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TOWARDS MODELING HUMAN INFORMATION PROCESSING AND CONTROL IN ECONOMIC SYSTEMS: AN APPROACH BASED ON MANNED VEHICLE SYSTEMS ANALYSIS*

BY DAVID L. KLEINMAN†

Recent successes in modeling human performance in manned vehicle systems are examined to assess whether the modeling techniques may find application to study human decision making in an econometric context. The optimal control model of man-vehicle performance is discussed, and several results are presented. The important features of the model, that hold potential for studying economic system control, are discussed, specifically, the concept of an "internal" model. The similarities and differences between man-vehicle control and man-econometric system control are discussed in terms of the man model structure. Requirements for extending the existing man model to economic systems are presented.

1. INTRODUCTION

An econometric system evolves in time largely under the control of humans. The man as a central element is required to correlate and process information arriving from several sources. When this information is combined with human experience and judgement, there ensues the basis for man's control decisions. Depending on the specific context these decisions may range from adjusting the price of a commodity to regulating a natural money supply. However, all situations that we study are assumed to have a common feature: The human's information processing-control cycle is dynamic, i.e. the man is acting in a feedback control mode to regulate the system about some desired condition.[1] To be sure, an understanding of human control in an econometric context is a difficult challenge. But it is a necessary step if one's methodology is first to model a system, and then to use the model to help improve overall system effectiveness.

The analysis of man's behavior as an information processor and control element in a dynamic system extends beyond econometric contexts. Humans function as controllers in literally hundreds of situations. It is therefore prudent to explore the state-of-the-art of other fields to determine whether tools and techniques exist for human analysis that may have application to economics systems. One modeling area that has enjoyed considerable attention over the past several years is the manual control of transport vehicles. Recent efforts in human response theory have been aimed at developing models of the human operator that could be systematically and easily used to predict human behavior and system performance in complex vehicle control tasks.

One of the most general, and most versatile models of human response that has been developed in a man–vehicle context is the optimal control model of Kleinman, Baron and Levison [1–3]. This modeling approach is rooted in modern

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[1] We confine our attention to the behavior of a single human, as opposed to "team" control.

estimation and control system theory. It is based on the assumption that the well-trained, well-motivated human operator behaves in an optimal manner subject to his inherent limitations and constraints, and his task requirements.

This paper examines the potential for extending the optimal control model for human information processing and control behavior as developed in a manned-vehicle context, to study human control in an econometric context. The optimal control model is reviewed, the similarities and differences between man–vehicle and human–economic system modeling are noted, and the model features that have analogue in economic systems are discussed.

2. Human Operator Models

The basic problem that we consider is characteristic of most dynamically evolving systems that contain a man in the loop. The generalized loop structure is shown in Figure 1. The human makes observations, **Y**, on the system, and on the basis of these observations generates control inputs, **u**. The human's task is to choose his control inputs so that the resulting system outputs, **Y**(t), remain "close" to some desired values, **Y***(t), as time evolves. Generally there will exist external random and/or bias inputs, **w** and **z**, that disturb the system from its desired or nominal operating point. These unwanted deviations must be countered by the human's control inputs. The basic question is then, how does man, with his inherent limitations on the rate and volume of information processing, perform in a stochastic and dynamic environment?

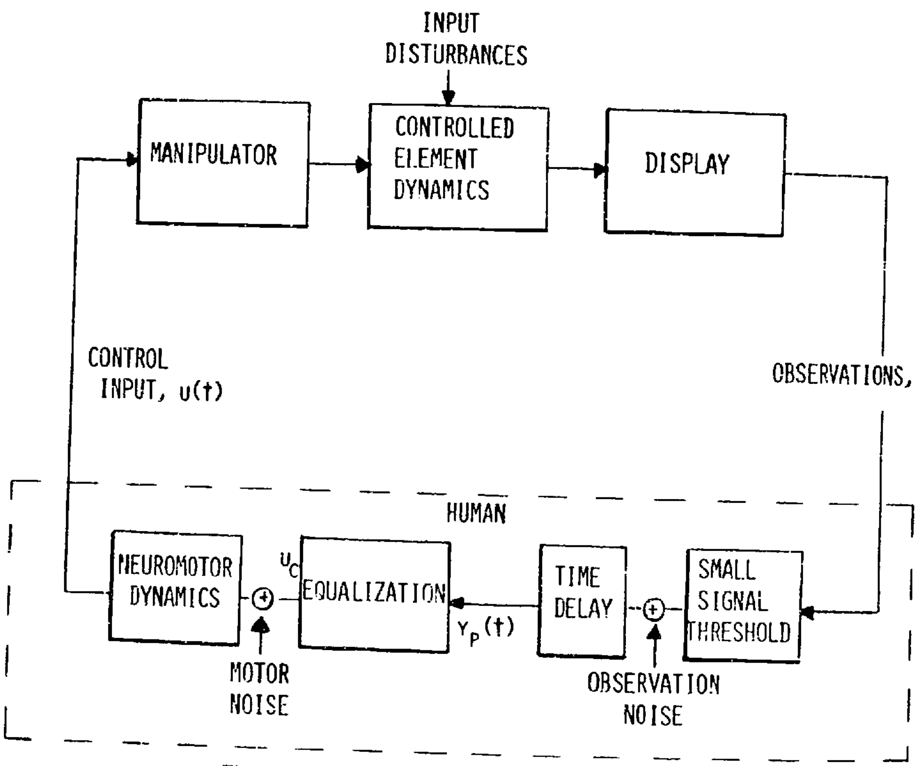

Figure 1 Man as a generalized feedback control element

2.1. *System Dynamics*

The types of manned-vehicle problems that have been studied to-date are those in which the controlled element dynamics are well-defined in terms of a physical model. This includes aircraft, automobiles, and laboratory systems among others. Thus, the optimal control model assumes that the system (i.e. vehicle) to be controlled, which may include sensor and manipulator dynamics, can be described by a set of linearized equations

