Toward a Unifying Theory for Aircraft Handling Qualities

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A structural model of the human pilot that has been used to study a variety of problems in manual control tasks is applied to the study of aircraft handling qualities. A physical theory for handling qualities is reviewed and interpreted in terms of the model. The theory postulates that, in manual control tasks, rate-control activity on the part of the human is the sole determining factor in the generation of pilot opinion ratings. Using the structural model, rate-control activity is related to the power in a proprioceptive feedback signal proportional to vehicle output-rate due to control input. By appealing to single-axis tracking tasks, the model and theory are shown capable of demonstrating the manner in which three major determinants of aircraft handling qualities can effect pilot opinion ratings. A brief comparison with a handling qualities metric derived from the optimal control model is made.

Introduction

HANDLING qualities can be defined as those qualities or characteristics of any vehicle that determine the ease and precision with which a human is able to perform the tasks required in support of the vehicle's role.[1] The majority of handling qualities research to date has been concerned with flying vehicles and has been largely empirical in nature. The continuing reliance upon experimentation is primarily due to the fact that the system element that defines and assesses handling qualities, the human pilot, is not particularly amenable to precise analytical description. This is not to say that successful pilot models have not been developed or utilized in handling qualities work,[2,3] but rather that, with one exception,[4] they have not led to the development of an underlying physical theory for this discipline. The existence of such a theory becomes particularly important when a type of aircraft is developed that exhibits dynamic characteristics that are fundamentally different from those that preceded it.

The impetus behind the research to be described is that of building upon the fundamental physical theory for handling qualities introduced by Smith,[4] and to do so by utilizing a structural model of the human pilot that has been successful in unifying the entire base of single-axis tracking data. This included describing the pilot's adaptive behavior in compensatory tracking,[5] describing the pilot's nonlinear, pulsive control behavior in controlling higher-order vehicle dynamics,[6] describing the development of higher levels of skill development in the pilot,[7] and, finally, examining the effects of manipulator characteristics on pilot/vehicle performance.[8]

The Structural Model

The structural model of the human pilot for compensatory tracking is shown in much simplified form in Fig. 1. Note that in an inner feedback loop, manipulator (control stick) output is fed through compensation in which a model of the controlled element dynamics explicitly appears. As such, the signal u_m is seen to be proportional to vehicle output rate $\dot{m}$, due to control activity u_δ, and is a form of rate feedback. It is interesting to use the model to form the open-loop transfer function Y_pY_c for three elemental controlled element dynamics: K, K/s, and K/s^2.

$$Y_c=K \qquad Y_pY_c=\frac{K_eK}{K_{\dot{m}}Ks+1}$$

$$Y_c=\frac{K}{s} \qquad Y_pY_c=\frac{K_eK}{s(K_{\dot{m}}K+1)}$$

$$Y_c=\frac{K}{s^2} \qquad Y_pY_c=\frac{K_e/K_{\dot{m}}}{s[s(1/K_{\dot{m}}K)+1]} \tag{1}$$

As Smith demonstrated, by proper selection of the model gains K_e and $K_{\dot{m}}$, the open-loop transfer function Y_pY_c can be made similar to the well-known "crossover" model of the human operator/controlled element combination in the crossover frequency region, i.e.,[9]

$$Y_pY_c=(K_p/s)e^{-\tau_e s} \tag{2}$$

where the simple model of Fig. 1 does not yet include an operator time delay.

It is possible to generalize Fig. 1 and develop a model of the human operator for compensatory tracking that is capable of exhibiting dynamics that closely match those of the human operator in single-axis compensatory tracking tasks. This model is shown in Fig. 2. This model and its antecedents have been discussed at some length in the literature (Refs. 5-8), but a brief description is in order here.

Figure 2 has been divided into "central nervous system" and "neuromuscular system" components, a division intended to emphasize the nature of the signal processing activity involved. A central time delay of τ_0 s is included to account for the effects of latencies in the visual process, motor nerve conduction times, etc., The resulting signal, $u_c(t)$, provides a command to a closed-loop system containing a model of the open-loop neuromuscular dynamics of the particular limb driving the manipulator, Y_{p_n}. Other system components include elements Y_f and Y_m, which emulate, at least approximately, the combined effects of the muscle spindles, Golgi tendon organs, and the dynamics associated with higher-level signal processing. The form of Y_m is determined by the nature of the controlled element dynamics Y_c in the region of open-loop crossover. Y_m is uniquely parameterized by the integer k, which, in most cases, is merely the integer that is obtained by

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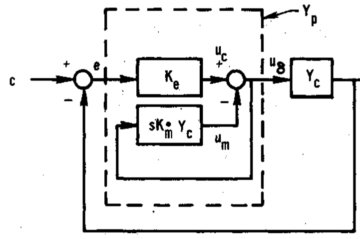

Fig. 1 A simplified structural model of the human operator for compensatory tracking.

