Automatica, Vol. 16, pp. 237–253
Pergamon Press Ltd. 1980. Printed in Great Britain

0005-1098/80/0501-0237 $02.00/0

Human Dynamics in Man–Machine Systems*

D. McRUER†

Structural-isomorphic (classical control) and algorithmic (modern control) models of human dynamics provide similar results for some features and offer different, yet complementary, prespectives for other facets of human behavior.

Key Words—Adaptive systems; bang-bang control; biocontrol; crossover model; human dynamics; man–machine systems; optimal systems; physiological models; structural isomorphic model.

Abstract—The dynamic behavior of human operators in manual control systems has long served as a compelling target for control theory explanations. While many theoretical attempts have been found wanting, some classical and modern control theory concepts have proved useful in practice. In this paper some human dynamic properties are outlined to illustrate the variety of human behavior, and some suitable theoretical treatments are summarized. Time-optimal control theory is used to characterize one form of human behavior. Other behavioral aspects are quantified by the two predominant models in current use—a structurally isomorphic cause–effect model and an algorithmic model utilizing linear–quadratic–gaussian optimal control. Many of the procedures developed to achieve practical utility for these models have parallels useful for automatic control as well.

INTRODUCTION

THE HUMAN OPERATOR in a man–machine system is the archetype hierarchical, adaptive, optimalizing, decision-making controller. Control theories can also be classified using similar adjectives, so it is not surprising that almost every new advance in control theory has led to attempts to better understand additional aspects of human behavior in the perspective of this advance. Sometimes, but not always, these attempts have been fruitful, and a control theory paradigm has evolved which is useful in quantifying the human's operations. Just as theory has been used to 'explain' experiment, so unexplained experimental results beget new theory. The results of this widespread synergistic activity have been documented in hundreds of research papers and in a series of summary surveys which have appeared aperiodically. (A chronological listing of surveys is given at the end of this paper, preceding the reference list.) As a consequence, much of the successful art is now mature. Furthermore, it has become a fundamental mode of thinking on the part of technical practitioners in the fields of operator/vehicle control system integration, vehicle handling qualities and, indeed, all aspects of interactive man–machine systems.

Besides the technological aspects of manual control, interdisciplinary activities between control engineers, physiologists, and experimental psychologists have led to control theory descriptions of human subsystem behavior and to the interpretation of the human's psycho-physiological outputs in control engineering terms. These interdisciplinary areas have been especially productive in building psycho-physiological models of those human subsystems involved in the human controller, in understanding biodynamics as affected by environmental variables, and in interpreting objectively the effects of alcohol, drugs, fatigue, etc., as operator impairments.

From this rich variety there are many aspects of man–machine control that one could address, but the emphasis in this paper will be on just a few examples. Although the models treated do not represent an exhaustive cross-section of the field, those chosen include both classical and modern control theoretical viewpoints. I shall begin with a description of some of the ways in which humans behave as controllers and thereby introduce some of the mysterious complexities which face researchers in this field. A neat, almost too easy, application of optimal control theory is then shown for a situation wherein the human operator behaves like a time-optimal programmed controller. From these starting points, the discussion will be expanded to include other features of human behavior, and the two currently predominant types of human operator modeling used to describe this behavior are discussed in some detail. The first of these is a

*Received April 2 1979; revised December 7 1979. The original version of this paper was presented at the 7th IFAC World Congress on A Link between Science and Applications of Automatic Control which was held in Helsinki, Finland during June 1978.

The published Proceedings of this IFAC Meeting may be ordered from: Pergamon Press Limited, Headington Hill Hall, Oxford, OX3 0BW, England.

This paper was recommended for publication in revised form by associate editor B. Gaines.

†Systems Technology, Inc., 13766 South Hawthorne Boulevard, Hawthorne, CA 90250, U.S.A.

structural model which attempts to account for many of the subsystem aspects of the human controller as well as the total input–output behavior. The second model treated is algorithmic, which primarily attempts only to mimic the human operator's total response. This model is an outstanding practical application of optimal control theory, and many of the tricks and procedures developed to achieve its practical utility for this purpose are useful to applications in automatic control as well.

THE SEVERAL NATURES OF MAN–MACHINE CONTROL— A CATALOG OF BEHAVIORAL COMPLEXITIES

The human controller is complicated to describe quantitatively because of his enormous versatility as an information processing device. The constituent sensing, data processing, computing, and actuating elements are connected as internal signal processing pathways which can be reconfigured as the situation changes. Functional operations on internal signals within a given pathway may also be modified. Thus, we have adaptation both of the pathways involved and of the functions performed.

Figure 1 shows the general pathways required to describe human behavior in an interactive man–machine system wherein the human operates on visually sensed inputs and communicates with the machine via a manipulative output. This control system block diagram indicates the minimum number of the major functional signal pathways internal to the human operator needed to characterize different behavioral features of the human controller. The specific internal signal organizational possibilities shown are obtained by manipulating experimental situation (e.g., by changing system inputs and machine dynamics). By this means we are able to isolate different combinations of the specifc blocks shown in this diagram.

To describe the components of the figure start at the far right with the controlled element; this is the machine being controlled by the human. To its left is the actual interface between the human and the machine—the neuromuscular actuation system, which is the human's output mechanism. This in itself is a complicated feedback control system capable of operating as an open-loop or combined open-loop/closed-loop system, although that level of complication is not explicit in the simple feedback control system shown here. The neuromuscular system comprises limb, muscle, and manipulator dynamics in the forward loop and muscle spindle and tendon organ ensembles as feedback elements. All these elements operate within the human at the level from the spinal cord to the periphery.

There are other sensory sources, such as joint receptors and peripheral vision, which indicate limb output position. These operate through higher centres and are subsumed in the proprioceptive feedback loop incorporating a block at the perceptual level further to the left in the diagram. If motion cues were present, these too could be associated in a proprioceptive-like block.

The three other pathways shown at the perceptual level correspond to three different types of control operations on the visually presented system inputs. Depending on which pathway is effectively present, the control structure of the man–machine system can appear to be open-loop, or combination open-loop/closed-loop, or totally closed-loop with respect to visual stimuli.

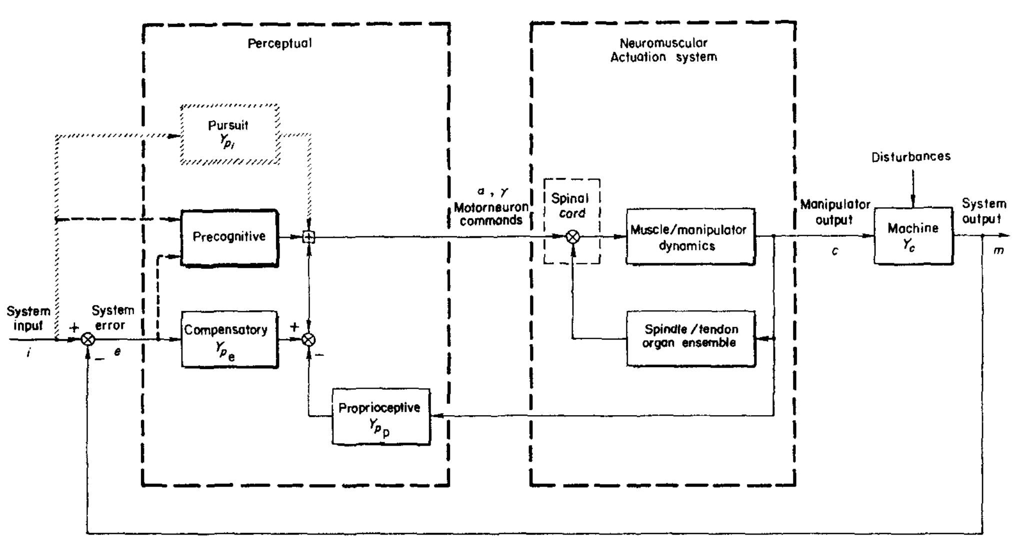


FIG. 1. Major human operator pathways in a man machine system.

When the *compensatory* block is appropriate at the perceptual level, the human controller acts in response to errors or controlled element output quantities only. With this pathway operational, continuous closed-loop control is exerted on the machine so as to minimize system errors in the presence of commands and disturbances. Compensatory behavior will be present when the commands and disturbances are random-appearing and when the only information displayed to the human controller consists of system errors or machine outputs.

When the command inputs can be distinguished from the system outputs by virtue of the display (e.g., **i** and **m** are shown or detectable as separate entities relative to a reference) or preview (e.g., as in following a curved pathway), the *pursuit* pathway joins the compensatory. This new pathway provides an open-loop control in conjunction with the compensatory closed-loop error-correcting action. The quality of the overall control can, in principle, be much superior to that where compensatory acts alone.

An even higher level of control is possible. When complete familiarity with the controlled element dynamics and the entire perceptual field is achieved, the operator can generate neuromuscular commands which are deft, discrete, properly timed, scaled, and sequenced so as to result in machine outputs which are exactly as desired. These neuromuscular commands are selected from a repertoire of previously learned control movements. They are conditioned responses which may be triggered by the situation and the command and control quantities, but they are not continuously dependent on these quantities. This pure open-loop programmed-control-like behavior is called *precognitive*. Like the pursuit pathway, it often appears in company with the compensatory operations as dual-mode control—a form where the control exerted is initiated and largely accomplished by the precognitive action and then may be completed with compensatory error-reduction operations.

