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RESEARCH ON NEW TECHNIQUES FOR THE ANALYSIS OF MANUAL CONTROL SYSTEMS

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I. INTRODUCTION

The major effort during this reporting period was concentrated in the following areas: (1) study of the adaptive behavior of human operators following transitions in controlled element dynamics; (2) identification of unknown sampling frequencies in dynamic systems; (3) modification of the data acquisition system used with manual control experiments, and (4) software development.

II. ADAPTIVE BEHAVIOR OF HUMAN CONTROLLERS

Personnel: A. V. Phatak, G. A. Bekey

Research efforts for the past six months have mainly been in the study of models to describe the adaptive characteristics of the human operator in response to step changes in effective vehicle dynamics. As described in our Progress Report No. 4[1] the human operator is controlling a pure inertia basic airframe with rate and attitude gyro augmentation. Failure of one or both of these two augmentation loops causes a step change in the effective vehicle dynamics controlled by the operator. The failure of the gyro feedbacks may be accompanied by failure transients (ramp or hard-over) which in turn require the operator to introduce a bias in his control effort in order to maintain stability. Table I of Progress Report 4 shows the effective vehicle dynamics for the four different levels of augmentation.

Two different sets of transitions were explored experimentally. These are given in Table I below. For the first set, there are three distinct post-failure vehicle dynamics and six different types of transition possible. The "soft" failure refers to the absence of any failure transient, while the "ramp" and "hard" failures indicate the type of transient, namely, a linear or step change in feedback signal.

Table I. List of Failures Simulated

Pre-Failure Augmentation	Post-Failure Augmentation
1. Rate plus Attitude	Rate only - soft
	Rate only - ramp
	Rate only - hard
	Attitude only - soft
	Attitude only - hard
	None - soft
2. Rate only	None - soft
	None - hard

For each of the four levels of augmentation, it is possible to predict, from existing data, the steady-state describing function models. They fit a four-parameter model of the form:

$$Y_{H.0}(j\omega) = KP \frac{(j\omega + zp)}{(j\omega + pp)} e^{-(TAU)j\omega}$$

Approximate values for the four parameters based on closed-loop servo analysis and available operator data[2] are presented in Table II. Notice that there is a large difference in the describing function parameter values for the four different levels of augmentation, and is quite akin to a change in structure of the compensation itself.

Table II. Approximate Values of Parameters for Steady-State Describing Functions

Augmentation Level	KP	TAU	ZP	PP
Rate plus Attitude	8.0	0.4	3.0	0.2
Rate only	17.0	0.24	-	-
Attitude only	6.0 x60.0	0.1	0.2	60.0
None	3.8 x 60.0	0.39	0.2	60.0

Any adaptive model for the operator must satisfy the boundary constraints of prefailure and postfailure steady-state describing function parameters[3]. Also, the model must incorporate the decision processes involved in making a successful change of structure[4] while maintaining stability. Since there are many alternative dynamics possible after failure, the operator adaptation algorithm must be of a sequential nature where the structural changes in compensation can be carried to conclusion or terminated in the middle depending upon the post-failure dynamics. In other words, the adaptation philosophy must be based on the Principle of Optimality from Dynamic Programming concepts. At present, the following is being done:

1. Data from strip chart records is being digitized and the results used to obtain phase-plane plots for various transitions. Preliminary results indicate that the adaptation seems to accur in three distinct phases:

a) Detection of occurrence of failure

b) Sequential structural adaptation to the required post-failure compensation. This incorporates decision logic to stop the adaptation at a given point in the sequence.

c) Adjustment of parameters to minimize error.

The detection of failure seems to be based on values of error, error rate etc. and the criterion may be taken as deterministic in nature to a first approximation. The operator tracks the maximum (or mean-square) values of the error, error rate and so on, for the prefailure vehicle dynamics and retains these values in memory as upper bounds for the various signal magnitudes. If the error and/or its derivatives exceed the above limits by a certain factor (say two), then failure is assumed to have occurred. Initial results using such a criterion for detection seem promising.

2. Following detection of a failure, the modification of the operator compensation must be carried out with sufficient speed to maintain system stability. One such structural modification scheme with stops at places in between is presently being tested using digital simulation. Again, results look encouraging.

