A BRIEF OVERVIEW OF THE THEORY AND APPLICATION OF THE OPTIMAL CONTROL MODEL OF THE HUMAN OPERATOR

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SUMMARY

This tutorial reviews the Optimal Control Model of the human operator. First, underlying motivation and concepts are presented, along with a review of the development and application of the model. Then, the structure of the model is described. Finally, results validating the model are presented.

INTRODUCTION

This paper reviews the Optimal Control Model (OCM) of the human operator developed principally by Kleinman, Levison, and the author (refs. 1 and 2, for example) at Bolt Beranek and Newman Inc. The OCM was originally developed for describing and predicting total system performance in continuous, manual control tasks. However, the model (or portions of it) has proven to be useful in a broader range of problems. Moreover, though not intended to be a structural analog of the human operator, many features of the model have interesting interpretations from an information processing view of human performance (ref. 3). The aim of this paper is to provide the reader with an overview of the OCM and a guide to the literature for more detailed information. Accordingly, it begins with a discussion of underlying motivation and a review of the development and application of the model. This is followed by a discussion of the important structural features of the model, some basic validation results and brief concluding remarks.

MOTIVATION AND REVIEW

The human controller is self-adaptive and, if motivated and given information about his performance, will attempt to change characteristics so as to perform better. On the other hand, human performance is limited by certain inherent constraints or limitations and by the extent to which the human understands the objectives of the task. These observations serve as the basis for the fundamental assumption underlying the OCM, namely, that the well-motivated, well-trained human operator will act in a near optimal manner subject to the operator's internal limitations and understanding of the task. This assumption is not new in manual control (e.g., (ref. 4)) or in traditional human engineering (e.g., Simon (ref. 5) calls it the Principle of Bounded Rationality). What is novel are the methods used to represent human limitations, the inclusion in the model of elements that compensate optimally for these limitations, and the extensive use of state-space concepts and the techniques of modern control theory.

Clearly, if the basic optimality assumption is to yield good results, it is necessary to have reliable, accurate, and meaningful models for human limitations. Insofar as possible, these models (or their parameters) should reflect intrinsic human limitations or should depend primarily on the interaction of the operator with the environment and not on the specifics of the control task. It is also desirable that the description of human limitations involves as few parameters as possible and that it be commensurate with the modern control system framework that is being employed. These principles have guided the development of the models for human limitations that will be described below.

There were several reasons for employing a modern control approach to analyzing manual control tasks, even though methods based on classical control techniques had been fairly successful. Initially, the principal motivation was provided by the basic logic of the optimality assumption and by the belief that state-space techniques provided a systematic approach to multi-input, multi-output systems that avoided some of the difficulties associated with the application of multi-loop analysis to man-in-the-loop problems. The powerful computational schemes associated with these techniques also were attractive in light of the complex monitoring and control problems that were becoming of interest. The basic approach to human limitations and the optimality assumption appeared to suggest a model that might adapt to task specifications and requirements "automatically" and not through a subsidiary set of adjustment rules. Finally, it was expected that the use of a normative model[1] and time-domain analysis would facilitate "modular" and "graceful" development of the model as new facets of human behavior were considered and understood.

A review of the progress and evolution of the OCM will provide some feel for the extent that the above-mentioned objectives and expectations have been fulfilled. Further insights will be provided by the discussions of the model and the validation results.

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[1]The model is normative in that it predicts what the human should do, given his limitations and the task. Thus, for a new situation, one need only determine the operative limitations and what should be done. The fact that this assumption works well is testimony to the adaptability and capability of the trained human operator.

