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EFFECTS OF WHOLE-BODY MOTION SIMULATION ON FLIGHT SKILL DEVELOP--ETC(U)

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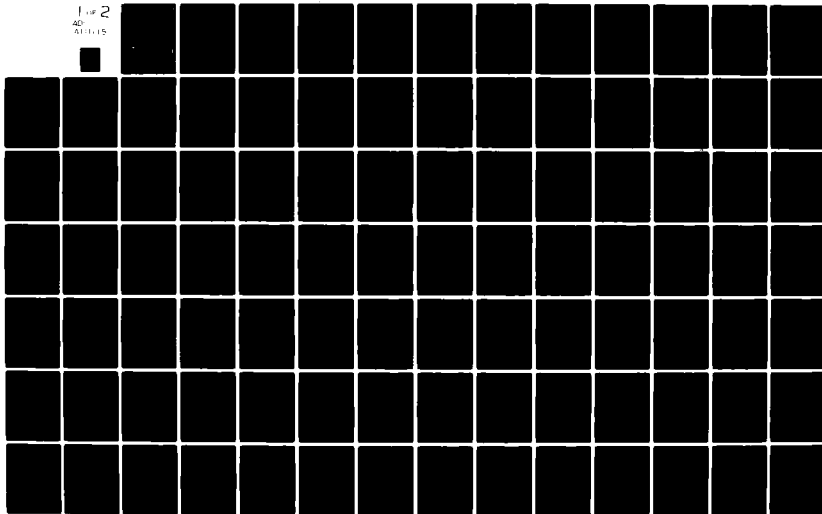
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Effects of Whole-Body Motion Simulation on Flight Skill Development

W.H. Levison

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October 1981

Prepared for:
Air Force Office of Scientific Research

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REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER AFOSR-TR- 82 0066	2. GOVT ACCESSION NO. AD A111 115	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Effects of Whole-Body Motion Simulation on Flight Skill Development		5. TYPE OF REPORT & PERIOD COVERED Final 6/1/78 - 9/30/81
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) William H. Levison		8. CONTRACT OR GRANT NUMBER(s) F49620-78-C-0073
9. PERFORMING ORGANIZATION NAME AND ADDRESS Bolt Beranek and Newman Inc. 10 Moulton Street Cambridge, MA 02238		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 61103F 231A/A2
11. CONTROLLING OFFICE NAME AND ADDRESS Air Force Office of Scientific Research Bolling AFB DC 20332 NK		12. REPORT DATE October 1981
		13. NUMBER OF PAGES 111
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified
		16. DECLASSIFICATION/DOWNGRADING SCHEDULE
16. DISTRIBUTION STATEMENT (of this Report) Approved for public release; distribution unlimited.		
17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)		
18. SUPPLEMENTARY NOTES		
19. KEY WORDS (Continue on reverse side if necessary and identify by block number) human operator technology, human operator modeling, learning, optimal control model, parameter identification, motion cueing		
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) Progress was made toward the development of models for piloting skill acquisition. The following tasks were accom- plished: (1) design of an experiment to study visual and motion cue integration in a multi-axis control tasks; (2) enhancement of the optimal control pilot model; (3) further development of a scheme for automatic identification and significance testing of "pilot-rated" model parameters; (4) analysis of control strategy		

development; (5) study of the relationship between task structure and pilot response limitations; (6) test of a multiplicative motor noise model; and (7) a brief literature search on adaptive control and identification algorithms for potential application to models for control-strategy development.

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1. INTRODUCTION

1.1 Objectives

Because the cost of airborne operations has increased dramatically in recent years, ground-based simulators have come to play an ever-increasing role in the training of Air Force pilots. Consequently, one of the major forces (if not the major force) driving training costs is the number of trainee and instructor hours required to achieve desired proficiency in the training simulator. Procedures that can improve training efficiency have the potential to improve the flying skills of Air Force pilots while substantially reducing training costs.

Aside from issues of cost, ground-based simulators exhibit both advantages and disadvantages with regard to training effectiveness. The primary disadvantage is that the perceptual environment experienced in actual flight must be approximated to some extent in the simulator. For example, limited motion travel inherent in ground-based simulators cannot provide the same whole-body motion stimuli encountered in a free-moving airplane. Similarly, it is not practical at present to attempt to replicate the external visual scene in every detail. On the other hand, perceptual environment created in the simulator may be designed to optimize training. In particular, there exists the option to

increase training efficiency by enhancing cues normally present in flight and/or providing additional cues not normally present.

One of the primary tasks of both the designer and user of training simulators is to optimize the perceptual environment, in a manner consistent with limitations of cost and technology, to maximize training effectiveness and efficiency. At present, however, there is no detailed, validated theory that allows one to predict, from knowledge of the informational environment, the degree and rate of acquisition of flying skills.

Prior to this study, a multi-year program of research was conducted for the Air Force to begin development of an analytical model that would allow one to reliably predict the effects of whole-body motion cues on pilot response behavior in a variety of situations [1-4]. Development of a mathematical model of this sort was desired to allow one to address analytically the following issues:

1. The extent to which a trained pilot uses motion cues in specific control situations.
2. The influences of motion cues on the rate at which a trainee pilot learns a specific control task.
3. Effects of simulator limitations on the pilot's ability to use motion cues at various stages of learning.

4. Design of control laws for ground-based motion simulators.
5. Extrapolation of fixed-base simulation to a moving-base environment.

The study program reviewed in this report was initiated to pursue the same long-term goal of modeling the effects of whole-body motion cues on pilot performance. During the course of the study, emphasis was shifted to the area of flight-skill development and, in particular, to the development of a model for relating skill acquisition to the perceptual environment. Significant progress was made during this program in terms of methodological development and in terms of analytically characterizing the influence of task structure on operator response behavior in continuous control tasks.

1.2 Organization of Material

The major tasks completed during this study are described in Chapter 2, largely in the order in which they were performed. To aid the reader in assimilating the important results, these task descriptions are presented in the format of expanded summaries. Detailed documentation is contained in the Appendices.

The following tasks were performed:

- a. Experiment Design. A set of experiments was designed to test hypotheses concerning attention-sharing penalties among whole-body motion cues and instrument visual cues. While Air Force research priorities did not provide for performance of this experiment, various issues of multi-modality cue utilization remain to be resolved, and the design is included in this report as a potential guide to future research (Section 2.1; Appendix A).
- b. Model Extension. The computerized implementation of the pilot model was extended to allow both (1) a revised treatment of certain motor-related model parameters, and (2) consideration of a deficient model of the task environment on the part of the pilot (Section 2.2; Appendix B).
- c. Identification of Independent Model Parameters. An existing scheme for automatically identifying "pilot-related" model parameters from experimental data was refined and extended to allow qualitative tests of significance (Section 2.3; Appendix C).
- d. Analysis of Control Strategy Development. Manual control data obtained in a study of delayed motion cues were analyzed to quantify the relationship between

pilot-related model parameters, the state of training, and the presence or absence of whole-body motion cues (Section 2.4; Appendix D).

- e. Limitations on Psychomotor Performance. Additional model analysis was conducted to further define the relationship between pilot response limitations and task structure, both for subjects trained to asymptotic performance levels and for subjects early in training (Section 2.5; Appendix E).
- f. Multiplicative Motor Noise Model. A small study was performed to explore the utility of a multiplicative motor noise process to account for certain apparent task-related changes in independent model parameters (Section 2.6; Appendix F).
- g. Literature Review. A brief literature review was conducted on adaptive control and identification algorithms that might prove useful in formulating models for the learning process in continuous control and estimation tasks (Appendix G).

Before summarizing the results obtained in this study, we first provide a brief review of the optimal control model (OCM) for pilot/vehicle systems that is the basis for the analytical work described in this report.

1.3 The Optimal Control Model (OCM)

The reader is assumed to be generally familiar with the optimal-control model. This model has been used in numerous studies performed for the Air Force [1-4]. For the reader's convenience we review here the pilot-centered components of the model.

We consider two categories of pilot-related model elements: parameters that reflect the human's perceptual-motor (information-processing) limitations, and elements related to the operator's adaptive response strategy.

The following parameters reflect perceptual-motor limitations:

1. Observation noise. Each perceptual variable utilized by the operator is assumed to be perturbed by a white Gaussian noise process that is linearly uncorrelated with other pilot-related or external noise sources. In certain idealized laboratory tracking situations, the variance of the observation noise tends to scale with the variance of the corresponding display variable [5], in which case we may characterize this limitation by an observation noise/signal ratio. A more complex submodel for observation noise may be considered to account for limitations such as perceptual thresholds [6,7] and attention-sharing [8,9]. In general, the observation noise

accounts for most of the operator's "remnant" -- the portion of the control input that is linearly correlated with external inputs. For trained subjects, remnant may reasonably be attributed to fundamental information-processing limitations as suggested above (provided the system to be controlled is linear -- an underlying assumption of the OCM). For untrained subjects, observation noise may reflect within-trial variations in the linear aspect of the operator's response strategy.

2. Time Delay. A single (scalar) time delay is added to each display variable to account for the various sources of delay associated with information acquisition, transformation, and response execution.
3. Motor Time Constant. The operator's control response is assumed to be smoothed by a filter that accounts for an operator bandwidth constraint. In the model, this constraint arises directly as a result of a penalty on control rate introduced into the performance criterion. The constraint may mimic actual physiological constraints of the neuromotor system or it may reflect subjective limitations imposed by the operator. The time constant of this first-order filter is called the "motor time constant".

4. Motor Noise. Just as an observation noise is postulated to account for perceptual and central processing inadequacies, a motor noise is introduced to account for an inability to generate noise-free control actions. In many applications this noise level is insignificant in comparison to the observation noise, but where very precise control is important to the conditions being analyzed, motor noise can assume greater significance in the model. Early implementations of the model treated this noise as a disturbance added to the control response commanded by the operator. In current OCM usage, motor noise is generally considered to be added to commanded control rate in order to provide a better match to low-frequency response behavior to the pilot describing function at low frequencies [1].
5. Cost Functions. Except for the cost weighting on control rate, which we relate to a motor time constant as discussed above, the coefficients of the quadratic performance index are generally considered as part of the task description, rather than as human operator limitations. Nevertheless, the operator can only minimize what he perceives to be the performance index. To the extent this perception differs from the "true" performance index (as defined by the experimenter), the performance index must be considered as an operator-related

parameter. One might expect such differences to occur early in training.

The adaptive portion of the operator's response is represented collectively by three elements of the human operator model: The Kalman estimator, optimal predictor, and optimal control law. The function of the Kalman estimator and predictor is to generate the best estimate of the current state of system variables, based on the noisy, delayed perceptual information available. It is assumed in these elements that the operator has both an internal model of the dynamics of the system being controlled, and a representation of the statistics of the disturbances driving the system.

Given the best estimate of the current system state, a set of control gains or weighting factors are assigned to the elements of the estimated state, in order to produce control actions that will minimize the defined performance criterion. As might be expected, the particular choice of the performance criterion determines the weighting factors, and thus the effective control law gains.

2. SUMMARY OF RESULTS

2.1 Design of a Multi-Axis, Multi-Cue Experiment

The results of recent studies of motion cue utilization have been consistent with the hypothesis that attention must be shared between visual and motion cues in the same axis of control; that is, the pilot's ability to perceive and use cues from one modality is degraded by the requirement to use cues from the other modality [1-4]. The data are not sufficient, however, to determine conclusively whether or not such interference effects need to be considered when modeling closed-loop pilot/vehicle systems.

As part of this contractual effort, a set of experiments was designed to test various hypotheses regarding interference (or lack thereof) among whole-body motion cues and visual cues, both within a single axis of control and between two uncoupled control tasks. Experimental conditions were selected to provide a task environment for which performance would be sensitive to attention-sharing limitations. The experiment design was based, in part, on the then-existing response capabilities of the Multi-Axis Tracking Simulator (MATS) facility at AMRL.

This experiment was not conducted during the course of this three-year effort, as originally anticipated, because of a shift in Air Force research priorities. Nevertheless, the issues addressed

by the proposed experiment are still very much relevant to the problem of understanding pilot performance in realistic in-flight and in-simulator control tasks. We therefore present, in Appendix A, the results of this design effort as a potential guide to future experimentation.

A two-axis attitude regulation task is defined in which the pilot's task is to maintain a simulated fighter-like vehicle in straight and level flight in the presence of gust-like disturbances. Model analysis indicates that the recommended task environment will provide a sensitive test of various hypotheses concerning the interaction between the presence or absence of whole-body motion cues, task loading, and pilot/vehicle performance. Model predictions contained in Appendix A also can be used to help select gust amplitudes and control gains for implementation of the experiment.

Six experimental conditions are suggested: (1) pitch regulation alone, fixed base; (2) roll regulation alone, fixed base, (3) pitch regulation alone, moving base, (4) roll regulation alone, moving base, (5) combined pitch and roll regulation, fixed base, and (6) combined pitch and roll regulation, moving base.

2.2 Model Extension

A small effort was undertaken to update the computer implementation of the optimal-control pilot/vehicle model to include two modifications made since the original implementation [1,10]. Both modifications had been formulated and implemented in separate computer programs previously; they were implemented in the same program under this contract.

The two model refinements combined were: (1) modification of the treatment of motor noise[1], and (2) consideration of a non-faithful "internal model" for the human operator [10].

The revised treatment of motor noise was accomplished in the preceding multi-year study (AFOSR Contract No. F44620-75-C-0060) and consisted of two modifications: (a) treatment of motor noise as a noise process added to the operator's control-rate, rather than to his "commanded" control; and (b) the distinction between a "driving" motor noise process injected into the controlled plant, and a "pseudo" (or "internal") noise process used in determining the operator's response strategy. This modification is described in Levison, Baron and Junker [1], and the revised model has been applied to subsequent studies of roll-axis motion.

Another modification to the model, described by Baron and Berliner [10], was performed under contract to another agency to

allow consideration of an 'internal' model that incorrectly reflects one or more aspects of the characteristics of the actual control-task environment (e.g., controlled plant dynamical response properties, system delays, statistical properties of external inputs). Prior to the current study, this model was not used by us in performing model analysis of data obtained in motion-cue studies. The rationale for assuming a correct internal model was that a subject well trained on a tracking task involving a relatively wideband plant would develop an internal model of the task that was adequate for generating an appropriate response strategy. The considerable saving in computation requirements, compared to the implementation allowing for a deviate internal model, provided further motivation for assuming a correct internal model.

When plans were made to analyze data from an experiment exploring delayed motion cues [11], we foresaw the likelihood that the test subjects would have an incorrect perception (at least early in training) of the relative phasing of visual and whole-body motion cues. We therefore modified the computer implementation of the OCM to allow both the revised treatment of motor noise and the flexibility to consider deviant internal models.

Appendix B describes the formulation of the revised pilot model.

2.3 Automated Identification of Pilot-Related Model Parameters

The automated gradient search scheme for identifying pilot-related OCM parameters, originally reported by Lancraft and Kleinman [12], was refined and extended under this contract. This scheme identifies the set of independent model parameters that provides the least-squared-error joint match to experimental variance, gain, phase, and remnant measurements, and is described in detail in Appendix C.

As currently implemented, the parameter identification scheme places no constraints (other than non-negativity) on the identified values. Now, if all independent model parameters are allowed to vary freely to obtain a best match to a given data set, all parameters will generally vary from one data set to the next. In order to interpret such results, we need some method for determining which parameter changes are "significant"; that is, which parameter changes are necessary to account for changes in operator response behavior due to learning or to some change in experimental conditions. Relative magnitudes of various parameter changes are not reliable indicators of significance: a large change in the value of a particular model parameter may simply reflect insensitivity of the matching error to the value of that parameter.

The cross-comparison method described in Appendix C provides a qualitative significance test on parameter differences obtained from modeling the results of two experimental conditions. This method employs a numeric, non-analytic sensitivity test as described below.

Assume that we wish to analyze two data sets, corresponding to, say, the "baseline" and "test" experimental conditions; specifically, we wish to determine whether or not different parameter values are required to match these data. The null hypothesis, then, is that a single set of parameter values yields a near-optimal match to the "baseline" and "test" data.

To test the null hypothesis, we first identify three sets of pilot parameters using the gradient search scheme: (1) the set that best matches the baseline data, (2) the set that best matches the test data, and (3) the set that provides the best joint match to the baseline and test data. For convenience, we shall refer to the parameters identified in step 3 as the "average parameter set".

We next compute the following four matching errors:

$J(B,B)$ = matching error obtained from baseline data, using parameters identified from baseline data (i.e., best match to baseline data).

$J(B,A)$ = matching error obtained from baseline data, using average parameter set.

$J(T,T)$ = best match to test data.

$J(T,A)$ = matching error obtained from test data, using average parameter set.

Finally, we compute the following "matching error ratios":
 $MER(B) = J(B,A)/J(B,B)$, $MER(T) = J(T,A)/J(T,T)$ and, if we wish to reduce the results to a single number, the average of these two error ratios.

In a qualitative sense, the greater the matching error ratios, the more significant are the differences between the parameters identified for the baseline and test conditions. For example, if both matching error ratios are unity (the theoretical minimum), then the null hypothesis is supported: there exists a single set of parameters that provides an optimal match to both data sets. Any differences between the baseline and test parameter sets must be considered insignificant and can be attributed to imprecision of the identification procedure. Conversely, if one or both matching errors ratios are substantially greater than unity, one must reject the null hypothesis and consider the differences in model parameters to be "significant"; i.e., to represent true differences in operator response behavior.

2.4 Analysis of Control Strategy Development

An experimental study was performed by the Air Force's Aerospace Medical Research Laboratory and the Human Resources Laboratory to explore the effects of simulator delays on performance during various stage of training. Analysis of the experimental data was undertaken by BBN under Contract No. F33615-76-C-5001, and was continued under the subject AFOSR study, to explore the effects of whole-body motion cuing on control strategy development. Preliminary results of this study have been reported by Levison, Lancraft and Junker [11]. The results of this task are summarized briefly here and in more detail in Appendix D.

Five separate subject groups received initial training on a simulated roll-axis tracking task as follows: one group trained with instrument visual cues only (the "static" group); another group trained with combined, synchronized visual and motion cues ("synchronous motion"); and the remaining groups trained with motion cues delayed with respect to visual cues by 80, 200, and 300 msec. All groups were trained to apparent asymptotic mean-squared error in their initial tasks. After training, all but the synchronous motion group trained to asymptotic performance in the synchronous motion condition.

Pre- and post-transition learning trends for the various subject groups are shown in Figure 1. Mean-squared error is plotted as a function of training session, where each session consisted of four experimental trials of approximately three minutes each. A clear performance trend is evident, with increased asymptotic MS error scores associated with increasing motion-cue delay. Exponential fitting of the learning curves (see Levison, Lancraft and Junker) showed a trend toward increasing learning rate with decreasing delay.

Frequency-response measures were obtained from selected subjects in the static and synchronous motion groups at various stages of training. Figure 2 compares these measures for one member of the static group at early and late stages of pre-transition training. The trends shown in this figure are consistent with the improved MS error performance over the course of training: specifically, amplitude ratio (pilot "gain") increased at all frequencies, high-frequency phase lag was reduced, low-frequency remnant was reduced, and high-frequency remnant was increased.

The identification scheme described above was used to identify pilot-related OCM parameters for various stages of training. The following comparisons were made: (1) early pre-transition training versus asymptotic pre-transition training, static group; (2) early

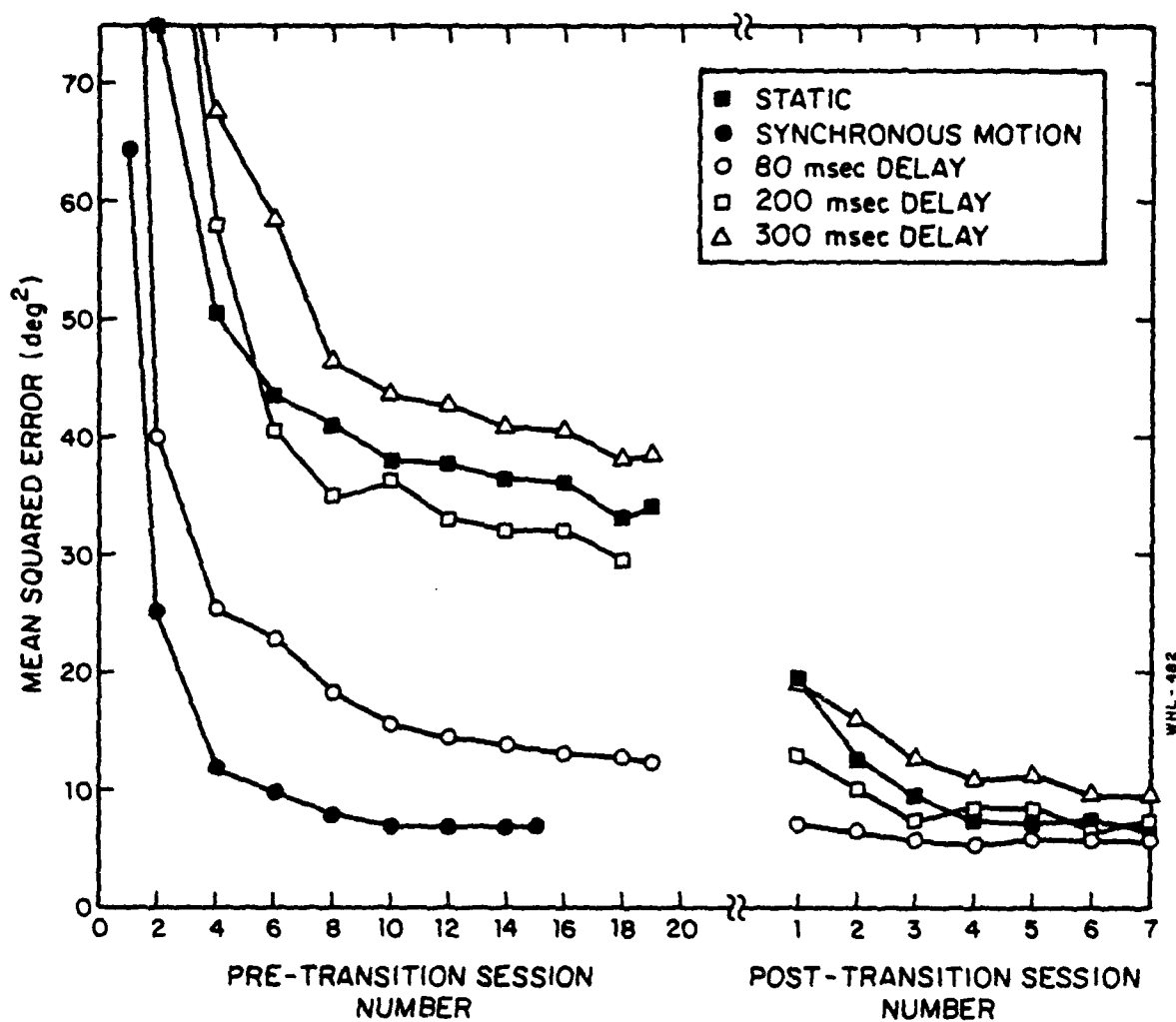


Figure 1. Learning Curves
Average of 4-5 Subjects, 4 trials/subject

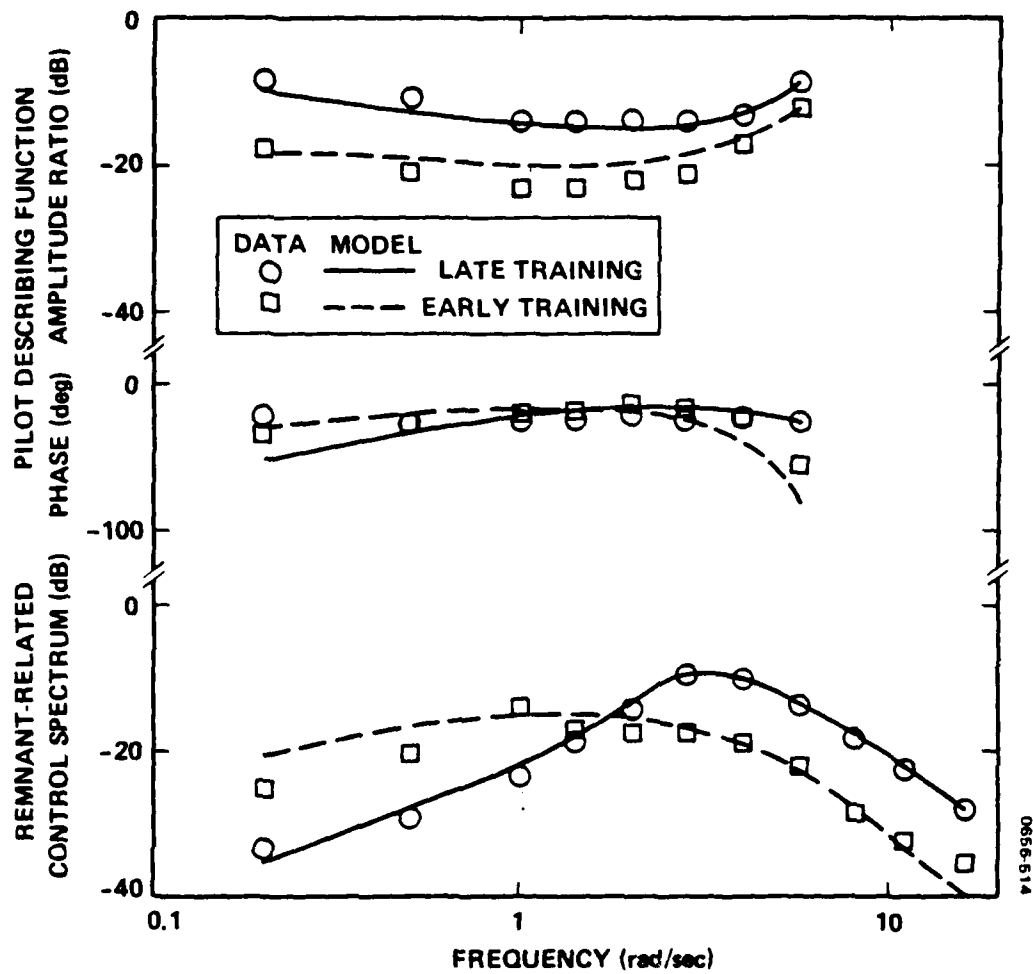


Figure 2. Effects of Training on Frequency Response
Subject CP, Average of 4 trials

post-transition training versus asymptotic post-transition training, static group; and (3) early post-transition training, static group versus 80-msec option group.