The above description of pathways available for human control activities has emphasized the visual modality. Similar behavior patterns are present in other modalities as well. Thus, man's interactions with machines can be even more extraordinarily varied than described here, and can range completely over the spectrum from open loop to closed loop in character in one or more modalities. Just what pathways of the overall system are present at a particular time depends on the detailed nature of the specific task at hand and the corresponding perceptual situation. A rather complete example, in which all of the fundamental pathways are involved in the various maneuvers, is driving (e.g., McRuer and co-workers, 1977; Weir and McRuer, 1970).

TIME-OPTIMAL CONTROL

One might anticipate that the ultimate in human performance and skill associated with precognitive operations would correspond to that ultimate in the machine world—the time-optimal programmed controller—when inputs are step-like and the disturbance environment is benign. Even with a compensatory display which shows only the system error the operator reaction time permits the step input to be completely perceived once it is applied. Thus, the input is completely known. Similarly, by dint of extensive practice, the dynamics of the machine can also be thoroughly imprinted, and an appropriate control repertoire established. In these circumstances, the precognitive pathway of the man–machine system should be exercised.

To test these conjectures consider the sample system responses (McRuer and co-workers, 1968) to step inputs for machines which have transfer functions of K_c/s^2 and K_c/s^3. These responses are shown in Fig. 2. The operator's output control movements are somewhat rounded off, but nevertheless have the essential bang-bang character of time-optimal control. After the operator's initial dead time the control movements are quite similar to the responses of an ideal limited-output programmed controller operating to obey a minimum time criterion. The limited control deflection is an internal constraint imposed by the operator for the given situation and is not

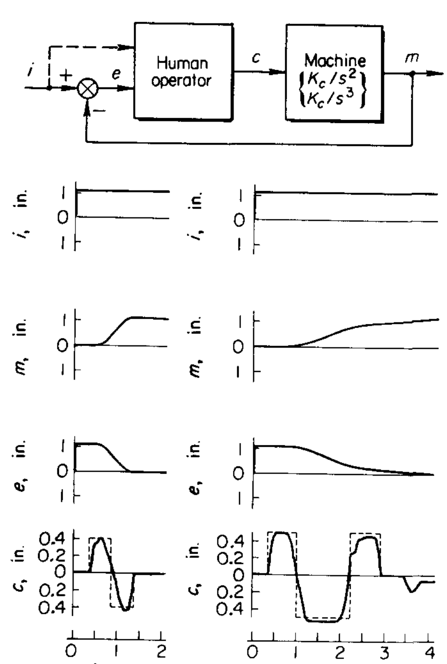


FIG. 2. Step response data.

necessarily a physical limit. Feedback is present only to the extent required for the human to estimate the appropriate switching points when the phase trajectory intersects the time-optimal switching surfaces. Because the task is thoroughly learned and practiced, the delays internal to the operator (after the initial reaction time to the randomly applied step) are internally accounted for and the time-optimal control paradigm is suitable for the main transient control action. After the error is reduced to very small values, the feedback afforded by the compensatory pathways is utilized to maintain the error within reasonable bounds. This dual-mode action of the human is entirely consonant with the dual-mode programmed countrollers normally required to achieve practical time-optimal control.

As shown by a number of investigators (McRuer and co-workers, 1968; Miller, 1970; Smith, 1962), time-optimal behavior is indeed representative of the best the human can do when the inputs are either initial conditions or steps and the disturbances are minimal. In this case, the human's operations appear to be shaped by the purpose of minimum time system response, and the minimum time performance criterion is invariant across systems. For these particular precognitive behavioral conditions then, an algorithmic optimal control model can be formulated which is teleological in character.

COMPENSATORY OPERATIONS

The compensatory pathways in the visual modality have been by far the most extensively studied in man–machine systems. Thousands of experiments have been performed, and most of the adaptive features of the human operator associated with these kinds of operations are well understood. This experimental data base offers an exceptionally fertile field for the application of new advances in control theory. It also provides a practical norm against which various theoretical approaches can be assessed and accepted or rejected as possible schemes for the modeling and explanation of human behavior. At present both classical control and optimal control theoretical formulations are available to predict steady-state and dynamic performance.

Figure 3 illustrates in vector block diagram form a general system configuration appropriate to closed-loop man–machine control. The diagram shows the human operating on a number of perceived quantities, $\mathbf{y}(\mathbf{t})$, and exerting control over a machine by actuating a number of controls, $\mathbf{u}_n(\mathbf{t})$. The response of the machine to actuation of the controls and to disturbances is presented on a 'display.' As used here, display includes dynamic geometrical perspectives of the visual field, other visual stimuli present on physical display elements either on the machine or in the surround, and proprioceptive, tactile, aural, and other information impinging on the operator. From the display the human separates the information needed for monitoring from that required for control purposes. Only the latter directly affects the human's operations as a controller, although both present attentional demands and thereby affect workload.

After receiving the displayed information the human operator internally selects and equalizes appropriate signals and sends the results on to the neuromuscular actuation subsystem for control action. The equalization and neuromuscular properties depend on the task variables (machine dynamics, display, and inputs); they in fact constitute the operator's adaptive features whereby he attempts to offset any dynamic deficiencies of

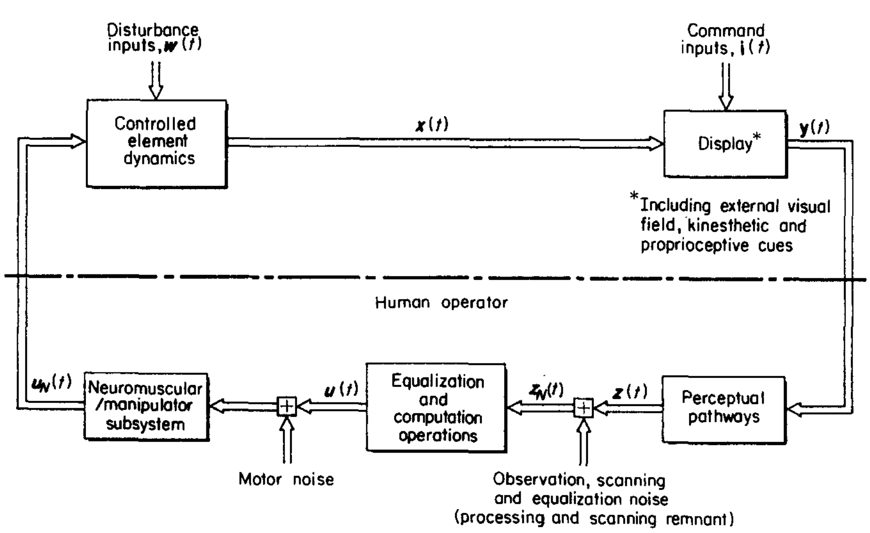


FIG. 3. A generalized man–machine system structure.

the remaining system elements. In the process of accomplishing control the human operator introduces observation, scanning, equalization, and motor noises (together constituting 'remnant'). These unwanted components of the operator's signals are functions of the task and the qualities of the display.

Two types of human operator models are available to handle the details in Fig. 3. The first is a multiloop, multi-modality model, based on describing functions, which is structurally isomorphic in that its component dynamics are intended to parallel the dynamics of more or less identifiable human operator subsystems. The emphasis is on cause and effect relationships having similarity in form and structural connections with those of the human operator. The second type of model is algorithmic. It uses linear–quadratic–gaussian optimal control theory, modified to permit a pure time delay and operator-induced noises to be given quantities along with the machine characteristics.

Both types of models represent the man–machine system as quasi-linear in the sense that the response to a given input is divided into two parts—a component which corresponds to the responses of equivalent linear elements driven by that input and a 'remnant' or noise component which represents the difference between the response of the actual system and an equivalent system based on the linear element. Verbal-analytical instructions which express the adaptation of the human population to the task variables are an important formal feature of the structural isomorphic model and have counterparts, such as the specification of the performance index, in the algorithmic model form. For limited situations, both representations can be used to predict human operator dynamic behavior (in some sense), operator-induced noises (remnant), workload indices, visual scanning effects, and overall system performance such as mean-squared system errors and control activities.

The major fundamental differences between the models are their conceptual bases, i.e., causal and structural isomorphic as contrasted to algorithmic and (potentially) teleologic; the computational techniques associated with the exercise of the model; and the nature of model identification processes. At the present time there are other differences between the structural isomorphic and algorithmic models relating to their regimes of application and their validated capabilities for prediction. These latter differences are not, however, fundamental; instead, they reflect the relative maturity and extent of application.

Both the structural isomorphic and the algorithmic model approaches will be described below. As a preliminary let us first examine some of the general characteristics of human operator dynamic response in compensatory man–machine systems by considering an elementary example. Fig. 4a shows a display and functional block diagram of a simple single-loop man–machine system. The machine or controlled element dynamics are given by:

$$Y_c = \frac{K_c}{s(Ts+1)}. \tag{1}$$

The compensatory display presents the operator with a visual stimulus which shows only the difference between the system forcing function and the system output. (Historically this is the definition of *compensatory*; modern usage applies the word compensatory to the *situations* wherein the human operates on errors regardless of the display details.) The operator's task is to minimize the presented error signal by attempting to keep it superimposed on a stationary point or line on the display. This is accomplished by the manipulative control action $c(t)$ which affects the controlled element, and gives rise to the system output $m(t)$ being controlled. The usual purpose of a system of this nature is to make the system output closely resemble the system forcing function or, in other words, to make the output follow the input. The quality of the following is indicated by the system error, which is, of course, the operator's visual stimulus.