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{E}\mathbf{w}(t) + \mathbf{z}(t). \tag{1}$$

Here, $\mathbf{x}(t)$ is a vector that describes the vehicle state, i.e. the deviation of the system motion from some desired trajectory $\mathbf{X}^*(t)$: $\mathbf{u}(t)$ are the human-generated corrective control inputs. The terms $\mathbf{w}(t)$ and $\mathbf{z}(t)$ represent the external disturbances. Without loss of generality $\mathbf{w}(t)$ can be assumed to be a zero-mean white noise with covariance

$$E\{\mathbf{w}(t)\mathbf{w}(\tau)\} = \mathbf{W}(t)\delta(t - \tau).$$

The component $\mathbf{z}(t)$ represents non-random or bias input disturbances. Finally, the matrices $\mathbf{A}$ and $\mathbf{B}$ in equation (1) may be time-varying in cases where the system dynamics change with time.

Several system outputs

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t) \tag{2}$$

may be of concern to the human, and it is assumed that they are presented continuously to the man via some visual display. The quantities $\mathbf{y}(t)$ are the deviations of system variables from their desired output values $\mathbf{Y}^*(t)$. In the man–vehicle control context, it is assumed that if a quantity $y_i(t)$ is presented to the human, he implicitly derives the rate-of-change $\dot{y}_i(t)$, but no higher derivative information. The total observations of $\mathbf{y}(t)$, including the variable rates, represents the information base from which the human must generate his control action.[2]

2.2. *Human Limitations*

Any reasonable mathematical model of the human operator must include within its framework, the various psychophysical limitations inherent in the human. The optimal control model contains time-delay, human randomness, small signal threshold phenomenon, among others as shown in Figure 1. Possible discontinuous, or pulsatile control behavior is not considered. The description of the human's limitations, and his resulting compensation or equalization is the essence of the optimal control model.

2.2.1. *Time-delay*. The various internal human time-delays associated with visual, central processing and neuromotor pathways are combined in the optimal control model. They are modeled conveniently by a single lumped, "equivalent" perceptual time-delay, τ.

2.2.2. *Randomness*. It is assumed that the various sources of inherent human randomness are manifested as errors in observing displayed quantities and in executing intending control movements. Thus, "observation" noise and "motor"

[2] Note that an obvious design problem is to maximize the "information" content of $\{\mathbf{y}(t)\}$.

noise are lumped representations of controller central processing and sensory randomness. These noises represent the combined effects of random perturbations in human response characteristics, time variations in response parameters, and random errors in observing system outputs and generating system inputs. These noises are also associated with the level of training of a human, i.e. they are related to the degree to which the human "knows" the system dynamics (1) being controlled. Thus, a well-trained person can be expected to be less "random" than a novice.

In the optimal control model an equivalent "observation" noise vector is added to $y(t)$. A single noise $v_{yi}(t)$ is associated with each display variable $y_i(t)$. The noises v_{yi} are assumed to be independent, Gaussian white-noise processes with covariances

(3) $$E\{v_{yi}(t)v_{yi}(\tau)\} = V_{yi}(t)\cdot\delta(t-\tau).$$

Furthermore, it has been found from experiment [4] that the covariance V_{yi} scales with the magnitude of the signal to which it is associated,

(4) $$V_{yi}(t) = \rho_{yi}\cdot E\{y_i^2(t)\}.$$

Thus, in a very reasonable manner, the human's errors in perceiving a given quantity depend on the magnitude of that quantity. The noise/signal ratios ρ_{yi} depend on the relevant features of the display, the external environment, and the level of human training, among numerous other factors.

2.2.3. *Scanning and interference*. When there is more than one display indicator, the human must allocate his attention among the various displays. Let us assume that there are K sources of information and let η_k denote the human's attentional allocation to indicator K. Thus, neglecting switching time,

(5) $$\sum_{k=1}^{K}\eta_k = 1; \qquad 0 \le \eta_k \le 1.$$

In the optimal control model, if displayed variable $y_i(t)$ is obtained from indicator k, the effect of attention sharing is to modify the noise/signal ratio ρ_{yi} according to

(6) $$\rho_{yi} = \rho_{yi}^0/\eta_k$$

where ρ_{yi}^0 is the noise/signal ratio that corresponds to full attention on indicator k. The human is assumed to choose the η_k to "optimize" his information base vis-à-vis the control requirements. Methods for determining "optimal" η_k within the human modeling context are discussed in Refs. [2-3]. In some cases a simple assumption of equal division of human attention among the primary display channels, i.e. $\eta_k = 1/K$, suffices for model applications.

2.2.4. *Small signal effects*. If a particular signal y_i is very small in magnitude, a human may not be capable of detecting its non-zero value (visual threshold). Alternatively, he may choose not to react to such small perturbations (indifference threshold). These threshold phenomena represent human nonlinear characteristics for small signals. Specifically, if a signal y is displayed, the human will react to a signal y' given by

$$y' = f(y)$$

where

$$f(y) = \begin{cases} y - a & y \geq a \\ 0 & -a < y < a \\ y + a & y \leq -a \end{cases} \tag{7}$$

and a is the threshold level associated with y.

The total signal $\mathbf{y}_p$ that is *perceived* by the human must reflect the time-delay and observation noise limitations discussed above. Thus, the human perceives the quantities

$$y_{pi}(t) = f(y_i(t - \tau)) + v_{yi}(t - \tau) \tag{8}$$

i.e., delayed, noisy and modified replicas of the signals actually presented on the display. As shown in Figure 1, it is the signal $\mathbf{y}_p$ that is "processed" internally by the human (through some equalization network) to yield a commanded control, $\mathbf{u}_c$.