The effects of continued training were similar for both the pre-transition and post-transition training phases (comparisons 1 and 2). In both cases, training resulted in a reduction in the motor time constant as well as observation noise/signal ratios. The training effect on motor time constant was more important than the effect on observation noise. (That is, a substantially worse match to the joint data sets is obtained by using an average motor time constant than by matching with average observation noise variances).

The transfer-of-training comparison (no. 3 above) showed changes in observation noise/signal ratios to be the only significant effect. Specifically, analysis of performance immediately following transfer to the synchronous motion condition revealed lower noise levels for the subjects initially trained with 8-msec delayed motion than for the subjects trained fixed base. Thus, training with delayed motion (for this particular delay) was more effective than fixed-base training in terms of training the subject to efficiently process relevant perceptual information in the simulated "operational" (i.e., synchronous motion) task.

Training-related reductions in observation noise confirmed pre-experimental expectations. Recall that the observation noise process in the OCM accounts for most of the pilot "remnant" (i.e., the portion of the pilot's control activity that is not accounted for by a time-invariant linear response strategy. Now, there are a number of potential sources of remnant in any control situation, including: (1) within-trial fluctuations in the response strategy, (2) nonlinear response behavior, (3) a general signal-to-noise-ratio limitation with respect to human information processing, and (4) perceptual resolution limitations. The first two sources should be especially influenced by training. One would expect a subject unfamiliar with the experimental tracking task to attempt different control behaviors early in training in his search for the optimal response strategy. Similarly, a certain amount of training would be required for a naive subject to learn to respond in a linear fashion. Thus, reductions in observation noise with continued training can be readily explained.

The transfer-of-training differences found for observation noise are also expected. One might reasonably postulate that subjects trained initially with the 80-msec delayed motion cues were exposed to a perceptual situation more like the transfer task than were subjects trained fixed base, and were therefore able to more quickly learn to process faithful motion cues and adopt the appropriate control strategy in the transfer condition.

The observation noise results do show one unexpected trend, however, in that observation noise reduction occurs mainly with regard to utilization of tracking error, rather than error rate. Now, one would expect that naive trackers would initially rely on position information and, only after a period of training, would they learn to effectively utilize rate information. These results indicate the opposite trend. While it is possible that our preconceptions are wrong and that subjects more readily learn to use rate than position information, a more believable explanation is that the large observation noise identified for error perception is a result of assuming a perfect internal for model analysis when, in fact, the subjects have important deviations (or uncertainties) associated with their internal models early in training. This hypothesis remains to be tested.

The training-related change in motor time constant also remains to be explained, especially since this model parameter undergoes the most significant variation. One hypothesis is that the relatively large motor time constant identified early in training is, in fact, a manifestation of imperfections in the human operator's internal model of the task environment. This issue is explored in the following section.

2.5 Limitations on Psychomotor Performance

Subjects well-trained on relatively wide-band, single-variable tracking tasks tend to reveal similar performance capabilities as characterized by the pilot-related OCM parameters. We have seen that when subjects are not fully trained, parameter values deviate from nominal in the direction of degraded performance capabilities. A similar degradation is found for well-trained subjects when the system dynamics controlled by the subject are high-order (or low bandwidth).

In this section we explore certain hypotheses for these systematic parameter variations, with emphasis on the notion that deficiencies exist in the pilot's internal model of the task environment. Two classes of manual control situations are analyzed: (1) tasks in which subjects have been trained to near-asymptotic levels of performance, and (2) tasks in which the effects of training have been studied.

2.5.1 Effects of Task Environment on Asymptotic Performance

A small study was performed to explore the effects of task parameters on pilot-related OCM parameters in single-variable tracking tasks in which subjects had been trained to near-asymptotic levels of performance. No new experiments were performed; rather, existing manual control data were re-analyzed using the identification technique described in this report.

The control tasks analyzed ranged from simple proportional control and rate control to control of relatively high-order plants. Details of the experimental configurations and of the results of this investigation are documented in Appendix E. The following trends are revealed: (1) the motor time constant appears to increase with the order of the plant, (2) large observation noise/signal ratios are associated with perception of error displacement for acceleration-control and higher-order plants, and (3) a relatively large time delay is identified for the plants configured by cascading rate control with low-bandwidth filters.

Now, since all subject populations were well trained, and since different groups of subjects tend to perform the same on a given task (given equivalent training), it is unlikely that these differences in pilot-related model parameters reflect different inherent information-processing capabilities among the experimental subject populations. We are left with two more likely explanations for the apparent trends: (1) subjects were motivated differently by the different task configurations, and (2) internal modeling difficulties associated with higher-order plants have been reflected as differences in noise and response time parameters because of modeling constraints.

The notion of task-related motivational differences are explored in Appendix E. Sensitivity analysis performed with the

OCM suggests that motivational factors might account, in part, for the relatively large observation noise. The model indicates that, in these tasks, the overall performance criterion (essentially, mean-squared tracking error) is relatively insensitive to observation noise covariance. To the extent that suppression of self-generated noise increases task workload [8,9], the test subjects may well have been unmotivated to reduce noise levels to that found in tasks more sensitive to this parameter.

Motivational factors do not explain the task-related changes in motor time constant. Model analysis has not shown a consistent relationship between the magnitude of the motor time constant and the sensitivity of mean-squared error to reductions in this parameter.

2.5.2 Effects of Training

In section 2.4 (and in greater detail in Appendix D) we showed that, compared to asymptotic training, early training was manifested as deviations in pilot-related parameter values consistent with degraded performance capabilities. Plausible explanations have been offered above for the differences in observation noise levels. We now address the issue of training-related changes in motor time constant--the parameter that was most significantly influenced by training.

Four potential causes of training-related variations in motor time constant are considered: (1) pilot response-bandwidth capabilities increase with training, (2) the pilot becomes more willing to generate larger control rates with training, (3) early stages of learning are characterized by a large multiplicative motor noise, (a way of treating uncertainties in the pilot's internal model), and (4) apparent variation in the motor time constant is an artifact of the modeling procedure and stems from the assumption (for modeling purposes) of a perfect internal model when, in fact, the subject's internal model is seriously deficient early in training.

Experimental trends observed in the delayed-motion experiment tend to refute the first two hypothesis. As shown in Appendix D, the identified motor time constant for the static group immediately decreased from 0.13 to about 0.087 upon exposure to combined (and concurrent) visual and motion cues. It seems unlikely that an inherent inability or reluctance to generate large rates of change of control would suddenly be modified.

The hypothesis of a progressive training-related decrease in multiplicative motor noise is consistent with the observed decrease in observation noise and would account, at least partially, for training-related changes in motor time constant.

This particular approach is reviewed below in section 2.6 and in more detail in Appendix F. Additional research is needed to determine whether or not this modeling approach can provide a consistent explanation for the trends observed over the available data base.

The multiplicative motor noise process may be considered as a special type of internal modeling difficulty; namely, uncertainty as to the effects of the pilot's control input. It seems obvious that subjects would not have as accurate and precise an internal model early in training as after considerable practice.

The training results presented in Section 2.4 are suggestive of internal model discrepancies. Specifically, the experimental data obtained early in training were not matched as well as data obtained from the same subjects late in training, even though model parameters were adjusted to provide the best match in both cases. (See Figure 2.) This phenomenon would be expected if the structure of the OCM as applied to the initial data sets was at least partially in error (i.e., a perfect internal model assumed when, in fact, the subject has a deviate internal model).

2.6 Multiplicative Motor Noise Model

In an attempt to account for the apparent task-related changes in motor time constant, a small study was performed by Caglayan and

Levison [13] to explore the utility of a multiplicative motor noise model. The notion of a multiplicative motor noise process is consistent with the empirical finding that, in idealized control situations, both motor noise and observation noise appear to scale with the variances of corresponding control and display variables. In previous studies, these processes have been considered to affect only the estimator (Kalman filter) portion of the model; in this treatment, however, we considered the multiplicative motor noise process to influence the control gains and, hence, the motor time constant (which is the inverse of the feedback gain relating commanded control rate to instantaneous control force).

Initial application of this submodel has been encouraging: for the few experimental cases explored, variations in motor time constant were accounted for by fixed values assigned to the cost of control rate and to the parameters of the multiplicative motor noise process. Further work is required to determine the extent to which a fixed set of cost and noise parameters can explain human operator behavior across a variety of task conditions. In addition, for this concept to be useful in a predictive model, consistent adjustment rules would be required to relate multiplicative motor noise to perceptual cueing and, as we shall shortly demonstrate, to the nature and amount of training on the control task.

Multiplicative motor noise may be considered one aspect of an internal modeling deficiency on the part of the human operator. As shown by Ku and Athens [14], one may consider the more general case of multiplicative disturbances on the operator's internal model of system dynamics. In effect, the multiplicative noise concept is a representation of the operator's uncertainty about system response behavior. One might well expect that such uncertainty would be reduced both by improving the information available to the pilot (e.g., provide motion cues) as well as by continued training.

Further details may be found in the paper by Caglayan and Levison, which is included in this report as in Appendix F.

2.7 Concluding Comments

We have shown how the structure of the tracking task and the degree of training can influence model parameters that we relate to the human operator's information-processing limitations. A number of hypotheses have been considered to account for these effects, and the most likely explanation appears to be that the accuracy and/or precision of the operator's internal model is improved with enhanced perceptual information and with continued training. The notion that learning relates to internal model development is consistent with existing theories of learning [15-18].

Despite the focussing on potential imperfections in the operator's internal model, the reader should not conclude that current modelling philosophy (in which the OCM is formulated with a perfect internal model) is necessarily inappropriate. This philosophy has been found to yield accurate predictions of pilot/vehicle performance in a variety of tasks, and it is especially useful in the design of experiments, where one is primarily interested in predicting performance trends with respect to changes in the task environment.

A more accurate human operator model is required, however, to account for the interactions between cue set, training, and performance. Because results to date suggest that the operator's internal model is influenced by both cue set and learning, a subsequent study has been initiated to explore this aspect of the pilot model (Air Force Contract No. F33615-81-C-0157). To guide this effort, a brief literature review has been completed with regard to adaptive-control and identification algorithms and is presented in Appendix G of this report.

3. PUBLICATIONS AND PRESENTATIONS

The following publications and presentations relate, in full or in part, to work completed under this contract.

3.1 Written Publications

1. Levison, W.H., R.E. Lancraft and A.M. Junker, "Effects of Simulator Delays on Performance and Learning in a Roll-Axis Tracking Task", Proc. of the Fifteenth Annual Conference on Manual Control, Wright State University, Dayton, OH, March 1979.
2. Lancraft, R.E. and D.L. Kleinman, "On the Identification of Parameters in the Optimal Control Model", Proc. of the Fifteenth Annual Conference on Manual Control, Wright State University, Dayton, OH, March 1979.
3. Caglayan, A.K. and Levison, W.H., "The Effects of Multiplicative Motor Noise on the Optimal Human Operator Model," Proc. of the Sixteenth Annual Conf. on Manual Control, Cambridge, MA, May 1980.
4. Baron, S., and Levison, W.H., "The Optimal Control Model: Status and Future Directions", Proc. 1980 Int. Conf. on Cybernetics and Society, Cambridge, MA, Oct. 8-10, 1980.

5. Levison, W.H., and G.L. Zacharias, "An Optimal-Control Model for the Joint Use of Visual and Motion Cues in Continuous Tracking Experiments: Theory and Experiments", J. Cybernetics and Information Science, Vol. 3, No. 1-4, 1980.
6. Levison, W.H., "A Quasi-Newton Procedure for Identifying Pilot-Related Parameters of the Optimal Control Model", Proc. of the Seventeenth Annual Conf. on Manual Control, Los Angeles, CA, June 1981.

3.2 Oral Presentations

Oral presentations were given at the conferences cited above. The following additional oral presentations were given relevant to work performed during this study:

1. W.H. Levison: "A Model for the pilotTGS Use of Motion Cues in Roll-Axis Tracking Tasks", presented at the Review of Air Force Sponsored Basic Research in Visual Processes and Human Operator Control, Sinclair Community College, Dayton, OH, September 26-28, 1978.
2. W.H. Levison: "Effects of Delayed Motion Cues on Performance and Learning in a Roll-Axis Tracking Task", presented at the Review of Air Force Sponsored Research in Flight and Technical Training, ASAF Academy, Colorado Springs, CO, March 27-29, 1979.

3. Levison, W.H., "Measurement and Modelling of Skill Development in a Continuous Tracking Task", 1980 APA Convention, Montreal, Sept. 1-5, 1980.

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APPENDIX A

DESIGN OF AN EXPERIMENT TO EXPLORE THE PILOT'S USE OF
COMBINED MULTI-AXIS VISUAL AND MOTION CUES

The results of recent studies of motion-cue utilization have been consistent with the hypothesis that attention must be shared between visual and motion cues in the same axis of control; that is, the pilot's ability to perceive and use cues from one modality is degraded by the requirement to use cues from the other modality [1-3]. The data are not sufficient, however, to determine conclusively whether or not such interference effects need to be considered when modeling closed-loop pilot/vehicle systems.

As part of this contractual effort, a set of experiments was designed to test various hypothesis regarding interference (or lack thereof) among whole-body motion cues and visual cues, both within a single axis of control and between two uncoupled control tasks. Experimental conditions were selected to provide a task environment for which performance would be sensitive to attention-sharing limitations. The experiment design was based, in part, on the then-existing response capabilities of the Multi-Axis Tracking Simulator (MATS) facility at AMRL.

A.1 Description of the Tracking Task

Analysis was performed for the general task of attitude control consisting of either (1) roll control only, (2) pitch control only, or (3) combined pitch and roll control. The task consisted of either regulating attitude in the presence of simulated gusts, or following a simulated target in attitude. Simultaneous gust-regulation and target-following was not explored.

Vehicle transfer functions relating plant output P to control input U were functions of the axis of control and of the nature of the input (target or gust disturbance) as shown in Figure A1. $V(s)$, the experimental variable, represents the transfer function between commanded attitude rate and unit control input. The first-order lag at 15 rad/sec is a close approximation to the identified dynamics of the rotating simulator in both pitch and roll, and the Pade network having a critical frequency of 33.3 rad/sec is an approximation to the 60 msec cumulative time delay anticipated from filtering, digital update, and display operations.

Roll-axis dynamics used in previous experiments [2,4] were used to provide a tie to published results; these dynamics are intended to be representative of roll-axis response of high-performance fighter aircraft. Pitch response characteristics were selected to represent high-speed, high-altitude response for the disturbance-regulation task [5]. In addition, pitch dynamics containing a 5-sec divergence time constant were explored as a means for providing a task for which performance is highly sensitive to the nature of multi-cue interference.

General form:

$$\frac{P}{U}(s) = K_u \cdot V(s) \cdot \frac{15}{s+15} \cdot \frac{1}{s} \cdot \frac{-s+33.3}{s+33.3}$$

$$V(s) = \frac{5}{s+5}$$

Roll,
All Tasks

$$= \frac{(4.3)^2}{1.4} \cdot \frac{s+1.4}{s^2 + 2(.5)(4.3)s + (4.3)^2}$$

Pitch,
Target Input

$$= \frac{(3.11)^2}{.804} \cdot \frac{s+0.804}{s^2 + 2(.348)(3.11)s + (3.11)^2}$$

Pitch (stable)
Disturbance Input

$$= \frac{0.2}{s-0.2}$$

Pitch (unstable),
Disturbance Input

Figure A1. Controlled Element Dynamics

The input forcing function was either a first- or second-order Butterworth noise process having a break frequency at either 0.5 or 1.0 rad/sec. Table A1 shows the input parameters assigned to the various tracking tasks considered in this analysis. These parameters were chosen to provide tracking tasks such that vehicle attitude and its first and second derivatives would not exceed the limits shown in Table A2. The disturbance input was added in parallel with the pilot's control input $u(t)$; the target input was added to the plant output $p(t)$.

A.2 Perceptual Submodel

We review here the perceptual submodel of the optimal-control model for pilot/vehicle systems. The reader is assumed to have a working knowledge of the basic model; a review of the optimal-control model and its application to studies of motion-cue utilization is provided in Levison, Baron, and Junker [1].

Past studies indicate that, in general, the pilot may be assumed to obtain displacement and rate information from symbolic visual display elements [6-8]. For situations in which the frequency content of platform motion is within the passband of the pilot's vestibular sensing mechanism, good model predictions can be obtained by adopting a simple informational model; that is, one may assume that platform motion provides displacement, rate, and acceleration cues.

Table A3 lists the perceptual variables assumed to be available to the pilot for the various tasks explored in this analysis. Cues provided by motion cues in the target-following task are different from those provided by visual cues; the former relate

TABLE A1

INPUT PARAMETERS

Axis	Input	Order	ω_i (rad/sec)
ROLL	Target	2	0.5
	Disturbance	2	1.0
PITCH	Target	2	0.5
	Disturbance	1	0.5

TABLE A2

SIMULATOR LIMITATIONS

Variable	Roll	Pitch
Displacement (deg) *	30	30
Rate (deg/sec) **	60	30
Acceleration (deg/sec ²) **	100	100

* Desired Maximum

** Hardware Constraint

solely to the position and motion of the simulated vehicle, whereas the latter relate to the difference between vehicle and target motion. In the case of disturbance regulation -- where attitude error is simply the vehicle attitude -- motion and visual cues overlap, with visual cues providing better displacement information, and motion cues providing the acceleration information missing from the visual cues. Both visual and motion cues are assumed to be good sources of rate information.

TABLE A3

ASSUMED PERCEPTUAL VARIABLES

Sensory Mode	Tracking Task	
	Target Tracking	Disturbance Regulation
Static	Attitude Error	Attitude
	Attitude Error Rate	Attitude Rate
Motion	Attitude	Attitude
	Attitude Rate	Attitude Rate
	Attitude Acceleration	Attitude Acceleration

The effects of perceptual interference are reflected in the optimal-control model as adjustments to the "observation noise" associated with perceptual inputs. If we assume negligible threshold- and saturation-related phenomena, we represent observation noise as

$$v_{yi} = \sigma_{yi}^2 \cdot \frac{P_o}{F_i} \quad (1)$$

where V_{y_i} is the covariance of the white noise process associated with perception of the variable y_i , $\sigma_{y_i}^2$ is the variance of y_i (we assume a zero-mean steady-state tracking task), P_0 is the noise/signal ratio generally found for single-variable tracking tasks, and f_i is the attention allocated to the variable y_i . This model of task interference, or attention-sharing, is based on research performed with visual cues only [8,9] as well as combined visual and motion cues [1-5].

Values of approximately -20 dB for noise/signal ratio have been identified from tracking data obtained in a variety of single-variable manual control situations [2,6-8]. Accordingly, we have associated this value with a relative attention of unity for the analysis performed as part of this experimental design. Because lower values have been found for some tasks [8,10], we cannot consider -20 dB to literally represent "full attention"; rather, it serves as a convenient anchor point that we can associate with performance of a well-motivated and well-trained subject on a task of moderate demand.

Good model results have been obtained with the assumption that there is no interference among cues obtained from the same physical display indicator (either a symbolic visual display or platform motion). Therefore, we have assumed that a value f_v may be assigned to all visual perceptual variables in a given task situation, and that an attention of f_m may be assigned to all motion-derived perceptual variables.

Previous results with multi-axis tracking tasks indicate that task interference may be modeled as attention-sharing between the perceptual variables associated with the various axes of control [8,9]. For static (fixed-base) tracking, the following model is assumed:

$$f_v = 1 \quad \text{single-axis} \quad (2)$$

$$f_{v_\theta} + f_{v_\phi} = 1 \quad \text{combined pitch and roll}$$

where the subscripts θ and ϕ refer to the pitch and roll axes, respectively. All attentional quantities are constrained to lie between 0 and 1.

Various assumptions are postulated regarding attention-sharing effects among motion cues in combined visual and motion tracking. The assumptions considered in this analysis, and their representation in terms of the model of Equation (1), are outlined below.

Interference Between Visual and Motion Cues. In this least optimistic assumption of attention-sharing requirements, we assumed that the pilot has to share attention not only between pitch and roll tasks, but also between visual and motion cues within a task. This assumption is modeled as

$$f_v + f_m = f_T \quad (3)$$

where f_T is the attention to the task (pitch or roll). The f_T are assumed to sum to unity across the two tasks.

Parallel Processing of Visual and Motion Cues. Attention-sharing requirements across tasks are assumed the same for motion cues as for visual cues, but multi-sensory cues are assumed to be obtained in parallel (i.e., without interference) within an axis. Thus,

$$f_v = f_m = f_T \quad (4)$$

No Attention-Sharing Decrements Associated with Motion Cues.