Figure 4b (McRuer and Krendel, 1974) presents typical time histories in this system when a random-appearing forcing function is applied. The first thing to notice about the time histories is that the system output, m, does indeed follow the forcing function, i, very closely. Only a slight time lag keeps the output from being a nearly identical duplicate of the forcing function, although there are some small, random wiggles here and there on the output. On the other hand, the operator's output does not correspond at all well with the system error, even if the error is delayed. However, the operator output lagged by $(s+1/T)$ is approximately proportional to the error signal delayed by about 0.16 sec. Thus, as an approximation, the operator's transfer characteristic can be inferred to be:

$$Y_p \doteq K_p(Ts+1)e^{-\tau s}. \tag{2}$$

This result states that the operator develops a lead which is approximately equal to the first-order lag component of the controlled element dynamics and that the operator's response lags his stimulus by τ sec. The open-loop man–

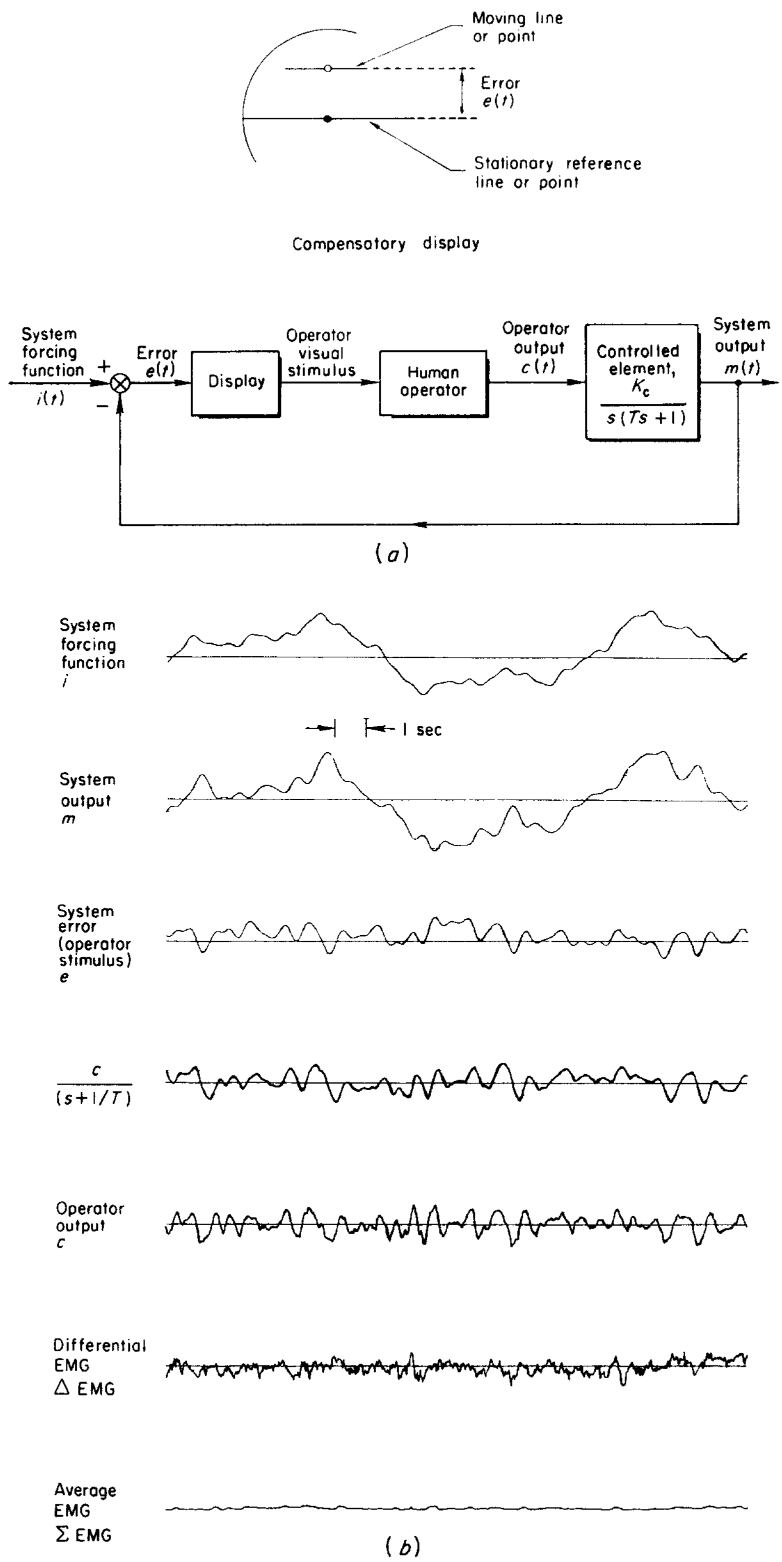


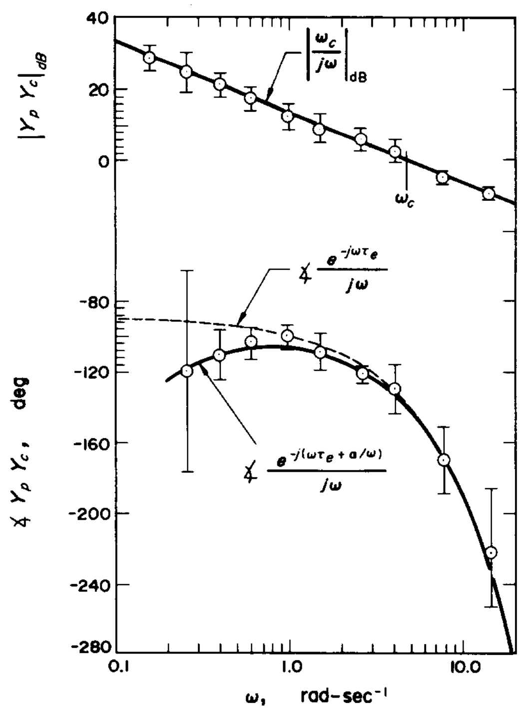
FIG. 4. Simple compensatory system and operator responses.

machine transfer characteristic appears as:

$$G = Y_p Y_c \doteq \frac{[K_p(Ts+1)e^{-\tau s}]K_c}{s(Ts+1)} \tag{3}$$

$$= \frac{K_p K_c e^{-\tau s}}{s} = \frac{\omega_c e^{-\tau s}}{s}. \tag{4}$$

The data of Fig. 5 illustrate how well this latter relationship is obeyed for a variety of subjects. The agreement with the amplitude ratio is excellent over a broad range of frequencies. The phase agreement is good in the region of the crossover frequency, ω_c, but departs somewhat at lower frequencies. Figure 5 also shows the extended



[ω_c = 4.75 rad-sec^{-1}, τ_e = 0.18 sec, a = 0.11 rad-sec^{-1}]

FIG. 5. Data and crossover models for a simple rate-control-like controlled element.

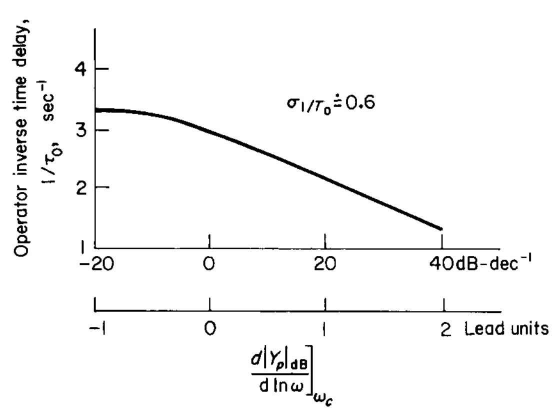


FIG. 6. Variation of crossover model dynamic stimulus–response latency with degree of operator lead equalization.

operator model wherein a time constant, $1/\alpha$, describes those phase contributions in the crossover region which arise from leads and lags below the crossover frequency band. This phase contribution is represented by $e^{-j\alpha/\omega}$. It is an approximation not intended to extend to extremely low frequencies.

If now a large variety of controlled element forms are used and similar measurements are taken, the human transfer characteristics will be different for each controlled element. But, for a very wide range of controlled element dynamics, the *form* of the total open-loop transfer characteristic about the crossover frequency will remain substantially invariant. In other words, experiment shows that equation 3 has some pretention to general applicability. The effective time delay, τ, which is of course only a low-frequency approximation to all manner of high-frequency leads and lags, is not a constant. It depends primarily on the amount of lead equalization required of the operator, as shown in Fig. 6 (McRuer and Krendel, 1974). This indicates that operator equalization to offset controlled element dynamic deficiencies has an associated computational time penalty. With this proviso on τ, the equation 4 relationship becomes the well-known simplified *crossover model* of compensatory manual control theory. The human operator's adaptation to controlled element dynamics is implicit in the relationship, i.e., for a particular set of controlled element dynamics defined by Y_c the human will adopt a crossover region transfer characteristic $Y_p \doteq \omega_c e^{-\tau s}/sY_c$. The general form of the human's response would thus be determined by the specifics of Y_c, and changes in this task variable evoke changes in Y_p such that the crossover model open-loop transfer characteristic form is preserved.

