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IDENTIFICATION OF HUMAN OPERATOR PERFORMANCE MODELS UTILIZING TIME SERIES ANALYSIS

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I. INTRODUCTION

One of the missions of the Aerospace Medical Research Laboratory (AMRL) is to define the effects of stress encountered in Air Force missions upon man, and to use this understanding to develop means to alleviate the harmful effects of the stresses or to advise aircraft designers of the limits of man's capacity to withstand these stresses. A second mission of the Laboratory is to develop an understanding of how a man achieves control of a complex, dynamic system, such as an aircraft, in order that aircraft designers can use this understanding to build work space environments, display systems, and control systems which optimize man's control capability.

Until recently, accomplishment of both of these mission goals has been achieved through the classic disciplines of environmental medicine and physiology on the one hand and performance and engineering psychology on the other hand. Both of these approaches have contributed a substantial amount of information and data to the aerospace vehicle designer and have also advanced the state of our understanding of man as a subsystem of a larger, complex system. Neither of these approaches, however, provides data or information concerning man as a subsystem of a larger system which can be directly equated to the type of information which an engineer uses in the design and development of an airframe.

To design a control system for an aircraft, an engineer needs to know the performance specifications of the aircraft, the variables available to him for control of the airframe, the equations of motion to the aircraft and the associated stability coefficients, and the characteristics of the signals which will be used to provide inputs to the controller. For example, consider building a control system with one or more of these pieces of information unspecified or unavailable. Consider further the possibility of not having accurate information about the effects of the flying environment upon the integrity or stability of the components which must be used in building the controller or the components of the airframe.

Man, as a subsystem in a larger system, is usually a controller. He uses information available to him to effect changes in the controls available to him in order to achieve some level of performance of the whole system. He must cope with both dynamic changes in the characteristics of the controlled system due to environmental effects and with changes in himself due to the effects of the environment and the motion of his vehicle. The primary hypothesis recently advanced by the AMRL is that adequate descriptions of man as a controller, expressed in equations usable by the design engineer, can be used to understand how man is affected by stress and how man achieves control of complex, dynamic systems. Further, these equations can be used to optimize the performance capability of the entire system by lessening the stress effects and creating a more efficient man-machine division of labor.

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In an attempt to describe man as a subsystem in manned weapon systems, several approaches to the modeling of the human operator have been tried. This paper presents the results of an effort performed by Sperry Systems Management Division (SSMD) for AMRL in applying time series analysis as a tool for modeling the human operator. In addition, it indicates how this technique can be utilized for determining the variation of the human transfer function under various levels of stress. The approach is useful as it does not require the postulation of a model and then checking its adequacy or inadequacy with actual performance. Instead, the method determines the human operator's model based on actual input and output data from a tracking experiment.

II. HUMAN OPERATOR PERFORMANCE MODELING

a) Previous Human Modeling Efforts

A multitude of mathematical models exist to describe human operator performance.[1] Although a study of these models leads one to conclude that they look at the problem from relatively narrow viewpoints, previous modeling efforts served to provide knowledge and greater understanding of this complex problem. The approach of these previous models has been to postulate models, and then to check their predictive capability against actual data. Analysis of these previous efforts has resulted in the use of "remnant components" which represent those portions of the actual data which the model cannot account for. The remnant represents primarily the components due to nonstationarity, nonlinearities, and time variability of the human response. In many cases, the remnant represents the major portion of the output. This shortcoming of previous human modeling approaches is overcome with time series analysis which determines the human operator's model based on actual input and output data from a tracking experiment.

b) AMRL Modeling Efforts

AMRL has been involved in human operator modeling efforts for the past eight years. The Crossover model (AFFDL 65-15) and its adjustment rules have been exercised by several divisions in the Laboratory and at the School of Aerospace Medicine at Brooks AFB, Texas, to measure the effects of motion and drugs upon humans. Further, as an indirect measure of the parameters of a model for a human controller, the first and second order Unstable Tracking Task has been widely used. The development efforts of the laboratory have included research into analog parameter trackers, frequency and time domain methods for identification of human operators. Specific models of anti-aircraft gunners have also been developed under sponsorship of AMRL based upon the Optimal Control Model representation of human operators. The Laboratory has, therefore, participated in the entire range of human operator modeling, from the basic research into identification techniques to the development of models to be used by the design and analysis engineering communities.