Motion cues are so compelling that the information provided by platform motion is not degraded by the presence of other tasks. In this case,

$$f_v = f_T$$

$$f_m = 1 \quad (5)$$

A.3 Model Analysis

Model analysis was performed to predict the effects of motion cues and task loading on performance for various assumptions regarding attention sharing. Presence or absence of motion was reflected by the set of perceptual variables included in the model; effects of attention-sharing were accounted for by variations in noise/signal characteristics as described below. Other pilot-related model parameters were held constant, or nearly so. Time delay was fixed at 0.2 seconds for all model runs. The relative weighting on control rate was adjusted to provide a "motor time constant" of 0.1 seconds, with one exception: on the basis of recent results [4], a time constant of 0.13 seconds was used for static roll-axis tracking. Driving motor noise was negligible, and "internal" (or "pseudo") motor noise was set at values consistent with past results (between -50 and -40 dB, relative to control-rate variance). The "pilot" was assumed to be attempting to minimize mean-squared tracking error.

Predicted mean-squared error was obtained as a function of "relative attention" (i.e., noise/signal ratio) for both static and motion tracking to indicate the interaction that might be

expected between motion cues and attention. For target-tracking tasks, equal attentions were assigned to the variables shown in the left column of Table A3. This treatment corresponds to the assumption of parallel processing of visual and motion cues as expressed in Equation (4). For disturbance tracking, equal attentions were assigned to attitude and attitude rate for static tracking and attitude, attitude rate, and attitude acceleration to approximate the assumption of parallel processing.*

Predicted effects of motion and attention are shown in Figure A2 for target following and in Figure A3 for disturbance regulation. All performance scores have been normalized with respect to mean-squared tracking error predicted for static tracking with a relative attention of unity (i.e., noise/signal ratio = -20 dB).

Figure A2 shows that motion cues should have a greater effect on roll-axis performance than on pitch-axis error for the target-following tasks considered in this analysis. For single-axis tracking, motion-static differences in predicted MSE are about 35% for roll tracking and about only 10% for pitch tracking. The latter difference is likely to be too small to show statistical significance in an experiment using a relatively small subject population (say, 4-8 subjects).

Figure A2 shows little interaction between motion cue effects and task loading. Static-motion differences are relatively constant for various levels of attention to the task. (Because scores are shown on a logarithmic scale, a given vertical distance indicates a constant fractional change in MSE score.)

* To more accurately reflect the assumption of parallel processing, attentions to variables assumed to be obtained from both visual and motion sources should be doubled. This was done in the analysis described later.

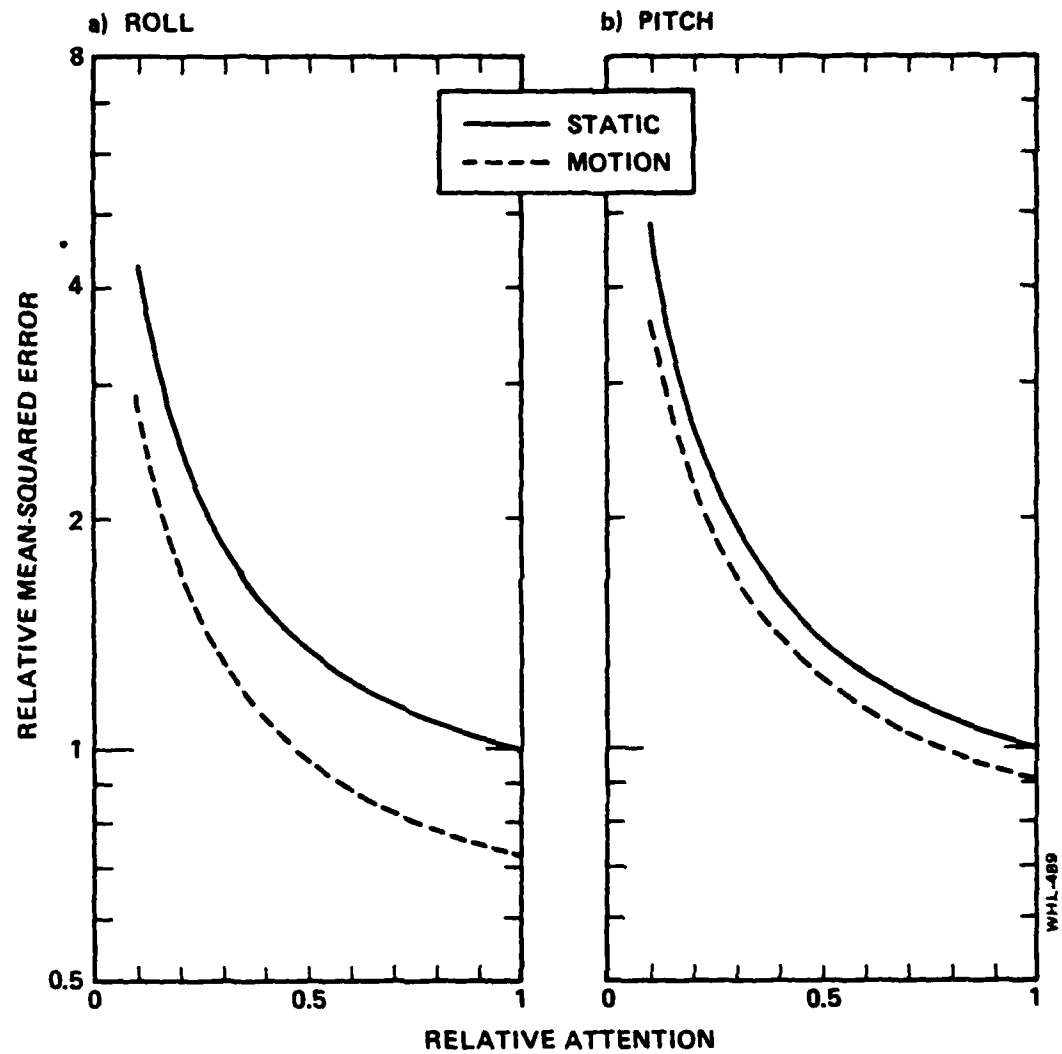


Figure A2. Effects of Attention and Motion on Relative Mean-Squared Error: Target Following

Figure A3 shows that predicted static-motion differences in MSE are greater for the disturbance-regulation tasks. Predictions for both the stable and unstable pitch tracking tasks are shown in Figure A3b. Predicted single-axis differences are about 80% for roll, 35% for stable pitch, and 70% for unstable pitch. Any of these changes is likely to be statistically significant with a population size of 4-8 subjects.

A negative interaction between motion-cue effects and task loading is predicted for disturbance regulation: the fractional difference between static and motion MSE scores decreases as attention to the task is decreased. This trend, predicted for both roll and pitch tasks, is counter to that reported in the literature [11].

Figure A4 shows relative mean-squared error scores predicted for the various attention-sharing hypotheses defined in Section A.2. Scores relating to 2-axis tasks were obtained under the assumption of 50% allocation to pitch and roll tasks. (By adjustment of the forcing functions and/or by appropriate weighting of the individual MSE scores in the total "cost", the subjects can be made to devote nearly equal attention to the two axes.) Figure A4a indicates that the target-following task, while perhaps being of operational interest, is not likely to provide a good experimental test of the various attention-sharing hypotheses. Motion cues are likely to have no statistically significant effect on tracking error for pitch tracking; roll tracking, while more sensitive to the presence or absence of motion cues, is also not expected to provide a sensitive test of all hypotheses considered here.

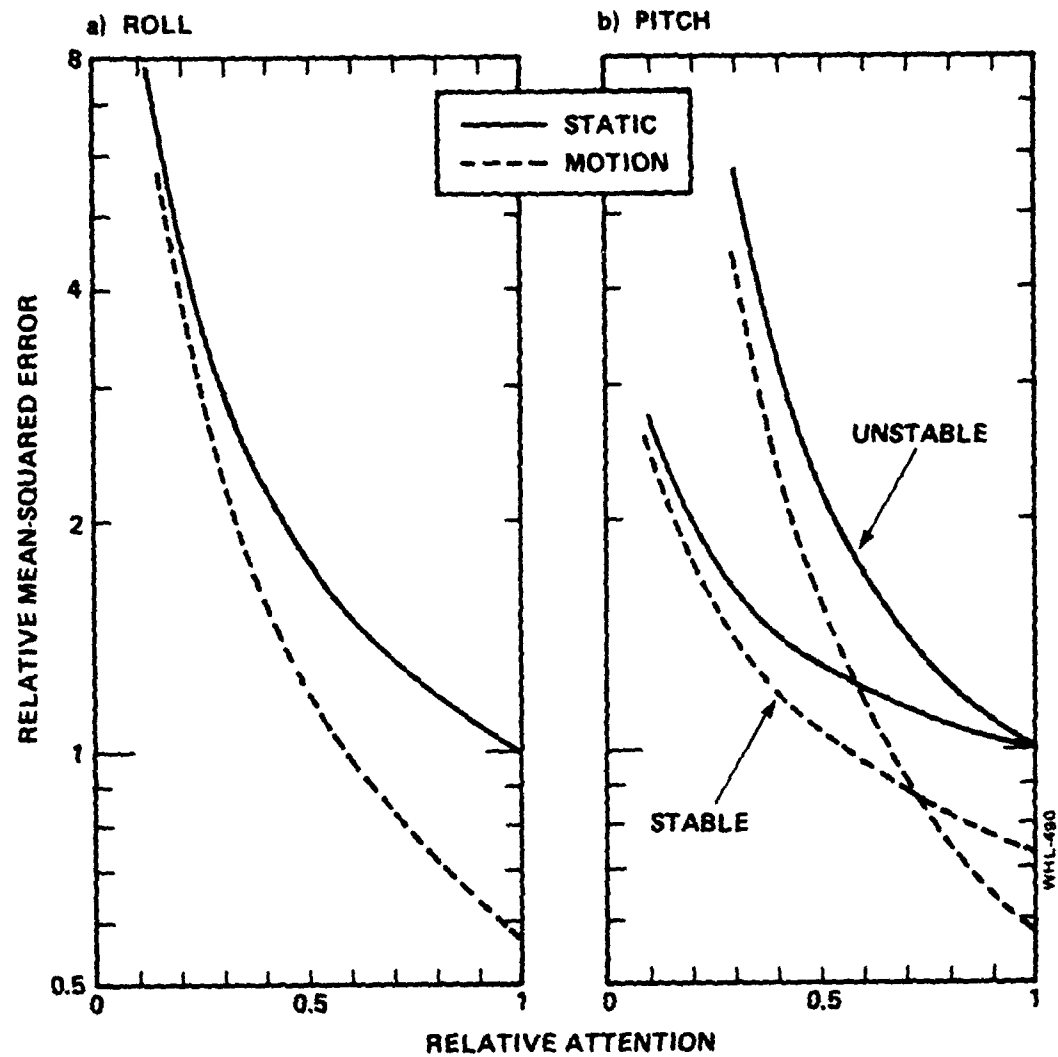


Figure A3. Effects of Attention and Motion on Relative Mean-Squared Error: Disturbance Regulation

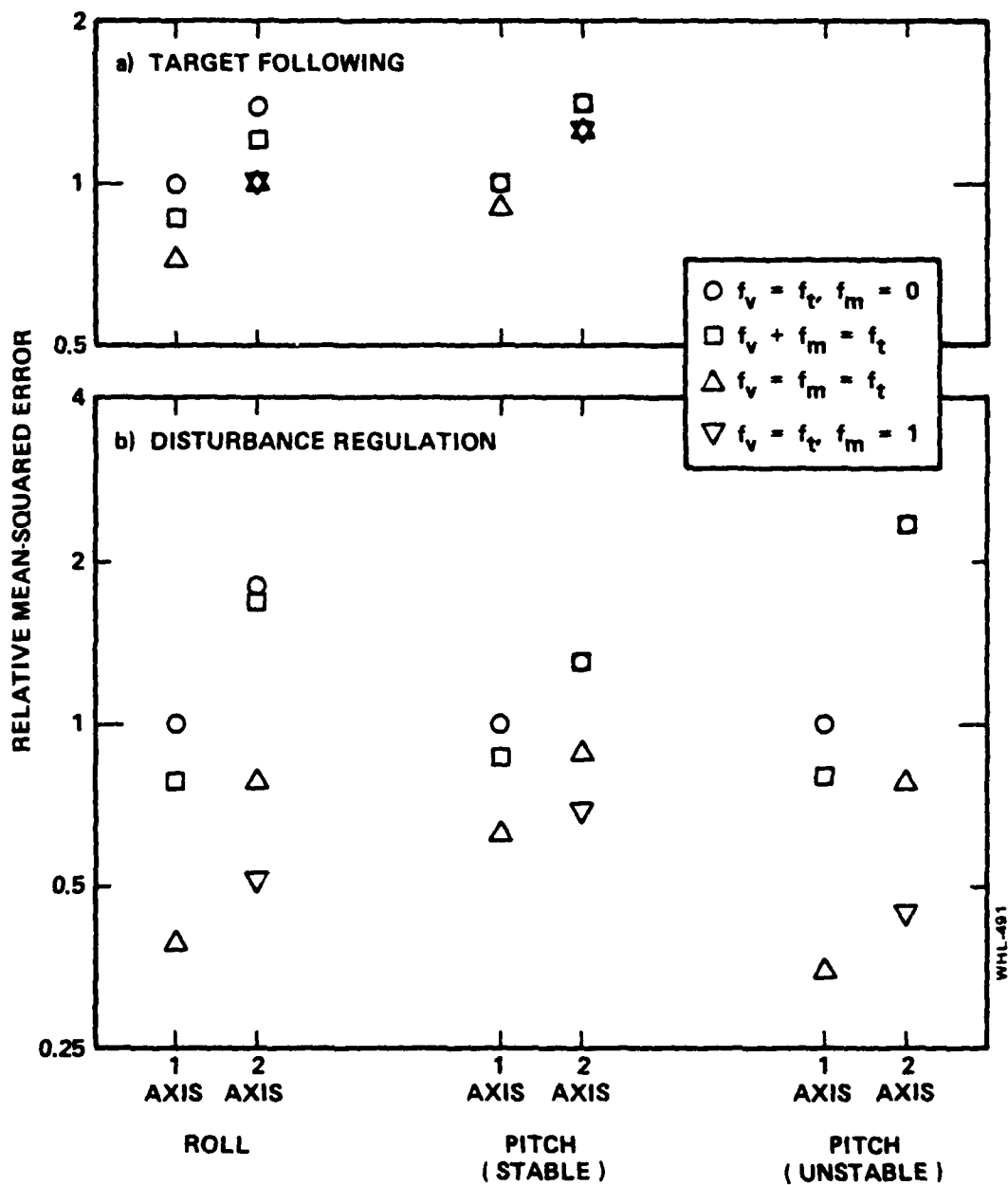


Figure A4. Model Predictions for Various Attention-Sharing Hypotheses

Tasks involving disturbance regulation would appear to allow a more sensitive test of attention-sharing hypotheses. Considering both single-axis and two-axis tasks, predicted differences are sufficiently large so that tests of statistical significance should allow one to select the best model. Although motion-cue effects are greater for the unstable pitch tasks, static-motion differences (at least for the more optimistic models) should be statistically significant for the stable pitch task as well.

A.4 Recommended Experiment

It is recommended that an experiment be conducted using the roll and stable pitch disturbance-regulation tasks described above. These tasks should provide a suitable means for exploring the interaction between motion cues, task load, and performance. Furthermore, these experimental tasks can be related to flight tasks of operational importance (e.g., air-to-ground attack in turbulence with an airplane having good handling qualities.)

Forcing-function amplitudes and control forces and vehicle motions are within desired limits. Guidance to selection of these parameters can be obtained from Table A4, which shows predicted RMS scores for various system variables for all five tasks considered in the foregoing analysis. For example, if the input amplitude is reduced by about a factor of 5 for pitch disturbance regulation (column 4), the probabilities of exceeding the simulator limits on pitch and its derivatives (Table A2) should be acceptably small; yet, signal amplitudes should be sufficiently large to minimize perceptual threshold effects. Note that control gain would have to be increased by about 5 to maintain required control forces of reasonable levels.

TABLE A4

PREDICTED RMS PERFORMANCE SCORES

Variable	Target Input		Disturbance Input		
	Roll	Pitch	Roll	Pitch (stable)	Pitch (unstable)
σ_{P_T}	10	10	-	-	-
$\sigma_{\dot{P}_d}$	-	-	15	10	10
K_u	15	10	15	10	10
σ_e	2.47	1.90	-	-	-
$\sigma_{\dot{e}}$	6.12	5.90	-	-	-
σ_p	10.6	10.3	4.47	9.34	.656
$\sigma_{\dot{p}}$	7.19	7.15	10.7	27.1	1.54
$\sigma_{\ddot{p}}$	22.4	28.1	45.0	130.	6.18
σ_u	.587	.474	1.46	1.29	3.47
$\sigma_{\dot{u}}$	3.05	2.16	6.24	7.91	23.0

Scores predicted for static tracking, observation noise/signal ratio = -20 dB.

P_T = target, $\dot{P}_d$ = disturbance, u = control, e = tracking error, p = plant.

Subjects should be instructed to minimize mean-squared tracking error when tracking either pitch or roll singly. When tracking combined pitch and roll, subjects should be instructed to minimize a scalar cost that consists of a weighted sum of mean-squared pitch error and mean-squared roll error. Weightings on the component scores should be selected so that performance on each task would contribute equally to the total cost when equal attention is paid to pitch and roll. Predicted performance scores shown in Table A4 provides guidance with regard to selecting weightings for component pitch and roll scores.

Subjects should be trained to near asymptotic performance on the following six tasks: (1) pitch, static, (2) pitch, motion, (3) roll, static, (4) roll, motion, (5) combined pitch and roll, static, (6) combined pitch and roll, motion. Subjects should be provided with knowledge of performance after each training trial. In the case of two-axis trials, the subjects should be told the total performance score plus the individual contributions to that score of roll- and pitch-axis errors.

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APPENDIX B

MODIFICATIONS TO THE PILOT/VEHICLE MODEL

A modification of the existing implementation of the optimal control model for pilot/vehicle systems was carried out for this study. Specifically,

- (i) the pilot's internal model of the vehicle was allowed to differ from the true model.
- (ii) The human was assumed to generate control-rate corrupted by motor noise. The control signal input was assumed to be estimated along with other variables.

The base line optimal control model employed in this study has been well documented in the literature [1-5]. To make the discussion here brief, we shall only sketch the necessary equations for the modified model used in this study. The concept of wrong internal model is explained in detail in [6]. The motivation for considering motor noise on control rate input is explained in [7].

Let the system to be controlled by the human operator be described by the linear equations

$$\dot{\underline{x}}(t) = \underline{A} \underline{x}(t) + \underline{B} \underline{u}(t) + \underline{E} \underline{w}(t) \quad (1)$$

$$\underline{y}(t) = \underline{C} \underline{x}(t) + \underline{D} \underline{u}(t) \quad (2)$$

where $\underline{x}$ is an n_x -dimensional vector of system state variables, $\underline{u}$ is an n_u -dimensional vector of control inputs, $\underline{y}$ is an n_y -dimensional vector of displayed outputs and $\underline{w}$ is an n_w -dimensional vector of a zero-mean, gaussian, white noise process with

autocovariance

$$E\{\underline{w}(t_1) \underline{w}'(t_2)\} = \underline{W} \delta(t_1 - t_2) \quad (3)$$

We shall assume that the parameter matrices A, B, C, D, E and W are time-invariant and consider only the steady state response of the system.

The structure of the human operator model is illustrated in Figure B1.

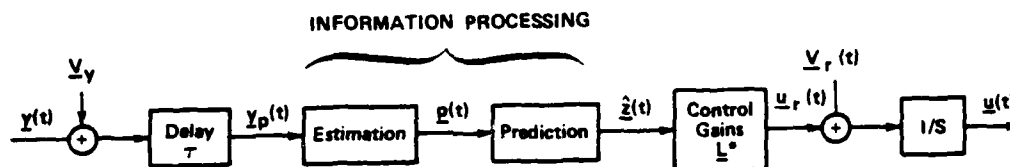


Figure B1. Structure of Human Operator Model

The structure and equations of Figure B1 have been documented extensively (see, e.g., [4]). We summarize them briefly to aid the subsequent development. Human limitations of perceptual noise and inherent delays result in the "perceived" output $y_p(t)$ being a noisy, delayed version of the displayed variables $y(t)$, i.e.*

* We assume zero thresholds on perception for convenience in derivation. The computer program allows such thresholds to be included.

$$\underline{y}_p(t) = \underline{y}(t - \tau) + \underline{v}_y(t - \tau) \quad (4)$$

where τ is a "lumped" delay and $\underline{v}_y(t)$ is a zero-mean, gaussian, white noise uncorrelated with $\underline{w}$ and with autocovariance

$$E\{\underline{v}_y(t_1) \underline{v}_y(t_2)\} = \underline{v}_y \delta(t_1 - t_2). \quad (5)$$

The human operator is assumed to "act" upon the information $\underline{y}_p(t)$ to generate the commanded control rate $\underline{u}_r(t)$ which results in the system input $\underline{u}(t)$ via the relation

$$\dot{\underline{u}}(t) = \underline{u}_r(t) + \underline{v}_r(t) \quad (6)$$

Here $\underline{v}_r(t)$ is a zero-mean, gaussian, white noise, uncorrelated with $\underline{v}_y$ and $\underline{w}$, and with autocovariance

$$E\{\underline{v}_r(t_1) \underline{v}_r'(t_2)\} = \underline{v}_r \delta(t_1 - t_2). \quad (7)$$

Equations (6) and (7) may be appended to (1) - (3) to define an augmented system with the following equations

$$\underline{x}_1 = \begin{bmatrix} \underline{x} \\ \underline{u} \end{bmatrix}, \quad \underline{A}_1 = \begin{bmatrix} \underline{A} & \underline{B} \\ \underline{O} & \underline{O} \end{bmatrix}, \quad \underline{B}_1 = \begin{bmatrix} \underline{O} \\ \underline{I} \end{bmatrix}$$

$$\underline{w}_1 = \begin{bmatrix} \underline{w} \\ \underline{v}_r \end{bmatrix}, \quad \underline{E}_1 = \begin{bmatrix} \underline{E} & \underline{O} \\ \underline{O} & \underline{I} \end{bmatrix}, \quad \underline{w}_1 = \begin{bmatrix} \underline{w} & \underline{O} \\ \underline{O} & \underline{v}_r \end{bmatrix}$$

$$C_1 = [\underline{C} \mid \underline{D}] \quad (8a)$$

and

$$\dot{\underline{x}}_1(t) = \underline{A}_1 \underline{x}_1(t) + \underline{B}_1 \underline{u}_r(t) + \underline{E}_1 \underline{w}_1(t)$$

$$\underline{y}(t) = \underline{C}_1 \underline{x}_1(t). \quad (8b)$$

Equations (8) have the same form as (1) - (3) so the standard results from modern control and estimation theory may be applied directly to these equations.