The crossover model also applies when the machine dynamics are smoothly time varying (McRuer and co-workers 1966). The crossover frequency tends to be constant for a given set of task variables. It increases slightly as forcing function bandwidth is increased and is reduced for very small input amplitudes. This is a consequence of the operator's indifference threshold, which is the most important nonlinearity to be considered in connection with crossover model transfer characteristics.

The second component of the operator's response is operator-induced noise or remnant. This can, in principle, result from several sources, but in single-loop systems with linear manipulators the basic cause appears to be random time–varying behavior within the operator primarily associated with fluctuations in the effective time delay. This can be interpreted as a random change in phase, akin to a random frequency modulation, or to variations of internal sampling rate, in a sampled data interpretation of the operator (Bekey and Biddle, 1967; Jex and Magdaleno, 1969; Levison, Baron, and Kleinman, 1968; McRuer and co-workers, 1966; McRuer and Krendel, 1974; Schweizer, 1972). In any event, the remnant is a continuous, relatively broadband, power spectral density which, as shown in Fig. 7, scales approximately with the mean-squared error.

Task variables other than the machine dynamics, as well as environmental and operator-centered variables, can change open-loop gain, effective time delay, and remnant. Accordingly, ω_c and τ variations become a quantification of changes or differences in the task, environmental,

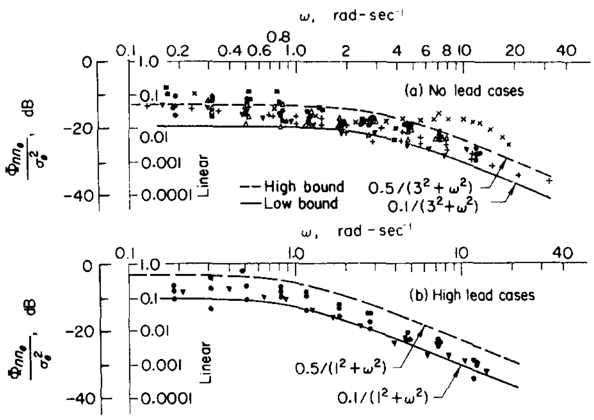


FIG. 7. Normalized remnant spectra.

and operator-centered variables expressed directly in terms of the operator's control actions. In measuring the effects of training, for instance, ω_c increases with trials until stable conditions are obtained for that particular subject and set of constant task and environmental variables. Similarly, the remnant may also change as a function of the control situations. For instance, comparison of Figs. 7a and 7b shows the change in remnant bandwidth and level associated with the lead equalization required to offset controlled element lags. As another example, Allen and co-workers (1975) show that operator gain is decreased and remnant is increased as a consequence of the ingestion of alcohol.

To generalize these remarks, the total operator action can be thought of as that of an adaptive plastic sensory-motor link—adaptive in that the operator is task-adjusted to offset controlled element dynamic deficiencies and to respond to forcing function commands or regulate against disturbances; plastic in that the adaptive characteristics are further shaped by the external and internal (operator-centered) environments. These behavioral features must be accounted for in either the structural isomorphic or algorithmic models. A general description of these models and some of their chacteristics follows.

THE STRUCTURAL ISOMORPHIC HUMAN OPERATOR MODEL

The extensive analytical and experimental studies of closed-loop man–machine systems conducted since World War II have had as a principal goal the mathematical quantification of human dynamic behavior and the development of laws which permit this behavior to be predicted. In general, emphasis has been on the human operator as a complete entity rather than as a summation of functional subsystems.

In recent years, the precision and dynamic range of measurements taken with the total human operator have increased greatly to the point that certain of the measurements made over certain frequency ranges can be associated with human subsystem dynamics. Thus, the study of the human operator as a whole has now arrived at the stage where not only must subsystem models sum up to be compatible with the total human dynamic model, but subsystem and total system studies can be directly related. Accordingly, control engineering descriptions of the overall human (see, e.g., the list of surveys), dynamical descriptions of the human motor coordination system (Houk, 1963; Okabe and co-workers, 1962; Stark, 1968; Sun, Eisenstein, and Bomze, 1966; Vossius, 1965, 1972; Vossius and Werner, 1970; Young and Stark, 1965), studies of predictive control conducted for physiological understanding (Stark, 1968; Vossius, 1965), and studies of neuromuscular actuation systems (Gordon-Smith, 1970; Kraiss, 1972; Magdaleno and McRuer, 1971; Magdaleno, McRuer, and Moore, 1968; McRuer and co-workers, 1968), which were originally separated disciplines, now become united.

As described by McRuer (1973), the adaptive and plastic properties of the operator permit the experimenter to set the stage and write a script calling for a particular form of action. Table 1 illustrates some of the experimental procedures which can be used to evoke various types of behavior.

By properly selecting combinations of these procedures and techniques, particular channels of human dynamic operations can be isolated, examined, and measured. Appropriate models which 'explain' each of these varieties of behavior and which are also compatible with what is known from other views of experimental psychology and physiology can then be constructed to form a current version of the structural isomorphic model. One such construction, which is somewhat simplified, is given in Fig. 8. Here the controlled element and display blocks constitute the machine, whereas all the remaining detail reflects the man.

Starting at the far right is the neuromuscular actuation system. Because the man–machine system depicted here is operating on random-appearing signals which have essentially stationary statistics, the neuromuscular system is fluctuating about an operating point which in general corresponds to some steady-state or average tension. This is graphically illustrated by examination of the average and differential EMG signals shown in Fig. 4b. Consequently, the dynamic operations of muscles, which can act only in contraction, can be treated as positive or

TABLE 1. EXPERIMENTAL PROCEDURES TO EVOKE HUMAN OPERATOR BEHAVIORAL CHANGES

Procedure (effects)	Behavioral modification (examples)
Controlled element adjustment	Equalization changes and associated time delay increments
Manipulator modification	Scaling of joint movement and force ranges; Activation of proprioceptive pathways
System forcing function changes	
Bandwidth	Fine tune task-induced stress;
Amplitudes	Adjust average neuromuscular tension and associated time delay increments; Operator gain (for amplitudes near indifference threshold)
Additional visual inputs	Scanning, operator gains as affected by parafoveal and foveal viewing
Excitation of additional modalities	Activation of additional internal pathways (e.g., vestibular, kinesthetic) and consequent equalization changes
External environmental modification	Change task-induced stress; Differentially change some internal subsystem dynamics
Drugs	Modify operator-centered variables Differentially affect various internal signal pathways

negative fluctuations of many agonist/antagonist pairs about a steady tension bias value. This permits a great simplification in depicting the dynamic essentials in terms of a block diagram. The forward path of the neuromuscular system shown includes ensembles of muscles operating on coupled skeletal and manipulator dynamics. The feedback path sensors operating at the spinal level are primarily spindle and Golgi tendon organs. The net feedback effects, in company with alpha motor neuron commands from higher centers, can be measured fairly easily with surface electrodes, but the individual actions of specific sensors are difficult to separate in the intact human. Consequently, the system shown has a feedback element labeled as spindle/tendon organ ensembles. The spindle characteristics may very well be predominant for the small motions and relatively light forces involved in most of the measurements thus far accomplished. The effective dynamics of the closed-loop neuromuscular system from the alpha motor neuron command signals to manipulator force can be approximated over a wide frequency range by the third-order transfer function shown. This form is also compatible with small perturbation dynamics based on analytical models of muscle and manipulator characteristics (Magdaleno and McRuer, 1971; Magdaleno, McRuer, and Moore, 1968). The parameter values are strongly dependent on the steady-state neuromusculat tension, γ_0, due to the gamma motor system. The gamma commands also affect the dynamics of the spindle ensembles and, in fact, provide another pathway (not shown) capable of actuating the neuromuscular system via the spindle ensembles. These features are pictured by the arrows indicating variation in the Z_{sp} and P_{sp} factors in the neuromuscular system feedback block and in the γ_b and γ_0 inputs.

This rudimentary level of neuromuscular actuation system description is a minimum to have value even in gross physiological descriptions. It is an essential feature in the study of human operator characteristics in vibratory environments (Jex and Magdaleno, 1978) and is also often needed for the study of limb/manipulator system dynamics in driving, aircraft control, etc. For many other man–machine system applications, however, the neuromuscular actuation dynamics are so high in frequency as to be relatively unimportant in their details. In these cases, a pure time delay, τ_{nm}, or a first-order lag can be used as a low-frequency approximation. There is, however, some evidence that the very-low-frequency phase lag associated with α in the extended crossover model derives from neuromuscular system properties.