The first large-scale attempt at using the machinery of optimal control theory to model the human controller was initiated by Elkind et al. (ref. 6). Their study demonstrated the feasibility of predicting control characteristics and display requirements by systems analysis techniques based on optimal control theory. However, extremely simple versions of the human's limitations, information processing behavior, and compensation were used, leading to gaps and deficiencies in the results. What is essentially the current structure of the OCM was first proposed by Baron and Kleinman (ref. 1). They also proposed a visual scanning model that could be included in the optimization framework. Levison, Baron, and Kleinman (ref. 7) established the connection between observation noise and controller remnant, thus relating a measurable human limitation to parameters of the OCM and providing a mechanism for predicting remnant. Baron, Kleinman, et al. (ref. 8) used the remnant results and the structure developed previously to predict human performance in a complex, multi-loop VTOL hover task. These results demonstrated that one could proceed from relatively simple calibration experiments on single displays to prediction and explanation of human behavior in more realistic tasks involving two displays. This study also revealed the importance of including bandwidth limitations and randomness (motor-noise) at the controller's output as part of representation of human limitations.

Kleinman, Baron, and Levison (ref. 2) showed that the model could be used with a relatively invariant set of parameters quantifying human limitations to predict performance in three basic tracking tasks involving a range of control strategies. Excellent agreement between experimental data and model predictions of describing functions, remnant spectra, and state and control variances was obtained. This provided the most detailed validation of the model and demonstrated its capability for adapting to different control situations without resorting to auxiliary adjustment rules.

Baron and Kleinman (ref. 9) applied the model to study the human's precision control of a hovering VTOL-type vehicle. The effects of changes in aircraft stability derivatives on rms hovering performance were computed using the model. The results were compared with experimental simulator data and showed excellent correlation (within $\pm 1\ \sigma$ in the data) in most cases. In this study, parameters characterizing the pilot were essentially the same as for the basic tracking tasks mentioned above.

Kleinman and Baron (ref. 10) analyzed a piloted approach-to-landing task to evaluate pictorial display requirements. This problem involved a time-varying information base for the pilot. The effects of different display formats and display symbology were predicted in cases where the aircraft was subjected to turbulence and/or constant updrafts. The ability of the pilot to estimate these external disturbances and take the appropriate corrective action to minimize glide path errors was analyzed. Predictions of system performance were compared with data obtained in independent experimental investigations. The model-data agreements were excellent and demonstrated the model's ability to predict the time-varying adaptability of a pilot to updraft disturbances. In addition, the agreement between model results and data for cases in which there was no turbulence disturbing the aircraft provided further evidence of the validity of the model for human randomness (remnant).

Theoretical and empirical work proceeded to extend the model to more realistic situations and more complex systems. Levison et al. (ref. 11) developed and tested a mechanism for predicting task-interference in multi-task environments (not involving scanning). In addition, a method for estimating the relative attentional workload associated with a given task was devised. Levison (ref. 12) also investigated the relationship between observation noise and certain display characteristics. This provided direct empirical evidence for the scaling observation noise model and also showed how an equivalent observation noise could be used to account for perceptual thresholds. Levison and Kleinman (ref. 13) modeled a carrier-approach task that involved varying display gains, sudden changes in information base, and a more complex time-varying disturbance. Baron and Levison (ref. 14) used the model as a basis for a display analysis methodology and applied it to the analysis of vertical situation displays for STOL. The response to wind shears and the design of flight directors were also considered. These latter two studies were analytic in nature and did not involve any experimental verification.

Kleinman and Killingsworth (ref. 15) used the OCM to predict pilot performance during the flare and touchdown phase of STOL aircraft landing. This was an ambitious modelling effort since the vehicle dynamics were highly complex, ground effects and turbulence affected the motion of the aircraft, and the pilot was required to land within a short touchdown area. To analyze this situation, the model was extended to include the generation of open-loop commands by the human operator. In this study, model predictions were made first; subsequent comparison of these results with the test data showed very good agreement.

Kleinman and Perkins (ref. 16) used the OCM in an antiaircraft tracking task. The operator's task was to track an aircraft target in both azimuth and elevation using a visual gunsight. The dynamics of the sight and associated gun mount varied with time, making the tracking task very difficult. In addition, the target motion could be quite arbitrary (although not stochastic) and was unknown a priori by the gunner. Comparison of model vs. human ensemble statistics for the several typical aircraft trajectories showed good qualitative and quantitative agreement. Baron and Levison (ref. 17) also applied the OCM to data obtained from a simulated antiaircraft tracking task. This application demonstrated the model's utility in analysis and interpretation of experimental data. In particular, it showed that parameters of the perceptual portion of the OCM were affected in consistent ways by manipulation of experimental variables related to visual processing.