The blocks in Fig.B1 labeled estimation and prediction together model human information processing. For these processes to be performed "optimally" it is necessary to have perfect knowledge of the system $\{\underline{A}, \underline{B}, \underline{C}, \underline{D}, \underline{E}\}$, the driving noise-statistics $\{\underline{W}\}$, and the parameters describing human limitations $\{\tau, \underline{T}_N, \underline{V}_y, \underline{V}_m\}$. The control gains, $\underline{L}^*$, model human control-command generation or compensation and are selected so as to minimize a quadratic cost functional of the form

$$J(u) = \lim_{T \rightarrow \infty} E \left\{ \frac{1}{T} \int_0^T \left(\sum_i q_{x_i} x_i^2(t) + q_{y_i} y_i^2(t) + q_{u_i} u_i^2(t) + q_{r_i} \dot{u}_i^2(t) \right) dt \right\}. \quad (9)$$

To compute $\underline{L}^*$, it is necessary to know $\{\underline{A}, \underline{B}\}$ and the weighting coefficients $(q(.))_i$ in Equation (9). Thus, there are three classes of quantities or parameters that are required to be

known by the human operator if he is to perform optimally.
These are:

$$\text{System: } \{\underline{A}, \underline{B}, \underline{C}, \underline{D}, \underline{E}, \underline{W}\} \quad (10a)$$

$$\text{Human: } \{\tau, \underline{T}_N, \underline{V}_y, \underline{V}_m\} \quad (10b)$$

$$\text{Cost: } \{q_{x_i}, q_{y_i}, q_{u_i}, q_{r_i}\}. \quad (10c)$$

There are many assumptions that can be made concerning the human operator's knowledge of the requisite information in Equation (10). We assume the human operator knows the cost functional weightings (Equation 10c) and his own limitations of delay, neuromotor-lag and observation noise. On the other hand, we allow the human's internal models of system matrices and driving noise covariances to differ from the actual system, even as to dimensionality. The rationale for these assumptions is the same as that in [6].

To implement the above assumptions, we assume the human operator's internal model of (8) to be

$$\dot{\underline{z}}(t) = \tilde{\underline{A}}_1 \underline{z}(t) + \tilde{\underline{B}}_1 \underline{u}_r(t) + \tilde{\underline{E}}_1 \tilde{\underline{w}}_1(t) \quad (11)$$

$$\underline{y}(t) = \tilde{\underline{C}}_1 \underline{z}(t) \quad (12)$$

$$E\{\tilde{\underline{w}}_1(t_1) \tilde{\underline{w}}_1'(t_2)\} = \tilde{\underline{W}}_1 \delta(t_1 - t_2) \quad (13)$$

where

$$\tilde{\underline{A}}_1 = \begin{bmatrix} \tilde{\underline{A}} & \tilde{\underline{B}} \\ 0 & 0 \end{bmatrix}, \quad \tilde{\underline{B}}_1 = \underline{B}_1 = \begin{bmatrix} 0 \\ \underline{I} \end{bmatrix}, \quad \tilde{\underline{E}}_1 = \begin{bmatrix} \tilde{\underline{E}} & 0 \\ 0 & \underline{I} \end{bmatrix}$$

$$\tilde{\underline{C}}_1 = \{ \tilde{\underline{C}} \mid \tilde{\underline{D}} \} , \quad \tilde{\underline{W}}_1 = \begin{bmatrix} \tilde{\underline{W}} & \underline{0} \\ \underline{0} & \tilde{\underline{V}}_m \end{bmatrix} . \quad (14)$$

The perceived variables are (still)

$$\underline{y}_p(t) = \underline{C}_1 \underline{x}_1(t - \tau) + \underline{v}_y(t - \tau)$$

inasmuch as the "true" $\underline{y}$ is displayed to the operator. The "internal state" $\underline{z}$ need not have the same dimension as $\underline{x}_1$. However, we assume that $\underline{y}$ and $\underline{u}$ in the internal model have the same dimensions as the corresponding vectors of the system.

It is now assumed that the human will perform "optimally" subject to his information concerning the system. In other words, the estimation, prediction and control processes will be chosen to be optimal for the internal system model of Equations (11) - (14). Thus, the minimum variance estimate of the delayed internal state, $\hat{\underline{z}}(t - \tau) \triangleq \underline{p}(t)$, is generated by the Kalman filter

$$\dot{\underline{p}}(t) = \tilde{\underline{A}}_1 \underline{p}(t) + \underline{B}_1 \underline{u}_r(t - \tau) + \tilde{\underline{K}} [\underline{y}_p(t)] - \tilde{\underline{C}}_1 \underline{p}(t) \quad (15)$$

where,

$$\tilde{\underline{K}} = \tilde{\underline{\Sigma}} \tilde{\underline{C}}_1' \underline{V}_y^{-1} \quad (16)$$

and

$$\tilde{\underline{\Sigma}} \tilde{\underline{A}}_1' + \tilde{\underline{A}}_1 \tilde{\underline{\Sigma}} + \underline{E}_1 \tilde{\underline{W}}_1 \underline{E}_1' - \tilde{\underline{\Sigma}} \tilde{\underline{C}}_1' \underline{V}_y^{-1} \tilde{\underline{C}}_1 \tilde{\underline{\Sigma}} = \underline{0} . \quad (17)$$

The "least mean-squared" prediction process is

$$\dot{\underline{z}}(t) = \tilde{\underline{A}}_1 \hat{\underline{z}}(t) + \underline{B}_1 \underline{u}_r(t) + e^{\tilde{\underline{A}}_1 \tau} \tilde{\underline{K}}[\underline{y}_p(t) - \tilde{\underline{C}}_1 \underline{p}(t)]. \quad (18)$$

The commanded control rate is given by

$$\underline{u}_r(t) = -\tilde{\underline{L}} \hat{\underline{z}}(t) \quad (19)$$

where $\tilde{\underline{L}}$ is chosen to minimize (9)* subject to

$$\dot{\underline{z}} = \tilde{\underline{A}}_1 \underline{z} + \tilde{\underline{B}}_1 \underline{u}_r$$

Combining Equation (8) with (15), (18) and (19) yields for the closed-loop system

$$\begin{aligned} \dot{\underline{x}}_1(t) &= \underline{A}_1 \underline{x}_1(t) - \underline{B}_1 \tilde{\underline{L}} \hat{\underline{z}}(t) + \underline{E}_1 \underline{w}_1(t) \\ \dot{\hat{\underline{z}}}(t) &= (\tilde{\underline{A}}_1 - \underline{B}_1 \tilde{\underline{L}}) \hat{\underline{z}}(t) + e^{\tilde{\underline{A}}_1 \tau} \tilde{\underline{K}}[\underline{C}_1 \underline{x}_1(t - \tau) - \tilde{\underline{C}}_1 \underline{p}(t) + \underline{v}_y(t - \tau)] \\ \dot{\underline{p}}(t) &= \tilde{\underline{A}}_1 \underline{p}(t) - \underline{B}_1 \tilde{\underline{L}} \hat{\underline{z}}(t - \tau) + \tilde{\underline{K}}[\underline{C}_1 \underline{x}_1(t - \tau) - \tilde{\underline{C}}_1 \underline{p}(t) + \underline{v}_y(t - \tau)]. \end{aligned} \quad (20)$$

These equations are delay-differential equations and are infinite-dimensional for general $\tilde{\underline{A}}$.

* Terms involving $\underline{x}_1^2$, $\underline{u}_1^2$ in (9) are replaced by appropriate terms in $\underline{z}^2$. The weighting coefficient q_{r_i} will be chosen to result in control gains corresponding to $\underline{u}_i$ to be approximately 10 so that the "neuro-muscular time constants" are about 0.1.

The delay-differential character of Equation (20) can be estimated by approximating $\underline{\hat{z}}(t - \tau) = \underline{u}_r(t - \tau)$ via a Padé approximation for purposes of computing system scores ($\overline{x^2}$, $\overline{u^2}$, etc.) only. This approach results in a finite dimensional problem but the equations for $\underline{x}_1$, $\underline{\hat{z}}$ and $\underline{p}$ remain coupled and of undesirable high dimensionality. An approach that reduces the computational load significantly is to introduce the Padé approximation in the problem formulation directly. Thus, we modify the structure of Figure B1 to that of Figure B2. Note that we introduce the Padé delay at the human output, which usually has a lower dimension than his input $\underline{y}(t)$.

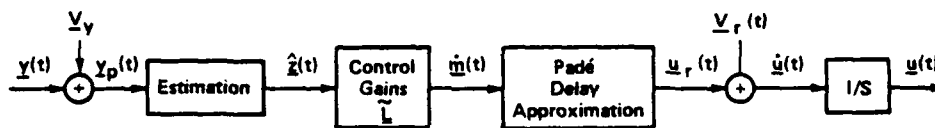


Figure B2. Modified Model Structure

In practice, the delay is now considered part of the system dynamics (except for computation of describing functions). It is a part that is assumed known to the human operator; so there will be some compensation for the delay. In particular, Equations (1) and (2) are augmented to account for the delay prior to any augmentation for control rate.

Let $\underline{x}_p$ represent the n_p -Padé states in an n_p -th order approximation*

* The computer program allows $n_p = 1$ or 2.

$$\dot{\underline{x}}_p = \underline{A}_p \underline{x}_p + \underline{b}_p \dot{\underline{m}} \quad (22)$$

$$\underline{x}_r = \underline{C}_p \underline{x}_p + \underline{d}_p \dot{\underline{m}} \quad (23)$$

Equations (1), (2), (6), (22), and (23) are combined and the following state space representation is obtained:

$$\underline{x}_{21} = \begin{bmatrix} \underline{x} \\ \underline{x}_p \\ \underline{u} \end{bmatrix}, \quad \underline{A}_{21} = \begin{bmatrix} \underline{A} & \underline{O} & \underline{B} \\ \underline{O} & \underline{A}_p & \underline{O} \\ \underline{O} & \underline{C}_p & \underline{O} \end{bmatrix}, \quad \underline{B}_{21} = \begin{bmatrix} \underline{O} \\ \underline{b}_p \\ \underline{d}_p \end{bmatrix}$$

$$\underline{E}_{21} = \begin{bmatrix} \underline{E} & \underline{O} & \underline{O} \\ \underline{O} & \underline{O} & \underline{O} \\ \underline{O} & \underline{O} & \underline{I} \end{bmatrix}, \quad \underline{W}_{21} = \begin{bmatrix} \underline{W} \\ - \\ \underline{V}_r \end{bmatrix}, \quad \underline{C}_{21} = [\underline{C} \mid \underline{O} \mid \underline{D}]$$

$$\dot{\underline{x}}_{21} = \underline{A}_{21} \underline{x}_{21} + \underline{B}_{21} \dot{\underline{m}} + \underline{E}_{21} \underline{W}_{21}$$

$$\underline{y} = \underline{C}_{21} \underline{x}_{21} \quad (24)$$

With the above approximation there is no true-delay, $\hat{z}(t) = p(t)$, and Equations (20) reduce to

$$\begin{aligned} \dot{\underline{x}}_{21} &= \underline{A}_{21} \underline{x}_{21}(t) - \underline{B}_{21} \underline{L} \underline{z}(t) + \underline{E}_{21} \underline{w}_{21}(t) \\ \dot{\underline{z}}(t) &= (\tilde{\underline{A}}_{21} - \tilde{\underline{B}}_{21} \underline{L}) \hat{\underline{z}}(t) + \tilde{\underline{K}} [\underline{C}_{21} \underline{x}_{21}(t) - \tilde{\underline{C}}_{21} \hat{\underline{z}}(t) + \underline{v}_y(t)] \quad (25) \end{aligned}$$

This equation can be written in the form

$$\dot{\underline{\Psi}} = \underline{F} \underline{\Psi} + \underline{G} \underline{\omega}$$

by defining

$$\underline{\Psi}(t) = \begin{bmatrix} \underline{x}_{21}(t) \\ \underline{\hat{z}}(t) \end{bmatrix}, \quad \underline{F} = \begin{bmatrix} \underline{A}_{21} & -\underline{B}_{21} \tilde{\underline{L}} \\ \tilde{\underline{K}} \underline{C}_{21} & \tilde{\underline{A}}_{21} - \tilde{\underline{B}}_{21} \tilde{\underline{L}} - \tilde{\underline{K}} \tilde{\underline{C}}_{21} \end{bmatrix},$$

$$\underline{G} = \begin{bmatrix} \underline{E}_{21} & \underline{O} \\ \underline{O} & \tilde{\underline{K}} \end{bmatrix} \quad \text{and} \quad \underline{\omega} = \begin{bmatrix} \underline{w}_{21} \\ \underline{v}_y \end{bmatrix}.$$

Thus, if $\underline{\Psi} \triangleq \text{Cov } \underline{\Psi}$ then $\underline{\Psi}$ is the solution of

$$\dot{\underline{\Psi}} = \underline{F} \underline{\Psi} + \underline{\Psi} \underline{F}' + \underline{G} \underline{\Omega} \underline{G}' \quad (28)$$

$$\underline{\Omega} = \begin{bmatrix} \underline{w}_{21} & \underline{O} \\ \underline{O} & \underline{v}_y \end{bmatrix}$$

If $\underline{F}$ is a stable matrix, $\underline{\Psi}$ will reach a steady-state given by the solution of the algebraic equation

$$\underline{F} \underline{\Psi} + \underline{\Psi} \underline{F}' = -\underline{G} \underline{\Omega} \underline{G}' \quad (29)$$

The condition that $\underline{F}$ be stable is not automatically guaranteed as is the case when all matrices are known. Stability will depend on the choice of $\underline{A}_{21}$ and the resulting control gains. Therefore, it is necessary to check the stability of $\underline{F}$ in each case. When $\underline{F}$ is stable, performance in terms of the mean-squared values of all system variables can be determined from the solution of (29).

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APPENDIX C

IDENTIFICATION OF PILOT MODEL PARAMETERS

Numerous research programs in manual control -- including the series of BBN studies sponsored by AFOSR [1-6] -- have involved extensive analysis with the "optimal control model" (OCM) for the human controller. Model analysis has typically required the matching of model outputs to experimental data in order to identify (quantify) "pilot parameters"; i.e., independent model parameters related to human information processing limitations and capabilities. Pilot parameters identified from laboratory tracking data usually include time delay, motor time constant, motor noise covariance, and an observation noise covariance associated with each perceptual input variable used by the controller [1].

Until recently, such parameters have been identified by "manual search" procedures in which the analyst attempts to obtain a good model match through trial-and-error adjustment of pilot parameters [1]. While appropriate for testing certain theories of operator response behavior (e.g., that good model predictions can be obtained with a fixed set of pilot parameters), the manual search technique suffers from a number of limitations:

1. The procedure is inefficient if more than 2 or 3 parameters are to be identified.
2. There is usually no formalized "stopping criterion"; i.e., a rule for determining when the best match to the data has been obtained.
3. No confidence limits are obtained to indicate the reliability of the parameter estimates. Without some form of reliability measure, one cannot determine the significance of changes in parameter values across experimental conditions.

Two classes of automated search procedures have been explored for identifying OCM parameters: (1) a "maximum likelihood" method that operates on individual time histories, and (2) gradient search schemes that operate on a combination of time-domain and frequency-response statistics computed from single or multiple experimental trials. In general, the maximum likelihood method yields reliability estimates for each identified parameter [7]; attempts to apply this method to identification of OCM parameters, however, have been unsuccessful in identifying the full set of pilot parameters itemized above [8].

Lancraft and Kleinman [9] tested the following gradient search schemes: (a) Powell's method for general non-linear functions [10], (b) Powell's sum-of-squares method [11], and (c) a quasi-Newton (QN) search scheme. Identification of the pilot parameter set defined above was possible with each scheme, but because of the lack of reliability metrics, no confidence limits could be associated with the identified parameters.

Preliminary testing of the three search schemes indicated that the QN scheme would be more efficient (converge in fewer operations) than the other methods. Partly for this reason, and because of the potential to derive reliability metrics by analytic means, the QN scheme was studied further in this program phase. Emphasis was on improving computational efficiency and in developing methods of associating reliability estimates with identified parameters.

The following topics are covered in the remainder of this section: (1) review of mathematical concepts underlying the QN identification scheme; (2) tailoring of the method to analysis of manual control data; (3) methods for obtaining reliability estimates; and (4) a method for obtaining a single best model match to multiple data sets.

C.1 Mathematics of the Quasi-Newton Identification Procedure

C.1.1 Minimization Scheme

The QN scheme is generally implemented to minimize the following scalar modeling error:

$$J = \sum_i w_i e_i^2 \quad (1)$$

where e_i is the difference between the i^{th} measured data point and the corresponding model prediction, and w_i is a weighting coefficient. This expression may be written as the following matrix operation:

$$J = \underline{e}' \underline{W} \underline{e} \quad (2)$$

where

$$\begin{aligned} \underline{e} &= \text{col}[e_i] \\ \underline{W} &= \text{Diag}[w_i] \end{aligned}$$

Now, for a specific choice of model parameters p_1 , one obtains

$$J_1 = \underline{e}_1' \underline{W} \underline{e}_1 \quad (3)$$

For a new set of parameters $p_2 = p_1 + \Delta p$, one obtains a new modeling error

$$J_2 = (\underline{e}_1' + \Delta \underline{e}') \underline{W} (\underline{e}_1 + \Delta \underline{e}) = \underline{e}_1' \underline{W} \underline{e}_1 + \Delta \underline{e}' \underline{W} \underline{e}_1 + \underline{e}_1' \underline{W} \Delta \underline{e} + \Delta \underline{e}' \underline{W} \Delta \underline{e}$$

Noting that the first term is the original J_1 and that the second and third terms (being scalars) are equal, we obtain

$$J_2 = J_1 + 2 \underline{e}_1' \underline{W} \Delta \underline{e} + \Delta \underline{e}' \underline{W} \Delta \underline{e} \quad (4)$$

Let us assume that model predictions vary linearly with model parameters. Since the measured data points are constant, prediction errors will also vary linearly with model parameters. Thus,

$$\Delta \underline{e} = \underline{Q}' \Delta p \quad (5)$$

where

$$q(i,j) = \frac{\partial e_j}{\partial p_i}$$

The modeling error J_2 may now be expressed as

$$J_2 = J_1 + 2 \underline{e}_1' \underline{WQ}' \underline{\Delta p} + \underline{\Delta p}' \underline{QWQ}' \underline{\Delta p} \quad (6)$$

Let the minimum modeling error be defined as J_0 , and let the parameter set that yields this minimum error be defined as the "optimal" parameter set.* The derivative of J with respect to perturbations in parameter values about the optimal set must be zero; otherwise, some other parameter set could be obtained to yield a lower modeling error. Therefore,

$$\left. \frac{\partial J}{\partial \underline{\Delta p}} \right|_{J=0} = 0 = 2 \underline{Qwe}_1 + 2 \underline{QWQ}' \underline{\Delta p} \quad (7)$$

Thus, the following change in parameter values yields minimum modeling error, given the initial vector error $\underline{e}_1$ and the assumption of linearity:

$$\underline{\Delta p} = -[\underline{QWQ}']^{-1} \underline{Qwe}_1 \quad (8)$$

C.1.2 Sensitivity Analysis

In addition to obtaining the best match to a given set of data, one may also wish to determine some measure of the reliability of the identified parameter values. Ideally, one would like to associate a probability distribution with each of the identified values so that various tests of statistical significance could be performed. In order to determine such a probability distribution, one would have to know the probability distribution of the vector modeling error $\underline{e}$, and the functional relationship between modeling error and model parameters.

* In general, when dealing with real experimental data -- as opposed to "data" generated by an analytical model -- one does not obtain perfect correspondence between model predictions and experimental measurements. The matching error then, is not driven to zero but to some (presumably small) nonzero value.

A qualitative indication of parameter estimation reliability can often be obtained through sensitivity analysis relating changes in the scalar matching error to perturbations in model parameters. In general, estimates of parameters that have a high impact on modeling error can be considered more reliable than estimates of parameters having a smaller impact.

If model predictions are linear in the parameters, as assumed in the foregoing treatment, we may analytically derive the sensitivity of the scalar modeling error to perturbations in model parameters about the optimal (best-matching) set. One may compute the sensitivity to a given parameter with the remaining model parameters held fixed, or with remaining parameters reoptimized. The latter measure provides a more accurate reliability measure because it accounts for the potential tradeoffs that may exist among parameters in terms of matching the data.

We first compute the tradeoff among parameters. Assume that a specific parameter p_i has been set to a non-optimal value and that the remaining parameters are re-optimized to provide a least-square match to the data.

Equation (8) may be written as

$$\Delta p = -[QWQ']^{-1} QW(e_o + \Delta e) \quad (9)$$

where e_o is the vector corresponding to minimum matching error, Δe is the incremental error arising from a non-optimal choice of model parameters, and Δp is the change in model parameters that would minimize the function value.

Now, Δp must be zero for $e = e_o$; otherwise, further reduction in the modeling error would be possible. The above relationship may therefore be written as

$$\Delta p = -[QWQ']^{-1} QW\Delta e \quad (10)$$

Let us assume that the incremental error arises from a non-optimal choice of a single parameter p_i . With the remaining parameters (temporarily) fixed at their optimal values, the resulting incremental error is

$$\Delta e = q_i \Delta p_i \quad (11)$$

where

$$q_i = \text{col}(q_{i,1}, q_{i,2}, \dots)$$

Define the subscript "r" to indicate vectors and matrices that remain when rows and columns corresponding to the i^{th} model parameter are removed. The expressions of Eqs(10) and (11) may be combined to yield the following rule for re-optimizing model parameters, given that the i^{th} parameter is held fixed:

$$\Delta p_r = -[Q_r W Q_r']^{-1} Q_r W q_i \Delta p_i \quad (12)$$

Comparison of the elements of the vector Δp_r with p_i reveals the joint tradeoff between p_i and the remaining model parameters.

To compute the effect on the modeling error J of a change in p_i , with remaining parameters re-optimized, we construct a new vector Δp which is the composite of p_i and p_r . This vector is defined as

$$\Delta p = v \Delta p_i \quad (13)$$

where v is a column vector that has a value of unity for the i^{th} element and values for remaining elements as determined from Eq(12).

From Eqs (6) and (13) we obtain

$$J = J_0 + 2 e_0 W Q' v \Delta p_i + v' Q W Q v (\Delta p_i)^2 \quad (14)$$

We show by the following argument that the second term of the above expression is zero. Recall that the Δp computed by Eq(8) must be zero when $e = e_0$ since, by definition, e_0 corresponds to the optimal parameter set. Since the expression $[Q W Q]^{-1}$ is nonzero, the term $Q W e_0$ must be zero in order for Δp to be zero.

The expression of Eq(14) may then be written as

$$\Delta J = J - J_0 = \underline{v}' \underline{Q} \underline{W} \underline{Q}' \underline{v} (\Delta p_i)^2 \quad (15)$$

where J is the incremental function value arising from the deviation of parameter p_i from its optimal value. The change in function value, therefore, varies as the square of the change in the parameter value.

C.2 Application to Manual Control Studies

Application of the QN method for analysis of human operator performance in continuous control tasks has been reported by Lancraft and Kleinman [9]. Described below is a revised implementation that was used to perform the model analysis described elsewhere in this report.

C.2.1 The Parameter Set

All model analysis discussed in this report required identification of the following independent "pilot-related" model parameters:

1. time delay;
2. relative "cost weighting" on control rate, where the human operator was assumed to minimize a weighted sum of mean-squared tracking error and mean-squared control rate;
3. observation noise covariance: one such parameter for each perceptual variable assumed to be utilized by the pilot (tracking error, error rate, etc.); and
4. pseudo-motor noise covariance.

Readers not familiar with the optimal control model and its parameterization are referred to Levison et al [1] and related references cited therein.

For a fixed task structure, a one-to-one correspondence exists between the relative cost of control rate and the optimal control

gains. One such gain represents a feedback path from control force (or displacement) to desired rate-of-change of control; the inverse of this gain is termed the "motor time constant". Because of the near invariance of the motor time constant across a variety of laboratory tracking tasks, values of control-rate cost weighting are converted to the equivalent motor time constant for presentation. Similarly, to facilitate comparison with previous data, both observation and motor noise variances are normalized with respect to corresponding signal variances and presented as noise/signal ratios.