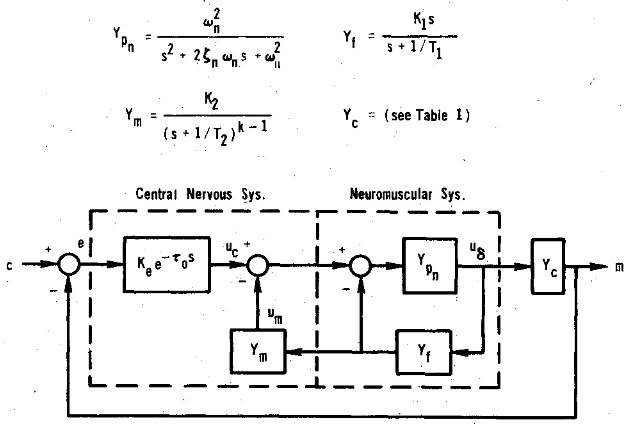

Fig. 2 The structural model of the human operator for compensatory tracking.

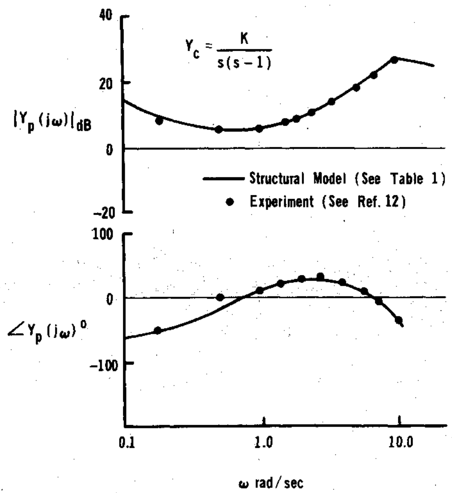

Fig. 3 A comparison of model-generated and experimental transfer functions, $Y_c = K/s(s-1)$.

representing Y_c as

$$Y_c(j\omega)\mid_{\omega=\omega_c} = K/(j\omega)^k \tag{3}$$

where ω_c represents the open-loop crossover frequency. Although the u_m/u_δ transfer function from Fig. 2 is not identical to that from Fig. 1 at all frequencies, the two are equivalent in the region of crossover for parameter values that yield acceptable matches between model and experiment. For example, consider $Y_c = K/s^2$. Here $k=2$ and, from Fig. 2,

$$\frac{u_m}{u_\delta} = \frac{K_1 K_2 s}{(s+1/T_1)(s+1/T_2)} \tag{4}$$

Figure 1 yields

$$u_m/u_\delta = K_m K/s \tag{5}$$

If $1/T_1$ and $1/T_2$ are significantly less than ω_c (which they are for acceptable overall matches with transfer functions obtained from experiment), then the u_m/u_δ of Eq. (4) looks very much like the integrator of Eq. (5) in the important region of crossover.

As evident in Fig. 1, in terms of the model, the human generates the equalization required in any task through proprioceptive feedback and not by any direct serial operation on the visual stimulus $e(t)$. The general characteristics of this equalization depend upon whether the proprioceptively sensed manipulator output u_δ is differentiated, simply attenuated, or integrated in the frequency range around crossover. The proper equalization is, in turn, dependent upon the order of the controlled element dynamics in the region of crossover. It should be noted that the general structure of Figs. 1 and 2 is compatible with that proposed by other researchers to describe human behavior in man-machine systems with the human operating on visually sensed errors and communicating with the machine via manipulative output.[4,9]

Handling Qualities

In Ref. 4, Smith introduced a novel theory for explaining the manner in which the pilot generates numerical ratings of a vehicle's handling qualities. Smith held that in any closed-loop tracking task, such as aircraft pitch-attitude regulation in turbulence, pitch-*rate* control is of fundamental importance to the pilot. Smith further hypothesized that the amount of rate-control activity was *the* determining factor in the pilot's rating of a vehicle's handling qualities. Smith held that a general physiological measure for such rate-control activity in single-axis tracking is the rate at which nerve impulses arrive at the point within the central nervous system where all signals originating due to rate control are summed. In proposing this theory, Smith utilized a simple conceptual model of the human pilot that is quite similar to the structural model of Fig. 1. In fact, the model of Fig. 1 was derived from Smith's model and differs primarily in the manner in which the rate-control information is assumed to be obtained. Whereas Smith held that inner-loop rate control was based upon visual cues, the models of Figs. 1 and 2 postulate proprioceptive cues. Because of its structural acceptability, Smith used an optimal control model (OCM) of the pilot[10] to predict the root-mean-square (rms) value of a feedback signal that corresponded roughly to the rate-control signal in his conceptual model. He went on to show that these rms values provided excellent correlation with Cooper-Harper ratings obtained from manned simulations for a variety of aircraft pitch-attitude tracking tasks.