The major reason for such a broad involvement in human operator modeling by AMRL is that the existing state-of-the-art in modeling capability is on the edge of providing significant breakthroughs in achieving the goals identified previously. In the laboratory setting, existing modeling approaches appear to be adequate. In the operational environment, however, the existing methodologies account for an insufficient amount of the output power of the human operator or do not effectively deal with the complex mixture of multiple discrete and continuous control paths used by man.

c) Effects of Stress on the Human Controller

Stress (an ill-defined word but a usable concept) can affect man physically, such as by acceleration forces; physiologically, such as by altered central nervous system function in response to drugs; and psychologically, by anxiety and fear. The modeling of human transfer functions which can account for stress is of great interest. Physical stresses can have a direct effect upon manual control capability. Physiologic and psychologic stress, however, can indirectly affect man's control capability. The manifestation of these indirect effects in changes in the human operator can be extremely subtle. There are tests, which can be given to a stressed man, which are more sensitive in exposing altered human performance due to the stress than can be currently developed by the manual control community. Rather than being an affront to the methodologies used by the manual control community, this fact is an accolade to man's capability to compensate for the indirect effects of the stresses. Total system performance may not measurably change until the physiologic and psychologic structure of the man cannot sustain intelligent responses on his part.

That man, as a controller, is changing under mild physiologic stress is assumed to be true; and the fault with existing methodologies for human operator identification is assumed to be their lack of sensitivity in elucidating these changes. The study which is reported upon here was designed to expose the veracity of the above statement.

d) The Experiment Analyzed

AMRL has the facilities to expose man to a number of differing kinds of stress and combinations of stress. Acceleration stress, as one of its effects upon man, causes both local tissue and system c hypoxia. In order to separate the physical effects of acceleration stress from the hypoxic effects, a short study was run using three subjects and breathing mixtures representative of sea level and 15,000 feet altitude ($PA_{O_2} \approx 60\%$ saturation). The subjects were instructed to perform a single axis compensatory tracking task consisting of a random forcing function and a third order representation of the pitch axis dynamics of a high performance aircraft. Randomization of the sequence of altitude exposures and multiple replications of the runs were accomplished to maximize the accuracy of the measurement of the error variance. The study concluded with the observation that the variance and mean of tracking error for the two minute task was not affected by the changes in altitude. The data acquired during the two minute runs consisted of the forcing function, the tracking error, and the control stick output sampled at 20 msec intervals. This data was subsequently analyzed using time series analysis.

Figure 1 illustrates the experimental compensatory tracking configuration utilized. The forcing function, n(t), represented the resultant output of a noise generator. The transfer function of the plant, H, was set at 1, 1/s, and $1/s^2$. The human operator was attempting to track the input of a compensatory tracking display in a simulated F-4 cockpit.

For purposes of this report, the three subjects utilized for this study will be referred to as subjects A, B, and C. In order to gain flexibility in analyzing the experiments, several runs were repeated the same day and on other days in order to determine variations due to time, learning, adaptability, etc.

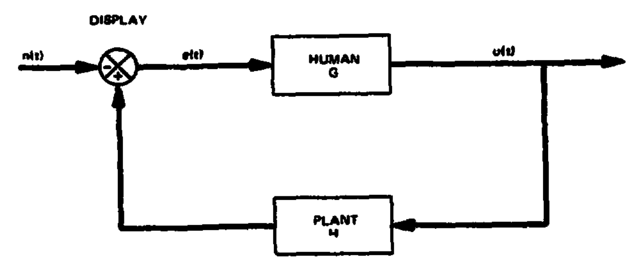

Figure 1. Experiment Block Diagram

III. DATA REDUCTION USING TIME SERIES ANALYSIS

a) Time Series Representation

Time series representation of discrete linear random processes consists of linear difference operations which relate the time series data x_t to a white noise process, z_t. A purely white noise process is represented by

$$x_t = z_t \tag{1}$$

An autoregressive (AR) model of order p is represented by

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots + \phi_i x_{t-i} + \dots + \phi_p x_{t-p} + z_t \tag{2}$$

where ϕ_i for i = 1,..., p are the model coefficients. By defining the backward shift operator

$$Bz_t = z_{t-1} \tag{3}$$

then the general AR equation can be given by

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_i B^i - \dots - \phi_p B^p)\, x_t = z_t \tag{4}$$