C.2.2 Matching and Convergence Criteria

Two criteria must be defined in order to apply the QN identification procedure: (1) a definition of a scalar modeling error to be minimized by the QN scheme, and (2) convergence criteria to determine when the minimum modeling error has been approached sufficiently closely to justify termination of the minimization procedure.

Modeling error is similar to that used by Lancraft and Kleinman:

$$J = \frac{1}{N} \sum_{i=1}^{N_1} \left(\frac{G_i - \hat{G}_i}{\sigma_{G_i}} \right)^2 + \frac{1}{N_2} \sum_{i=1}^{N_2} \left(\frac{P_i - \hat{P}_i}{\sigma_{P_i}} \right)^2 \quad (16)$$

$$+ \frac{1}{N_3} \sum_{i=1}^{N_3} \left(\frac{R_i - \hat{R}_i}{\sigma_{R_i}} \right)^2 + \frac{1}{N_4} \sum_{i=1}^{N_4} \left(\frac{S_i - \hat{S}_i}{\sigma_{S_i}} \right)^2$$

where:

N_j = number of valid measurements in the j^{th} measurement group.

G_i = magnitude (gain) of the i^{th} describing function point to be matched, dB.

P_i = phase shift of the i^{th} describing function point to be matched, degrees.

R_i = "remnant" (control power not correlated with the tracking input) of the i^{th} frequency point to be matched, degrees.

S_i = i^{th} variance score to be matched (units different for different tracking variables).

σ : indicates standard deviation of experimental data point.

"^" : "hat" indicates model prediction.

Inclusion of the experimental standard deviations in the scalar modeling error allows each error component to be weighted inversely by the reliability of the data. To prevent the matching criterion from giving excessive weights to variables that have very low experimental variability (typically, run-to-run measurements from the same subject), the following minimum standard deviations are imposed: 0.5 dB for magnitude and remnant, 3 degrees for phase, and 5% for the ensemble mean for variance scores.

Inverse weighting by standard deviation also converts each error term into a dimensionless number, thereby allowing conglomeration of matching errors of unlike qualities. Essentially, minimization of the modeling error defined in Eq(16) is equivalent to minimizing the average number of standard deviations of mismatch. A numerical score of $J=4$ reflects an average modeling error of 1 standard deviation (i.e., an average score of unity per measurement group).

The minimization procedure terminates when the following conditions jointly obtain for two successive iterations: (1) reduction of the matching error by less than 0.5%, and (2) changes in all identified parameters by less than 2%. The first criterion is based on the fact that the sensitivity of matching error to small perturbations of model parameters is relatively low in the vicinity of the minimum (a consequence of the quadratic matching error). The second criterion prevents termination resulting from a compensating "overshoot"; i.e., a situation in which successive

estimates of one or more parameters bound the optimal values in such a way as to yield essentially the same modeling error.

C.2.3 Log-Linear Assumption

The QN scheme may be used when modeling error is linearly related to a functional transformation of the parameters, provided the inverse functional operation is unique. (That is, given a numerical value for the function $f(p)$, one can uniquely compute p). In this case, the identification scheme proceeds as described in Section C.1, except that all operations are performed on the functional transformation of the parameter set until convergence is achieved; the inverse functional operation is then performed to yield the identified parameter vector p . As described below, the identification scheme has been implemented to operate on the logarithms of the model parameters.

Because of the logarithmic operations used in defining some of the measurements included in the modeling error of Eq(16) -- specifically, describing function magnitude and remnant -- implementation of the QN method is consistent with the assumption that model outputs are linearly related to the logarithms (in dB) of the model parameters. Thus, the elements of Δp are interpreted as logarithmic increments, and the partial-derivative matrix Q is redefined as:

$$q(i,j) = \frac{\partial e_j}{\partial p_{dB_i}} = \frac{\partial e_j}{\partial p_i} \bigg/ \frac{\partial p_{dB_i}}{\partial p_i} \quad (17)$$

where $p_{dB_i} = 10 \log_{10}(p_i)$ and

$$\frac{\partial p_{dB_i}}{\partial p_i} = 10 \frac{1}{p_i} \log_{10}(e) = \frac{4.343}{p_i} \quad (18)$$

Partial derivatives are computed numerically as

$$q(i,j) = \frac{p_i}{4.343} \frac{\Delta e_j}{\Delta p_i} \quad (19)$$

where Δe_j is the incremental error resulting from an increment (in absolute units) of $\Delta p_i = 0.05 p_i$. The 5% "step size" was chosen after a study of alternatives.

Once the partial derivatives are computed, the computation indicated by Eq(8) yields the following increment in parameter space:

$$\Delta p_{dB} = -[QWQ']^{-1} QWe \quad (20)$$

The following operation then translates the dB change computed above into an increment in problem units:

$$p_{i2} = p_{i1} * 10^{(\Delta p_{dB}/10)} \quad (21)$$

where p_{i1} is the base value for p_i used in obtaining the gradient and p_{i2} is the next best guess for this parameter.

Implementation of the log-linear assumption prevents any one parameter value from changing sign from one iteration to the next. Since all model parameters are theoretically non-negative, this variation of the minimization scheme avoids assignment of out-of-bounds values to model parameters.

Sensitivity analysis is performed analytically as indicated in Eq(15), where the quantity Δp_i is interpreted as a logarithmic (i.e., dB) change.

C.2.4 Reduction of the Parameter Set

Numerical difficulties in performing the QN minimization procedure may be encountered whenever the modeling error becomes relatively insensitive to changes in one or more model parameters (or linear combinations of parameters). In this case, the expression QWQ' is ill-conditioned for inversion, and poor estimates of model parameters may be obtained.

Numerical difficulties of this sort are minimized by removing from the search procedure, at a given iteration, each model

parameter that has a negligible effect on modeling error. The following steps are performed at each iteration of the QN minimization procedure:

1. The increment Δp is computed for the full parameter set according to Eq(8), and the sensitivity measure of Eq(15) is computed for each parameter.
2. "Non-influential" parameters are defined as those for which a 50 dB change is predicted analytically to increase the scalar modeling error by less than 4 units (corresponding to an average matching error of one standard deviation). (The 50 dB criterion was selected on the basis of a parametric study that showed this criterion to generally yield minimum matching error.)
3. A new Δp is computed for the reduced parameter set consisting of only influential parameters.
4. The subsequent iteration of the QN procedure is initialized with a set of parameter values for which (a) influential parameters are incremented as determined in Step 3, and (b) non-influential parameters remain unchanged.

Note that the entire parameter set is considered at each iteration. Thus, a parameter omitted from the computation of Δp at a given stage is not necessarily discarded from the remainder of the identification process. A further restriction is placed on the minimization procedure to reduce the chances of convergence to a local minimum appreciably removed from the global minimum. Specifically, an individual parameter is allowed to change by no more than 10 dB (i.e., ten-fold increase or reduction) from one iteration to the next.

C.2.5 Line Search

As noted previously, nonlinear relationships between model parameters and model outputs will tend to impair the efficiency of the QN scheme; in extreme cases, this method will not converge.

Typically, if a suitable initial set of parameter values is chosen, the direction of the vector Δp computed by Eq(8) has the potential to reduce scalar modeling error, but the magnitude will be non-optimal, sometimes leading to a larger modeling error.

A simple binary search procedure is used. First, Δp is computed as described above, the parameter vector p is incremented accordingly, and a new modeling error is computed. If the new modeling error is lower than the initial error, the QN procedure continues (or terminates, if the convergence criteria are satisfied). On the other hand, if error increases, the original Δp (in dB) is halved, another parameter vector p is computed with the reduced increment, and modeling error is again tested. This procedure is repeated until (1) matching error is reduced from one iteration to the next, or (2) until four attempts fail to reduce matching error, at which point the minimization scheme terminates.

C.2.6 Initialization

As is the case with any other search procedure, application of the QN scheme requires a suitable initial set of values for the model parameters; some rule or procedure is generally required to allow proper initialization.

Fortunately, the independent parameters of the OCM -- the parameters we term "pilot-related" and attempt to identify -- appear to be relatively independent of task parameters. For a variety of laboratory tracking situations, one can achieve a reasonable match to experimental data by using a fixed set of rules for selecting pilot parameters. Accordingly, identification results presented in this report were obtained with model parameters initialized as shown in Table C1.

Table C1

Initial Selection of Model Parameters

Symbol	Parameter	Adjustment Rule
TD	Time Delay	Set to 0.20 seconds
G	Relative Cost of Control Rate	Adjust to yield motor time constant of 0.1 seconds
VUP	Pseudo motor noise covariance	Adjust to yield noise/signal ratio, relative to control-rate variance, of $10^{-5} \pi$ (-50 dB)
VY _x	Observation noise covariance	Adjust to yield noise/signal ratio, relative to the variance of signal "x", of 0.01π (-20 dB)

- (1) Scalar control assumed.
- (2) Driving motor noise assumed to be zero.

C.3. Tests for Significance

In the following discussion we assume that the data base being subjected to model analysis reflects a significant difference in human operator response behavior, as determined by some standard quantitative test for significance. The significance test to be performed on identified model parameters is not, therefore, to determine whether performance differences are due to "experimental error" (that issue having been resolved by analysis of mean-squared error scores and the like), but rather to test the (null) hypothesis that the various data sets can be modeled by the same set of model parameters.

Three potential methods for determining the significance of changes in identified parameters are explored: (1) direct analysis of model parameters, (2) determination of probability densities for model parameters, and (3) a more qualitative cross-comparison procedure.

C.3.1 Direct Analysis of Model Parameters

Perhaps the simplest method of testing for significance is to treat the identified parameters as data and perform some standard test for significance. A parametric test may be used if one has a basis for assuming the form of the underlying probability distribution of model parameters; otherwise, a non-parametric test is appropriate.

This method for determining statistical significance has certain drawbacks, however. Model analysis must be performed on a number of data sets in order to provide the required statistical base; one cannot simply compare average performance in Condition "A" with average performance in Condition "B". Thus, computational requirements are relatively high. Furthermore, a sufficient number of replications may not be obtainable, as may be the case with data obtained early in training where appreciable run-to-run learning effects are observed.

An equally serious limitation is the possibility that this test may declare "significant" a difference in parameter values having little to do with actual differences in operator response behavior. For example, suppose that the motor noise ratios identified for Condition "A" tend to cluster around -40 dB, whereas those identified for Condition "B" cluster around -60 dB. Suppose further that modeling error in both conditions is insensitive to values of motor noise in this range. Though "significant" in terms of a statistical test, such a difference would not be meaningful because of the inability to precisely identify the value for the

motor noise parameter. A similar statistical "false alarm" can arise if changes in one parameter compensate for changes in another parameter in terms of overall modeling error.

C.3.2 Computation of Probability Densities

The limitations cited above can, in principle, be overcome by an analytic procedure that allows one to compute the joint probability density of the identified parameters. Effects of insensitivity and "trade-off" among parameters are accounted for, and one has the potential for analyzing parameters obtained from average data or from a single experimental trail.

If the probability distributions of the model parameter estimates are to be computed, there must be a known, consistent, and mathematically tractable relationship between the vector modeling error (equivalently, model predictions) and the parameters to be identified. Computation is usually facilitated if this relationship is linear.

In order to determine the feasibility of deriving probability distributions for identified model parameters, the assumption of linearity was tested empirically against data obtained in one of the cases explored in the study of delayed motion cues [12]. This case was selected because of the large range in error/parameter sensitivity across the various pilot parameters.

Rather than test the linearity of each element of the vector error $\underline{e}$, we tested the relationship of the scalar error J to changes in individual parameter values (with remaining parameters reoptimized). As shown previously in Eq(15), the scalar modeling error should vary about its minimum value in proportion to the square of the deviation of a given parameter about its optimum value. Failure of this quadratic relationship to obtain would indicate a nonlinear relationship between model parameters and model outputs.

Empirical sensitivity tests were performed as follows. First, the following six OCM parameters were adjusted to provide the best match to the data: three observation noises (position, rate, and acceleration), pseudo motor noise, time delay, and control-rate weighting. The analytic sensitivity computation defined in Eq(15) was performed to predict the change (in dB) in each parameter--with remaining parameters reoptimized--that would increase modeling error by 4 units. Let us call this parameter increment ΔdB_0 . Note that this quantity is related inversely to the sensitivity of modeling error to parameter deviation.

An empirical sensitivity test was performed for four of the six parameters whereby increments in modeling error about the minimum were computed for parameter variations of ΔdB_0 and $\Delta dB_0/2$. Very large values for ΔdB_0 dictated the use of smaller test increments for the remaining parameters. Modeling error increments computed in this manner were compared to those predicted by the analytic relationship of Eq(15).

Table C2 shows that the degree of correspondence between computed and predicted error increment tended to vary directly with the sensitivity of modeling error to parameter deviation. Correspondence was greatest for time delay ($\Delta dB_0 = 1.0$) and least for pseudo motor noise and rate observation noise ($\Delta dB_0 = 88.7$ and 154 , respectively). Sensitivity was highly asymmetric for the latter two parameters, showing virtually no effects for deviations in one direction and large effects for deviations in the other.

These results should not be generalized to other data sets. That is, one should not conclude that time delay will always be the most tightly defined parameter, nor that rate observation noise will be ill-defined. Experience with the QN identification scheme reveals that the quantitative and qualitative relationship between model parameters and outputs will vary with the particular experiment.

Table C2

Sensitivity of Modeling Error to Parameter Change
with Remaining Parameters Re-optimized

Parameter Deviation	Modeling Error Incr. Predicted Computed	
a) VY_e $\Delta dB_O = 16.7$		
+16.7	4.0	6.3
+8.35	1.0	2.6
-8.35	1.0	10.6
-16.7	4.0	52.5
b) VY_e^* $\Delta dB_O = 154$		
+40.0	0.27	-0.1
+20.0	0.067	-0.1
-20.0	0.067	37.2
-40.0	0.27	78.5
c) VY_e^{**} $\Delta dB_O = 6.5$		
+6.5	4.0	6.6
+3.25	1.0	2.7
-3.25	1.0	3.6
-6.5	4.0	15.2

Parameter Deviation	Modeling Error Incr. Predicted Computed	
d) VUP $\Delta dB_O = 88.7$		
+44	0.98	108.3
+22	0.25	10.3
-22	0.25	- 0.5
-44	0.98	- 0.5
e) TD $\Delta dB_O = 1.0$		
+1.0	4.0	4.7
+0.5	1.0	1.2
-0.5	1.0	1.0
-1.0	4.0	4.4
f) G $\Delta dB_O = 1.6$		
+1.6	4.0	4.0
+0.8	1.0	0.7
-0.8	1.0	2.0
-1.6	4.0	7.1

all entries in dB

ΔdB_O = theoretical change required to increase modeling error
by 4 units.

The principal conclusions to be derived from the results of this sensitivity test are that, (1) assumptions of linearity are not valid for performing analytic operations on identified parameters, and (2) the relationship between model parameters and output differs qualitatively across model parameters. As a consequence, computation of probability densities for pilot-related model parameters does not seem feasible.

C.3.3 A Cross-Comparison Method

A cross-comparison test may be used to determine the qualitative significance of differences in identified parameter sets for two experimental conditions. This method employs a numeric, non-analytic sensitivity test as described below.

Assume that model parameters have been identified from two data sets corresponding to, say, the "baseline" and "test" experimental conditions; our task is now to test the null hypothesis that a single set of model parameters provides a near-optimal match to the baseline and test data. To perform this test, we first identify the following three sets of pilot parameters: (1) the set that best matches the baseline data, (2) the set that best matches the test data, and (3) the set that provides the best joint match to the baseline and test data. For convenience, we shall refer to the parameters identified in step 3 as the "average parameter set".

We next compute the following four matching errors:

$J(B,B)$ = matching error obtained from baseline data, using parameters identified from baseline data (i.e., best match to baseline data).

$J(B,A)$ = matching error obtained from baseline data, using average parameter set.

$J(T,T)$ = best match to test data.

$J(T,A)$ = matching error obtained from test data, using average parameter set.

Finally, we compute the following "matching error ratios": $MER(B) = J(B,A)/J(B,B)$, $MER(T) = J(T,A)/J(T,T)$, and, if we wish to reduce the results to a single number, the average of these two error ratios.

In a qualitative sense, the greater the matching error ratios, the more significant are the differences between the parameters identified for the baseline and test conditions. For example, if both matching error ratios are unity (the theoretical minimum), then the null hypothesis is supported: there exists a single set of parameters that provides an optimal match to both data sets. Any differences between the baseline and test parameter sets must be considered insignificant and can be attributed to imprecision of the identification procedure. Conversely, if one or both matching errors ratios are substantially greater than unity, one must reject the null hypothesis and consider the differences in model parameters to be "significant"; i.e., to represent true differences in operator response behavior.

As shown below in Section C.4, a good approximation to the joint match to multiple data sets can be obtained by simply matching the average data. Thus, to obtain the "average parameter set", one would first obtain a point-by-point ensemble average of the (reduced) baseline and test data, and then identify parameters to match the average data set. This procedure is valid if the same task description applies to the two experimental conditions; i.e., if both tasks can be modeled identically except for quantitative differences in pilot-related parameters. Experiments designed to explore training effects, environmental stress, or interference from other concurrent tasks often meet this restriction.

This scheme may also be used to test a single parameter or a subset of parameters. Suppose, for example, one wishes to test apparent differences in the time delay parameter. The matching errors $J(B,B)$ and $J(T,T)$ would be computed as described above. The errors $J(B,A)$ and $J(T,A)$, however, would be computed with only the time delay parameter fixed at its "average" value; remaining parameters would be re-optimized.

The primary disadvantage of the cross-test method is that it yields qualitative, rather than quantitative, results. For example, one cannot state the probability of falsely rejecting the null hypothesis, given a particular modeling error ratio. Rather, if this ratio is greater than some threshold (which must be selected on the basis of engineering judgment), the identified parameter difference is considered "significant".

Despite its qualitative nature, the cross-comparison method has a number of important advantages compared to the alternatives:

1. No restriction is imposed on the form of the relationships between model parameters and model predictions.
2. If necessary, significance tests can be performed on the basis of a single trial per experimental condition.
3. Identification of model parameters from averaged data avoids the computational expense of matching individual experimental trials.
4. Significance tests can be performed for the entire parameter set as a whole, for individual parameters, or for groupings of parameters.

Application of this methodology to the study of human operator performance is illustrated in Appendix D.

C.4 Joint Match to Multiple Data Sets

In this section we show that, under certain conditions, obtaining the best joint match to multiple data sets is equivalent to matching the average of the data sets. The major assumption we must make is that the same linearized task description applies to the various experimental conditions of interest. This assumption holds for the training effects reported in Appendix D, where the performance differences compared were due entirely to differences in pilot response behavior.

Although all comparisons discussed in this report are between pairs of data sets, any number of data sets can theoretically be considered. Assume that we wish to minimize the following scalar modeling error:

$$J = \sum_{i=1}^N \underline{e}_i' \underline{W}_i \underline{e}_i \quad (22)$$

where $\underline{e}_i$ is the vector modeling error for the i^{th} data set, $\underline{W}_i$ is the corresponding matrix of weighting coefficients, and N is the number of data sets.

Assume that an initial guess at pilot parameters yields a modeling error of value J , and that a second set of parameter values yields the error J_1 . The new error is given as

$$\begin{aligned} J_1 &= \sum_{i=1}^N (\underline{e}_i' + \underline{\Delta e}_i') \underline{W}_i (\underline{e}_i + \underline{\Delta e}_i) \\ &= J + 2 \sum_{i=1}^N \underline{\Delta e}_i' \underline{W}_i \underline{e}_i + \sum_{i=1}^N \underline{\Delta e}_i' \underline{W}_i \underline{\Delta e}_i \end{aligned} \quad (23)$$

Now, if the same model applies to all data sets, we can write

$$\underline{\Delta e}_i = \underline{Q}' \underline{\Delta p} \text{ for all "i"} \quad (24)$$

where $\underline{Q}$ is the matrix of partial derivatives defined in Section C.1. Eq(23) may now be written as:

$$J_1 = J + 2 \underline{\Delta p}' \underline{Q} \sum_{i=1}^N \underline{W}_i \underline{e}_i + \underline{\Delta p}' \underline{Q} \left[\sum_{i=1}^N \underline{W}_i \underline{Q}' \underline{\Delta p} \right] \quad (25)$$

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$$\Delta \mathbb{E}[\sigma_1 + \sigma_2 + \sigma_3]$$

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Following the logic presented in Section C.1, we increment the model parameters as follows:

$$\Delta \underline{p} = [\underline{Q} \sum_i \underline{W}_i \underline{Q}']^{-1} \underline{Q} \sum_i \underline{W}_i \underline{e}_i \quad (26)$$

Let us further assume that the matrix of weighting coefficients is the same for all data sets. In this case, $\underline{W}_i = N \underline{W}$,

and the above expression is written as

$$\Delta \underline{p} = [\underline{Q} \underline{W} \underline{Q}']^{-1} \underline{Q} \underline{W} \frac{1}{N} \sum_i \underline{e}_i \quad (27)$$

Thus, for the assumptions made here, identification of the parameter set that best matches multiple data sets is equivalent to the parameter set that best matches the average data set.

C.5 References

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APPENDIX D**ANALYSIS OF CONTROL STRATEGY DEVELOPMENT**

An experimental study was performed jointly by the Air Force's Aerospace Medical Research Laboratory and the Human Resources Laboratory to explore the effects of simulator delays on performance during various stages of training. Analysis of the experimental data was undertaken by BBN under Contract No. F33615-16-C-5001, and was continued under the subject AFOSR study, to quantify and model the interaction between motion cue delay and learning, including transfer between initial training with delayed motion and subsequent training with synchronous visual and motion cues.

Initial results of the BBN analytical study have been presented by Levison et al [1]. We first briefly review the early results, and we present additional results obtained through application of the identification procedure described in Appendix C.

D.1 Review of Experimental Study

The experimental task consisted of maintaining a simulated fighter-like aircraft wings level in the presence of random turbulence. Five groups of subjects naive with respect to this task participated. One group trained initially with instrument-like visual cues only (the "static" condition); another group trained with combined, synchronized visual and motion cues ("synchronous motion"); and the remaining groups trained with motion cues delayed with respect to visual cues by 80, 200, and 300 msec. All groups were trained to apparent asymptotic mean-squared error performance in their initial tasks. After training, all but the synchronous motion group trained to asymptotic performance in the synchronous motion condition.

Pre- and post-transition learning trends for the various subject groups are shown in Figure D1. Mean-squared error is plotted as a function of training session, where each session consisted of four experimental trials of approximately three minutes each.

The training curves were ordered with respect to motion-cue delay as one would expect; increasing mean-squared error was associated with increasing delay. For the most part, static performance scores lay between the scores associated with 200 msec and 300 msec delays. All groups training initially with delayed motion (or no motion) showed an immediate reduction in tracking score when presented with synchronous visual and motion cues.

D.2 Effects of Training on Pilot Model Parameters

The identification procedure described in Appendix C was used to quantify pilot-related model parameters for selected experimental conditions. Qualitative tests of significance for parameter differences were conducted using the "cross-comparison" technique. The following training effects were analyzed: (1) pre-transition learning, (2) post-transition learning, and (3) effects of pre-transition training on response behavior immediately following transition to synchronous motion.

D.2.1 Pre-Transition Learning

As shown in Figure D1, initial (pre-transition) training was accompanied by large reductions in mean-squared tracking error. This improvement in overall man/machine system performance was accompanied by substantial changes in the subjects' response strategy.