2.2.5. *Neuromotor dynamics.* Because of central processing and neuromuscular dynamics, a human cannot effect control action instantaneously. Thus, there is a lag between the internal "commanded" control and the actual control input generated by the human. We model the neuromotor dynamics as a first-order system

$$\mathbf{T}_N\dot{\mathbf{u}} + \mathbf{u} = \mathbf{u}_c. \tag{9}$$

However, the dynamics (9) are not imposed *directly* in the human operator model structure. We include them indirectly in perhaps a somewhat more natural manner, by implicitly limiting the human's control rate, $\dot{\mathbf{u}}$. This aspect of the model will be discussed further in Section 2.3.

2.2.6. *Motor noise.* The motor noise $\mathbf{v}_u(t)$ is the second component of modeled human randomness. This noise is used to represent the effects of random errors in executing the intended control movements (tremor), or the fact that the human does not have perfect knowledge of the system input $\mathbf{u}(t)$ because of "noisy" proprioceptive feedback channels. The motor noise is added to $\mathbf{u}_c(t)$. Thus,

$$\mathbf{T}_N\dot{\mathbf{u}} + \mathbf{u} = \mathbf{u}_c(t) + \mathbf{v}_u(t). \tag{10}$$

The noises $\mathbf{v}_u(t)$ are assumed to be white Gaussian processes, with covariances V_{ui} that scale with the control magnitude,

$$V_{ui}(t) = \rho_{ui} \cdot E\{u_i^2(t)\}. \tag{11}$$

2.3. *Control task representation*

Our basic assumption in man-modeling is that the well-trained human behaves in an optimal manner subject to his inherent limitations. The human's limitations have been discussed: it remains to define what is meant by "optimal." In the optimal control model it is assumed that the control task is adequately reflected in the human's choice of a control input that minimizes the quadratic cost functional

$$J(u) = E\left\{\frac{1}{T}\int_0^T (\mathbf{y}'Q\mathbf{y} + \dot{\mathbf{u}}'G\dot{\mathbf{u}})\,dt\right\} \tag{12}$$

conditioned on the perceived information $\mathbf{y}_p(\cdot)$ in equation (8). The terminal time T may approach ∞ if we are interested solely in modeling man's steady-state performance.

The cost functional (12) was chosen because of its physical appeal (the human's task is to keep the variations $\mathbf{y}(t)$ small), its mathematical tractability, and the resulting analytic simplifications it provides. The cost functional weighting parameters $Q = \text{diag}(q_i)$ and $G = \text{diag}(g_i)$ may be either objective (specified by the experimenter or designer), or subjective (adopted by the human in performing and relating to the task). Clearly, the selection of any subjective cost weightings is a nontrivial matter and is tantamount to mathematically quantifying the *human's* control objectives. In some simple cases weighting selection can be chosen on the basis of task requirements. However, in complex multivariable situations, representative values for q_i and g_i may have to be elicited by model-data matching procedures or by questionnaire.

As mentioned earlier, the neuromotor dynamics are not included directly among the inherent limitations of the human. However, note that included in $J(\mathbf{u})$ is a cost on control rate. This term may represent an objective or a subjective weighting on control rate. (It should be noted that rapid control movements are rarely made by trained operators.) Alternatively, this term could account indirectly for the physiological limitations on the rate at which a human can effect control action. Including the control rate term in $J(\mathbf{u})$ introduces a first-order lag in the optimal controller. In the optimal control model, therefore, these dynamics can be associated with the dynamics often attributed to the "neuromotor" system.

2.4. *The Optimal Control Model of Human Response*

Within the postulated framework, the human's control characteristics are determined by the solution of a well-defined optimal linear regulator problem with time-delay and observation noise. Figure 2 shows the feedback loop structure of the optimal control model. The control that minimizes $J(u)$, conditioned on the "perceived" information $\mathbf{y}_p(\cdot)$, is generated by the linear (separable) feedback law,

$$\mathbf{T}_N\dot{\mathbf{u}} + \mathbf{u} = -\mathbf{L}\hat{\mathbf{x}}(t) + \mathbf{v}_u(t) \tag{13}$$

where $\hat{\mathbf{x}}(t)$ is the "human's" best estimate of the system state $\mathbf{x}(t)$ based on the perception $\mathbf{y}_p(\sigma)$, $\sigma \leq t$. The feedback gains $\mathbf{L}$ are time-varying when $T < \infty$ in equation (12) or when the system dynamics are nonstationary. The first-order lags and time-constant matrix $\mathbf{T}_N$ are the consequences of weighting $\dot{\mathbf{u}}$ in the cost functional.[3] The parameters $\mathbf{L}$ and $\mathbf{T}_N$ are obtained from the solution of a nonlinear matrix equation (Riccati equation) once values are chosen for the weightings $\mathbf{Q}$ and $\mathbf{G}$.

The correspondence between the control rate weightings $\mathbf{G}$ and the values of $\mathbf{T}_N$ allows for (indirect) adjustment of $\mathbf{T}_N$. In this manner $\mathbf{T}_N$ can be chosen to be commensurate with human performance data concerning neuromotor lags. Thus, the neuromotor dynamics discussed earlier are included naturally in the man-model through the weighting of $\dot{\mathbf{u}}$.

[3] In general, weighting $u^{(m)}$ in the cost functional will give rise to m-th order dynamics in the resultant feedback loop.