The research to be described builds upon Smith's work, but will utilize the structural model of Fig. 2 to evaluate the handling qualities metric that Smith investigated, i.e., the rms value of the signal associated with rate feedback. Under the assumption of stationarity, this rms value (called σ_{u_m} here) can be given by

$$\sigma_{u_m} = \sqrt{\frac{1}{\pi}\int_0^\infty \left|\frac{u_m}{c}(j\omega)\right|^2 \Phi_{cc}(\omega)\mathrm{d}\omega} \tag{6}$$

The effects of operator noise injection (remnant) have been omitted from Eq. (6) but will be discussed in what follows. As Fig. 1 indicates, c is a command signal, however, it can also be thought of as an equivalent disturbance. As will be seen, the structural model provides a framework within which to investigate the influence of (a) vehicle dynamics (including control system sensitivity), (b) command signal characteristics, and (c) display quality, on aircraft handling qualities.

Vehicle Dynamics

Using the structural model of the human operator, a quantitative correlation between σ_{u_m} and handling qualities will first be demonstrated for seven different controlled elements. The handling qualities that have been associated with these controlled elements span the range from very easy to control to nearly uncontrollable. It should be noted that this exercise is not merely a restatement of Smith's results, since here, the structural model itself will be utilized to generate σ_{u_m} (rather than the OCM), and the model parameters corresponding to each controlled element will have been selected to yield acceptable matches to experimentally derived human operator transfer functions. The one exception to this procedure will be in choosing the model gain K_e so that the $Y_p Y_c$ transfer functions for all seven of the human operator/controlled element combinations have the same crossover frequency.

The experimentally derived transfer functions were culled from a variety of studies, some of which used a command input, others which utilized a disturbance. In calculating σ_{u_m} here, a command input modeled as white noise passed through a first-order filter with a break frequency of 2.0 rad/s was employed throughout. The bandwidth of this command input was close to, and in some cases identical to, that used in the actual experiment in which the transfer functions were measured. The differences in the experimental transfer functions that might accrue with command as opposed to disturbance inputs (or vice versa) were felt to be negligible for the purposes of this study.

It is assumed here that, in any tracking task in which human operator opinion is solicited, the human compares the relative effort required to maintain comparable performance capabilities between competing systems and uses this information to quantify his subjective opinion of handling qualities for each system. It is important to realize that comparable performance capability may not be evident simply in rms tracking scores obtained from experiment. A more suitable measure would be closed-loop system bandwidth or, equivalently, open-loop system crossover frequency. The unique dependence of closed-loop performance capabilities upon open-loop crossover frequency is a well-known feedback system characteristic, whether the system be manual or automatic. For this reason, the metric σ_{u_m} was calculated using model parameters identical to those that yielded acceptable transfer function matches with experiment, with the one exception that the parameter K_e was increased or deceased to allow all the $Y_p Y_c$ transfer functions to exhibit identical crossover frequencies and thus reflect human operator characteristics when attempting to achieve comparable performance capabilities with competing systems. The question of whether K_e variation, alone, constitutes the mechanism by which the human would actually obtain comparable crossover frequencies can be answered in the affirmative based upon established "adjustment rules" for simple crossover models of the human operator.[11] The common crossover frequency was chosen as 2.5 rad/s. This is larger than the input bandwidth, but smaller than the maximum value that would imply unstable closed-loop behavior in any of the systems studied.

Summarizing briefly, the preceding discussion has suggested that the crossover frequencies measured in steady-state tracking tasks may not be representative of those that the human may adopt (if for only brief periods of "high-gain" operation) in an attempt to force a system to have comparable performance capability with one or more competing systems. To avoid the problem of estimating just what this maximum ω_c might be for any system, a common ω_c value has been chosen for all the systems. Choosing it to be larger than the input bandwidth is certainly a reasonable choice, but nonetheless, somewhat arbitary.