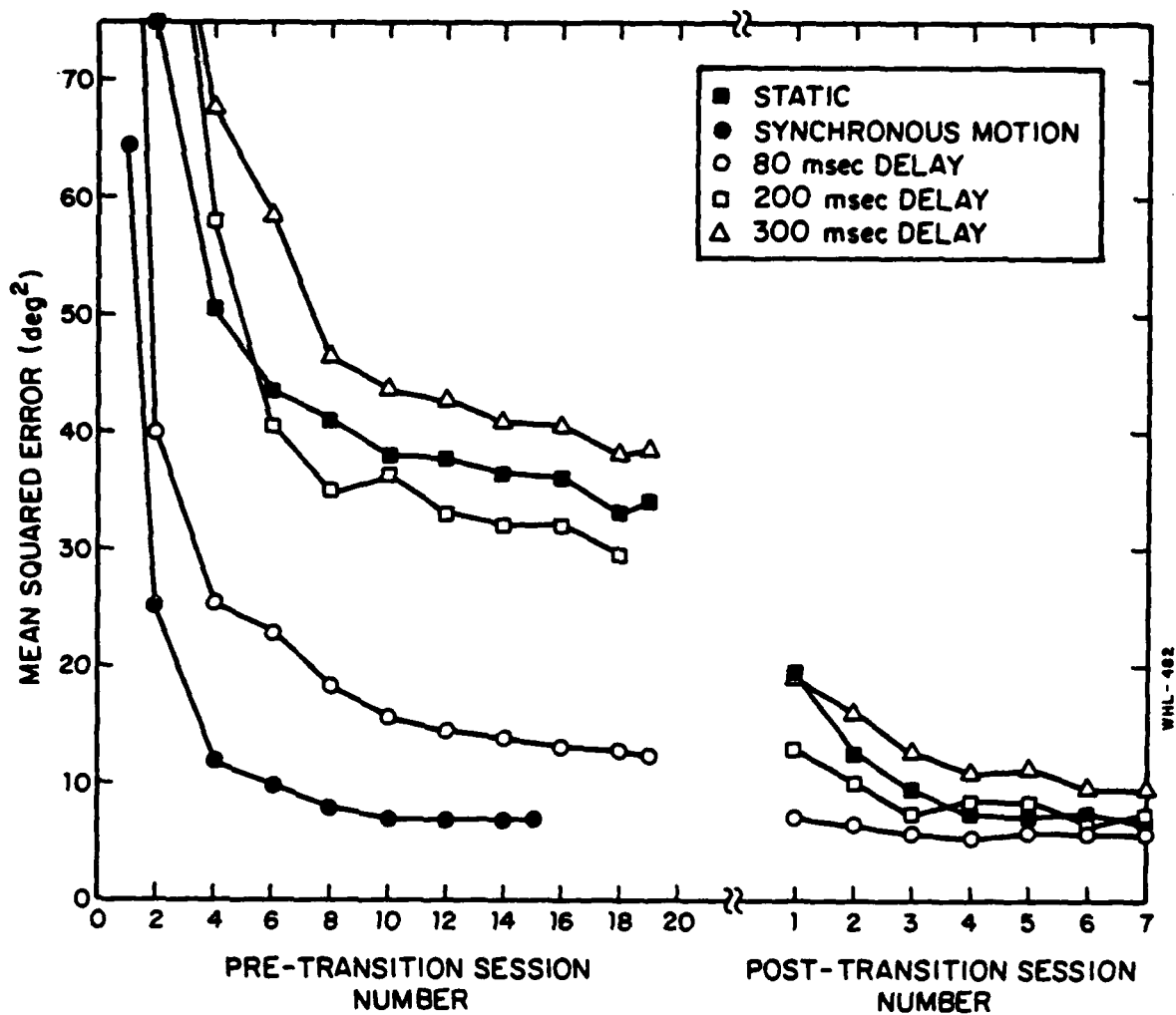


Figure D1. Learning Curves

Average of 4-5 subjects, 4 trials/subject.

Effects of training on frequency response measures for one subject are shown in Figure D2. During the course of training, amplitude ratio increased at all response frequencies, high-frequency phase lag was reduced, low-frequency remnant was reduced, and high-frequency remnant was increased.*

Increased gain and reduced phase lag are generally indicative of improved tracking efficiency. Remnant results appear ambiguous, since both reductions and increases in response randomness are seen. It should be noted, however, that the spectrum of the pilot's response (both remnant and input-correlated) is a function of the closed-loop system response properties as well as of intrinsic "pilot noise". The remnant trends observed here are consistent with the hypothesis that training leads to decreased response variability and increased man/machine response bandwidth.

The following pilot-related model parameters were identified for selected experimental conditions: (a) observation noise variances for tracking error, error-rate, and (where motion cues were available) error acceleration, (b) pseudo motor noise variance, (c) time delay, and (d) relative cost weighting on control rate. To facilitate comparison with previously published results, noise variances were converted to equivalent noise/signal ratios as described in Table D1, and the control-rate cost weighting was converted to a motor time constant.

* In all figures showing frequency response, 0 dB amplitude ratio indicates 1 pound control force₂ per degree roll angle, and 0 dB control power indicates 1 pound² control power per rad/sec.

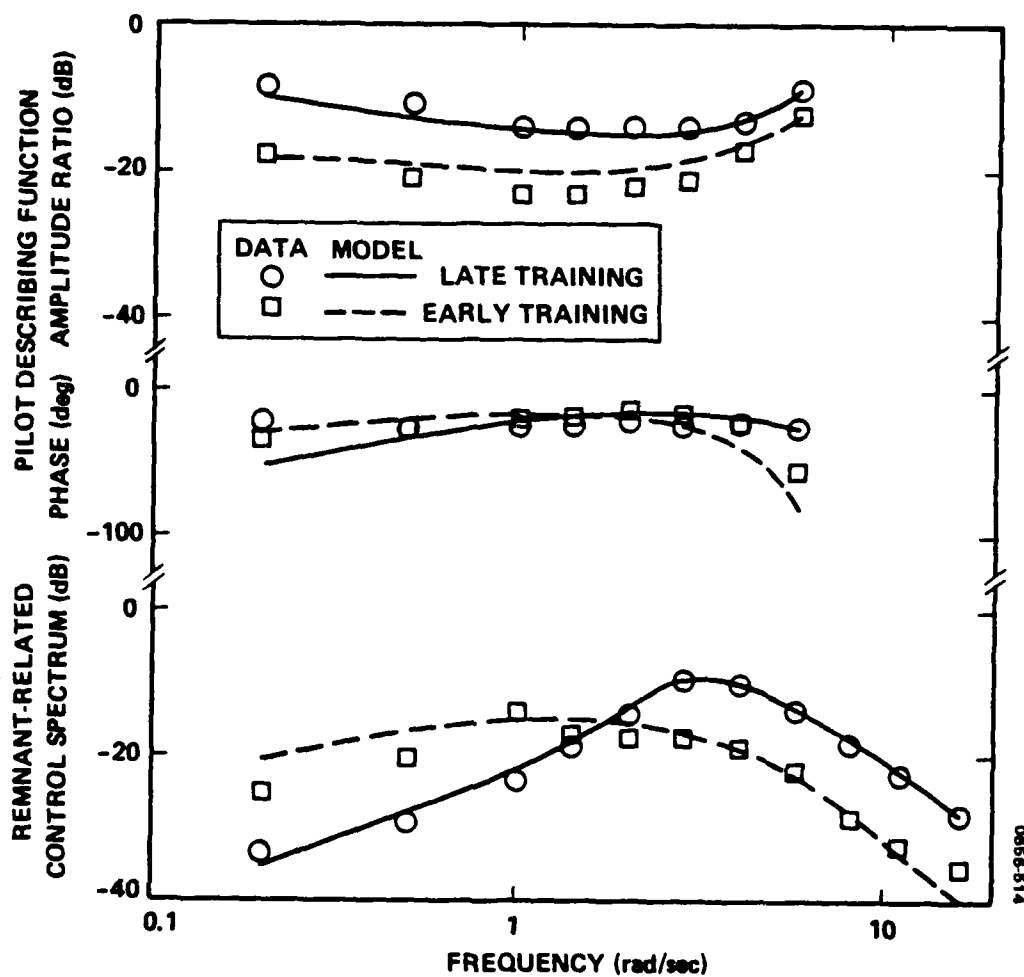


Figure D2. Effects of Training on Frequency Response
Subject CP, average of 4 trials.

Table D1

Definition of Pilot-Related Model Parameters

Parameter	Units	Definition
PY_x	dB	Observation noise/signal ratio associated with variable "x", computed by normalizing observation noise variance with respect to variance of "x".
PUP	dB	Pseudo motor noise/signal ratio, computed by normalizing pseudo motor noise variance with respect to control-rate variance.
TD	sec	Time delay
TN	sec	Motor time constant, related directly to cost of control-rate.

Changes in pilot parameters with initial (pre-transition) training are shown in Table D2 for two test subjects in the static group. Parameters are shown for an average of 2-4 trials very early in training ("Early Pre") and for the average of the final four pre-transition trials ("Late Pre"). The difference between "Late" and "Early" represented about 70 training trials.

Both subjects exhibited a sizeable decrease in observation noise on tracking error as well as a marked decrease in motor time constant. Changes in rate observation noise were relatively small and inconsistent. One subject showed a sizeable decrease in time delay with training, whereas the other showed a large increase in motor noise.

The cross-comparison qualitative test for significance described in Appendix C was applied to model parameters individually and in groups to determine which of the observed

TABLE D2

EFFECTS OF TRAINING ON PILOT-RELATED MODEL PARAMETERS

State of Training	Subject Group	Subject	Pilot Parameter					
			PY _e	PY _e	PY _e	PUP	TD	TN

a. Effects of Pre-Transition Training

Early Pre	Static	CP	-5.3	-18.6	--	-28.2	.230	.343
Late Pre			-21.6	-16.4	--	-29.3	.162	.169
Early Pre	Static	TB	-11.0	-15.9	--	-70.1	.198	.162
Late Pre			-21.2	-17.4	--	-56.9	.219	.121

b. Effects of Post-Transition Training

Early Post	Static	Average 5 Subj	-22.5	-18.0	-21.7	-50.2	.265	.0365
Late Post			-20.0	-21.8	-29.4	-62.9	.256	.0510

c. Effects of Pre-Transition Training on Post-Transition Performance

Early Post	Static 80-msec	Average 5 Subj	-22.5	-18.6	-21.7	-50.2	.265	.0365
			-35.8	-21.8	-27.2	-53.2	.228	.0969

parameter changes reflected real differences in operator behavior. "Testing" a parameter, or group of parameters, consisted of computing the modeling error with the parameter(s) fixed at the value(s) determined from matching the average data set; remaining parameters not being tested were readjusted in a quasi-Newton (QN) search procedure to yield minimum modeling error. A "modeling error ratio" was then computed for each of the two conditions being compared by normalizing the modeling error computed in this test by the corresponding minimum modeling error obtained in the QN search over the entire parameter set. The two error ratios were then averaged to yield a single metric relating to the importance of the parameter difference(s) being investigated.

Tests were performed for the following sets of parameters: (a) the entire set, (b) "response time parameters" (time delay and motor time constant) as a group, (c) observation noise parameters as a group, (d) motor time constant individually, and (e) time delay individually. Modeling error ratios were computed separately for subjects CP and TB.

Figure D3 shows that, taken as a whole, changes in pilot-related model parameters during the course of training were highly significant. Average model parameters yielded modeling errors that were from about 8 to 20 times as great as those obtained with the optimal parameter sets. This result is not surprising, given the substantial training-related changes in operator response behavior shown in Figure D2.

Training-related differences in both the response-time parameter group and the noise parameter group were important. Differences associated with response time were more significant in the sense that error ratios for this grouping were about 50% higher than ratios associated with the noise parameters.

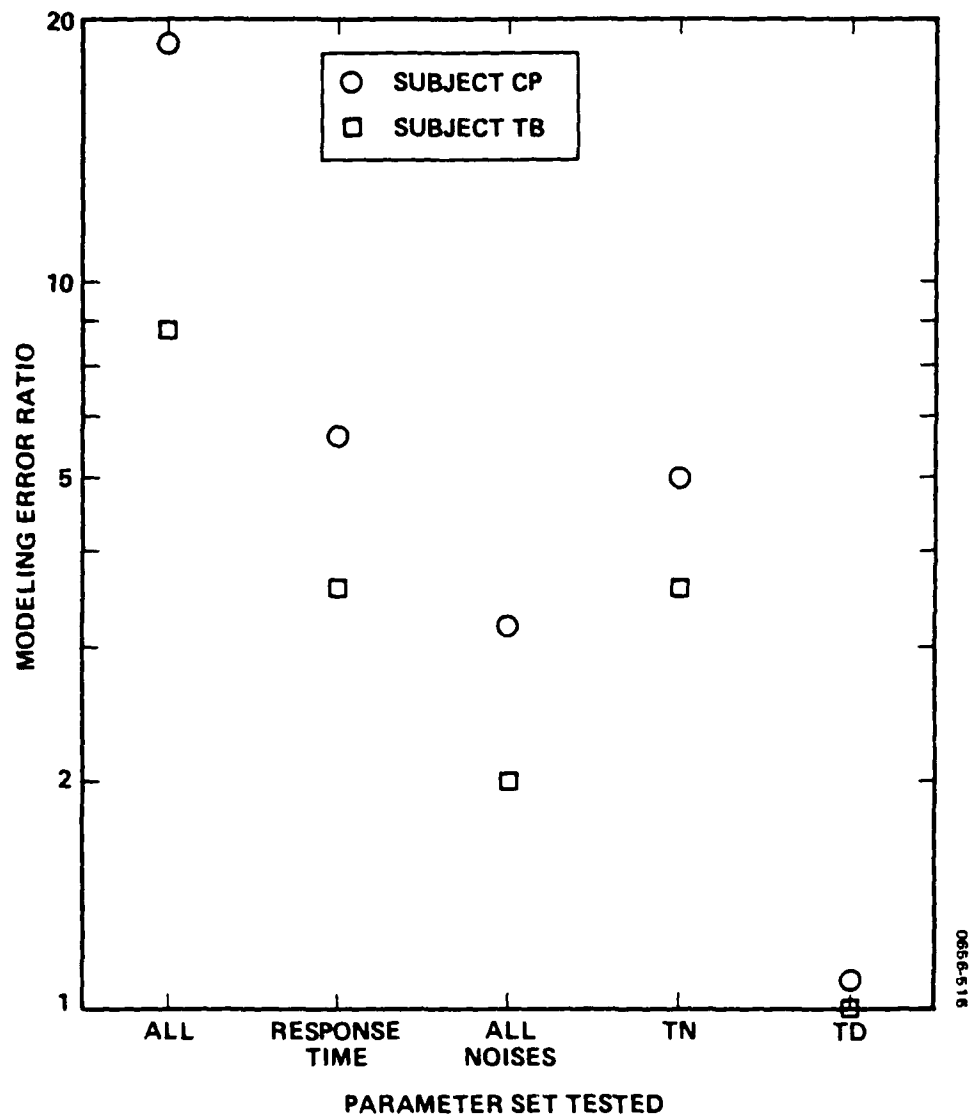


Figure D3. Test of Model Parameter Differences, Early Training, Static Group

Separate investigations of the motor time constant and time delay parameters reveals that the significance of response-time differences may be attributed almost entirely to training-related changes in motor time constant. Fixing the time delay by itself yielded error ratios only slightly greater than unity. (A ratio of unity indicates no effect.) Thus, the approximate 70-msec reduction in time delay found for subject CP appears to reflect a relative insensitivity in the identification procedure (for these particular data sets), rather than a true change in the subject's information-processing capabilities.

An additional test (not shown in Figure D3) was performed to determine the qualitative significance of the large training-related increase in motor noise ratio found for subject TB. Model parameters were adjusted to find the best match to the early pre-transition performance data, with the restriction that the pseudo motor noise ratio be fixed at the value identified for late pre-transition performance. The modeling error computed in this way was only about 2% greater than the error computed when the motor noise parameter was optimized, indicating that the apparent change in motor noise reflected an identifiability problem rather than a training problem. This analysis allows us to draw some limited conclusions with regard to the effects of training for these two subjects. Specifically, the most important effect of pre-transition training on pilot-related model parameters was to decrease the motor time constant (equivalently, reduce the relative cost penalty on control-rate activity). Reduction in observation noise was a lesser but also important effect.

D.2.2 Post-Transition Learning

Table D2b shows the effects of training on parameters identified for the static subject group, following transition to the synchronous-motion condition. Results are shown for data averaged over the first four experimental trials obtained after transition ("Early Post") and for the final four trials of the post-transition training phase ("Late Post").

Training was accompanied by a reduction in the noise/signal ratios, taken as a group, and by a reduction in response-time parameters (primarily motor time constant). Results of the cross-comparison significance test for parameter differences are given in Table D3a. An average modeling error of 8.0 was computed with all parameters fixed at their average values, which suggest that the aggregate change in parameter values during the course of post-transition training was significant.

Table D3

Modeling Error Ratios

State of Training	Subject Group	Parameter Set Tested		
		All	Response Time	All Noises

a. Post-Transition Training

Early vs. Late Post	Static	8.0	2.5	1.3
---------------------	--------	-----	-----	-----

b. Effect of Pre-Transition Training on Initial Post-Transition Performance

Early	Static vs 80-msec	10.3	1.0	2.1
-------	-------------------	------	-----	-----

It would appear that training had a more significant influence on response-time parameters than on noise parameters. Fixing response time parameters increased modeling error on the average by a factor of 2.5, whereas fixed noises gave a modeling error ratio of only 1.3.

In conclusion, for the data base reviewed here, similar learning trends were found for pre- and post-transition training. Both phases showed progressive decreases in both response-time and noise parameters, with changes in response-time parameters being of apparently greater significance.

D.2.3 Effect of Pre-Transition Training

One indication of the effectiveness of a particular training methodology is the nature of operator response behavior immediately upon transition to the operational task, compared to asymptotic performance in the operational task. If, for example, asymptotic operator response strategy were revealed upon transition, we would conclude that the training method was effective in developing the required perceptual, information-processing, and motor-response skills. Similarly, if two or more training methodologies were compared, the one yielding post-transition performance closest to asymptotic operational performance would be judged the most effective.*

With regard to the delayed motion-cue experiment described earlier, let us consider the task with synchronous visual and motion cues as the "operational" task, and let us compare the effectiveness of training fixed-base (i.e., static) to training with platform motion delayed by 80 msec. Figure D1 shows that training with minimally-delayed motion cues was substantially more

* Efficiency and cost-effectiveness of training methodologies are also important considerations but are not germane to this discussion.

"effective": post-transition mean-squared tracking error was very nearly at asymptotic levels and was less than half that observed for static training.

Frequency-response measures shown in Figure D4 show that delayed-motion training allowed the subjects to operate with less response variability (remnant) and with generally higher gain than did fixed-base training. Model parameters shown in Table D2c are consistent with these results and reveal lower observation-noise ratios for training with platform motion. Changes in response-time parameters were inconsistent.

Table D3b shows that parameter differences were significant in the aggregate. When subgroups of parameters were tested, only the noise parameters showed a potentially significant effect; modeling error, on the average, was unaffected by fixing response-time parameters at average values.

D.3 Discussion of Model Results

The foregoing analysis provides some indication of the effects of training on operator response capabilities, and it also demonstrates certain important aspects of the analytical methodology itself. Implications as to response capabilities are discussed in the main text and are not treated here. Methodological factors are discussed below.

The model analysis summarized above demonstrates that a large variation in a model parameter is not necessarily a significant variation. In three separate examples, relatively large variations in time delay, motor noise, and observation noise were found to have little impact on the ability to match the experimental data. In general, then, some form of sensitivity analysis is required to determine which parameter changes are necessary to account for differences in operator response behavior.

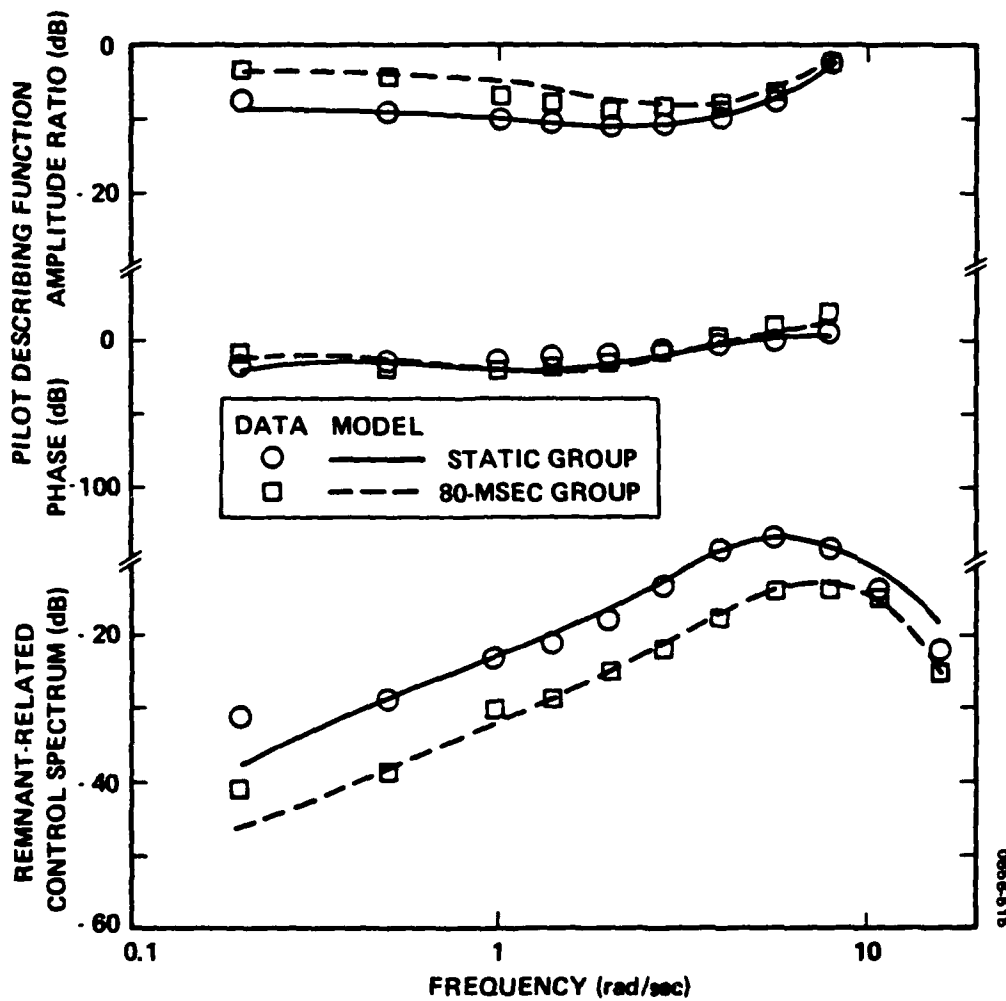


Figure D4. Effects of Initial Training on Early Post-Transition Frequency Response
Average of 5 subjects, 4 trials/subject.

The reader may have noticed from the modeling error ratios shown in Figure D3 and Table D3 that effects are not additive. For example, the increase in modeling error associated with fixing the response time parameters at their average values, when added to the increase in modeling error associated with fixing the remaining (i.e., noise) parameters, is less (sometimes substantially so) than the error increase computed when all parameters are fixed at average values. Thus, we cannot simply explore the parameters one at a time to determine their individual contributions to the total modeling error.