A moving average (MA) process of order q is represented by

$$x_t = z_t - \theta_1 z_{t-1} - \theta_2 z_{t-2} - \cdots - \theta_i z_{t-i} - \cdots - \theta_q z_{t-q} \quad (5)$$

In terms of the backward shift operator B, this equation is given by

$$x_t = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_i B^i - \cdots - \theta_q B^q) z_t \quad (6)$$

A general mixed AR/MA process is given by

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + z_t - \theta_1 z_{t-1} - \theta_2 z_{t-2} - \cdots - \theta_q z_{t-q} \quad (7)$$

In terms of the B operator, this equation is given by

$$(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_i B^i - \cdots - \phi_p B^p)\, x_t = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_i B^i - \cdots - \theta_q B^q) z_t \quad (8)$$

Differencing of the data is necessary to induce stationarity, if the data is comprised of nonstationary processes such as a ramp or random walk in addition to a stationary process. The representation of one difference of data is given by

$$x_t - x_{t-1} = (1 - B)\, x_t \quad (9)$$

The representation of d differences of data is given by

$$(1 - B)^d\, x_t \quad (10)$$

b) Model Building Approach

Data reduction using time series analysis produces a mathematical model by reducing a wave form to white noise while identifying the correlated portion of the time series. The mathematical model is obtained by a three stage iterative procedure based on identification, estimation, and diagnostic checking. The identification process is concerned with the generation of the series in order to determine a class of models that should be investigated. The estimation phase uses the data to make inferences about parameters conditioned on the sufficiency of the model chosen. Diagnostic checking analyzes the fitted model with the data in order to determine any model inadequacies and obtaining model improvements.

c) Identification

In the identification stage of model building, the observations x_t are differenced as many times as required to induce stationarity. The resulting AR/MA process is then identified by analyzing the autocovariance function (ACVF), the autocorrelation function (ACF), and the partial correlation function (PCF)[1]. These functions are also useful for obtaining approximate estimates of the parameters which are useful in the estimation stage for providing initial values needed by the iterative estimation procedures. As shown in Figure 2, the pure AR and MA processes are duals of one another, and opposite behavior of ACF and PCF indicates a pure AR or MA process.

d) Estimation

The estimation technique for determining the ϕ and θ parameters used Marquardt's Algorithm[3]. This nonlinear estimation approach performs an optimum interpolation between two traditional nonlinear estimation techniques - the Gauss (Taylor Series) method and the method of steepest descent. The algorithm combines the advantages of the ability of the steepest descent to converge from an initial guess which may be far from the final value, and the ability of the Gauss method to close in on the converged values quickly once the vicinity of the final value has been reached. In addition, Marquardt's algorithm overcomes the disadvantages of the slow final convergence of the steepest descent and the possible divergence of the successive iteration with the Gauss method.

e) Diagnostic Checking

The diagnostic checking step is concerned with examining the white noise residuals, z_t, from the fitted models in order to determine any lack of randomness. Analysis of z_t can indicate whether the model is adequate or inadequate, and yield information on how to better describe the series. Modified models would then be refitted and resubjected to diagnostic checking.

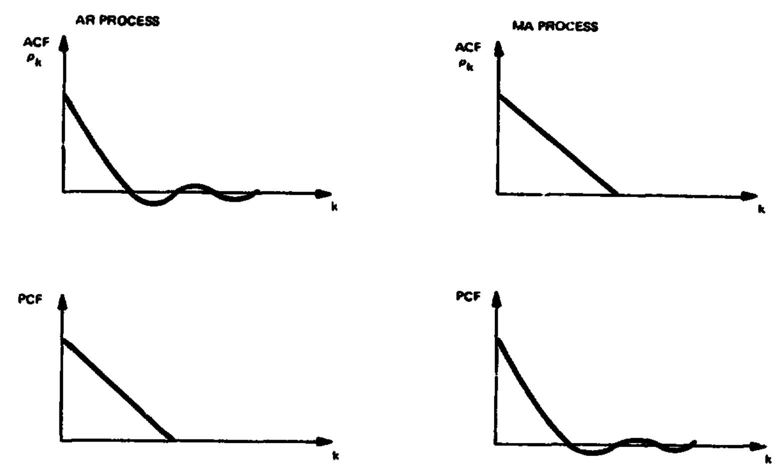

Figure 2. Comparison of ACF and PCF for Pure AR and MA Processes

f) <u>Transfer Function Development</u>

Time series analysis techniques can be extended to obtain discrete linear transfer functions of systems having an input time series x_t and an output time series y_t. For the system illustrated in Figure 3, it is assumed that the system can be adequately represented by the impulse response parameters, v_0, v_1, v_2, v_3, v_4, and v_5. Therefore, y_t is related to x_t by

$$y_t = (v_0 + v_1 B + v_2 B^2 + v_3 B^3 + v_4 B^4 + v_5 B^5)\, x_t \qquad (11)$$