Harvey and Dillow (ref. 18) applied the OCM to predict pilot performance in air-to-air combat. They reported that "The major conclusion is that the model worked!" and that it was "reasonably simple to develop." Significantly, they used model parameters which, with the exception of motor noise, corresponded to those used in previous applications of the OCM.

The model was also being used to develop systematic design procedures for systems involving closed-loop control. As noted above, Baron and Levison (ref. 14) proposed a display design methodology based on the OCM. This methodology utilized performance/workload tradeoffs generated by the OCM to arrive at information requirements and certain display requirements to meet system specifications. Similar ideas were utilized to analyze both display and control characteristics for an aircraft with an advanced avionics configuration (ref. 19). Hess (ref. 20) proposed a more formal display design procedure using the OCM and included predictions of pilot rating as part of the process. Hoffman, Curry, et al. (ref. 21) developed a methodology aimed at display design for highly automated aircraft. They examined problems of simultaneous monitoring and control and explored different metrics for monitoring performance and workload with the aim of developing techniques for investigating tradeoffs between control and display sophistication.

Although display problems have received the most attention, other aspects of the system design problem have not been neglected completely. Levison (ref. 22) has explored the use of the model in analyzing control stick design problems in a vibration environment. Stengel and Broussard (ref. 23) have used the basic structure of the OCM, along with some assumptions concerning suboptimal adaptation, to determine stability boundaries in high-g maneuvering flight. And, recently, Schmidt (ref. 24) has proposed a design procedure for stability augmentation systems based on closed-loop analysis with the OCM.

The increased interest in flight simulators has spurred some additional extensions and applications of the model. Grunwald and Merhav (ref. 25) and Wewerinke (ref. 26) have incorporated mechanisms for describing the utilization of external visual cues in the OCM and have obtained preliminary experimental validation of their approaches. Although the subtleties and complexities associated with human perception of a complex scene are by no means resolved, these studies do suggest that the OCM could be useful for analyzing closed-loop control behavior based on external visual cues. The OCM has also been used to model continuous control performance in a multi-cue environment. Levison and Junker (ref. 27) studied roll-axis tracking in disturbance-regulation and target-following tasks and compared performance when only visual cues were available with performance when the visual cues were augmented with confirming motion cues. They found that the OCM could provide a task-independent framework for explaining performance under all possible experimental conditions. The availability of motion cues was modelled by augmenting the set of perceptual variables to include position, rate, acceleration, and acceleration rate of the motion simulator. This straightforward informational model allowed accurate model predictions of the effects of motion cues on a variety of response measures, for both the target-following and disturbance-regulation tasks.

In a somewhat different vein, Baron, Muralidharan, and Kleinman (ref. 28) used the OCM to develop a closed-loop model for analyzing engineering requirements for flight simulators. They predicted the effects on performance of certain simulation design parameters, such as an integration scheme and a sample rate. Model predictions were later verified in an empirical study by Ashworth et al. (ref. 29).

The above studies all focused on the operator in continuous control tasks. But the structure of the OCM, particularly the information processing submodel, also lends itself to modelling tasks in which monitoring and decision-making are the major concerns of the operator. The first attempt to exploit this aspect of the OCM was by Levison and Tanner (ref. 30) who studied the problem of how well subjects could determine whether a signal, embedded in added noise, was within specified tolerances. Their experiments were a visual analog of classical signal detection experiments except that "signal-present" corresponded to the situation of the signal being within tolerance. They retained the estimator/predictor and the equivalent perceptual models of the OCM and replaced the control law with an optimal (Bayesian) decision rule just as has been used in some popular behavioral decision-theory models. Model predictions compared favorably with experimental data for a variety of conditions involving different signal/noise ratios and different noise bandwidths.