Lack of additivity arises from the non-orthogonality of the parameter set. In general, there is some overlap in the effects that individual parameter variations have on model predictions, so that a change in one parameter can be partially (if not entirely) offset by compensating changes in one or more of the remaining parameters. One could attempt to derive a new, orthogonal, set of independent model parameters through a linear transformation of the OCM pilot parameters; but this would likely result in different parameterizations for each data set, thereby hindering interpretation of the model analysis.

As a final comment, we note that cross-comparison procedure adopted in this study is a relatively conservative scheme for assessing the significance of changes in pilot model parameters. By allowing all but the test parameters to be re-optimized, we favor non-rejection of the null hypothesis that a fixed set of parameter values can provide a near-optimal match to two or more sets of experimental data.

D.4 References

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APPENDIX E

LIMITATIONS ON PSYCHOMOTOR PERFORMANCE

Subjects well-trained on relatively wide-band, single-variable tracking tasks tend to reveal similar performance capabilities as characterized by the independent (or "pilot-related") OCM parameters. When subjects are not fully trained, however, or when the controlled element is relatively low-band (or high order), systematic deviations from nominal parameter values are observed. Such differences are generally in the direction of degraded performance capabilities.

In this Appendix we explore certain hypotheses for these systematic parameter variations, with emphasis on the notion that deficiencies exist in the pilot's internal model of the task environment. Two classes of manual control situations are analyzed: (1) tasks in which subjects have been trained to near-asymptotic levels of performance, and (2) tasks in which the effects of training have been studied.

E.1 Effects of Task Environment on Asymptotic Performance

Identified parameters for various single-axis tracking tasks are given in Table E1. Stated performance objectives were either to minimize simple mean-squared error or to minimize a weighted sum of mean-squared error and mean-squared plant acceleration. In all cases, subjects were given knowledge of performance after each trial and were trained to an apparent asymptotic level of performance before data collection was begun. Descriptions of experiments involving each of the simulated plant dynamics can be found in the references cited at the end of the Appendix. (Some of the model results have been recently obtained and are therefore not found in the references.)

Plant dynamics may be described as follows:

TABLE E1
PILOT-RELATED MODEL PARAMETERS, FIXED-BASE TRACKING,
TRAINED SUBJECTS

Config. Index	Plant Dynamics	Pilot-Related Parameters					
		Ref.	P_e	P_e^*	τ	T_n	G
1	$K \cdot \frac{200}{s+200}$	1	-21.0	-19.5	0.17	0.082	.40
2	K/s	2	-23.6	-18.2	0.15	0.073	.0092
3*	$\frac{K}{s} \cdot \frac{2^2}{s^2 + \sqrt{2} \cdot 2 \cdot s + 2^2}$	2	-18.5	-17.6	0.26	0.14	.0011
4*	$\frac{K}{s} \cdot \frac{1}{s^2 + \sqrt{2}s + 1}$	2	-22.4	-13.3	0.35	0.18	.0011
5	$\frac{K}{s} \cdot \frac{5}{s+5} \cdot \frac{19}{s+19}$	3	-22.1	-16.6	0.19	0.13	--
6	$K/s^2 \cdot \frac{19}{s+19} \cdot e^{-.06s}$	4	-4.6	-21.0	0.21	0.11	.027
7**	(approximate 2nd-order)	5	-10	-20	0.20	0.13	--
8**	(approximate 3rd-order)	5	-10	-20	0.20	0.19	--

P_e = displacement observation noise, dB

P_e^* = rate observation noise, dB

τ = time delay, seconds

T_n = motor time constant, seconds

G = relative cost of control rate, relating (lbs/sec)² control rate to (arc-deg)² error.

*Observation noise of about -19dB associated with perception error acceleration.

**Approximate pilot parameters determined from manual search.

References: (1) Levison (1981); (2) Levison (1971); (3) Levison, Lancraft, and Junker (1979); (4) Levison (1980); (5) Levison, Baron, and Junker (1976)

Configuration 1: Proportional control. (The pole at 200 rad/sec was introduced primarily to facilitate model analysis.)

Configuration 2: Rate control.

Configuration 3: Rate control plus 2 rad/sec 2nd-order Butterworth filter.

Configuration 4: Rate control plus a 1 rad/sec 2nd-order Butterworth filter.

Configuration 5: Approximate roll-axis fighter response characteristics including simulator lag.

Configuration 6: Acceleration control plus simulator lag and delay.

Configuration 7: High-order plant having approximate acceleration control in the mid frequency range.

Configuration 8: High-order plant having approximate acceleration-rate control in the mid frequency range.

The following parameters are shown in Table E1: observation noise/signal ratios for error and error rate; time delay; motor time constant; and, for studies in which tracking error was indicated by the parallel displacement of an error bar from a reference bar, the relative weighting on cost of control rate. Motor noise/signal ratios were also identified but are omitted from the table because of their high variability and relatively small contribution to the overall matching error. For two of the configurations, an observation noise/signal ratio was also identified for error acceleration.

Except for the higher-order plants, model parameters appear to lie in a reasonably small range: observation noise on the order of -20 dB, time delays in the range 0.15 to 0.2 sec, and motor time constants of about 0.1 sec. These values have been typical of those used to obtain model predictions in the absence of experimental data.

Careful inspection of the model results, however, reveals certain trends: the motor time constant appears to increase with the order of the plant; large observation noise/signal ratios are associated with perception of error for the K/s^2 and higher-order plants; and a relatively large delay is identified for the K/s plants cascaded with low-bandwidth filters.

Now, since all subject populations were well trained, and since different groups of subjects tend to perform the same on a given task (given equivalent training), it is unlikely that these differences in pilot-related model parameters reflect different inherent information-processing capabilities among the experimental subject populations. We are left with two more likely explanations for the apparent trends: (1) subjects were motivated differently by the different task configurations to perform to capacity, and (2) internal modeling difficulties associated with higher-order plants have been reflected as differences in information-processing-related parameters because of modeling constraints.

Motivational factors may explain the relatively large observation noise/signal ratios associated with error perception. A sensitivity analysis of predicted rms tracking error to observation noise will show that, for K/s^2 -like plants, performance is considerably more sensitive to noise on error-rate than to noise on error displacement. (This is not unexpected, since the pilot's

control strategy in such tasks is largely to act as a differentiator.) If we assume a workload penalty for reducing observation noise [6], then the noise/signal ratio exhibited in a given task may reflect a tradeoff between minimizing tracking error and minimizing attentional workload.

We are not yet in a position to comment on the apparent task-related changes in time delay. A significance test of the type described above needs to be performed to determine whether or not the identified differences in delay are meaningful. (As we shown in Appendix D, apparent learning-related differences in time delay failed the test of significance.)

Differences in motor time constant are more interesting in that they are largely significant and cannot be entirely explained on the basis of performance sensitivity.

Because the relationship between motor time constant and relative control-rate weighting is task dependent, we should first ascertain whether or not the subjects are simply maintaining relatively constant performance indices across tasks.

Inspection of the right-hand column of Table E2 refutes this hypothesis. Relative cost of control rate varies over two orders of magnitude among the various tasks for which meaningful comparisons can be drawn. Clearly, motor time constant is a more consistent descriptor of pilot performance limitations than is relative cost of control rate.

To test the hypothesis that motivational factors influenced the motor time constant, model analysis was performed to determine the sensitivity of rms tracking error to rms control rate. Table E2 presents the predicted sensitivity (fractional change in rms error per fractional change in rms control rate) for selected task configurations. For each configuration, the sensitivity is shown for the T_n that best matched the data.

TABLE E2
SENSITIVITY OF MS ERROR TO MS CONTROL RATE

Config. Index	T_n	$\frac{\Delta\sigma_e}{\sigma_e}$	$\frac{\Delta\sigma_{\dot{u}}}{\sigma_{\dot{u}}}$
2	.07		-.26
3	.14		-.20
5	.13		-.27
5 (with platform motn)	.09		-.04
6	0.11		-.30
8	0.19		-.08

Configurations defined in Table 2.

T_n indicated for best match to data.

As the sensitivities range from -0.04 to 0.30, we must reject the hypothesis that the subjects selected a motor time constant to reflect a consistent tradeoff between tracking performance and control activity. Most compelling are the differences in sensitivity shown in the 3rd and 4th rows of Table E2, which contain results for the same tracking task with and without cuing provided by whole-body motion. When motion cues were provided, the subjects operated in a region where error performance was much less sensitive to response bandwidth than when motion cues were absent. One must conclude, at least for this case, that the motor time constant was related more to the quality of information available than to the relative effectiveness of control activity.

As shown in Appendix D, the motor time constant is not only a function of the specifics of the control task, it also appears to

be a function of the pilot's state of training. Now, the pilot-related model parameters presented in this discussion and in the preceding discussion of learning effects were obtained with the OCM structured to include a perfect internal model of the task environment. It is possible, then, that what appear to be task- and training-related differences in motor time constant (and perhaps other parameters as well) are reflections of imperfect internalizations of the task by the experimental subjects. This issue is discussed further in the main text.

E.2 References

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Report No. 4645

Bolt Beranek and Newman Inc.

APPENDIX F

THE EFFECTS OF MULTIPLICATIVE MOTOR NOISE ON
THE OPTIMAL HUMAN OPERATOR MODEL

by

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William H. Levison

presented at the

Sixteenth Annual Conference on Manual Control
Massachusetts Institute of Technology
Cambridge, Massachusetts May 5-7, 1980

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THE OPTIMAL HUMAN OPERATOR MODEL

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ABSTRACT

The effects of a multiplicative motor noise model on the optimal-control human operator model have been analyzed. A study of the interaction between multiplicative motor noise variance, plant dynamics, and predicted operator response behavior shows that, in general, an increase in motor noise variance produces a decrease in operator gain and a decrease in high-frequency remnant. An increase in multiplicative motor noise variance is also reflected by an increase in the effective motor time constant; in the absence of a cost penalty on commanded control, the motor time constant equals the motor noise variance.

INTRODUCTION

A substantial body of manual control data, obtained in a variety of laboratory tracking tasks, has been analyzed with the "optimal-control" pilot/vehicle model. For many of these studies, pilot response behavior has been reflected in terms of a relatively invariant set of values for pilot-related parameters; specifically, a "motor time constant" of between 0.08 and 0.1 seconds, a "time delay" of between 0.15 and 0.2 seconds, and an "observation noise/signal ratio" of about -20 dB ¹⁻³. These tasks have largely involved wide-band dynamics with minimal delays.

Consistent deviations from these "nominal" values have been noted for certain kinds of tasks. Of particular interest here are the larger values for motor time constant (implying reduced operator bandwidth) that have been found for tasks involving control of slowly-responding systems ⁴⁻⁶.

The predictive capability of the optimal-control model will be enhanced if we can find either an alternate set of pilot-related parameters that are more nearly invariant, or a consistent rule for adjusting the current parameter set according to the characteristics of the task. The apparently consistent trend of the motor time constant with respect to the response characteristics of the controlled element suggests that this goal is achievable.

In this paper we explore the possibility that changes in motor time constant reflect, in part, a multiplicative motor noise process underlying human controller response behavior. The notion of a multiplicative noise process is consistent with the empirical finding that, in idealized control situations, both motor noise and observation noise appear to scale with the variances of corresponding control and display variables. In previous studies, these processes have been considered to affect only the estimator (Kalman filter) portion of the pilot model; in this paper, however, we consider the multiplicative motor noise process to influence the control gains.

OPTIMAL HUMAN OPERATOR MODEL WITH MULTIPLICATIVE MOTOR NOISE

The following linearized description of the vehicle dynamics will be assumed:

$$\dot{x}(t) = Ax(t) + Bu_p(t) + Ew_g(t) \quad (2.1)$$

where x is the n -dimensional state vector including the variables corresponding to the gust states, u_p is the r -dimensional operator input, and w_g is the white Gaussian process noise with covariance $W_g\delta(t-s)$. We will assume the following multiplicative motor noise model for the human operator's input dynamics:

$$\dot{u}_{p_i}(t) = u_{c_i}(t) + u_{c_i}(t)w_{m_i}(t) \quad (2.2)$$

where u_{c_i} is the i 'th component of the commanded control rate in the absence of motor noise and w_{m_i} is the i 'th component of the r -dimensional motor noise which is a white Gaussian process with covariance $W_m\delta(t-s)$. The effective additive noise, $u_{c_i}w_{m_i}$, in equation 2.2 will have the following properties for the stationary case:

$$Eu_{c_i}w_{m_i} = 0 \quad (2.3)$$

$$E[u_{c_i}(t)w_{m_i}(t)][u_{c_i}(s)w_{m_i}(s)] = (Eu_{c_i}^2)W_{m_{ii}}\delta(t-s) \quad (2.4)$$

Comparison of the covariance of the effective additive noise with that of the empirical relationship in 1 reveals that the variance of the multiplicative motor noise in the model above corresponds to the motor noise ratio in 1 with a scale factor of π . The multiplicative motor noise model specified by equation 2.2 would also allow correlation between the noise components w_{m_i} for the multi-input case through the off-diagonal elements in the motor noise covariance W_m . The task requirements for the human operator will be expressed by the standard quadratic cost functional:

$$J = \frac{1}{2} E \int_0^{\infty} (x_0(t) Q x_0(t) + u_c(t) G u_c(t)) dt \quad (2.5)$$

where x_0 is the state vector augmented with the operator input u_p .

It can be shown ⁸⁻¹⁰ that under suitable regularity conditions the optimal human operator control in the space of linear controls with full state feedback will be given by:

$$u_c^*(t) = -F x_0(t) \quad (2.6)$$

where the feedback gain F is defined by

$$F = (G + P(K))^{-1} B_0' K \quad (2.7)$$

with the positive-semidefinite matrix $P(K)$ defined by

$$P(K)_{ij} = K_{n+i, n+j} W_{mji} \quad i, j = 1, 2, \dots, r \quad (2.8)$$

where K is the positive definite solution of the algebraic Riccati equation

$$K A_0 + A_0' K + Q - K B_0 (G + P(K))^{-1} B_0' K = 0 \quad (2.9)$$

with the augmented system matrices A_0 and B_0 (of dimension $n+r \times n+r$ and $n+r \times r$, respectively) given by

$$A_0 = \begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix} \quad B_0 = \begin{bmatrix} 0 \\ I \end{bmatrix} \quad (2.10)$$

The comparison of the Riccati equation above with that given in reference 1 shows that the control dependent noise effectively increases the control weighting G further by the term $P(K)$ relative to the case with additive motor noise. For a fixed set of control weightings Q and G , the effect of the multiplicative motor noise is to reduce the control gains of the human operator from their values corresponding to the additive motor noise case. This effect of the multiplicative motor noise model is expected since the control effort has some destabilizing effect on the system through the control dependent noise. This relationship between the motor noise and the control gains should be useful in modelling the learning behavior of inexperienced human operators ¹¹.

The term $G + P(K)$ in the Riccati equation 2.9 can be considered as an effective control weighting matrix. If the multiplicative motor noise covariance W_m is chosen to be positive definite, then $P(K)$ will be positive definite even when the commanded control is not penalized in the human operator's cost function (i.e. $G=0$). This result is intuitively pleasing in that the multiplicative motor noise models the human operator's inherent constrained

control capability. That is, even if no explicit or subjective penalty is associated with control activity, the predicted control gains will remain finite.

While it is possible to find an equivalent commanded control rate weighting, G_e , for any solution of the Riccati equation (2.9) corresponding to a certain Q, G combination ($G_e = G + P(K)$), the multiplicative motor noise model brings new interpretations to the motor time constant and control gains and provides a link between the human operator's control gains and the motor noise ratio. These issues will be discussed in the later sections. In the multi-input case, the equivalent control rate weighting G_e would have off-diagonal terms when the control dependent noise components are correlated. Therefore, trial and error search for an equivalent control rate weighting G_e would be more complicated for the multi-input case.

The effect of the multiplicative motor noise on the human operator model characteristics has been studied using several plant dynamics. A lower order Riccati equation (2.9) excluding the gust state variables is first solved using an algorithm similar to that in ¹⁰ and then the gains on gust variables are obtained by solving a linear algebraic equation similar to the deterministic case. For these studies, the filtering part of the human operator model has been taken from the pseudo motor noise model in ⁴. In order to differentiate between the different motor noise ratios, we will call the one used for the control computations as the control motor noise ratio, the one used for the estimator computations as the filter motor noise ratio (called pseudo motor noise ratio in ⁴), and the real driving motor noise as the actual motor noise ratio. In the sequel, "motor noise ratio" without an explicit reference will imply control motor noise ratio.

EFFECTS ON THE MOTOR TIME CONSTANT

In the single input case, with G and W_m scalars in (2.8) and (2.9), ($G = g$, $W_m = v$), the motor time constant, T_N , defined as the inverse of the gain on pilot input u_p , will be given by

$$T_N = \frac{g}{p} + v \quad (3.1)$$

where p is the lower right element $K_{n+1, n+1}$ of the solution of the Riccati equation (2.9). As can be seen from equation (3.1), the motor time constant is composed of two terms: The first one, g/p , is directly proportional to the control rate weighting in the human operator's objective function. The second term, v , is equal the variance of the multiplicative motor noise and corresponds to the motor noise ratio defined in ⁴, scaled by a factor of π .

The effects of multiplicative motor noise on the optimal human operator model has been studied using the following set of vehicle dynamics:

Rate Dynamics:

$$\dot{x} = \begin{bmatrix} -2. & 0. \\ 1. & 0. \end{bmatrix} x + \begin{bmatrix} 0. \\ 1. \end{bmatrix} u + \begin{bmatrix} 1. \\ 0 \end{bmatrix} w \quad 3.2$$

$$y = \begin{bmatrix} 0. & 1. \\ 1. & 0. \end{bmatrix} x + \begin{bmatrix} 0. \\ 1. \end{bmatrix} u \quad 3.3$$

Yaw Dynamics:

$$\dot{x} = \begin{bmatrix} -1. & 0. & 0. & 0. & 0. \\ 533. & 0. & 0. & 0. & 0. \\ -16. & 1. & -33.3 & 0. & 0. \\ 0. & 0. & 19. & -19. & 0. \\ 0. & 0. & 0. & 1. & 0. \end{bmatrix} x + \begin{bmatrix} 0. \\ 533. \\ -16. \\ 0. \\ 0. \end{bmatrix} u + \begin{bmatrix} 1.41 \\ 0. \\ 0. \\ 0. \\ 0. \end{bmatrix} w \quad 3.4$$

$$y = \begin{bmatrix} 0. & 0. & 0. & 0. & 1. \\ 0. & 0. & 0. & 1. & 0. \\ 0. & 0. & 0. & 1. & 0. \\ 0. & 0. & 19. & -19. & 0. \end{bmatrix} x \quad 3.5$$

Filtered Rate Dynamics:

$$\dot{x} = \begin{bmatrix} -2. & 0. & 0. & 0. \\ 0. & 0. & 1. & 0. \\ 0. & -1. & -1.414 & 1. \\ 1. & 0. & 0. & 0. \end{bmatrix} x + \begin{bmatrix} 0. \\ 0. \\ 0. \\ 1. \end{bmatrix} u + \begin{bmatrix} 1. \\ 0. \\ 0. \\ 0. \end{bmatrix} w \quad 3.6$$

$$y = \begin{bmatrix} 0. & 1. & 0. & 0. \\ 0. & 0. & 1. & 0. \end{bmatrix} x \quad 3.7$$

In each case, $\tau = .2$ sec. for the human operator time delay, -90 dB for the actual motor noise ratio, -40 dB for the filter motor noise ratio, -20 dB for the observation noise ratio were used for the model parameter values. The plant with the rate dynamics represent a velocity control task under a velocity disturbance created by a first order noise spectrum with a break frequency 2 rad/sec. The filtered rate dynamics is the same plant as the rate dynamics with a two-pole Butterworth filter of cutoff frequency 1 rad/sec. Yaw dynamics represent k/s^2 dynamics with approximately 60 msec. time delay.

The effects of different multiplicative motor noise levels on the motor time constant have been analyzed using the dynamics above. The control rate weighting, g , was chosen to obtain a nominal value of .1 sec. for T_N at the -40 dB motor noise level. In general, an increase in the motor noise level produced a higher motor time constant T_N . The results are tabulated in Table I. Bringing up the motor noise ratio to the -20 dB level resulted in a 10% increase in the motor time constant T_N compared to the negligible motor noise case (-40 dB) in all of the three dynamics tested.

As predicted by equation (3.1), the motor noise ratio starts effecting the motor time constant T_N when its value is around -20 dB. This level corresponds to a motor noise ratio of $v=.0314$.

Since the term p in (3.1) is a function of both g and v and since increasing v results in a higher p , the term g/p decreases as the motor noise ratio is increased to -20 dB level. However, in all of the three cases tested, the decrease due to the g/p term was more than compensated by the increase in the motor noise ratio v .

When the commanded control is not weighted (i.e. $g=0$), a motor noise ratio of -15 dB, as predicted by equation 3.1, resulted in a motor time constant $T_N=.1$ sec for all the dynamics tested. In this case with no penalty on commanded control rate, the motor time constant T_N is equal to the variance of the multiplicative motor noise (3.1). That is, the motor noise ratio value completely specifies T_N independent of the plant dynamics. In this case, the human operator's cost function (2.5) would only consist of mean-squared error which is the real objective in a compensatory tracking task.

EFFECTS ON THE HUMAN OPERATOR TRANSFER FUNCTION

The effects of varying the multiplicative motor noise variance on the human operator's equivalent describing function have been analyzed by using the plant dynamics in the previous section. Figure I shows the results for the filtered rate dynamics.

In general, for increasing motor noise ratio, the human operator's equivalent describing function gain decreases as expected with greatest variation occurring for frequencies $\omega < 1$ rad/sec and $\omega > 8$ rad/sec. Motor noise ratio variation has a small effect on the phase of human operator's transfer function. The greatest change is around the 8-10 rad/sec range since increasing the motor noise ratio to -17 dB from the -40 dB level results in the shift of pole due to the motor time constant from 10 rad/sec to 8.5 rad/sec. "Remnant" (control activity not correlated with the tracking input ⁷) decreases at high frequencies ($\omega > 8$ rad/sec) as the motor noise ratio is increased to -17 dB level. This result is to be expected since the bandwidth of the controller is decreased due to the increase in the control dependent noise. These results indicate the conservative nature of the feedback controller based on a multiplicative motor noise model. In summary, an increase in the multiplicative motor noise variance causes a decrease in the gain and, at high frequencies, a decrease in the remnant for the human operator's equivalent describing function.