In general, for a dynamic system containing input observations x_t and output observations y_t,

$$y_t = v\,(B)\, x_t \qquad (12)$$

where $v\,(B)$ represents the impulse response function of the system.

The input/output relationship of the type of system represented by Figure 3 can also be represented by the following general linear difference equation:

$$(1 - \zeta_1 B - \cdots - \zeta_R B^R)\, y_t = (\omega_0 - \omega_1 B - \ldots - \omega_S B^S)\, x_{t-b} \qquad (13)$$

or

$$\zeta\,(B)\, y_t = \omega\,(B)\, x_{t-b} \qquad (14)$$

Solving for y_t, the following expression is obtained:

$$y_t = \zeta^{-1}(B)\ \omega(B)\ x_{t-b} = \zeta^{-1}(B)\, \omega(B)\ B^b\ x_t \qquad (15)$$

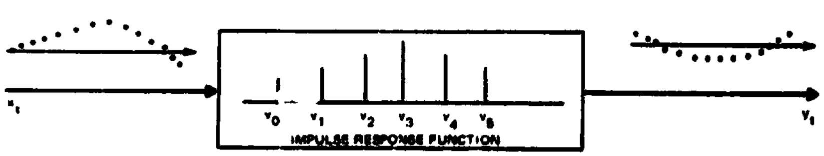

Figure 3. The Input/Output Model

By defining

$$\Omega\,(B) = \omega\,(B)\ B^b \qquad (16)$$

Equation 15 can be written as

$$y_t = \zeta^{-1}(B)\, \Omega\,(B)\, x_t \qquad (17)$$

Comparing Equation 17 with 12, we find that

$$v\,(B) = \zeta^{-1}(B)\, \Omega\,(B)$$

Using the definition of Equation 12 for the discrete transfer function of the system and substituting this into the difference Equation 13, the following identity is obtained:

$$(1 - \zeta_1 B - \cdots - \zeta_R B^R)\,(v_0 + v_1 B + v_2 B^2 + \ldots) = (\omega_0 - \omega_1 B - \cdots - \omega_S B^S) \qquad (18)$$

The following set of equations is obtained by equating like powers of B:

$$v_j = 0,\ j < b \qquad (19)$$

$$v_j = \zeta_1 v_{j-1} + \zeta_2 v_{j-2} + \cdots + \zeta_R v_{j-R} + \omega_0,\ j = b \qquad (20)$$

$$v_j = \zeta_1 v_{j-1} + \zeta_2 v_{j-2} + \cdots + \zeta_R v_{j-R} - \omega_{j-b},\ j = b+1, \ldots, b+S \qquad (21)$$

$$v_j = \zeta_1 v_{j-1} + \zeta_2 v_{j-2} + \cdots + \zeta_R v_{j-R},\ j > b+S \qquad (22)$$

The relationship of the v_j parameters from the impulse response function to the ζ and ω parameters of the difference equation representation are illustrated in Equations 19 through 22.

The transfer function model identification process is greatly simplified if the input to the system is white noise since the cross correlation function between a white noise input and the system output represents the impulse response function of the system. If the input is some other stochastic process, simplification is possible by performing an operation denoted as "prewhitening".[3] This approach was used in this study.

The estimation technique used for obtaining the ζ and ω parameters for difference Equation 15 is analogous to that given for the one dimensional modeling case. After applying Marquardt's Algorithm, the resulting model is of the form

$$y_t = \zeta^{-1}(B)\ \omega(B)\ \ B^b x_t + R_t \qquad (23)$$

where R_t represents the residual signal not correlated with the input. Solving equation 23 for R_t, the following expression is obtained:

$$R_t = \left[\, y_t - \zeta^{-1}(B)\ \ \omega(B)\ \ B^b\ \ x_t \,\right] \qquad (24)$$

