact encounter these factors (established through real-time parameter identification), advisory information that would aid the pilot in adjusting his piloting approach and changing his expectations of aircraft response can now be provided reliably by the system. A pilot will eventually notice these changes while flying the aircraft but a situation awareness/prediction aid based on the pilot behavior and aircraft dynamics may help tailor pilot's inputs more quickly so that PIO or an upset condition can be avoided.

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