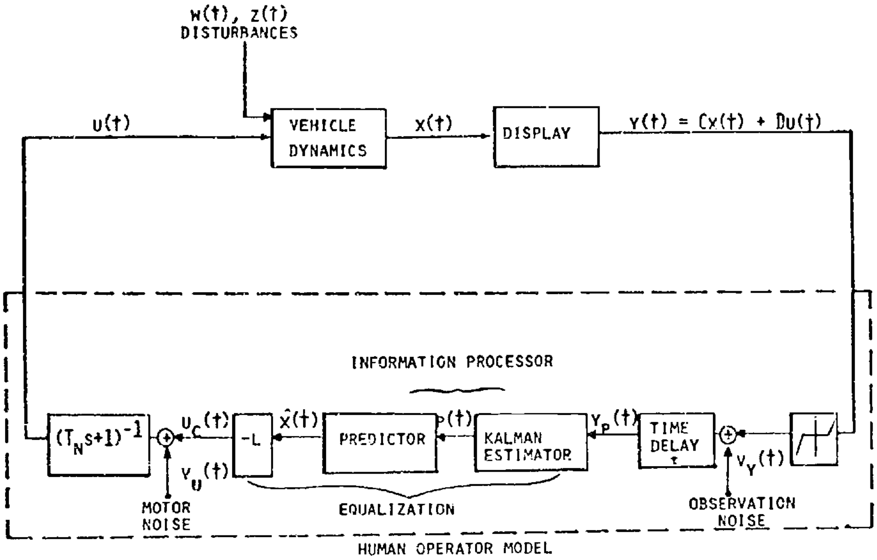

Figure 2 Optimal control model of human response

The best estimate of $\mathbf{x}(t)$ is generated by the cascade combination of a Kalman filter and a least mean-squared-error predictor. The Kalman filter compensates optimally for the human's observation noise to generate a best estimate of the delayed state

(14) $$\mathbf{p}(t) \equiv \hat{\mathbf{x}}(t-\tau|t) = E\{\mathbf{x}(t-\tau)|\mathbf{y}_p(\sigma), \sigma \leq t\}$$

according to

(15) $$\dot{\mathbf{p}}(t) = \mathbf{A}\mathbf{p}(t) + \mathbf{B}\hat{\mathbf{u}}(t-\tau) + \mathbf{K}[\mathbf{y}_p(t) - \mathbf{C}\mathbf{p}(t) - \mathbf{D}\hat{\mathbf{u}}(t-\tau)]$$

where $\hat{\mathbf{u}}$ is the human's best estimate of the actual control input, $\mathbf{u}$. The filter gains $\mathbf{K}$ are determined from a matrix differential equation.

The predictor compensates optimally for the human's inherent time-delay τ, generating an estimate of $\mathbf{x}(t)$ by predicting $\mathbf{p}(t)$ ahead by τ seconds. The estimate $\hat{\mathbf{x}}(t)$ is generated by

(16) $$\dot{\hat{\mathbf{x}}}(t) = \mathbf{A}\hat{\mathbf{x}}(t) + \mathbf{B}\hat{\mathbf{u}}(t) + \mathbf{\Phi}(t, t-\tau)\mathbf{K}[\mathbf{y}_p(t) - \mathbf{C}\mathbf{p}(t) - \mathbf{D}\hat{\mathbf{u}}(t-\tau)]$$

where $\mathbf{\Phi}(\cdot, \cdot)$ is the state transition matrix associated with $\mathbf{A}$. Thus, the human's equalization, as portrayed in Figure 1, is modeled as consisting of an optimal filter-predictor combination (information processor) that first estimates the state, followed by a set of optimal gains. The feedback process is sequential, i.e. first estimation and then control using the estimated signals.

3. Application of the Optimal Control Model in Man–Vehicle Systems

In order to use the human operator model to predict closed-loop system performance, it is necessary to prespecify various system/human parameters. It is assumed that the quantities $\mathbf{A}, \mathbf{B}, \mathbf{E}, \mathbf{C}, \mathbf{D}$ that specify the input-output characteristics of the controller system-display are known. The statistics of the input disturbances $\mathbf{w}(t)$ and $\mathbf{z}(t)$ must also be assumed known. The control task must be translated into mathematical terms via the selection of the cost functional weightings $\mathbf{Q}$. The specification of any human *subjective* weightings may be a nontrivial matter as noted earlier. Finally, it is necessary to choose values for the human response parameters τ, $\mathbf{T}_N$, ρ_{ui}, ρ_{yi} and thresholds a_i. Reasonable approximations to these quantities are available from various data in the manual control field. For example the effective time delay $\tau = 0.2 \pm 0.05$ sec. Human performance data concerning neuromuscular lags indicates that $(\mathbf{T}_N)_{ii} \simeq 0.1$ sec, and the control rate weightings $\mathbf{G}$ are adjusted accordingly. Experience with the optimal control model, and independent experiments, have shown that

$$\rho_{yi} \simeq 0.01\pi \quad (-20\,\text{dB noise/signal ratio})$$

$$\rho_{ui} \simeq 0.003\pi \quad (-25\,\text{dB noise/signal ratio}).$$

The thresholds a_i depend on man's physiological limitations. Typically, $a_i \simeq 0.05°$ visual arc for position and 0.05°/sec visual arc for rate observation. For most high-resolution, well-designed displays, the thresholds can be neglected.

We illustrate the wide spectrum of man-vehicle problems that have been studied using the optimal control model by discussing briefly some applications.

3.1. *Simple Error Regulation* [2, 3]

These laboratory experiments consisted of single-input single-output vehicle dynamics in the transfer function form

$$\frac{y(s)}{u(s)} = k, \frac{k}{s}, \frac{k}{s^2}. \tag{17}$$

The task was to regulate mean-squared error $y^2(t)$ when the system was subjected to a random noise disturbance. This is a steady-state error minimization task, i.e. $T \to \infty$ in the cost functional. Since the vehicle dynamics are stationary, the human's feedback control strategy becomes time-invariant (after an initial learning period) and may be described in the frequency domain by a transfer function

$$u(s) = h(s)y(s). \tag{18}$$

The transfer function $h(s)$ can be measured experimentally and can also be predicted by the model. A comparison of both results serves as a model validation. Figure 3 shows the data-model comparisons of the magnitude and phase of $h(s)$, over the pertinent frequency range, for k/s^2 dynamics. The agreement is excellent and shows that the model can describe man's input-output behavior in this simple, but important, class of problems.