The procedure determines the ζ and ω parameters by attempting to minimize the following sum of squares function:

$$S(\zeta, \omega) = \sum_{t=1}^{N} R_t^2 \qquad (25)$$

The diagnostic checking procedure is analogous to that given for the one dimensional case.

g) <u>Transfer Function Development in a Feedback Loop</u>

This study was concerned with modeling the human operator in a compensatory tracking system[1] as shown in Figure 1. The human transfer function G cannot be obtained directly by only considering the time series e_t and u_t, since the residual R_t must be independently distributed of e_t. For example, its cross correlation function must be zero for all lags:

$$E\left[(R_t - \bar{R})(e_{t+\tau} - \bar{e})\right] = 0 \qquad (26)$$

If this is violated, then the parameter estimates obtained are not consistent. Unfortunately, when a dynamical system as the human transfer function, is located within a feedback loop, the independence assumption between e_t and R_t does not hold.[4] In order to overcome the problem, the signals e_t and u_t must be analyzed with respect to the input signal R_t. Since R_t is an externally generated random noise series, it is uncorrelated with any noise generated within the system and present at the output or error signal.

Based on classical control Technique,[5,6] the following equations can be defined relating u_t to n_t, and e_t to n_t:

$$u_t = \frac{G(B)}{1 + G(B)\,H(B)}\, n_t + z_{1,t} \qquad (27)$$

$$e_t = \frac{1}{1 + G(B)\,H(B)}\, n_t + z_{2,t} \qquad (28)$$

where

G (B) Human transfer function

H (B) Plant transfer function

$z_{1,t}$, $z_{2,t}$ Noise components on the output signals uncorrelated with the input signal n_t

By redefining the control ratios

$$T_u(B) = \frac{G(B)}{1 + G(B)\,H(B)} \qquad (29)$$

$$T_e(B) = \frac{1}{1 + G(B)\,H(B)} \qquad (30)$$

the human transfer function G(B) can be obtained using the following equation:

$$G = \frac{T_u(B)}{T_e(B)} \qquad (31)$$

Therefore, the pilot transfer function in this experiment was obtained from transfer functions relating output/input and error/input.

IV. HUMAN OPERATOR PERFORMANCE MODELS

The human operator transfer functions and residual characteristics for the various experiments analyzed in which H = 1 are shown in Figure 4. Based on these results, the following general conclusions can be made concerning the experiments:

- All of the pilots exhibited a time delay of 0.2 second with a second order denominator.
- Two of the three models had a zero in the numerator.
- The controlling actions for all of the operators modeled resulted in over-damped systems.

An important result obtained from analyzing the residual terms of these models was that the human is a generator of seasonality characteristics. This is a very significant conclusion reached on this study which is not obtainable by means of conventional methods.

Seasonality characteristics indicate that an observation at a particular time is related to observations from previous times in some periodic manner. In order to eliminate the seasonality characteristics from the observations, it is necessary to difference the data by the periods of the seasonality. This operation nullifies the seasonality pattern and emphasizes the actual response. Therefore, the operation $B^s z_t = z_{t-s}$ played a particularly important role in the analysis of the seasonality time series and it was found that the simplifying operation $\nabla_s z_t = (1 - B^s) z_t$ was very useful.

Based on an analysis of the residuals for the three experiments shown in Figure 4, it was concluded that seasonalities were present. Figure 5 summarizes the results of the analysis of these seasonalities. Note that the seasonality periods determined, 0.4, 1.6, and 3.4 seconds, appear to be closely related to some multiple having a fundamental period of 0.4 seconds. It was concluded that the result is due to some "rhymic" motion of the subject operators in attempting to track the random inputs. It appears that the subjects were generating a seasonality variation which they were superimposing on their response in tracking the random inputs. This may be analogous to some of the "dither" inputs used by previous investigators who have postulated various models[7]. Verification of this rhymic effect is a very important result of this study and its origin needs to be investigated further.