Table 1 shows the controlled elements in question along with the model parameter values used to obtain transfer function matches with experiment.[12] Figure 3 exemplifies a typical transfer function match for $Y_c = K/s(s-1)$. Also included in Table 1 are the σ_{u_m} values. Figure 4 shows the σ_{u_m} values associated with the controlled elements placed in order of increasing difficulty (decreasing handling qualities). The ordering was ascertained as follows: Specific subjective ratings exist to support the relative ordering of four of the elements [$(K, K/s, K/s^2$, and $K/s(s-1))$].[13]

The ordering of the two elements with delays is based upon the fact that, with the delays present, the magnitudes of the delay-induced phase lags in Y_c at crossover are all less than that associated with K/s^2. Hence, the level of difficulty of these elements should lie between K/s and K/s^2, as shown in Fig. 4. Again, based upon controlled element phase lags at the crossover frequency, the cubic controlled element was placed between the K/s^2 and $K/s(s-1)$ elements in terms of difficulty. As Fig. 4 and Table 1 indicate, σ_{u_m} appears to be a sensitive metric for reflecting handling qualities. The σ_{u_m}

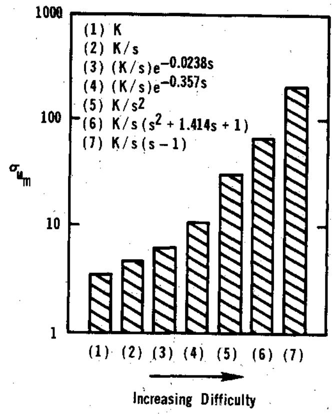

Fig. 4 σ_{u_m} for seven controlled elements of increasing difficulty.

Table 1 Parameter values for model of Fig. 2

	Model parameters									
Controlled element dynamics	k	K_e	K_1	K_2	T_1, s	T_2, s	τ_0, s	ζ_n	ω_n, rad/s	σ_{u_m}
K	1	11. (5.9)*	1.0	2.0	5.0	5.0	0.14	0.71	10.0	3.7
K/s	1	22. (9.9)	1.0	2.0	5.0	...	0.14	0.71	10.0	4.8
$(K/s)e^{-0.0238s}$	1	10.5 (9.5)	1.0	2.0	6.7	...	0.20	0.45	5.0	6.4
$(K/s)e^{-0.357s}$	2	4.2 (6.6)	1.0	5.0	2.5	2.5	0.20	0.75	6.0	11.0
K/s^2	2	26. (28.)	1.0	10.0	2.5	2.5	0.14	0.71	10.0	33.3
$K/s(s^2+1.414s+1)$	3	23.3 (51.0)	1.0	35.0	0.85	0.85	0.14	0.71	10.0	70.5
$K/s(s-1)$	2	90. (77.)	1.0	30.0	1.0	1.0	0.14	0.71	10.0	205.

*( )Indicates value of K_e yielding crossover frequency of 2.5 rad/s.

magnitudes vary by nearly two orders of magnitude from easiest to most difficult controlled element. Even the rather subtle difficulty increment encountered by including the 0.0238-s delay with K/s dynamics is reflected in a 33% increase in σ_{u_m}.

Using the metric σ_{u_m} and the very simple model of Fig. 2, it is interesting to explore the manner in which control system "sensitivity" may influence the human's perception of task difficulty or vehicle handling qualities. It is known that, for any particular controlled element and manipulator, a control system sensitivity exists that the human finds optimum. Larger or smaller values result in degraded human operator opinion ratings.[14] In addition, experimental evidence suggests that the human is quite capable of maintaining nearly constant crossover frequency across a large range of K values, despite these large variations in sensitivity-related task difficulty. As a means for analyzing this behavior, consider the transfer function u_m/c obtained from Fig. 1. Choosing $Y_c = K/s$ for convenience, and using the second of Eqs. (1) to define crossover frequency ω_c, one can show

$$\frac{u_m}{c} = \frac{sK_{\dot{m}}}{[(1+K_{\dot{m}}K)/K_eK]s+1} = \frac{sK_{\dot{m}}}{s/\omega_c+1} \tag{7}$$

Equations (6), (7), and the second of Eqs. (1) suggest that σ_{u_m} can be monotonically decreased by increasing K and adjusting K_e and $K_{\dot{m}}$ in reciprocal fashion to maintain a constant crossover frequency. This further suggests that task difficulty or handling qualities, itself, is a monotonic function of controlled element sensitivity. As has just been pointed out, however, experiment corroborates this prediction only for sensitivities *smaller* than the optimum value.

Again returning to the simple structural model of Fig. 1, it is unrealistic to assume that the very simple u_δ/u_m feedback loop can adequately describe the behavior of the human neuromotor system for all operating conditions. Factors such as the size of the particular muscle groups that drive the manipulator, the order of the controlled element dynamics around crossover, and the characteristics of the manipulator itself may alter the model of the neuromuscular system as a precise, compensating servomechanism. This is particularly true when large controlled element sensitivities reduce the required output forces and/or displacements to a small fraction of those associated with optimum sensitivities. An approximate, but simple way to account for such modeling limitations here, is to consider additive broadband noise to be injected in parallel with u_c, the command signal to the closed-loop neuromuscular system in Figs. 1 and 2.