3.2. *Pilot–Aircraft Studies*

3.2.1. *VTOL hovering task* [2, 3]. The model's application to study the human's precision control of a hovering VTOL-type vehicle represents an extension of the error regulation tasks described above to more complex dynamics. The effects of changes in aircraft stability derivations on rms hovering performance

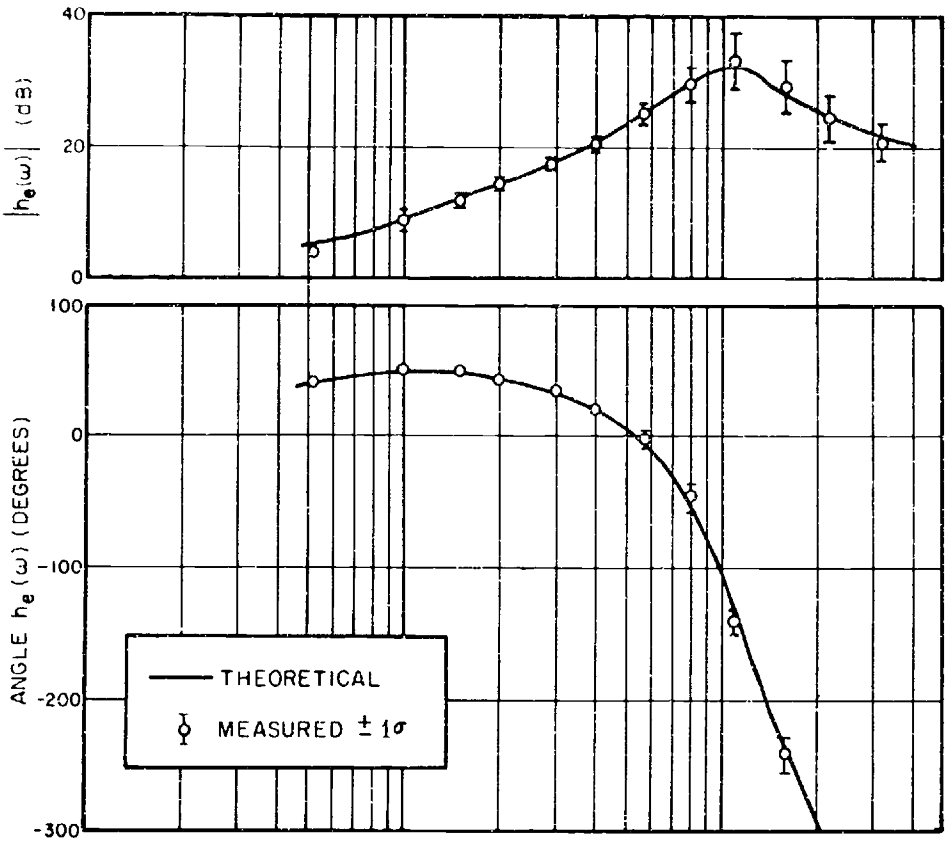

Figure 3 Model predictions and experimental human transfer functions, K/s^2 dynamics (average of three subjects)

were computed using the model. The results were compared with experimental flight simulator data, and showed excellent correlation.

3.2.2. *Aircraft display evaluation* [5]. A piloted approach-to-landing task of a light aircraft was studied using the model. 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 remarkable and demonstrated the model's ability to predict the time-varying adaptability of a pilot to bias (updraft) disturbances.

3.2.3. *STOL landing* [6]. In a recent effort, the optimal control model was applied to predict pilot performance during the flare and touchdown phase of STOL aircraft landing. This was an ambitious modeling 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. In modeling the pilot, it was assumed that the human generates a nominal flare path, and then tries to correct for deviations about this path caused by his own inherent randomness and the external disturbances. Thus, the model gives predictions of flare path and touchdown dispersions, as well as of numerous other performance measures. Figure 4 compares predictions of flare path dispersion (dotted lines) with the flight path data from ten simulation runs (scatter points). The agreement is quite good, for this complex task.

3.3. *Anti-Aircraft Tracking* [7]

In this modeling effort, the human'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.

The model outputs for this study consisted of the ensemble statistics of the tracking error waveforms in both axes. The mean, or average, error is the result