The multivariate program was also applied to model experiments in which the plant's transfer function was given by

$$H = \frac{1}{s} \qquad (32)$$

EXPERIMENT						RESIDUAL			
RECORD NO	RUN NO	DURATION (SECS)	SUBJECT	PLANT (H)	HUMAN - $G = \frac{u_t}{\epsilon_t}$	FORM	PARAMETERS	VARIANCE	SYSTEM CHARACTERISTICS
00000	00001	158.72	A	1	$G = \frac{0.488}{(1-0.548)(1+0.54B)}$	(2,0,1)	$\phi_1 = 0.22$, $\phi_2 = 0.52$, $\theta_1 = 0.192$	0.167	OVERDAMPED
00007	00001	153.6	B	1	$G = \frac{0.74(1-0.5288B)B}{(1-0.537B)(1-0.944B)}$	(1,0,1)	$\phi_2 = 0.285$, $\theta_1 = 0.107$	0.516	OVERDAMPED
00004	00001	243.2	C	1	$G = \frac{-0.65(1-0.833B)B}{(1-0.386B)(1-0.97B)}$	(2,0,0)	$\phi_1 = 0.202$, $\phi_2 = 0.108$	1.0[illegible]	OVERDAMPED

NOTE B - DELAY OF 0.2 SEC IN TIME (i.e., $Bx_t = x_{t-0.2}$)

Figure 4. Modeling Results for H = 1

in order to determine the change in the human transfer function when the plant changes. In order to compare performance, the experiment that subject C performed in Record No. 00014, Run No. 00001, was analyzed and compared with his performance when H = 1, in Record No. 00004, Run No. 00001, using the time series method. The results of the two models obtained are compared in Figure 6. Analysis of these two models indicates that the most significant difference with H = 1/s is that a transportation lag does not exist in the numerator, leading one to conclude that the integrator, H = 1/s, provides memory to the system from which the operator is better able to anticipate and predict future actions using the two numerator lead factors of (1-0.958B) and (1+8.75B). However, since the coefficient of the B term, 8.75, is very much greater than the coefficient of 1 in the term (1 + 8.75B), it is interpreted to mean that although there is a small instantaneous response, the predominant response is delayed by 0.2 sec. Therefore, the numerator does approximate a transportation lag with the following result:

$$G = \frac{-3.02\,(1 - 0.958B)B}{(1-0.872B)\,(1 + 0.64B)} \qquad (23)$$

The interpretation of the increase in operator gain from 0.65 in the original transfer function with H = 1, to 3.02 in the approximated new transfer function with H = 1/s is attributed to the decrease in open-loop gain caused by the H = 1/s. Thus, when the operator is controlling the plant H = 1/s, it is necessary that he increase his gain to compensate for the attenuation caused by the plant in order to achieve a desirable bandwidth. This problem was not present with H = 1. Therefore, it is seen that the change in the plant from H = 1 to 1/s supplies the operator with memory from which he is better able to anticipate future action, and also decreases the open-loop gain causing the operator to increase his gain in order to achieve a desirable bandwidth.

RECORD NO.	RUN NO.	SUBJECT	RUN LENGTH (SECS.)	PLANT H	SEASONALITY PERIOD PRESENT IN RESIDUAL (SECS.)
00000	00001	A	158.72	1	3.4
00007	00001	B	153.6	1	0.4
00004	00001	C	243.2	1	1.6

Figure 5. Seasonality Periods Generated by the Human Operator

	Human $G = \frac{u_t}{\epsilon_t}$
Model with H = 1 Record No. 00004, Run No. 00001	$G = \frac{-0.65\,(1-0.833B)B}{(1-0.386B)\,(1-0.97B)}$
Model with H = 1/s Record No. 00014, Run No. 00001	$G = \frac{-0.245\,(1-0.958B)\,(1+8.75B)}{(1-0.872B)\,(1+0.64B)}$

Figure 6. Models of Subject C with Plants of H=1 and 1/s

Examination of the variability of the human transfer function was studied by analyzing experiments similar to those considered in Figures 4 and 5, where the three subjects A, B, and C repeated the compensatory tracking tasks. The program was also applied to examine 30-second "windows" (300 points spaced at 0.1 second intervals) over the duration of the three original experiments analyzed in Figures 4 and 5.

To check the repeatability of the human transfer function, the transfer functions [illegible] subject A repeating Record No. 00000, Run No. 00001, immediately, and for subject C repeating Record No. 00004, Run No. 00001, eleven days later were obtained. Figure 7 compares the two models obtained for subject A; Figure 8 compares the two models obtained for subject C.