The neuromuscular actuation system described thus far is appropriate when the manipulator is restrained by a stiff spring and the control actions involve very little joint movement. When significant joint movements are present, proprioceptive pathway elements enter into the neuromuscular actuation system dynamics. These derive from several sources, the most important

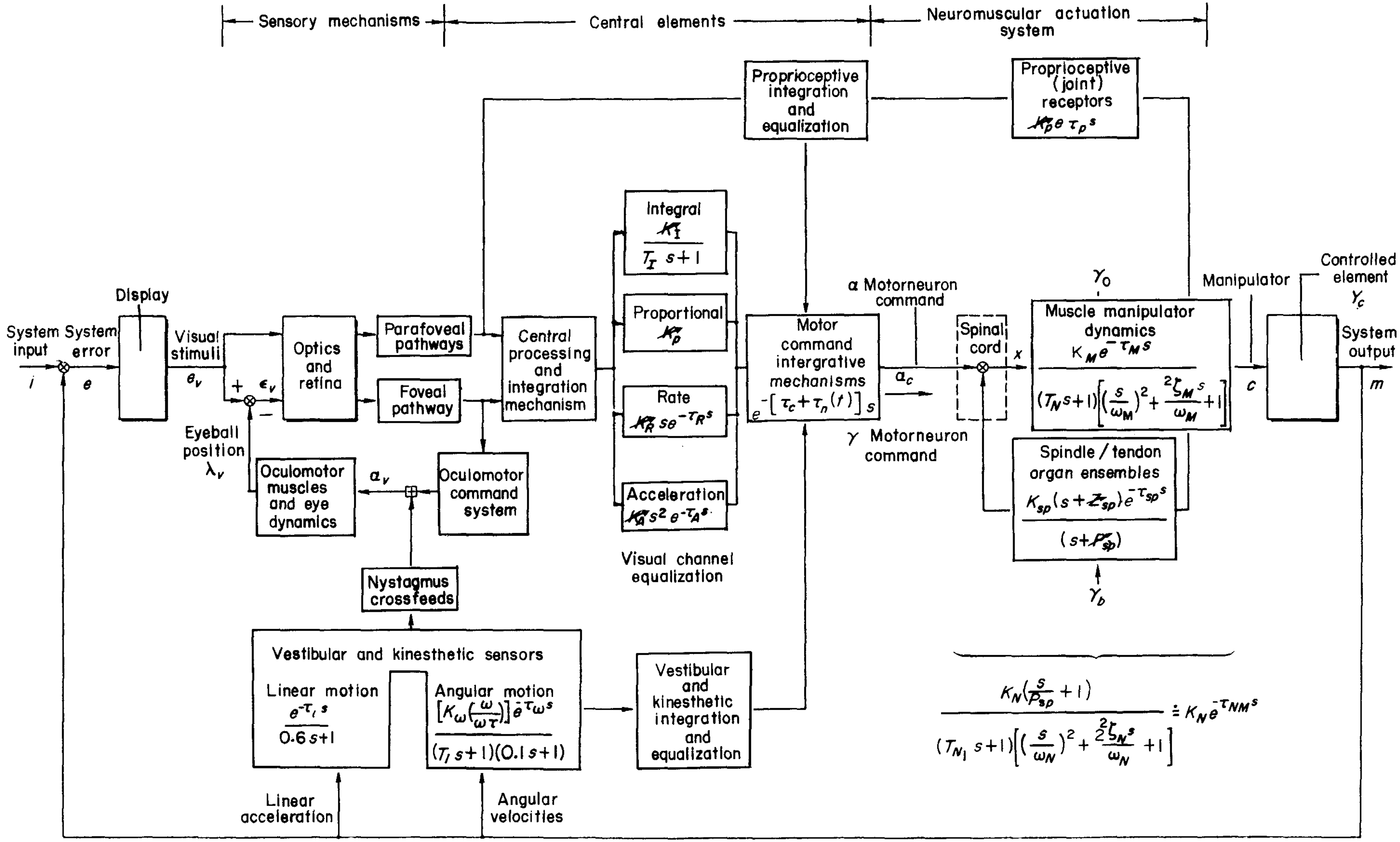


FIG. 8. Structural isomorphic model of man-machine system.

being peripheral vision and joint receptors in the limb. These feedbacks act through higher centers and thereby exhibit larger response time delays. When they are present, the neuromuscular actuation system bandwidth may be reduced significantly.

Proceed now to the sensory mechanisms at the far left of the human operator. A good deal of the detail in the visual pathway is intended to emphasize the parallel operations of parafoveal and foveal vision and the control of eye movements. The latter have been very extensively studied and need no further discussion here. An important feature of the visual pathways is that essentially continuous signals from a particular display element can be available to the operator, by virtue of the parallel foveal and parafoveal pathways, even when the eye is scanning. The essence of past work in man–machine systems involving many displays (Allen, Clement, and Jex, 1970; Levison and Elkind, 1967, 1969; McRuer and co-workers, 1967; McRuer and Krendel, 1974; Weir and Klein, 1970) shows that:

1. A fairly stationary scanning strategy evolves for a given task and display array.
2. The operator's output control motions are much more continuous than a discrete sampling of input signals coincident with foveal eye fixations would imply.
3. The first-order effects of scanning are to reduce gain and increase remnant in the scanned channels.

The degree of gain reduction depends on parafoveal viewing angle and relative parafoveal to foveal dwell times.

The other sensory elements are vestibular and kinesthetic (Meiry, 1965; Peters, 1969; Ringland and Stapleford, 1972; Shirley, 1968; Stapleford, Peters, and Alex, 1969), which are present when the operator is moving, such as when in a car or airplane. The operator contains neurological elements capable of sensing rotary and linear accelerations. These are primarily in the vestibular apparatus, althouth other sensors and pathways can also be involved. The rotary motion feedbacks usually associated with the semicircular canals act like signals from a highly overdamped angular accelerometer. Over the frequency range from about 0.2 to 10 rad/sec the output signal is proportional to angular rate, so the sensor can function as a rate gyro. For prolonged steady turning the sensor washes out; thus, spurious sensations occur in steady rotations or when the turning motion stops. This pathway has a threshold on the order of 1–2 deg/sec. Because the rotary motion sensing apparatus gives rise to an angular-rate-like cue directly, any need for generating angular rate information by means of a lead equalized visual cue may be reduced. This feedback can also be thought of as an inner loop which tends to reduce the effective operator time delay in the visual pathway. For instance, in terms of crossover model characteristics, the presence of rotary motion can reduce the effective time delay for otherwise visual tasks by as much as 0.1 sec.

The other functional operation of the vestibular and kinesthetic pathways is the provision of the 'nystagmus crossfeeds' to the oculomotor system. These produce involuntary eye motions as a function of the excitation of the vestibular apparatus. These eye movements can be helpful in properly directing the gaze, although many of their most interesting properties involve their effects in disorientation and illusions. The motion effects which conflict with the visual modality can seriously distort the operator's perception of the state of affairs and can be so severe as to affect the human's control capacity.

Turn now to the central elements. As shown there, the operator can develop a neuromuscular system input command which is the summation of a lag, proportional, lead, and double-lead function of the system error. The lag and proportional channels have a basic time delay, τ_c, associated with them. The higher derivative channels have additional incremental delays. These incremental time delays constitute the dynamic cost of lead generation. They are about 1/5 sec for rate, τ_R, and greater than 1/2 sec for the acceleration channel, τ_A. The proportional, rate, and acceleration equalization is shown as separate parallel channels primarily because of their respective latency differences. This independence of these channels is oversimplified, for common neurological apparatus is undoubtedly present for each function. These common elements are modeled here by the central processing and integration block preceding the visual channel and the motor command integrative mechanisms succeeding it. Besides the different time delays, the other evidence for parallel channels is the difference in response quality as a function of the low-frequency equalization supplied by the operator. For example, when very-low-frequency leads are present, as if operations were through the rate or acceleration channels, the operator's output tends to be more discrete and pulselike than when little or no lead is required.

The channel gains and the time constant T_I are all shown as variable quantities. These, in conjunction with the neuromuscular system variations with γ_0, constitute the principal adaptive changes in the operator characteristics as display, controlled element, and environmental conditions change. For a given controlled element, these are of course adjusted such that the crossover model applies over its frequency range of validity. Thus, the extremely complicated structural isomorphic model reduces to the visual and/or vestibular equalization actually present and with neuromuscular dynamics as pertinent to the task. When a higher degree of exactitude is required, the structural isomorphic model is adjusted via a series of analytical/verbal rules which take into account the details of the task variables (see McRuer and Krendel, 1974).

The adjustment rules can, in principle, be mechanized and the adjustments made automatically as part of a parameter optimization routine. Schemes can take advantage of the operator's tendency to minimize the rms error (Leonard, 1960; Roig, 1962) in normal compensatory situations. More elaborate fixed-form minimization procedures are also very useful. For example, in the 'Paper Pilot' series (Anderson, 1970, 1972; Anderson, Connors, and Dillow, 1970; Dillow, 1971; Teper, 1972), the form of the human operator model is assumed *a priori* as one which is pertinent to the control tasks being considered. The key parameters are then adjusted via a parameter optimization scheme to minimize an appropriate performance index.

ALGORITHMIC HUMAN OPERATOR MODEL

A significant development in man–machine systems theory in the past decade has been the application of modern optimal control theory to the estimation and description of human control behavior. The starting points in this evolutionary process were the well-founded theory of the linear–quadratic–gaussian stochastic control problem and manual control theory and data. To successfully marry these two elements is not easy, yet progress has been made (Baron and Kleinman, 1968; Baron and co-workers, 1970; Curry, Hoffman, and Young, 1976; Elkind and co-workers, 1968; Kleinman, 1969; Kleinman and Baron, 1971, 1973; Kleinman, Baron and Levison, 1970, 1971; Kleinman and Perkins, 1974). The concept rests on the presumption that human operator responses can be duplicated by an analogous optimal control system. The optimal system operates to minimize a quadratic performance index in the presence of various system inputs and noises. In doing so it provides a representation for at least some of the adaptability characteristics of the human operator. The basic consideration in this algorithmic approach is provision of techniques for imposing those characteristics of the human which represent both favorable (e.g., adaptation) and unfavorable (e.g., time delay and remnant) features so they are consonant with the theory. Related techniques must account for certain very fundamental human characteristics, such as the effective time delay and neuromuscular delays.