Now this noise, n_m, will be assumed to be white and to have constant covariance and, as such, can be thought of as a "residual" motor noise that does *not* scale with the variance of the signal to which it is added. The actual magnitude of the covariance is assumed to depend upon the conditions just mentioned, i.e., the size of the particular muscle groups that drive the manipulator, etc. Although the noise is present at all times, its effect upon tracking performance is noticeable only as K_e begins to decrease in magnitude. This can be seen by considering an equivalent noise, n_e, injected with the tracking error:

$$\Phi nn_e(\omega) = (1/K_e^2)\Phi_{nn_m}(\omega) \tag{8}$$

As K_e decreases in reciprocal fashion with increasing K, Φ_{nn_e} increases in magnitude at all frequencies. This will have a deleterious effect on error tracking performance. This can be demonstrated by the structural model of Fig. 2 using K/s controlled element dynamics and the model parameter values shown in the second row of Table 1 (with $\omega_c = 2.5$ rad/s). A white noise n_m with a covariance equal to approximately 1% of the mean-square value of u_c with $K = 1.0$ was injected in parallel with u_c for three different controlled element sensitivities: $K = 0.1$, 1.0, and 10. The appropriate model gains are adjusted in reciprocal fashion with K. The resulting rms tracking errors were $\sigma_e = 0.91$, 1.0, and 3.95. Thus, even with the relatively small covariance of n_m, over a 300% increase in tracking error was obtained with the high sensitivity.

Now any effort by the human to minimize tracking errors when controlled element sensitivities are increased beyond some "optimum" value must be accomplished by *increasing* K_e, not decreasing it. However, in order to maintain a relatively constant crossover frequency, $K_{\dot{m}}$ must also then increase. This is apparent from

$$\omega_c = \frac{K_eK}{1+K_{\dot{m}}K} \tag{9}$$

and for large control sensitivity K

$$\omega_c \simeq K_e/K_{\dot{m}} \tag{10}$$

But Eqs. (6) and (7) show that σ_{u_m} is directly proportional to $K_{\dot{m}}$. Thus, there appears to exist some optimum control sensitivity that results in $K_{\dot{m}}$ and consequently σ_{u_m} being a relative minimum.

Using the more complete structural of Fig. 2 and the error-injected remnant model of Eq. (8), σ_{u_m} can be shown to vary with controlled element sensitivity in a manner similar to pilot ratings. When K increases from the "optimum" value of 1.0 to 10.0, increasing K_e from 9.9 to 60.0 and K_2 from 2.0 to 240.0 yields an rms tracking error 0.86 and a crossover frequency still of 2.5 rad/s. The remaining model parameters are identical to those in the second row of Table 1. Figure 5 summarizes the σ_{u_m} variation with controlled element sensitivity and demonstrates how it follows the pilot rating variation reported in Ref. 14. It should be emphasized that $K = 1.0$ was forced to be the "optimum" sensitivity by the choice of the covariance of n_m (assumed to depend on muscle group size, etc.).

Finally, the results of tracking experiments qualitatively support the simple noise injection model discussed here. When controlled element sensitivities are inceased significantly over optimal values, one sees significant increases in the amount of power in the operator's output not linearly correlated with the input.[11]

Thus, the theory for handling qualities offered by Smith and adopted here, can also be used to provide a rationale for the human's well-documented subjective perference for an optimum controlled element sensitivity. It should be emphasized that the discussion here has been limited to visual stimuli only. It is quite possible that the presence of vestibular stimuli, such as acceleration cues, might influence the human's selection of an optimum controlled element sensitivity. Modeling such cues in the framework of the structural model is not impossible, but is well beyond the scope of this discussion.

Command Signal Characteristics

Any handling qualities theory based soley upon the characteristics of the vehicle dynamics will be unable to explain the demonstrable effect of command signal or disturbance characteristics on pilot acceptability. Chief among these is the effect of command signal bandwidth. For example in a well-controlled laboratory tracking task, Wickens et al.[15] recorded a threefold increase in subjective rating (indicating decreasing acceptability) by varying the command signal bandwidth from 0.3 to 0.6 Hz with simple first-order dynamics. This is shown in Fig. 6. It should be noted that Wickens was not using a Cooper-Harper rating scale. The connection between pilot acceptability and command signal bandwidth is implied from Eq. (6). Figure 7 shows the actual σ_{u_m} values calculated using the structural model for each of the controlled elements of Table 1 for the command signal bandwidths 0.5, 1.0, and 2.0 rad/s. This range of bandwidths was

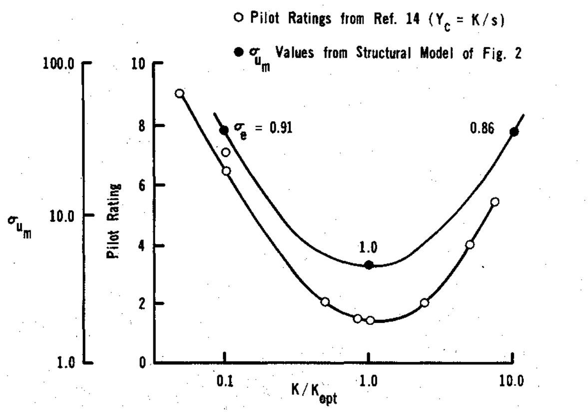

Fig. 5 σ_{u_m} and pilot rating variation with controlled element sensitivity ($Y_c = K/s$).