	HUMAN $G = \frac{u_t}{e_t}$	DURATION (SECS)	RESIDUAL FORM	RESIDUAL PARAMETERS	RESIDUAL VARIANCE	RESIDUAL SEASONALITY
ORIGINAL MODEL (Record No 00000, Run No 00001, 11/4/71)	$G = \frac{0.486}{(1-0.54B)(1+0.54B)}$	158.72	(2,0,1)	$\phi_1 = 0.22$, $\phi_2 = 0.52$, $\theta_1 = 0.19$	0.167	3.4 Secs
REPEATED MOC (Record No 00000, Run No 00002, 11/4/71)	$G = \frac{(0.032-0.33B)}{(1+0.752B)}$	789.28	(1,1,0)	$\phi_1 = -0.575$	0.108	3.4 Secs

Figure 7. Repeatability of Subject A with H = 1

	HUMAN - $G = \frac{u_t}{e_t}$	DURATION (SECS)	RESIDUAL FORM	RESIDUAL PARAMETERS	RESIDUAL VARIANCE	RESIDUAL SEASONALITY
ORIGINAL MODEL (Record No 00004 Run No 00001, 11/4/71)	$G = \frac{-2.66(1-0.66)B}{(1-0.388B)(1-0.97B)}$	243.2	(2,0,0)	$\phi_1 = 0.202$, $\phi_2 = 0.109$	1.06	1.6 Secs
REPEATED MODEL (Record No 00013, Run No 00002, 11/15/71)	$G = \frac{-0.51(1-0.974B)B}{(1-0.71B)(1-0.99B)}$	153.6	(1,0,0)	$\phi_1 = 0.566$	1.14	1.6 Secs

Figure 8. Repeatability of Subject C with H = 1

It is observed from Figure 7 that the model of subject A has changed considerably by having subject A immediately repeat the experiment. It is significant to note that a transportation lag does not exist in the numerator, leading one to initially conclude that the subject has learned the experiment very well and the numerator factor, (-0.032 - 0.33B), is behaving as an anticipation time constant. However, since the coefficient of the B term, -0.33, is very much greater than the coefficient -0.032, then it is concluded that the numerator approximates a transportation lag with the following result:

$$G = \frac{-0.33B}{(1 + 0.252B)} \qquad (34)$$

Note that the denominator for the repeated experiment only contains one smoothing delay time constant, as compared to the original model. In addition, note the variance of the white noise residual was reduced from 0.167 to 0.108. It was therefore concluded that the subject A had learned the experiment very well and was trying to behave without a transportation lag and required only one smoothing time constant.

For the repetition of the experiment by subject C, whose results are analyzed in Figure 8, it is observed that the form of both the original and repeated models were the same when the experiment was repeated eleven days later. His gain is down and the variance of the white noise residual is up, which could be due to several factors. The only revealing factor concerned with his new model is that the numerator factor (1-0.974B) nearly cancels the denominator factor (1-0.99B) resulting in

$$G = \frac{-0.51B}{(1-0.71B)} \qquad (35)$$

Therefore, it was concluded that there is some learning evidence here, since the subject now only needed one smoothing time constant. However, due to the long time delay between experiments, there isn't much evidence of learning in the set of experiments for subject C, as for the set of experiments for subject A.

Variability of the human transfer function over an entire run was also analyzed. E·perimental data concerned with the tracking performance of subject B in Record No. 00007, Run No. 00001, was chosen for analysis (see Figure 4). Windows located over the first and last 30 seconds of the experiment were modeled and compared with that previously obtained over the entire experiment which lasted 153.6 seconds. Figure 9 compares the original model obtained over the entire length of the experiment with those models obtained by investigating the 30 second windows located at the beginning and at the [illegible] of the experiment. Note from this table that for the Model Number 1, the pole at (1-0.94B) is fairly close to the zero at (1-0.93B) and could be cancelled to obtain the approximate model shown. In the case of models numbered 2 and 3, however, notice that there are poles and zeros which are exactly equal, or extremely close, and can be cancelled very precisely resulting in very good, approximate models as shown.