The general result is shown in Fig. 9. At the top are the machine properties involving the controlled element and display as acted on by disturbances. These are represented by linear state vector and display vector–matrix equations. The disturbance, $\mathbf{w(t)}$, is a vector of white gaussian noise processes. If the forcing functions are colored, they are represented by filtered white gaussian noise. The additional states required to represent the filter dynamics are appended to the controlled element state vector and result in expanded **A**, **B**, **C** and **E** matrices. Deterministic disturbances can be modeled by adding non-zero mean components to the disturbance vector, with the addition of still more elements to the state vector and associated matrices. The display variables are linear combinations of the system states and the operator output.

In the optimal control formulation the human operator's characteristics can be divided into two categories—those which represent intrinsic human limitations, and thus which are not subject to optimization, and those properties which are subject to adaptation and thus optimization. In the first category are the effective time delay, the remnant, and to some extent the neuromuscular system properties. In the optimal control model the remnant is accounted for by observation noise and motor noise, shown at the operator's input and neuromuscular command output points, respectively. The observation noise vector is added to the display output $\mathbf{y(t)}$. A separate noise component, $v_{y_i}(t)$ is associated with each display output component, $y_i(t)$. As noted in Fig. 7a, the remnant added at the operator's input is relatively wideband, so each component is assumed to be independent gaussian white noise processes. The spectral density is proportional to the mean-squared value of the displayed component, with a proportionality factor P_i, which is a noise-to-signal ratio. In general, the human operator is presumed to obtain both displacement and rate information from a single display variable, and excellent results have been obtained by assuming that P_i for the position and rate variables is the same. In single-loop control situations numerical values of P_i of about 0.01 are typical. As can be appreciated from Fig. 7a, this is relatively invariant over a wide range of system dynamics and input spectra. To the extent that this is so, the normalized observation noise can be considered to be primarily operator-dependent.

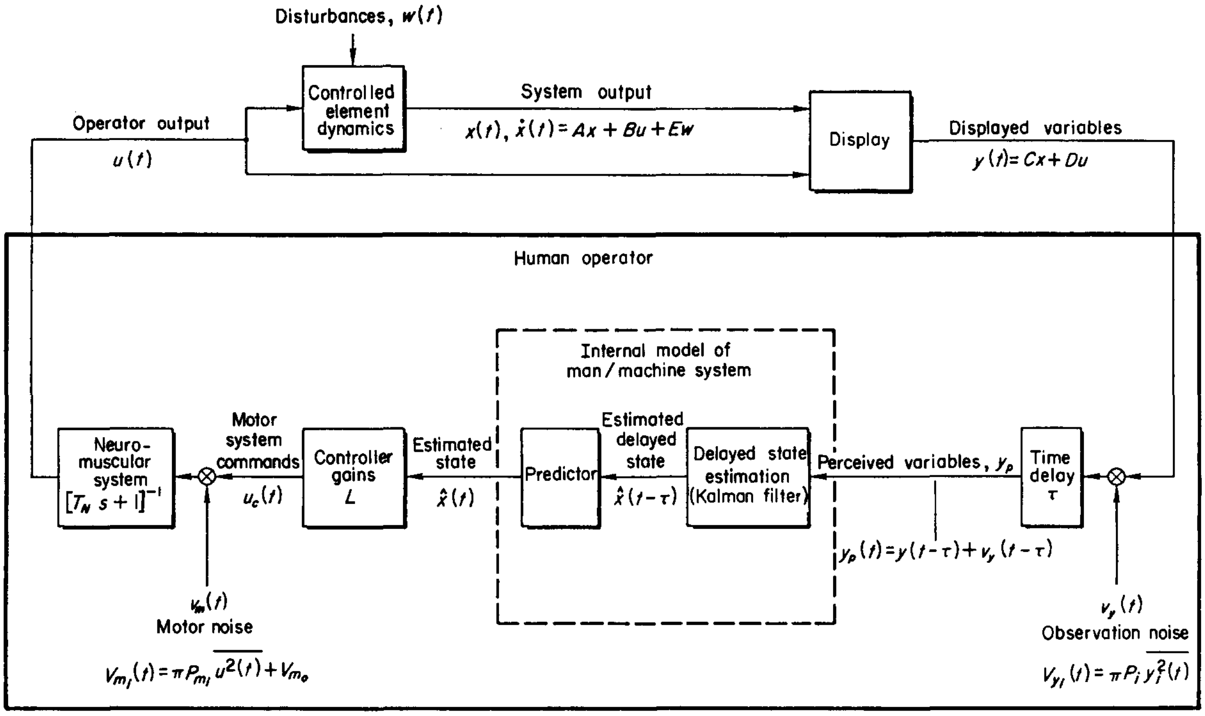


FIG. 9. Algorithmic (linear optimal control) model of man–machine system.

The many internal time delays associated with visual, central processing, integrative, and other operations are combined into a lumped perceptual delay, τ. For simplicity, it is assumed in the current model that all outputs are delayed by the same amount. (We have noted in connection with the structural isomorphic model that there is a delay increment associated with rate perception.)

The 'motor noise,' like the observation noise, is assumed to be a zero-mean gaussian white noise with spectral density proportional to the mean-squared operator output. An additional component, V_{m_0}, is sometimes included to account for the fact that the human operator introduces noise into an undisturbed system. A motor noise signal ratio, P_{m_i}, of 0.003 has been found to provide a good match to experimental data.

The neuromuscular system is represented by a lag matrix, T_N. This is not explicitly modeled as an inherent limitation. Instead, it is imposed by weighting control rate terms in the cost function used to generate the optimal control. For single-loop control problems with linear, wide bandwidth manipulators, this weighting is purposely selected to yield T_N of approximately 0.1 sec to represent this inherent limitation.

The remaining elements of the human operator are adaptive to the system characteristics and to changes in the explicit human operator limitations described above. Estimation of the delayed state vector is accomplished via a Kalman filter. This delayed state estimate is fed to a least-mean-squared predictor to yield the estimated state vector, $\hat{x}(t)$. The optimal gain matrix, L, is generated by solving the optimal regulator problem for a quadratic cost function of the form

$$J(u) = E\left\{\lim_{T\to\infty} \frac{1}{T}\int_0^T (y'Qy + u'Ru + \dot{u}'G\dot{u})\,\mathrm{d}t\right\} \tag{5}$$

Because the cost functional weightings preordain the details of the controller gain matrix, L, the selection of weightings is critical to the model's success. This is particularly the case when the model's purpose is to simulate human operator responses. For simple single-loop control situations, excellent agreement with experimental measurements has been obtained with a cost functional of the extremely simple form:

$$J(u) = E\left\{\lim_{T\to\infty} \frac{1}{T}\int_0^T (\dot{e}^2 + g\dot{c}^2)\,\mathrm{d}t\right\} \tag{6}$$

where e is the compensatory system error and $\dot{c} = \dot{u}$ is the operator's control rate. The value of g is selected as described above to yield an appropriate neuromuscular delay, T_N. For more complex situations, the relative weights are determined based either on maximum allowable deviations or limits or from a knowledge of human preferences and capabilities. This is similar to the technique suggested by Bryson and Ho (1969), wherein the weighting on each quadratic term is simply the inverse of the square of the corresponding allowable deviation. The solutions for this modified Kalman filtering prediction and optimal control problem are given by, for example, Baron and co-workers (1970); Curry, Hoffman, and Young (1976); and Kleinman, Baron and Levison (1971).

Some appreciation of the degree with which actual human operator data can be characterized by the optimal control model can be gleaned from Fig. 10. Theoretical and measured responses for an elementary single-loop system with a rate ($Y_c = K_c/s$) controlled element (Kleinman, Baron, and Levison, 1970) are compared. These data indicate that the model reproduces the essential characteristics of the human controller with excellent fidelity. Perhaps more important, the parameter values for other simple controlled elements, such as $Y_c = K_c$ and K_c/s^2 (Kleinman, Baron, and Levison, 1970) are very consistent, although the time delay needed to match the operator characteristics for K_c/s^2 dynamics was somewhat longer. This, of course, is to be expected from considerations described earlier and does not constitute a defect in the model.

The algorithmic and computational advantages of the optimal control model make it extremely valuable as a means to make quantitative estimates of the human operator's dynamic response in control tasks for which the model is appropriate. There are three aspects, however, which give some. difficulty. The first is philosophical and relates to the explicit requirement that the human operator description contain a complete internal model of the human's intrinsic characteristics and the system dynamics and disturbances. Thus, for the state estimation to be accomplished, the **A**, **B**, **C**, **D**, and **E** matrices plus the system disturbances and the human time delay, observation noise, and motor noise must all be known. Further, for the controller equalization (open matrix) adjustments, the **A** and **B** matrices plus the weights in the cost functional are needed. All of this amounts to an essentially complete 'knowledge' by the human of the man–machine system characteristics. Internal models have a long history in psychology for several purposes. For instance, their elaboration and refinement have served as a useful construct for the development of skill by dint of training. In fact, even the simple crossover model can be interpreted as an implicit internal model of the human and controlled element dynamic characteristics in the crossover region. The key problem is thus not with the concept of an internal model, but rather its degree of perfection, especially in extremely complex systems where the required internal model is equally complicated.