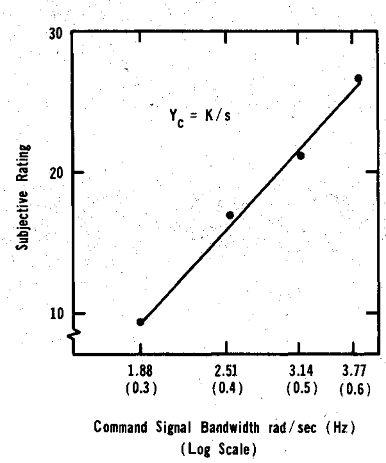

Fig. 6 Subjective ratings for one controlled element with varying command signal bandwidth (from Ref. 15).

chosen to be below the selected crossover frequency of 2.5 rad/s. The rms value of the command signal did not vary with bandwidth. The linearity that is evident in Figs. 6 and 7 suggests that numerical operator opinion may be linearly related to $\log(\sigma_{u_m})$, at least for the rating scale used by Wickens. It is interesting to note that Smith also found a linear logarithmic relationship between rate-control activity and Cooper-Harper ratings larger than 3.0. Once again, one sees that σ_{u_m} appears to be a sensitive metric for reflecting task difficulty or handling qualities and can quantify the dependence of handling qualities upon command signal bandwidth. While this area has not been explored in detail using the structural model, the fact that a parameter as fundamental as command signal bandwidth effects the proposed metric in a consistent and easily demonstrable fashion [via Eq. (6)] is encouraging. It should be pointed out that, if the command signal is actually a disturbance input that is filtered by the vehicle dynamics, the effect of bandwidth upon σ_{u_m} can be considerably mitigated. Finally, the effect of command signal intensity upon σ_{u_m} is readily discernible from Eq. (6). Here it is seen that σ_{u_m} is directly proportional to σ_c. Figure 8 demonstrates this. Here $\log(\sigma_{u_m})$ values are seen to be directly proportional to the logarithm of disturbance intensity. Note that pilot ratings, taken from Ref. 16, show the same type of linear variation with the logarithm of disturbance intensity.

Display Quality

For the purpose of discussion, display "quality" will be defined as those characteristics of a display that affect the ability of the human to perform single-axis compensatory tracking. This includes such characteristics as modality (e.g., aural vs visual), format (e.g., line vs dial), resolution (e.g.,

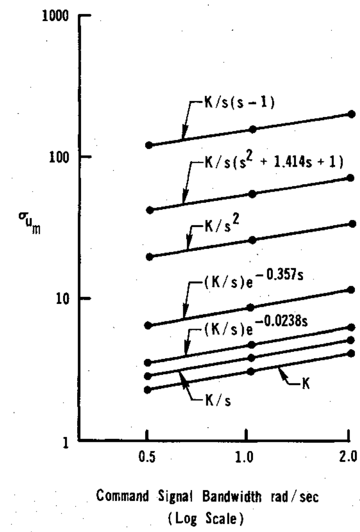

Fig. 7 σ_{u_m} for seven controlled elements with varying command signal bandwidth.

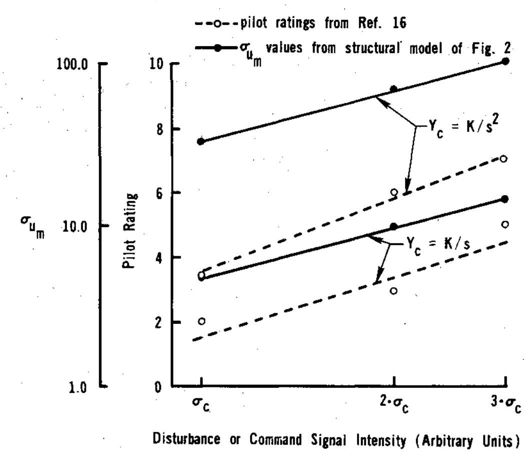

Fig. 8 σ_{u_m} and pilot rating variation with disturbance or command signal intensity.

quantization—number of lines per centimeter on raster), and viewing condition (e.g., foveal vs parafoveal). Experiments have shown that, in terms of measured pilot dynamic characteristics, the display characteristics just mentioned primarily affect the following parameters[17,18]: a) crossover frequency (poor display quality causes regression of ω_c), b) remnant power (poor display quality causes increase in remnant power), and c) effective time delay (poor display quality induces additional time delay in human operator transfer functions).