Based on these results, it was concluded that the models for the 30 second windows can be approximated very well be first order transfer functions. In addition, the model for the entire run can be approximated as a first order transfer function with lesser accuracy. Analysis of the results for the continuous time equivalent of the approximate model is quite interesting. It indicates that the gain of the human operator is constant over the entire experiment. However, the time constant changes over a wide range: 0.5 seconds for the first 30 second window; .2 seconds for the final 30 second window; an average of .3 seconds over the entire experiment. This would appear to indicate that

		Sampling Interval (Secs)	Definition of B	Exact Model	Approximate Model	Continuous Time Equivalents of the Approximate Model
				Human = $G = \frac{u_t}{e_t}$	Human $G = \frac{u_t}{e_t}$	Human = $G = \frac{Ke^{-0.2s}}{(s+a)}$
Model No 1	Model for Entire Experiment Lasting for 153.6 Seconds	0.2	$Bx_t = x_{t-0.2}$	$\frac{0.74(1-0.83B)B}{(1-0.54B)(1-0.94B)}$	$\frac{0.74B}{(1-0.54B)}$	$\frac{5e^{-0.2s}}{(s+3)}$
Model No 2	Model for Window Located Over First 30 Seconds of Data	0.1	$Bx_t = x_{t-0.1}$	$\frac{0.82(1-0.97B^2)B^2}{(1-0.68B^2)(1-0.98B^2)}$	$\frac{0.82B^2}{(1-0.68B^2)}$	$\frac{5e^{-0.2s}}{(s+2)}$
Model No 3	Model for Window Located Over Last 30 Seconds of Data	0.1	$Bx_t = x_{t-0.1}$	$\frac{0.64(1-0.90B^2)B^2}{(1-0.36B^2)(1-0.90B^2)}$	$\frac{0.64B^2}{(1-0.36B^2)}$	$\frac{5e^{-0.2s}}{(s+5)}$

Figure 9. Window Sample Analysis of Subject B with H = 1

the human operator is applying much more smoothing during the earlier part of the experiment than at the end. Therefore, his response time is faster towards the later part of the experiment indicating that he has learned and can anticipate changes, with the result that he can respond faster.

Time series analysis has the capability of modeling human operator transfer functions under task and/or environmental stress conditions. As an illustration of its application in this manner, consider a human operator in a compensatory tracking situation. It is desired to determine the variations of his model's parameters under hypoxia stress and he is required to perform the tracking task under simulated oxygen levels corresponding to sea level, 12,000 feet and 22,000 feet. For each of these three experiments, the program can determine the human transfer function directly from the data very efficiently.

It might also be desired to determine the parameter variation of the human transfer function under combinations of stress. For example, the program could be extended and applied for determining the human operator model while he is tracking a target on a compensatory display with various combinations of stress including hypoxia, roll, pitch, vibration, heat, etc. The program could be further applied for determining the effect of these stresses on such physiological parameters as blood pressure, heart rate, etc.

Due to budget limitations the program was not extended to model stress data. For the same reason, the program was not applied to model pilot compensatory tracking data for areas where the element H was changed to $1/s^2$.

CONCLUSIONS

This pioneering effort for applying time series analysis to model the human operator represents the first time that time series theory has been applied to this problem and its results have been most illuminating. The foremost conclusion found on this study is that the time series method is a very efficient, effective, and powerful method for modeling any dynamical process having an input and output which contains noisy observations. Application of the time series technique to modeling the human operator in a compensatory tracking situation indicated that he can be adequately represented in the B domain by the B-transfer function having the following form.

$$G(B) = \frac{K(1-T_1B)B}{(1-T_2B)(1+T_3B)} \tag{36}$$

plus a residual containing a completely modeled mixed AR/MA structure and white noise.

It was also concluded that when the plant's transfer function was changed from 1 to 1/s, the integrator, H = 1/s, provided memory to the system, and the operator was better able to anticipate and predict future actions. The resultant model, therefore, did not contain a transportation lag. However, a good approximation to this transfer function contained a transportation lag and it was found that the operator also had to increase his gain significantly. The interpretation of his increase in gain was caused by his compensation for the decrease in the open-loop gain due to the integrator H = 1/s. The operator basically increased his gain in order to achieve a desirable bandwidth.

It was also found that when an operator immediately repeated an experiment, he attempted to eliminate the transportation lag and one of the smoothing time constants.

This is a very significant result and is anticipated based on his ability to learn. However, due to the magnitude of the coefficient, the model still had an effective transportation lag from a practical viewpoint. It was also found that having an operator repeating an experiment several days later indicated very little learning ability.

Analysis of the variability of the human transfer function over the length of the experiment by means of analyzing a small number of points (window) indicated that the human operator is applying much less smoothing during the later part of the experiment. This was interpreted to mean that he has learned and can anticipate changes, with the result that he can respond faster.

A very significant result of this effort was measurements of a seasonality being generated by the operator. These seasonalities are interpreted as a rhymic effect that the operator is generating in order to track random noise.

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