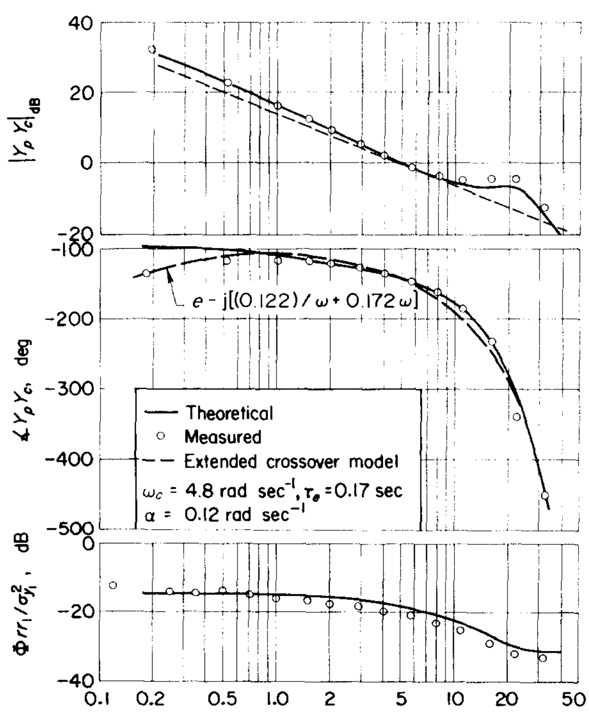


FIG. 10. Measured and predicted system dynamics and remnant for a path controlled element (adapted from Kleinman, Baron, and Levison 1970).

The second difficulty is that of attempting to identify the underlying model parameters from experimental data. Not only is this inverse problem fundamentally difficult, but the optimal control model reviewed here suffers from overparameterization. Thus, from an identification viewpoint, the observation and motor noises are not resolvable, and the feedback matrix and the observer gain matrix can only be determined up to a similarity transformation of the model (van Wyjk and Kok, 1977).

The third problem area is specification of the cost function. Unlike the time-optimal model for step-function-input precognitive behavior, the teleological character of the linear quadratic optimal model is imperfect because the performance criterion must be shaped to the task. As a practical matter, this has seldom posed a serious problem when the model has been applied by an experienced practitioner. Nonetheless, an aura of artistry is present in this requirement.

In the structural isomorphic model, a very large number of experimentally observed phenomena are accounted for. Since its inception, a great deal of effort has been devoted to similarly account for human operator behavior with the algorithmic model. This has required, in the main, adjustments in the cost function or in those properties associated with the human operator's limitations, such as normalized observation or motor noise. The model has proved to be quite flexible in accommodating most of the many behavior changes desired. Table 2 summarizes some procedures and techniques which have been found suitable to accomplish this accommodation (Baron and co-workers, 1970; Baron and Kleinman, 1968; Curry, Hoffman, and Young, 1976; Kleinman and Baron, 1971, 1973; Kleinman, Baron, and Levison, 1970, 1971; Kleinman and Perkins, 1974). These features are valuable not only for man–machine systems but for many automatic control systems wherein an approximate imitation to the adaptive optimalizing human operator would be an excellent choice for an automatic controller. In fact, the imitation of man–machine systems by automatic systems has often been a significant evolutionary step in past control applications. Optimal control, which has often been accused of impracticality, is highly practical for man–machine systems, and therefore the procedures and techniques found valuable to accomplish these practical results have very wide application in the design in inanimate controllers using modern control techniques. This message is, perhaps, more important on a broad scale than the fact that the algorithmic model works well for imitating human behavior.

CONCLUSIONS

This paper illustrates several ways in which the application of control theory to human operator dynamics can lead to enlightenment. The human's input–output and subsystem characteristics become better understood as the structural isomorphic model is improved; the algorithmic model provides useful insights about internal models; and the time-optimal control model reveals aspects of skill and purpose. There are also suggestions for the practical design of conventional automatic controls, e.g., the crossover model corresponds to an ancient rule of thumb prescription for design of simple feedback systems, and the appropriate use of various weightings and noises in the optimal control model to mimic human behavior can be adapted to establish a similar practical controller. Because actual behavioral patterns are aptly described using either scheme as a point of departure, the essential unity of the different approaches is emphasized and the desirability of an eclectic viewpoint to maximize understanding is underscored.

TABLE 2. PROCEDURES FOR ADJUSTMENT OF THE ALGORITHMIC MODEL

Feature to be modeled	Suitable procedures and means
Effective time delay accommodation	Least squares prediction applied to output of Kalman estimate of delayed states
Basic crossover behavior	Use of control rate weighting in distinction to control weighting in cost function
Effective neuromuscular lag T_N	Select ratio of control weighting to control rate weighting (e.g., 'g') in cost function
Selection of cost function weights on states and control	Choose weights to be inverse of squares of the respective maximum allowable values
Remnant	Observation noise covariances scaled with mean-squared state. Residual (non-scaled) observation noise component to account for imprecision due to lack of references.
	Motor noise to reflect inability to generate control motions precisely.
	Residual motor noise to reflect human's introduction of noise into an undisturbed system.
Low-frequency phase lag	Use larger motor noise level than actually present in determining Kalman filter gains
Perceptual and indifference thresholds	Scale observation noise inversely with equivalent gain (random input describing function for threshold)
Scanning effects	Scale observation noise inversely with attentional fraction (f_i) of each display, subject to the constraint that $(\Sigma f_i)+f_{\text{margin}} \leqq 1$, $f_i \geqq 0$.
	Different noise levels for foveal and parafoveal viewing.
Workload (attentional)	Attentional workload effects evaluated by examining performance as a function of the reserved workload margin, f_{margin}
Motion cues	Add model of human motion sensory apparatus (e.g., vestibular system, proprioception) to state and output equations.

LIST OF SURVEYS

Tustin, A. (1947). The nature of the operator's response in manual control and its implications for controller design. *J. IEE*, **94**, Pt. IIA, 190–207.

McRuer, D.T. and E.S. Krendel (1957). *Dynamic Response of Human Operators*. WADC-TR-56-524. (Also, The human operator as a servo system element. *J. Franklin Inst.*, **267** (1959), 381–403 and 511–536.

Licklider, J.C.R. (1960). Quasi-linear operator models in the study of manual tracking. In R.D. Luce (Ed.), *Developments in Mathematical Psychology*. The Free Press of Glencoe, Illinois, pp. 169–279.

Sheridan, T.B. (1962). The human operator in control instrumentation. In R.H. Macmillan, T.J. Higgins and P. Naslin (Eds.), *Progress in Control Engineering*, Vol. I. Academic Press, New York, pp. 141–187.

Elkind, J.I. (1964). A survey of the development of models for the human controller. In R.C. Langford and C.J. Mundo (Eds.), *Guidance and Control—II*, Vol. 13 of *Progress in Astronautics and Aeronautics*. Academic Press, New York, pp. 623–643.

Summers, L.G. and K. Ziedman (1964). *A Study of Manual Control Methodology with Annotated Bibliography*. NASA CR-125.

Young, L.R. and L. Stark (1965). *Biological Control Systems—A Critical Review and Evaluation*. NASA CR-190.

Costello, R.G. and T.J. Higgins (1966). An inclusive classified bibliography pertaining to modeling the human operator as an element in an automatic control system. *IEEE Trans. Human Factors in Elect.*, **7**, 174.

McRuer, D.T. and H.R. Jex (1967). A review of quasi-linear pilot models. *IEEE Trans. Human Factors in Elect.*, **8**, 231.

Young, L.R. (1973). Human control capabilities. In J.F. Parker, Jr., and V.R. West (Eds.), *Bioastronautics Data Book*. Chap. 16, 2nd ed., NASA SP-3006, pp. 751–806.

Sheridan, T.B. and W.R. Ferrell (1974). *Man Machine Systems: Information, Control, and Decision Models of Human Performance*. The MIT Press, Cambridge.

McRuer, D.T. and E.S. Krendel (1974). *Mathematical Models of Human Pilot Behavior*. AGARDograph 188.

REFERENCES

Allen, R.W., W.F. Clement and H.R. Jex (1970). *Research on Display Scanning, Sampling, and Reconstruction Using Separate Main and Secondary Tracking Tasks*. NASA CR-1569.

Allen, R.W., H.R. Jex, D.T. McRuer and R.J. DiMarco (1975). Alcohol effects on driving behavior and performance in a car simulator. *IEEE Trans. Syst., Man Cybern.*, **5**, 498.

Anderson, R.O. (1970). *A New Approach to the Specification and Evaluation of Flying Qualities*. AFFDL-TR-69-120.

Anderson, R.O. (1972). Theoretical pilot rating predictions. In *Handling Qualities Criteria*, AGARD Conf. Proc. 106.

Anderson, R.O., A.J. Connors and J.D. Dillow (1970). *Paper Pilot Ponders Pitch*. AFFDL/FGC-TM-70-1.

Baron, S. and D.L. Kleinman (1968). *The Optimal Controller and Information Processor*. NASA CR-1151. (Also *IEEE Trans. Man–Machine Syst.*, **10**, 1969, 9.)

Baron, S., D.L. Kleinman, D.C. Miller, W.H. Kleinman and J.I. Elkind (1970). *Application of Optimal Control Theory to the Prediction of Human Performance in a Complex Task*. AFFDL-TR-69-81.

Bekey, G.A. and J.M. Biddle (1967). The effect of a random-sampling interval on a sampled-data model of the human operator. In *Third Annual NASA-University Confecence on Manual Control*, NASA SP-144, 247.