Under the hypothesis that comparative subjective evaluations are carried out by the human across equivalent crossover frequencies, crossover regression per se, will not be considered a casual factor in subjective opinion. Remnant and time delay increments, however, can each have important effects on σ_{u_m} as given by Eq. (6). First, modifying Eq. (6),

$$\sigma_{u_m} = \sqrt{\frac{1}{\pi}\int_0^\infty \left|\frac{u_m}{c}(j\omega)\right|^2 [\Phi_{cc}(\omega) + \Phi_{nn_e}(\omega)]\,\mathrm{d}\omega} \tag{11}$$

Here, Φ_{nn_e} is remnant injected in parallel with e in Figs. 1 or 2.

The effects of display-induced remnant are evident from Eq. (11). However, using the simplified model of Fig. 1 and Eq. (11), it can be shown that the contribution of Φ_{nn_e} to σ_{u_m} will be relatively small compared with that due to Φ_{cc}, for injected remnant power induced by all but the poorest displays.

This leaves increments in effective time delay as a prime source of increments in σ_{u_m}. The effects of delay increments on σ_{u_m} have already been indicated in Fig. 4 for cases in which the delay was associated with the controlled element. It is of interest to demonstrate the relationship between display quality and resultant time delay increments in the human operator transfer function. The actual source of the delay increment (i.e., the human or the controlled element) is immaterial in terms of σ_{u_m} variation.

In Ref. 19, human performance in a series of compensatory tracking tasks was investigated in which controlled element dynamics and display quality were varied. Display quality was changed by the simple expedient of varying the level of quantization in the display as indicated in Fig. 9, i.e.., the coarser the display quantization, the poorer the display quality. Two of the controlled elements used in Ref. 19 were the K/s and K/s^2 elements used in Table 1 and Fig. 4. A workload measurement technique was employed in the study of Ref. 19 based upon the "adaptive cross-coupled critical task," which quantifies operator workload in terms of excess control capacity.[20] In addition, display-induced time delays were measured in indirect fashion by a series of critical tracking tasks.[21] Of particular interest here are the results for a) K/s dynamics with a continuous display (quanta level of 0 cm), b) K/s dynamics with a quantized display (quanta level of 0.580 cm), and c) K/s^2 dynamics with a continuous display.

The delay increment induced by the quantization for K/s dynamics was found to be approximately 0.023 s for a representative subject. For all practical purposes, this is equivalent to the 0.0238-s value used in Fig. 4. Figure 10 compares the workload index measured by the cross-coupled critical task (l/λ_s) and σ_{u_m} values from Fig. 4 for cases (a-c), just mentioned. The index l/λ_s is proportional to the amount of the human's control capacity absorbed by the particular controlled element and display used. This index has been found to correlate very well with Cooper-Harper handling qualities ratings obtained from simulation. This is demonstrated in Fig. 11, taken from Ref. 16.

Figure 10 demonstrates that $\log(\sigma_{u_m})$ follows the variations in l/λ_s quite closely, for both controlled elements and display quantization levels. The agreement would probably be closer if remnant effects were included in the calculation of σ_{u_m} for the quantized display. Thus, it would appear that σ_{u_m} is also a sensitive indicator of the effects of display quality upon vehicle handling qualities in single-axis tasks.

A Comparison with Optimal Control Model Results

A handling qualities measure derived from the optimal control model of the human pilot has been used successfully in the past in a variety of studies, e.g., Refs. 3 and 22. In these studies, actual pilot ratings were found to correlate well with the logarithm of the index of performance used in defining the optimal control model, itself. For the single-axis tasks that are the subject of the research reported here, the index of performance would take the form[23]

$$J=E\left(\lim_{T\to\infty}\frac{1}{T}\int_0^\infty [e^2(t)+r\dot{u}_\delta^2(t)]\,\mathrm{d}t\right) \tag{12a}$$

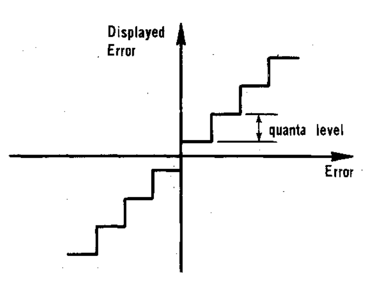

Fig. 9 Display quantization of Ref. 19.