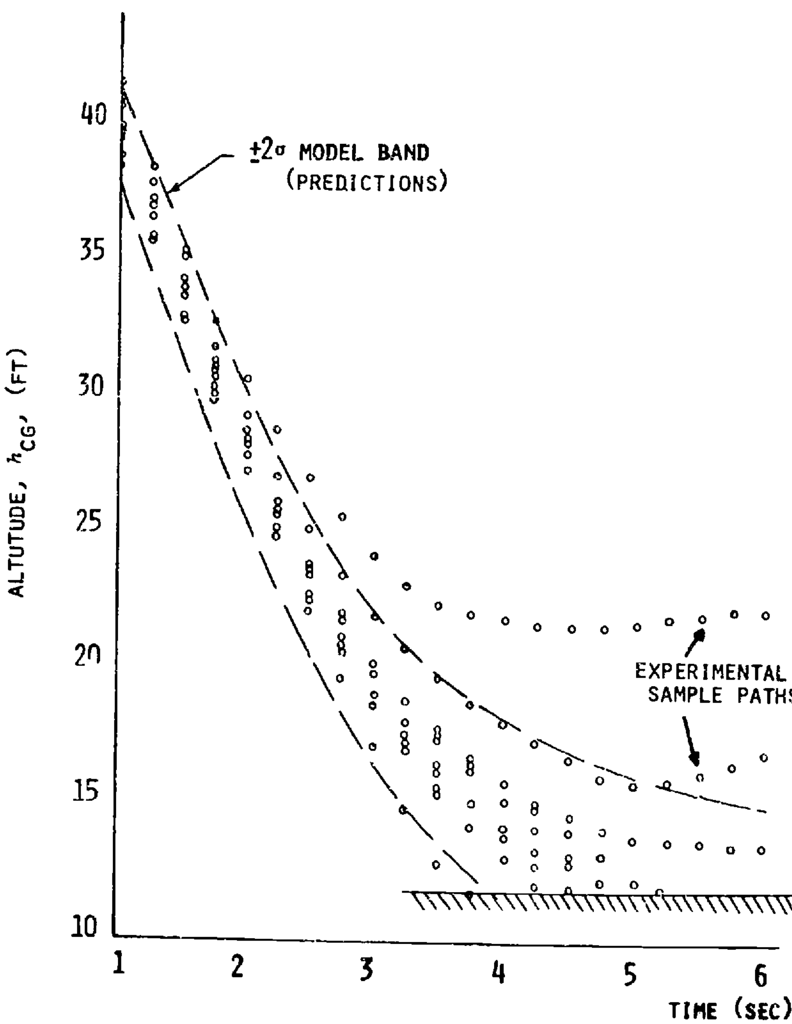

Figure 4 Flight path dispersions, during stol landing

one would expect to find by averaging the results of many experimental paths. The standard deviation about the mean is the run-to-run variability due to human and/or external system randomness. Figure 5 is a comparison of model vs. human ensemble statistics for the azimuth axis tracking error, as a function of time, for a typical aircraft trajectory. Although the experimental data is the average of only 10 sample paths, the results are in good qualitative and quantitative agreement.

3.4. *Summary*

By way of a brief overview of several case studies, we have shown the flexibility of the optimal control model to predict human response across a spectrum of manual control tasks. We have seen that modern control and estimation theory, coupled with human response theory, provides a unified framework for the analysis of manual control systems. Within a single optimality context, a model was developed for the human's inherent limitations and for his compensating information processing and control behavior. Indeed, the methods for representing these limitations, and the resulting compensating elements are the unique and crucial features of the model.

Although it has not been pointed out explicitly, the various input parameters, τ, T_N, ρ_{yi}, etc. associated with the human's limitations are assumed to be independent of the vehicle dynamics and control task. This is a reasonable assumption when the effects of the external environment (light, heat, stress, etc.) do not change in large measure. Therefore, if these parameters are independent of the control task, then complex control situations may be analyzed using the same parameters that

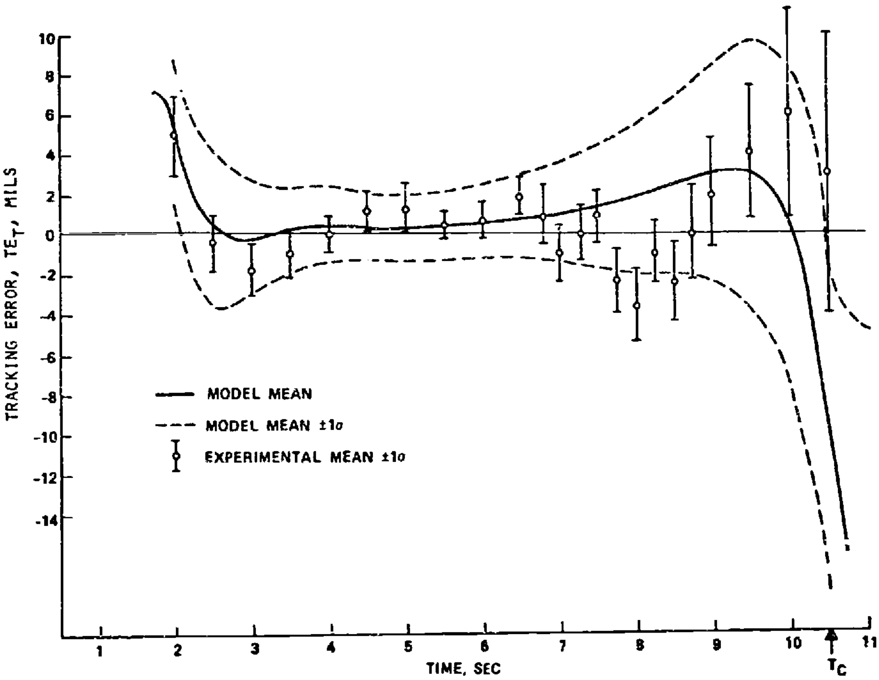

Figure 5 Traverse tracking error covariance

are applicable to simple tasks. Indeed, experience to date indicates that such an approach is possible. For example, all of the modeling case studies described above were performed with the same numerical values for the human response limitation parameters τ, T_N, ρ_{yi}, ρ_{ui}. The differences in human strategy from case to case arise in response to changes in the system dynamics and associated task requirements. In this respect the model may be considered "adaptive."

4. Potential for Economic System Modeling

The preceeding sections have described a validated model for the human in a manned-vehicle control context. Modern control theory supplied a generalized framework in arriving at a conceptual model of the human's information processing and control behavior. The state-space techniques are ideally suited to the analysis of complex multi-variable systems. The generality of modern control theory admits a highly flexible model—one capable of a modular "growth" as more complex facets of human behavior are considered and understood.

In this section we examine, albeit superficially without the benefit of example, the potential for extending the conceptual framework of the optimal control model to study human control in an economic context.

4.1. *Elements for Decision Making and Learning*

It is reasonable to expect that a human's role in an economic system will involve decision making and learning as well as control. Therefore, a model of human behavior in an econometric context must have the ability to treat man's decision making *and* control processes. The primary attribute of the optimal control model for studying human decision making lies in the characteristics associated with the Kalman filter-predictor submodels. The combination of these elements provides the framework for modeling the information processing behavior of the man, and consequently, his decision abilities. Several features of the information processing submodel are discussed.

4.1.1. *State estimate*. The output of the Kalman filter/predictor, $\hat{\mathbf{x}}(t)$ is the model's best (linearized) estimate of the system state $\mathbf{x}(t)$, generated on the basis of the perceived $\mathbf{y}_p(t)$. This "internal" estimate of system status is updated continuously and provides a mechanism for studying decision/detection phenomena that are wholly dependent on the vehicle state. Examples of such problems are decisions based on whether or not certain variables lie within desired limits at a given time. Thus, deciding to land or to go-around during aircraft approach is such a case.