VARIATION IN T_N WITH BANDWIDTH

In this section, we will discuss how the multiplicative motor noise model can be used in explaining the inverse variation of the motor time constant T_N with plant bandwidth. For this analysis, the following set of dynamics are used:

KSG Dynamics

$$\dot{x} = \begin{bmatrix} -2. & 0. \\ 15. & 0. \end{bmatrix} x + \begin{bmatrix} 0 \\ 20. \end{bmatrix} u_p + \begin{bmatrix} 2. \\ 0 \end{bmatrix} w \quad (4.1)$$

$$y = \begin{bmatrix} 0. & .1 \\ 1.5 & 0. \end{bmatrix} x + \begin{bmatrix} 0. \\ 2. \end{bmatrix} u_p \quad (4.2)$$

BW1 Dynamics

$$\dot{x} = \begin{bmatrix} -2. & 0. & 0. & 0. \\ 10. & 0. & 0. & 0. \\ 0. & 1. & -1.414 & -1. \\ 0. & 0. & 1. & 0. \end{bmatrix} x + \begin{bmatrix} 0. \\ 20. \\ 0. \\ 0. \end{bmatrix} u_p + \begin{bmatrix} 2. \\ 0. \\ 0. \\ 0. \end{bmatrix} w \quad (4.3)$$

$$y = \begin{bmatrix} 0. & 0. & 0. & .02 \\ 0. & 0. & .02 & 0. \\ 0. & .02 & -.028 & -.02 \end{bmatrix} x \quad (4.4)$$

BW2 Dynamics

$$\dot{x} = \begin{bmatrix} -2. & 0. & 0. & 0. \\ 10. & 0. & 0. & 0. \\ 0. & 4. & -2.82 & -4. \\ 0. & 0. & 1. & 0. \end{bmatrix} x + \begin{bmatrix} 0. \\ 20. \\ 0. \\ 0. \end{bmatrix} u_p + \begin{bmatrix} 2. \\ 0. \\ 0. \\ 0. \end{bmatrix} w \quad (4.5)$$

$$y = \begin{bmatrix} 0. & 0. & 0. & .02 \\ 0. & 0. & 0.02 & 0. \\ 0. & .08 & -0.056 & -.08 \end{bmatrix} x \quad (4.6)$$

These dynamics correspond to three laboratory tracking experiments. The plant with the KSG dynamics represents velocity control task under disturbance. BW1 and BW2 dynamics represent the same plant with a two-pole Butterworth filter of cutoff frequency 1 and 2 rad/sec, respectively. Model matching analysis of the actual data has shown that an increase in the value of T_N from .06 sec to .15 sec is needed as the bandwidth is decreased (change from KSG to BW1 dynamics). With the standard human operator model, these different values of T_N are obtained by selecting a different control rate weighting, g , value for each case. As Table II shows, with the multiplicative motor noise based model, it is possible to match the variation in T_N with only one value for the control rate weighting g and the motor noise ratio v .

CONCLUSIONS

The effects of a multiplicative motor noise model on the optimal-control human operator model have been analyzed. A study of the interaction between multiplicative motor noise variance, plant dynamics, and predicted operator response behavior shows that, in general, an increase in motor noise variance produces a decrease in operator gain and a decrease in high-frequency remnant. An increase in multiplicative motor noise variance is also reflected by an increase in the effective motor time constant; in the absence of a cost penalty on commanded control, the motor time constant equals the motor noise variance.

For the cases explored in this analysis, variations in the motor time constant were accounted for by fixed values assigned to motor noise ratio and cost of control. Thus, even though a new parameter was added to the optimal control model, the number of degrees of freedom required to account for variations in controlled-element dynamics was actually reduced! Further work is required to determine the extent to which a fixed set of cost and noise parameters can explain human operator behavior across a variety of task conditions, including the differences observed between inexperienced and trained human operators ¹¹.

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Dynamics	Motor Noise Ratio dB	g	T_N
k/s	-40	4×10^{-4}	0.1
k/s	-30	4×10^{-4}	0.101
k/s	-20	4×10^{-4}	0.11
yaw	-40	1.58×10^{-2}	0.1
yaw	-20	1.58×10^{-2}	0.106
fk/s	-40	8×10^{-6}	0.1
fk/s	-20	8×10^{-6}	0.107
fk/s	-17	8×10^{-6}	0.113

TABLE I. Variation of T_N with Respect to Motor
Noise Ratio

Dynamics	Motor Noise Ratio dB	g	T_N
k/s	-14.97	0.	.1
yaw	-14.97	0.	.1
fk/s	-14.97	0.	.1

TABLE II. Neuromuscular Delay with No
Penalty on Commanded Control

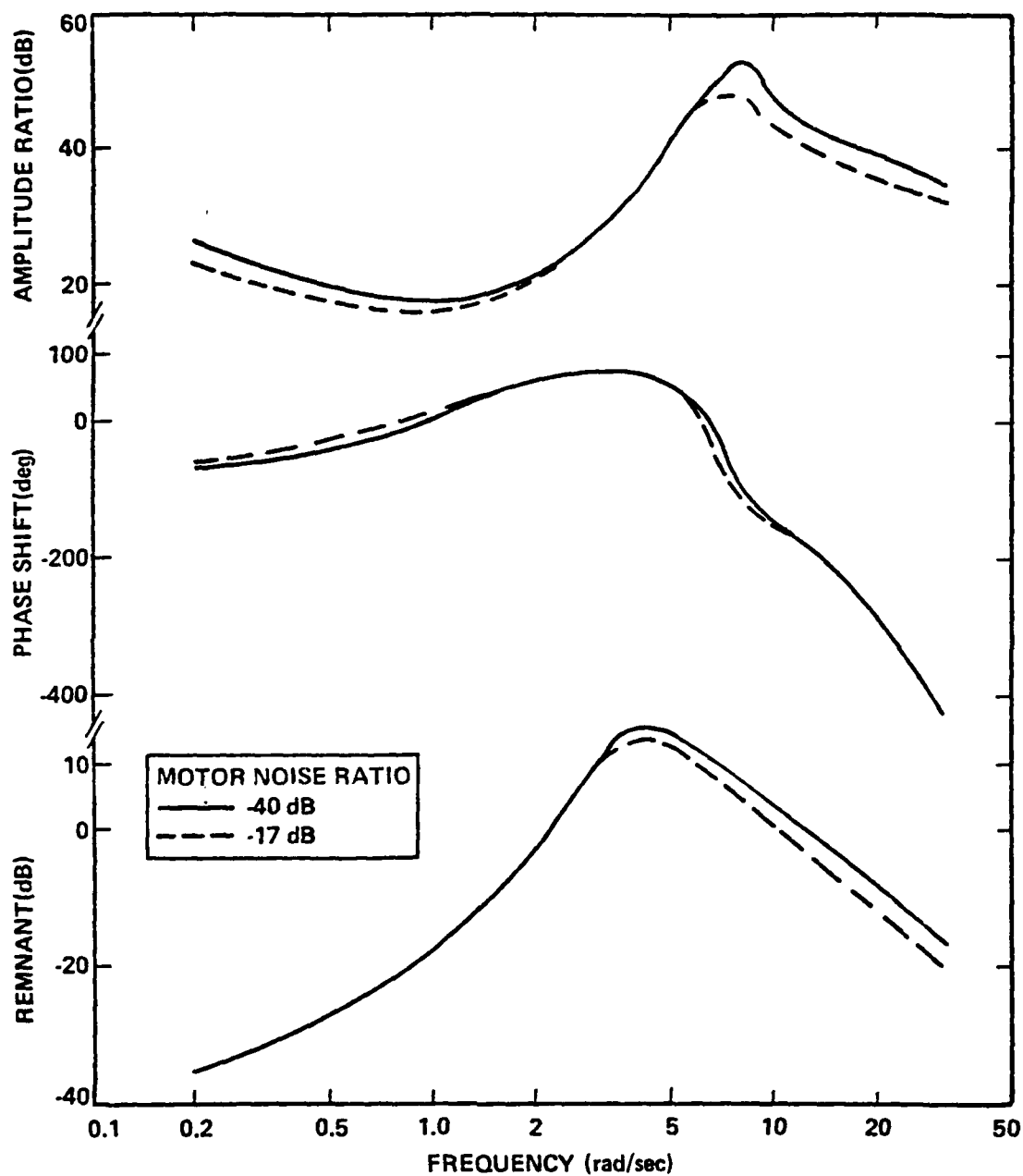


Figure 1. Human Operator Transfer Functions Variations Due to Motor Noise Ratio (filtered rate dynamics)

APPENDIX G

POTENTIAL ADAPTIVE-CONTROL SCHEMES FOR MODELING
PILOT LEARNING BEHAVIOR

prepared by

Timothy L. Johnson

G.1 Modeling the Effects of Training

Even within the narrow context of continuous manual tracking tasks, the effects of learning during training may be difficult to represent. While this discussion is primarily concerned with perceptual-motor learning that occurs during repeated practice of a fixed task, factors such as changes in environment, displays, controls, operating strategy and workload may have significant effects and must be carefully designed if meaningful results are to be obtained.

The process of perceptual-motor learning, in this context, may be viewed as having two inter-related aspects: (1) developing an understanding of the system being controlled, and (2) improving the strategy for controlling it. These effects are difficult to observe independently, though they may occur at different rates. To distinguish them is useful primarily for the construction of general purpose models of the effects of learning; no physiological basis is implied. In many situations, the learning process reaches an asymptotic state where the subject is unable to achieve further performance improvement. In this limit, the Optimal Control Model (OCM) of the well-trained, well-motivated pilot has been thoroughly validated. Thus, it would be desirable to have a model of the pilot-in-training which converged to the OCM as more and more experience were accumulated.

The OCM can in fact, be generalized to include the major effects of training, and can thus serve as the basis for a model of

perceptual-motor learning. The OCM of the trained pilot contains an optimal filter which estimates the states of the system being controlled, followed by optimal state-feedback gains. The filter and gain parameters are both selected on the basis of the dynamics of the actual system being controlled on the implicit assumption that all useful information about the system is exploited by a trained pilot. A natural model of the pilot-in-training is based on the assumption that the essential structure of the OCM is retained, while the parameters of the model* are adaptively modified during the training process.

The adaptive optimal control model (AOCM) of the effects of training must contain some mechanism for updating the internal model parameters of the optimal filter and state-estimate feedback gains. Desirable properties of this adaptation mechanism are:

- (a) Stability of the pilot's control and estimation strategy, whenever possible, during training.
- (b) Convergence of the gains of the adaptive controller to those of the OCM as asymptotic performance is achieved.
- (c) "Design" parameters in the adaptation algorithm to allow for different rates of learning by different trainees. These are in addition to the control and state-weighting parameters in the OCM.
- (d) Reasonable assumptions about the learning process.

These properties are not readily guaranteed, because the adaptation process,** unlike the control process, is highly and inherently nonlinear.

* And possibly model order and model structure.

** To be consistent with the terminology used by the control-theory community, we use the term "adaptation" here to refer to what we have called "learning" in the main text; namely, the adjustment of the control strategy over time to improve closed-loop system performance.

Although the development of an adaptive model of pilot motor learning is not a routine undertaking, several recent developments in the theoretical literature have established a firm basis upon which to build. The topic of adaptive control has come to subsume the issues of on-line parameter identification (which has previously been regarded as a separate topic) as well as adaptation in control strategy and gains; hence, most of the theoretical results to be reviewed lie in this domain. A survey of the available techniques and results is given in the following subsection. The final subsection concludes with a preliminary assessment of the applicability of these techniques to the problem of modelling human operator skill development.

G.2 Survey of Adaptive Control and On-Line Identification Methods

Since the literature in these topics has grown explosively within the last decade, only the key results which have bearing on the fundamental issues of pilot learning can be reviewed here.* The term "learning" has been used to characterize a variety of situations in which a person or device starting from some basis of prior information, accumulates additional information about an environment and uses this total information to interact with the environment more effectively in performing some task or tasks. In very general terms, it can be established that the accumulation of information always implies the potential for improved task performance.

Interactive learning processes are known to involve a trade-off of three conflicting objectives: control, estimation, and identification [4]. The available inputs to the system may, and often must, serve all three objectives. In general, the types of control inputs required to identify system structure and

* More general surveys are given by Astrom and Bohlin [1], Saridis [2] and Landau [3].

parameters, and to estimate the current system state on the basis of incomplete or noisy measurements, lead to increased control energy and degradation of control performance (in the short term). These phenomena are observed for both continuous-state and finite-state systems. The use of control inputs for both identification and control purposes is termed "active learning".

Automaton (finite-state) models of learning (in the noise-free case) require input-output experiments; from these experiments the state transition and readout maps can be constructed by traversing a decision tree, and thereafter the system may be controlled [5,6]. These models illustrate the general importance of using inputs for identification and estimation as well as control. They provide a basis for the modelling of human performance in decision tasks with a finite number of outcomes.

The dual use of controls for these purposes in continuous-state systems is still not fully understood, particularly in the case where system structure (as well as parameters) is to be identified [7,8]. In the identification of linear systems, inputs which are sufficiently "rich" in frequency content must be used to ensure uniqueness and robustness of parameter estimates [9]; this excitation condition may be satisfied by autonomous disturbances or operator inputs, or both. Under closed-loop control, there are fundamental limitations on the parameters which may be identified in the absence of disturbance inputs [10]. In linear or almost-linear systems, the choice of input often contributes relatively little to estimation accuracy, but even in closely-related situations where quadratic measurement nonlinearities occur, input probing is normally required in order to achieve uniqueness of state estimates. In the very special case of linear systems with gaussian noise inputs and quadratic performance criteria, when the system structure and parameters are known, the identification problem does not exist, and the control

and estimation problems separate because estimation accuracy is independent of the control input wave form. This is the basis for the pilot OCM.

When the controller does not inject inputs explicitly for purposes of estimation or identification, forms of learning which have been termed "passive learning" may still occur [4]. One form of passive learning is on-line adaptation of parameters in an internal model of the system and/or in the controller gains. Another manifestation of passive learning is the use of a cautious control strategy [11]. Many of the methods of statistics which do allow for identification of system structure within limited classes of models are also passive [12].

At present, passive learning is better understood, in theoretical terms, than active learning. In the context of developing appropriate response strategies for continuous tracking tasks, it would appear that passive learning models might be sufficient to characterize all but the first few experiences with a system; it is the longer time-scale of learning (i.e., training) with which we are most concerned. Thus, the following more detailed discussion pertains to the status of passive learning theories.

A significant recent development in the theory of passive adaptive control is the unification of model-reference and prediction-error methods which has resulted from successful efforts to prove the stability of certain adaptive control schemes [13-15]. A block diagram illustrating the synthesis of these ideas is shown in Figure G1. The important feature is that the reference model tracking error, e^* , and the error prediction, $\hat{e}$, can be combined (e) in order to produce convergent parameter estimation schemes. Previous algorithms which relied exclusively on either e^* or $\hat{e}$ were known to fail more frequently due to loss of stability in

either parameter estimation or control, respectively. Representative examples of some of the available algorithms are now reviewed.

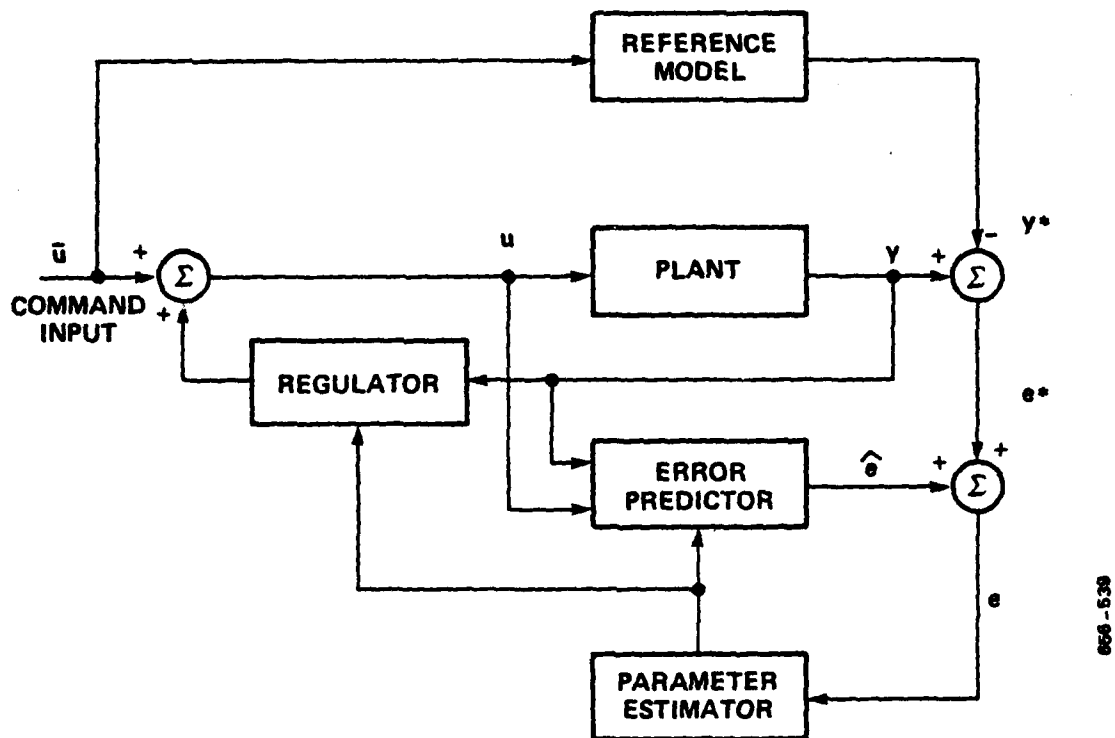


Figure G1. General Adaptive Control Block Diagram

G.2.1 Recursive Maximum Likelihood Methods

The plant parameters are viewed as random variables with known prior distributions; their values during an experiment are observed indirectly through dynamic measurements of the plant outputs. For the case of linear plants with gaussian disturbance inputs and measurement noises, a suboptimal stochastic control strategy is to update the control and filter gains of an LQG control law in

accordance with the current estimates of the plant parameters obtained by a recursive maximum-likelihood algorithm.

Referring to Figure G1, the reference model is absent in this case. The error predictor is a Kalman filter based on current parameter estimates, with innovations $\hat{e}$, and the parameter estimator is an implementation of the recursive maximum-likelihood algorithm; the regulator also contains a copy of the Kalman filter and gains based on the current parameter estimates.* In practice, the controller is constrained to be finite-dimensional by selecting parameters from a finite set and by computing and comparing the likelihoods of each parameter set, a scheme suggested by Lainiotis [16]. Two implementations of this scheme, for adaptive control of an F8 aircraft, have been evaluated. Stein, et al [17] used a control law based on a linear combination of the control laws for each parameter set, with weightings based on the likelihood ratios, while Athans et al [18] used a control law which switched control gains corresponding to the parameter set with the currently greatest likelihood; the first method yielded better performance, but neither method consistently converged to the parameter set which was "nearest" to the parameters of the actual plant. Random switching between parameter sets could occur, depending on properties of the plant disturbance or observation noise sample. In certain cases these phenomena resulted in instability of the control law as well as failure of convergence to the correct parameter set, as might be expected. In retrospect, the design efforts illustrated the importance of the stability and convergence analysis in adaptive control law design. Recursive maximum likelihood algorithms are perhaps the closest practical approximation to the intractable optimality conditions obtained

* Figure G1 is a conceptual block diagram; the practical implementations of most of the methods discussed can be developed from it by standard equivalence transformations.

from stochastic control theory, even though their stability has still not been fully investigated. Ljung [19] demonstrated inherent limitations on identifiability of closed-loop control systems, which imply that the choice of parameter sets for such algorithms must be carefully undertaken. The apparent rate of convergence in the parameter estimates of these algorithms is related to the assumed prior variances of the parameters, the plant noise statistics and the control law implementation.

G.2.2 Recursive Least-Squares (RLS) Algorithms

These algorithms are generally based on an autoregressive moving-average (ARMA) model of the plant rather than a state-space model; well-known methods can be used to transform a sampled-data state-space model into autoregressive form. The parameterization of linear state-space models is inefficient and the issue of uniqueness of parameter estimates can be treated more conveniently for ARMA models [20]. The parameters are often viewed as being deterministic, but with initially unknown values; estimates of these values are continuously updated in order to achieve tracking of the response of a reference model.

Referring to Figure G1, the error predictor includes an autoregressive plant model, while the parameter estimator involves a recursive least squares algorithm. An advantage of the ARMA formulation is that minimum-energy control gains are computed directly by the parameter estimator. Goodwin, Ramadge and Caines [15] have recently presented a multi-input, multi-output (MIMO) RLS adaptive control algorithm which is, in effect, a generalization of the single-input, single-output (SISO) self-tuning regulator algorithm originally presented by Astrom and Wittenmark [21] and cast into the desired form by Clarke and Gawthrop [22]. Under certain conditions, they are able to guarantee a weak form of stability and convergence for the algorithm. One of these

conditions effectively places a limit on the convergence-rate parameters of the RLS algorithm, which are otherwise free to be specified by the designer.

G.2.3 Model Reference Methods

Original model-reference methods [3] overlooked the importance of the error-predictor (see Figure G1) or resorted to numerically-sensitive differentiation techniques to approximate its effects. Monopoli [23] recognized that an "augmented error" signal (like $\hat{e}$ in Figure G1) would be required to establish Lyapunov stability of such algorithms. His convergence proofs were improved and generalized by Feuer and Morse [24] and Narendra and Valavani [14]. Egardt presented frequency-domain synthesis techniques for RLS model-reference controllers and illustrated how the two approaches could be viewed in a unified framework [13].

G.2.4 Adaptive Pole-Placement Methods

Egardt's technique for synthesis of direct-time ARMA-type adaptive controllers can also be regarded as a pole-placement method (i.e., the poles of the controlled system are to be aligned with those of the reference model). A continuous-time adaptive pole-placement method for single-input, single-output plants has also been presented by Elliot and Wolovich [25]. The parameters for an observer-based compensator are determined from the reference model and are updated according to a gradient method, based on the current estimates of plant parameters. The plant parameters, in turn, are identified based on filtered estimates of the derivatives of plant inputs and outputs. The convergence of this method, unfortunately, depends on a richness condition imposed on reference inputs (or equivalently, persistently exciting disturbances); further study of this requirement is necessary. The advantages of this algorithm are that it does not require stable or minimum-phase plants and that it includes design parameters through which the

rate of convergence of the controller gains and the identifier may be adjusted independently.

G.3 Candidates for Pilot Models with Learning

None of the methods which have been reviewed possesses all of the previously-stated properties which would be desirable in a model of pilot learning. Perhaps the best available candidate is the RLS adaptive control law of Goodwin, Ramadge and Caines [15].

This is a MIMO method which has some established convergence and stability properties. It is relatively simple to implement and contains design variables which can be used to adjust the rate of convergence of the parameter estimates. Possible drawbacks may arise from the fact that the control law is of minimum-energy type and may be unstable for systems (e.g., non-minimum phase systems) without stable inverses; as a consequence, there is no provision for trade-off between tracking errors and control energy, nor for independent rates of adaptation of control and identification algorithms. For SISO systems, the somewhat more complex algorithm of Elliot and Wolovich [25] may also deserve further consideration. While it does not suffer from minimum-phase or stability requirements, the restrictiveness of the richness condition on the plant inputs is not yet known. The features of being able to specify rates of parameter and control law adaptation are very desirable. It is likely that the method can be generalised to MIMO systems and that the identification procedure can be improved so as to remove the reference input restriction. It should be noted that real systems are always subject to some disturbances and that humans experience extreme difficulty in controlling unstable nonminimum phase systems; hence the theoretical limitations of Elliot and Wolovich's algorithm might not correspond to man-machine systems which would reach a testing stage.

The convergence of these adaptive control laws to an optimal control pilot model can be enforced by using the OCM as a reference model in the design. This raises the conceptual issue (which is not addressed in the OCM) of how the pilot could know about such a reference model prior to ever experiencing the system. An alternative possibility is to base the reference model on some "desired handling qualities", which are best matched to the pilots' manual control abilities and would be presumably known through experience.

The issue of identifying system structure during the learning process is not fully addressed by these algorithms, and it is in fact likely that the trainee will make some initial input-output experiments in order to identify general system properties. These may have more the character of a decision process, as described previously. It is possible to simulate some aspects of learning by initializing the parameter estimates of the algorithm to correspond to those of a lower-order plant model, for instance.

In conclusion, the process of training-subsequent to initial familiarization with a system - may be viewed as an adaptive control process. Existing adaptive algorithms demonstrate many but not all of the desired properties of an adaptive optimal control model of a pilot-in-training. Additional research is required in order to apply these ideas to human operator data.

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