Bryson, A.E. and Y.C. Ho (1969). *Applied Optimal Control*. Blaisdell, Waltham, MA.

Curry, R. E., W.C. Hoffman and L.R. Young (1976). *Pilot Modeling for Manned Simulation*. AFFDL-TR-76-124.

Dillow, J.D. (1971). *The "Paper Pilot"—A Digital Computer Program to Predict Pilot Rating for the Hover Task*. AFFDL-TR-70-40.

Elkind, J.I., P.L. Falb, D. Kleinman and W.H. Levison (1968). *An Optimal Control Method for Predicting Control Characteristics and Display Requirements of Manned-Vehicle Systems*. AFFDL-TR-67-187.

Gordon-Smith, M. (1970). An investigation into some aspects of the human describing function while controlling a single degree of freedom. In *Fifth Annual NASA-University Conference on Manual Control*, NASA SP-215, 203. (Also, *An Investigation Into Certain Aspects of the Describing Function of a Human Operator Controlling a System of One Degree of Freedom*. Univ. of Toronto, Inst. for Aerospace Studies, Rept. 149.)

Houk, J. (1963). *A Mathematical Model of the Stretch Reflex in Human Muscle Systems*. M.S. Thesis, MIT.

Jex, H.R. and R.E. Magdaleno (1969). Corroborative data on normalization of human operator remnant. *IEEE Trans. Man–Machine Syst.*, **10**, 137.

Jex, H.R. and R.E. Magdaleno (1978). Biomechanical models for vibration feedthrough to hands and head for a semi-supine pilot. *Aviat. Space Environ. Med.* **49**, 304.

Kleinman, D.L. (1969). Optimal control of linear systems with time-delay and observation noise. *IEEE Trans. Autom. Control* **14**, 524.

Kleinman, D.L. and S. Baron (1971). *Manned Vehicle Systems Analysis by Means of Modern Control Theory*. NASA CR-1753.

Kleinman, D.L. and S. Baron (1973). A control theoretic model for piloted approach to landing. *Automatica* **9**, 339.

Kleinman, D.L., S. Baron and W.H. Levison (1970). An optimal control model of human response, parts 1 and 2. *Automatica* **6**.

Kleinman, D.L., S. Baron and W.H. Levison (1971). A control theoretic approach to manned-vehicle systems analysis. *IEEE Trans. Autom. Control* **16**, 824.

Kleinman, D.L. and T. Perkins (1974). Modeling the human in a time-varying anti-aircraft tracking loop. *IEEE Trans. Autom. Control* **19**, 297.

Kraiss, K.F. (1972). A model for analyzing the coordination of manual movements. In R. Bernotat and K. Gartner (Eds.), *Displays and Controls*. Swetz and Zeitlinger N.V., Amsterdam, pp. 155–174.

Leonard, T.E. (1960). Optimizing linear dynamics for human-operated systems by minimizing the mean square tracking error, *IRE WESCON Convention Record*, 4, *Pt.* **4**, 57–62.

Levison, W.H., S. Baron and D.L. Kleinman (1969). A model for controller remnant. *IEEE Trans. Man–Machine Syst.*, **10**, 101. (Also, Bolt, Beranek, and Newman, Inc., Rept. 1731, 1968).

Levison, W. H. and J.I. Elkind (1967). *Studies of Multivariable Manual Control Systems: Two-Axis Compensatory Systems with Separated Displays and Controls*. NASA CR-875.

Levison, W.H. and J.I. Elkind (1969). *Studies of Multivariable Manual Control Systems: Four-Axis Compensatory Systems with Separated Displays and Controls*. Bolt, Beranek and Newman, Inc., Rept. 1965.

Magdaleno, R.E. and D.T. McRuer (1971). *Experimental Validation and Analytical Elaborationfor Models of the Pilot's Neuromuscular Sub-system in Tracking Tasks*. NASA CR-1757.

Magdaleno, R.E., D.T. McRuer and G.P. Moore (1968) *Small Perturbation Dynamics of the Neuromuscular System in Tracking Tasks*. NASA CR-1212. (Also, A neuromuscular actuation system model. *IEEE. Trans. Man Machine Syst.*, **9**, 61.)

McRuer, D.T. (1973). Human operator system and subsystem dynamic characteristics. In A. S. Iberall and A.C. Guyton (Eds.), *Regulation and Control in Physiological Systems*. Instrument Society of America, Pittsburgh, PA, pp. 230–235.

McRuer, D.T., R.W. Allen, D.H. Weir and R.H. Klein (1977). New results in driver steering control models. *Human Factors* **19**, 381.

McRuer, D.T., D. Graham, E.S. Krendel and W.C. Reisener, Jr. (1966). System performance and operator stationarity in manual control systems. Third IFAC Congress, London.

McRuer, D.T., L.G. Hofmann, H.R. Jex, G.P. Moore, A.V. Phatak, D.H. Weir and J. Wolkovitch (1968). *New Approaches to Human-Pilot/Vehicle Dynamic Analysis*. AFFDL-TR-67-150.

McRuer, D.T., H.R. Jex, W.F. Clement and D. Graham (1967). *Development of a Systems Analysis Theory of Manual Control Displays*. Systems Technology, Inc., TR-163-1.

McRuer, D.T. and E.S. Krendel (1974). *Mathematical Models of Human Pilot Behavior*. AGARDograph 188.

Meiry, J.L. (1965). *The Vestibular System and Human Dynamic Space Orientation.* MIT, Man-Vehicle Control Lab., Thesis T-65-1.

Merton, P.A. (1953). Speculations on the servo-control of movement. In J.L. Malcolm and J.A.B. Gray (Eds.), *The Spinal Cord; a Ciba Foundation Symposium*, Little, Brown and Co., Boston, pp. 247–260.

Miller, D.C. (1970). Human performance in time-optimal state regulation tasks. In *Fifth Annual NASA-University Conference on Manual Control*, NASA SP-215, 483.

Okabe, Y., H.E. Rhodes, L. Stark and P.A. Willis (1962). Transient responses of human motor coordination systems. In *MIT Research Lab. of Electronics*, QPR-66, pp. 389–395.

Peters, R.A. (1969). *Dynamics of the Vestibular System and Their Relation to Motion Perception, Spatial Disorientation, and Illusions.* NASA CR-1309.

Ringland, R.F. and R.L. Stapleford (1972). *Experimental Measurements of Motion Cue Effects on STOL Approach Tasks.* NASA CR-114458.

Roig, R.W. (1962). A comparison between human operator and optimum linear controller rms-error performance. *IEEE Trans. Human Factors in Elect.*, **3**, 18.

Schweizer, G. (1972). Some contributions to the theory of linear models describing the control behaviour of the human operator. In R.K. Bernotat and K.P. Gartner (Eds.), *Displays and Controls.* Swets and Zeitlinger N.V., Amsterdam, pp. 327–348.

Shirley, R.S. (1968). *Motion Cues in Man-Vehicle Control.* MIT, ScD Thesis, MVT-68-1. (Also R.S. Shirley and L.R. Young, Motion cues in man–vehicle control: effects of roll-motion cues on human operator's behavior in compensatory systems with disturbance inputs. *IEEE Trans. Man–Machine Syst.* **9**, 121.)

Smith, O.J.M. (1962). Nonlinear computations in the human controller. *IRE Trans. Biomed. Eng.* **9**, 125.

Stapleford, R.L., R.A. Peters and F.R. Alex (1969). *Experiments and a Model for Pilot Dynamics with Visual and Motion Inputs.* NASA CR-1325.

Stark, L. (1968). *Neurological Control Systems: Studies in Bioengineering.* Plenum Press, New York.

Sun, H.H., B.A. Eisenstein and H. Bomze (1966). Dynamic model for hand motor coordination system. In G.G. Vurek (Ed.), *Proceedings of the Annual Conference on Engineering in Medicine and Biology*, Vol. 8. Inst. Soc. of America, Pittsburgh, PA, p. 100.

Teper. G.L. (1972). *An Assessment of the "Paper Pilot"—An Analytical Approach to the Specification and Evaluation of Flying Qualities.* AFFDL-TR-71-174.

van Wyjk, R.A. and J.J. Kok (1977). Theoretic aspects of the identification of the parameters in the optimal control model. *Proceedings of the 13th Annual Conference on Manual Control*, MIT, Cambridge, MA, pp. 27–34.

Vossius, G. (1965). Der kybernetische Aspekt der Willkurbewegung. *Progress in Cybernetics.* Elsevier, New York.

Vossius, G. (1972), The functional organization of object-directed human intended-movement and the forming of a mathematical model. In R.K. Bernotat and K.P. Gartner (Eds.), *Displays and Controls.* Swets and Zeitlinger N.V., Amsterdam, pp. 389–413.

Vossius, G., and J. Werner (1970). Experimental and generalized mathematical analysis of the human motor system. In *Sixth Annual Conference on Manual Control*, AFIT/AFFDL, Wright-Patterson AFB, Ohio, pp. 269–276.

Weir, D.H. and R.H. Klein (1970). *The Measurement and Analysis of Pilot Scanning and Control Behavior During Simulated Instrument Approaches.* NASA CR-1535.

Weir, D.H. and D.T. McRuer (1970). Dynamics of a driver/-vehicle steering control. *Automatica* **6**, 87.

Young, L.R. and L. Stark (1965). *Biological Control Systems—A Critical Review and Evaluation.* NASA CR-190.