A continuous time, monitoring and decision model using the generated state estimate $\hat{\mathbf{x}}(t)$ has been suggested by Levison [8]. His basic assumption was that a human's decision involving $\mathbf{x}(t)$ is made on the basis of $\hat{\mathbf{x}}(t)$ and its error covariance (or uncertainty) matrix. The model was partially validated by an experiment in which subjects decided whether a signal was within given bounds on the basis of observing signal-plus-noise.

The modeling of a human's continuous-time state detection process is an important application of the optimal control model. However, this model needs considerable modification before it can be applied in an economic context, where decisions might be whether or not to raise taxes depending on whether certain key indicators are above given limits.[4] Concepts of utility theory will prove necessary in the modeling endeavor in determining the "cost" for a wrong decision vs. a correct decision. The familiar trade-off of false alarm vs. non-action will be encountered when setting thresholds on the state detection process. Despite the difficult modeling issues, it is reasonable to expect that the internal estimate $\hat{x}(t)$ will be of paramount importance for decision and control in any human econometric model that has a similarity to the optimal control model.

4.1.2. *Internal model*. It is important to note that in the description of the Kalman filter (15) and predictor (16) that comprise the information processer, there is an explicit model of the system dynamics (1) and (2) via the parameter matrices **A**, **B** and **C**. Put another way, the filter includes an *internal model* of the environment. This concept is important and appealing. In broad terms, an internal model characterizes the human's knowledge of the controlled vehicle dynamics, a process arrived at and refined through past perceptions, training and experience. The use of internal models in the description of human response is not new [9, 10]. Virtually all attempts to model human fault detection in manual control have postulated an internal model. Indeed, the concept of expected vs. unexpected response associated with detection implies some type of internal model of the controlled element dynamics. Within the context of internal models, one can view the phenomenon of human learning as the process by which man improves his internal model of his environment.

In the optimal control model, the human's entire information processing and control behavior is conditioned on the specific internal model. Generally, it has been assumed that the internal model is the same as the system being controlled. This assumption was reasonable as long as the system dynamics were simple, linear and the human was well-trained. However, the equivalence of system and internal models is not a necessary prerequisite in our modeling approach. What is necessary is that the internal model be a good (linearized)[5] "approximation" to the true system. Thus, in both the STOL landing and antiaircraft modeling efforts described in Section 3, the system dynamics were nonlinear yet internal models were chosen that well-approximated the true dynamics. This approach is reasonable in situations where the system dynamics have a well-defined structure.

In a more general, and potentially more complex case, where the system being controller was nonlinear, high-order, stochastic, and not well-understood, discovering the form of an internal model would not be an easy task. This problem may arise in human modeling within an econometric system, where the system model itself is not well-understood, not to mention the form of any internal human model. However, the concept of an internal model is still a valid—indeed, a necessary—ingredient in modeling human behavior in an econometric system. Future research efforts should concentrate on defining the process through which man develops his internal model from observed data, and the model's relationship to the actual system. Control theoretic results on learning and self-organizing systems will be of potential benefit in these endeavors.

[4] How much to raise taxes is the ensuing *control* problem.

[5] Although admitting simplicity, linearization is not necessary. Extended Kalman filtering or nonlinear filtering schemes could be used in the information processor.

4.1.3. *Innovations process.* Consider the method by which the Kalman filter (15) updates the estimate $\mathbf{p}(t) = \hat{\mathbf{x}}(t-\tau)$ as a function of time. The driving term

$$\mathbf{r}(t) = \mathbf{y}_p(t) - C\hat{\mathbf{x}}(t-\tau) - D\hat{\mathbf{u}}(t-\tau) \tag{19}$$

represents the difference between the human's perceived information $\mathbf{y}_p(t)$ and the filter's internal estimate of $\mathbf{y}(t)$. Thus, $\mathbf{r}(t)$ is the difference between actual and expected observations, and is called the residual or innovations process. Basically, $\mathbf{r}(t)$ is the new information that is brought to the filter by $\mathbf{y}_p(t)$.

In the nominal case, when the internal model in the Kalman filter adequately represents the controlled element dynamics, the process $\mathbf{r}(t)$ is a zero-mean, white Gaussian noise with covariance matrix $\mathbf{V}_y(t)$. In other words, $\mathbf{y}_p$ and $(C\hat{x} + D\hat{u})$ are statistically equivalent and their difference—which is tantamount to the human's observation or central processing noise—has no information content. However, when the internal model and system dynamics are not commensurate, the human's estimate of system behavior would deviate in a mean sense from observed dynamic behavior. These differences will produce a non-zero mean, correlated, innovations process. This fact provides the link between the state estimation process and the construction of an internal model. It may be postulated that, as a result of training, a human refines his internal model to "whiten" the innovations process, the mismatch between model and true system being reflected in the observation noise variance. Thus, it is more than coincidental that manual control experiments have shown lower observation noise levels for better trained subjects. The concept of learning, as modeled via the innovations process, may hold an approach to the difficult problem of selecting an appropriate internal model for complex human control tasks.

4.2. *Man–Vehicle vs. Econometric Modeling—Similarities and Differences*

The preceding sections have described a validated model of the human operator in a wide class of manual control tasks. Several attributes of this model that may be cornerstones for its extension to study man as a controller of an econometric system were discussed. Below, the similarities and differences between the man–vehicle and economic modeling contexts are discussed in more detail.

4.2.1. *System dynamics.* Modeling human response via the optimal control approach assumes that the system dynamics are well defined, and that the state evolves according to physical laws. This assumption is valid for vehicular systems that obey the laws of nature, but is dubious for econometric systems that may or may not obey the laws of man. There are, nevertheless, similarities between the physical man–machine systems, and the metaphysical man–socio-economic systems. Both are complex, multi-input, multi-output and stochastic. Input disturbances cause system behavior to deviate from desired norms. Measurements on these systems are generally corrupted by noise. The eventual mathematical analysis of such systems is well-suited to modern state space techniques.