Phatak and Kleinman (ref. 31) examined the application of the OCM information processing structure to failure detection and suggested several possible theoretical approaches to the problem. Gai and Curry (refs. 32 and 33) used the OCM information processing structure to analyze failure detection in a simple laboratory task and in an experiment simulating pilot monitoring of an automatic approach. They reported good agreement between predicted and observed detection times for both the simple and more realistic situations. In the latter case, the model was used in a multi-instrument monitoring task and accounted for attention sharing in the usual OCM fashion.

Finally, as indicative of future directions for OCM research, a recent study of Muralidharan and Baron (ref. 34) should be mentioned. In this work, the information processing structure of the OCM was used in conjunction with control and decision theoretic ideas to model ground-based operator control of a number of remotely piloted vehicles. Though the results have not been subjected to experimental validation, they demonstrate that these techniques are suited to the analysis of systems in which operators make decisions at discrete times and exercise direct control infrequently. In other words, the techniques appear suitable for supervisory control problems.

MODEL DESCRIPTION

In this section, the detailed structure of the OCM is reviewed. The discussion will be conceptual and verbal; the reader is referred to the previous references, particularly references 2 and 8, for mathematical details. Also, some relations to more traditional human performance theories will be mentioned.

In order to apply the OCM, the following features of the environment must be given: 1) a linearized state variable representation or model of the system being controlled; 2) a stochastic or deterministic representation of the driving function or environmental disturbances over which the operator must exert control; 3) a linearized "display vector" summarizing the sensory information utilized by the operator (including visual, vestibular, and other sources as appropriate); and 4) a quantitative statement of the criterion or performance index for assessing operator/machine performance. Criteria such as minimizing rms tracking error and control effort are typical. The specific assumptions concerning this description that are necessary to apply the theory are given in reference 2.

Given this environmental description, the model of the operator's behavior incorporates the elements shown in Figure 1. The figure illustrates only a single dimensional control task but the variables illustrated should be regarded as multi-dimensional vectors. First, the displayed variables are assumed to be corrupted by "observational noise" introduced by the human operator.[2] This noise is analogous to the internal noise level postulated in signal detection theory and provides one means by which the model can mimic human limitations in processing and attentional capacity. Different noise levels may be assumed for different displayed variables, and, if several visual displays are providing useful information, the noise level associated with each may be adjusted to account for the distribution of attention assigned by the operator. Alternatively, a model of attentional scanning (ref. 11) may be introduced to predict the noise level associated with each variable in order to produce optimal performance with respect to the criterion variable. This attention sharing model is crucial for predicting performance in complex, multivariable tasks. It can also serve as a basis for developing a variety of operator monitoring models (ref. 35).

At this point the model is dealing with a noisy representation of the displayed quantities. That representation is then delayed by an amount, τ, representing internal human processing delays. It is possible to assume differential delays for different sensory channels, but this additional complication has not been found necessary in past model applications to manual control data.

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[2]If visual or indifference thresholds are important, such as with nonideal displays or external visual cues, these can be introduced in the model at this point (ref. 10). The method employed involves a statistical threshold that results in a rapid increase in observation noise when the signal is below the assumed threshold value. This is directly analogous to the threshold notions of signal detection theory.

The central elements of the model are represented in the blocks described as the Kalman estimator and predictor. Their purpose is to generate the best estimate of the current state of the displayed variables, based on the noisy, delayed perceptual information available. These blocks compute the estimate of this state so as to minimize the residual estimation uncertainty. What is being captured is a representation of the operator's ability to construct, from his understanding of the system and his incomplete knowledge of the moment-by-moment state of the system, a set of expectancies concerning the system behavior at the next moment in time. It is in these blocks that it is assumed 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. This representation is analogous to the schema of current human performance theories, and it is interesting to note that, in this formulation, the schema must incorporate knowledge of both the expected signals and the system dynamics being controlled.

Given the best estimate of the current system state, the next block assigns a set of control gains or weighting factors 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.

Just as an observation noise is postulated to account for input processing inadequacies, a motor noise is introduced to account for an inability to generate noise-free output 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. Finally, the noisy output is assumed to be filtered or 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 excessive control rates 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.