or

$$J=\sigma_e^2+r\sigma_{\dot{u}_\sigma}^2 \tag{12b}$$

The weighting coefficient r can be shown to be related in approximate fashion to the open-loop crossover frequency ω_c by[23]

$$\omega_c \simeq (K/r^{1/2})^{m-n-1} \tag{13}$$

where n, m, and K are obtained from the controlled element dynamics expressed as

$$Y_c(s)=\frac{K(s^m+a_1 s^{m-1}+\ldots a_0)}{s^n+b_1 s^{n-1}+\ldots b_0} \tag{14}$$

Equation (12) can also be written

$$J=\frac{1}{2\pi}\int_{-\infty}^{\infty}\left|\frac{e}{c}(j\omega)\right|^2\Phi_{cc}(\omega)\mathrm{d}\omega$$

$$+r\frac{1}{2\pi}\int_{-\infty}^{\infty}\left|\frac{u_\delta}{c}(j\omega)\right|^2\Phi_{cc}(\omega)\mathrm{d}\omega \tag{15}$$

Using Eqs. (13-15) and the simplified structural model of Fig. 1, one can show

$$J\simeq \sigma_{u_m}^2/\omega_c^2K_m^2+r\sigma_{\dot{u}_\delta}^2 \tag{16}$$

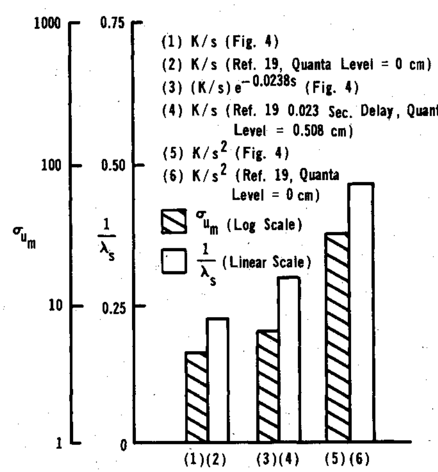

Fig. 10 Comparison of σ_{u_m} values with Ref. 19 workload index (l/λ_s).

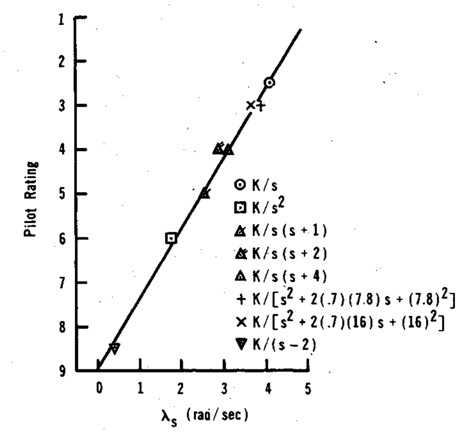

Fig. 11 Pilot ratings vs secondary task scores (Ref. 16).

or

$$\sigma_{u_m} \simeq \omega_c K_{\dot{m}} (J - r\sigma^2_{\dot{u}_\delta}) = \omega_c K_{\dot{m}} \sigma_e \tag{17}$$

Finally, the comparison can be made:

$$\log(\sigma_{u_m}) = \log(\sigma_e) + \log(\omega_c K_{\dot{m}}) \tag{18}$$

$$\log(J) = \log(\sigma^2_e + r\sigma^2_{\dot{u}_\delta}) \tag{19}$$

It is important to point out that applications of the optimal control model to handling qualities studies have not included the hypothesis that the human makes handling qualities assessments at comparable crossover frequencies. Thus, a direct comparison between the results obtained using $\log(\sigma_{u_m})$ and previous results using $\log(J)$ is, in general, not possible. However, one interesting point can be made. Assuming ω_c invariance, $\log(J)$ cannot reproduce the pilot rating variation that accompanies changes in controlled element sensitivity, since both components of J (σ^2 and $r\sigma^2_{\dot{u}_\delta}$) remain unchanged.[23] As has been shown here, however, this variation can be reproduced using $\log(\sigma_{u_m})$. In terms of the simplified structural model, Eqs. (18,19) indicate that the "missing parameter" in the optimal control model metric is the gain $K_{\dot{m}}$.

Conclusions

Based upon the research summarized in the preceding, the following conclusions can be drawn:

1) A unifying theory for aircraft handling qualities appears feasible. This theory has its basis in Smith's hypothesis regarding rate-control activity and has been corroborated by a structural model of the human pilot that, in itself, has unified the entire base of single-axis tracking data.

2) The theory/model combination is capable of directly demonstrating the manner in which three major determinants of aircraft handling qualities can affect pilot opinion ratings. These determinants are: vehicle dynamics (including control sensitivity), command signal bandwidth and intensity, and display quality.

3) A brief comparison with a handling qualities metric derived from the optimal control model of the human pilot indicates why the theory/model discussed here can reproduce the pilot rating variation with controlled element sensitivity, while, under the assumption of constant ω_c, the former cannot. This is due to the appearance of the gain $K_{\dot{m}}$ in the structural model metric.

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