The difficulty in modeling the econometric system being controlled looms as a major stumbling block for manual control analysis. Extending the optimal control modeling approach requires a specification of man's internal model of the environment. If the internal model is based on the true system's evolution, the modeling of the latter is necessary. The alternative is to postulate an internal model that is (at least partially) divorced from the true system, representing a simple relation between cause and effect. This may degrade seriously the applicability of any subsequent man–model.

The majority of efforts in manual control have been with continuous time systems, where the man continuously processes information and provides control. Certain economic systems are basically discrete in form, with economic indicators and control inputs supplied periodically, e.g. monthly or quarterly. The discrete time evolution of these systems does not present a problem for analysis via the modern control techniques. However, whether the mode of human behavior in systems with long sample intervals and stretched time scales is similar to that in continuous systems, is a matter for research.

4.2.2. *Concept of control.* In both man–vehicle and economic systems the human's control task is to minimize unwanted deviations in system response from a desired goal. These deviations result from external disturbances (noise and bias), as well as from human errors and randomness. In the vehicle control case the minimization of a quadratic error cost functional was used to generate a "human" control. The utility of quadratic cost functionals has been demonstrated by many researchers in econometric control. Thus, the use of this type of cost functional to describe a human's economic control objectives is not at odds with present thinking in this field. The most difficult aspect of this approach will be in determining subjective weightings, especially when they differ from the relatively straightforward objective weightings. The difficulty is often compounded by having different control objectives being expressed by different individuals.

In the optimal control model, the use of a quadratic cost functional results in a separable feedback control mode. First the human model generates a best estimate of the system status that is independent of his eventual control desires. Next, the estimated quantities are suitably combined into a *control policy*. Estimation and control proceed continuously. This type of human behavior seems entirely reasonable for a man in an econometric environment. The state estimation process is one of gathering facts, correlating information, and prediction or extrapolation. The control input is then some function of man's best estimate. However, unlike vehicle control, the time period for information processing is very long relative to a human's central processing time. Thus a man model in such a context would probably consist of long periods of information gathering and digesting, followed by a control decision, followed by a wait-and-see period and more information processing, etc.[6]

4.2.3. *Human limitations.* It is unlikely that all of the human limitations appropriate to vehicle control will find their counterparts in economic system control. Certain limitations are similar, e.g. human nonlinear threshold phenomena for small signals. However, other limitations may be more system-oriented than human-oriented. For example, the time-delay in obtaining information will probably dominate the various internal human processing delays. The neuromotor dynamics may not be pertinent in an explicit form: however, a subjective limitation on the rate of control input may be appropriate in view of public

[6] This type of human response is observed in controlling submarines and supertankers where system time constants are very long, giving the human more time to "think."

response. Observation noise may not have the same interpretation as in a man-vehicle context: however, this "noise" may be appropriate to represent the errors in a human's internal model of the environment as discussed earlier.

Other inherent limitations of the man and the system may be important, and would have to be modeled. Examples include political or policy constraints. However, the basic approach in human modeling would be to define and parametrize the important human limitations, and then to determine suitable values for the limitation parameters. Unfortunately, the "average" parameters that work so well in man-vehicle control will probably have little relation to economic control. Thus, data analysis and parameter identification techniques will be mandatory in the parameter selection task.

4.3. *Man-Econometric Modeling—Where to Now?*

The optimal control model for man-vehicle analysis has a flexible structure that holds potential for its adaptation to model human control in economic systems. The basic assumption, that the man behaves in an optimal manner subject to his inherent (and imposed) constraints is a valid hypothesis for the modeling work. Note that any such model eventually developed will be normative, i.e. we attempt to define what an experienced human *should* do. The fact that this assumption has worked well is evidence of man's adaptability and learning.

The extensions of the modeling techniques are nontrivial as noted. However, a representative problem or class of problems should be defined for a first analysis. The specific problem to be selected for a man-system modeling effort should be sufficiently well-defined. The system should have a mathematical representation that requires a low number of state variables and is not overly complex;[7] suitable descriptions of the input disturbances and data presented to the man are needed. This will permit an internal model to be constructed in the overall man model. The specific problem to be selected must also have sufficient data available that can be useful in the modeling effort. This data is mandatory for determining values of parameters associated with human limitations, for validating the system model and the subsequent man model, and for determining human-oriented control goals. The type of data needed includes time histories of the information presented to the man and the associated time histories of his control inputs.

It is quite likely that the type of data needed in developing the man-model may not be readily available from a real-world, well-defined economic subtask. In such a case, contrived and controlled laboratory experiments are in order, using experienced economists as subjects. If we can understand and model how this class of people implement control decisions in simple tasks, then perhaps this knowledge may have extension to more complex tasks. The ability to repeat laboratory tasks is a powerful tool, for it allows us to study intersubject differences, the effects of different information, and provides us with a measure of variability inherent in the human's decision processes. The successful modeling of complex man-machine systems interactions followed the path from simple laboratory cases.

[7] For example, the day-to-day adjustment of a commodity price is a more logical starting point, than the task of managing a large firm.

It appears likely that a similar approach will be successful in man–socio-economic modeling.

5. Conclusions

An existing, validated optimal control model of human response in man-vehicle control systems has been discussed. This model possesses a generalized structure that provides a conceptual framework for modeling human control in an economic context. Extending this model to a man–econometric system first requires an adequate description of the system being controlled. Necessary are descriptions of the information base and control inputs available to the man and his control objectives. The external inputs that disturb the system must also be modeled.

The successful development of a human model in such a control task depends on characterizing the human's internal model of the environment and specifying a suitable cost functional. Obtaining adequate data from which to determine values for the human-oriented parameters, and for model validation is a needed step in the development program. We are optimistic that human modeling techniques, based on modern control theory, and proven by application, hold promise for understanding man's role as a controller in dynamically evolving economic system.

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