As the previous discussion shows, control strategy and motor response are separated from information processing in the OCM. This structure allows the OCM to be modified so as to treat decision-making problems. The estimator/predictor portion of the model generates all the statistical information necessary for optimal decision-making, given the assumptions that have been made concerning the system. Thus, by simply replacing the control law with an appropriate decision rule, one has a theoretical model for human decision making. For a normative model, the decision rule must be determined from optimization of an appropriate decision criterion (such as expected utility).

This, then, provides a conceptual description of the elements of the Optimal Control Model of the human operator. It should be emphasized that the parameter values that must be provided by the investigator correspond to the human limitations that constrain behavior. With these limitations as the constraints within which performance is produced, the model predicts the best that the operator can do. A large backlog of empirical research provides the data necessary to make realistic estimates of the appropriate parameter settings in the manual control context. This research has shown that these parameters are relatively invariant with respect to changes in task environment, thus enhancing the model's predictive capacity.

OCM VALIDATION STUDIES

The Optimal Control Model has been validated against experimental data for a variety of tasks, and detailed results may be found in the previously cited references. Here, a few of these results are presented in order to provide the reader with more of the background and with some feeling for the modelling accuracy attainable with the OCM.

Figures 2 and 3 (from ref. 2) illustrate the model's validity for two simple, but important systems: rate (K/s) and acceleration (K/s^2) command systems. In the figures, measured and theoretical human controller describing functions (h_e) and remnant spectra (Φ_{rr}) are compared. The describing function gain and phase may be thought of as measures of control strategy, whereas the remnant may be considered a measure of operator randomness. As can be seen, the model reproduces the characteristics of the subjects with remarkable fidelity. Moreover, the parameters of the model that quantify pilot limitations are virtually constant for the two situations. Table 1 compares measured and theoretical scores for the above cases. Results for a position command (K) system and for two tasks involving attitude regulation of a high performance aircraft are also shown. It is important to note that these results were obtained with a highly constant, though not identical, set of parameter values. (See ref. 36.)

These early single-input single-output studies served as the basic means of validating the model, but the OCM was principally directed at modelling human performance in more complicated situations. As we have discussed, an important part of this modelling is accounting for attention-sharing on the part of the operator. The basic empirical validation for the attention-sharing model was obtained in a four-axis tracking task (ref. 11). In this task, subjects had to control four independent rate-control systems with the errors in each system presented on separated displays. The subjects were required to fixate one display and use peripheral vision for tracking the other axes throughout the experiment (i.e., scanning was not allowed). The results for each axis performed alone and for all four together are presented in Table 2. Again, theoretical and measured results are in close agreement. Note that the effect of interference on total score is predicted better than its effect on individual scores. This appears to be true in other tests of the interference model, too. Analytic investigations of the tasks show that, for these experiments, tradeoffs in performance between subtasks do not effect overall performance substantially. When this is the case, the subjects are not motivated to seek the "absolute" optimal allocation (and they may not obtain the necessary feedback in training). Then, idiosynchratic behavior becomes more acceptable. The effects of attention sharing on the operator's describing function and remnant are given in reference 16. The result of adding a task is an increase in remnant, a decrease in operator gain, and an increase in high frequency phase lag. All these effects are predicted quite accurately by the OCM and the attention-sharing model.

CONCLUDING REMARKS

To summarize, the OCM has proven capable of predicting or matching human performance with considerable fidelity in a variety of tasks. Model parameters that account for basic human limitations have been isolated and shown to be essentially independent of system dynamics and forcing function characteristics; this enhances the model's predictive capability. Furthermore, submodels and parameters that reflect changes in display characteristics (such as thresholds, multiple displays, etc.) have been developed. An advantage of the OCM is that it contains an explicit model for information processing that also allows it to be used for analyzing monitoring and decision-making behavior.

There are, of course, limitations and problems associated with the model and its application. A major problem is the selection of an appropriate performance index in complex, realistic tasks. Though fairly systematic methods exist for making this selection, there is no guarantee that human operators will optimize the criterion selected by the theorist rather than some other, subjective one. Another limitation is the assumption of a perfect internal model. While this works quite well for trained operators, it can cause problems in modeling the performance of naive subjects (such as those in training) and can increase computational complexity beyond that which is necessary.

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TABLE 1.- MEASURED AND THEORETICAL HUMAN PERFORMANCE

System	MS Error Meas.	Theor.	MS Control Meas.	Theor.
Position Control	.13	.14	.53	.54
Rate Control	.13	.12	4.2	3.83
Acceleration Control	.014	.014	1.43	1.28
High Performance Aircraft (Pitch)	.026	.026	.0032	.0034
High Performance Aircraft (Roll)	.03	.026	.080	.086

TABLE 2.- COMPARISON OF MEASURED AND PREDICTED ERROR VARIANCE

SCORES FOR 4-AXIS EXPERIMENT

	Viewing Condition					
	Measurement	Foveal	16° Periph Ref Ext.	16° Periph No Ref Ext	22° Periph No Ref Ext	Total Score
(a) Measured	1-axis	.11	.25	.42	.96	1.7
	4-axis	.27	.94	1.3	1.6	4.1
(b) Predicted:	1-axis	.11	.25	.39	.98	1.7
Optimal Behavior	4-axis	.49	.82	1.1	1.8	4.2

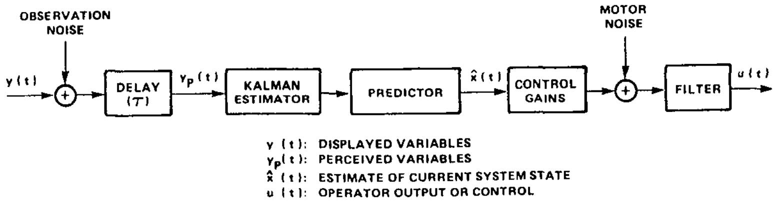

Figure 1.- Structure of OCM operator model.

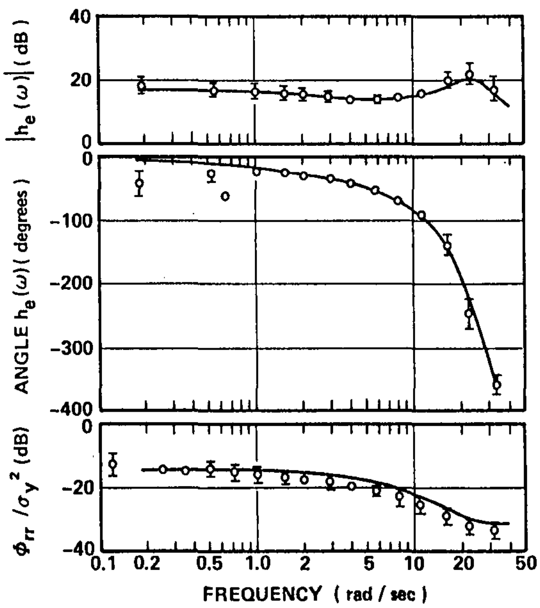

Figure 2.- Operator response - K/s dynamics.

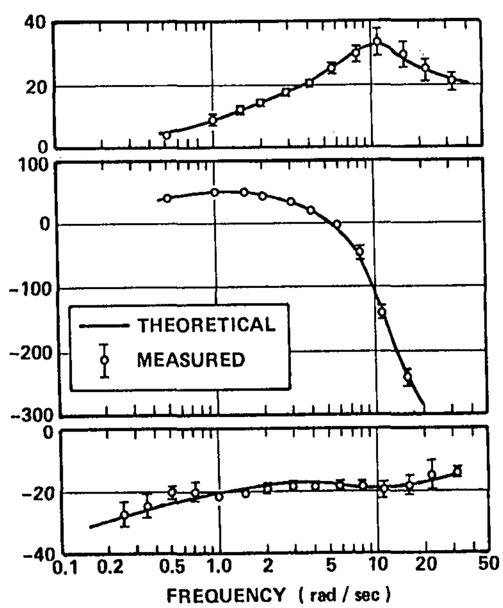

Figure 3.- Operator response - K/s^2 dynamics.