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III. IDENTIFICATION OF UNKNOWN SAMPLING FREQUENCIES IN DYNAMIC SYSTEMS

Personnel: C. B. Neal, G. A. Bekey, M. J. Merritt

The overall problem of identifying an unknown sampling frequency in a sampled-data system is currently thought of as being described by the following collection of increasingly difficult problems:

1a. Identification when the system and sampling are deterministic and the system is fairly well approximated by the model. (see Figure 1)

1b. Identification when the system and sampling are deterministic, but the model poorly approximates the system.

2. Identification when the system and sampling are deterministic and the model is approximate, but the system output is noise-corrupted.

3. Identification when the sampling is deterministic but the system has random parameter and the system output is noise-corrupted.

4. Identification when the sampling is random, the system has random parameters, and the system output is noise-corrupted.

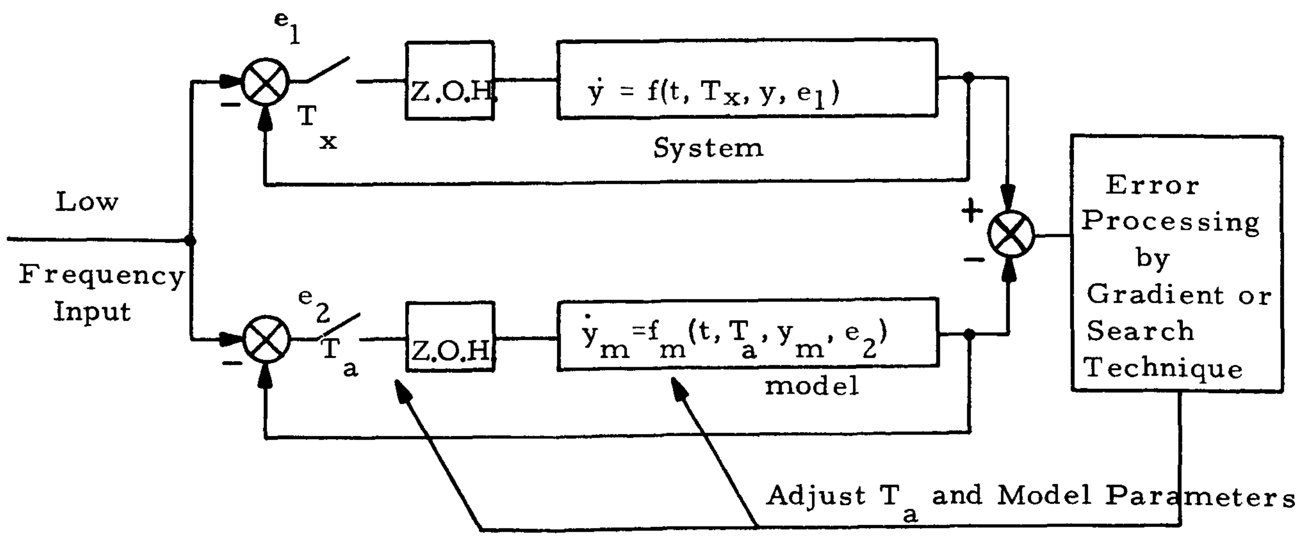

Figure 1 Sampling Interval Identification Scheme

The solution to problems (la) and (lb) has been found and was discussed in Progress Report No. 4 [(1)], a first draft of a report covering this phase has been prepared. During the last period most of the attention was given to Problem 2. However, a comprehensive literature search was conducted for analytical techniques for Problem 3 and 4. The following observations are possible concerning these problems:

1. While analytical treatments of the problem of estimation of movements of random parameters in linear systems have been given by Brainin[(2)], by Cumming [(3)], and by Bogdanoff and Kozin[(4)], the methods have been applied to only the simplest cases. Considerable work would be necessary before it might be possible to treat the case of both random parameter variations and observation noise. It is typical of these treatments that, in general, they necessitate the solution of a Fokker-Planck partial differential equation of the same order as the order of the system[(4)]. Two simple cases occur:

1. When the parameter variations are white noise or when they are gaussian. Then the moments are described by a system of deterministic ordinary linear differential equations.

2. It is not possible to apply any form of regression analysis when the system parameters are random. This is because only additive noise (not multiplicative noise) can be treated by this technique. Additionally, a sequential estimation technique of the Kalman type is ruled out; again, because noise must be additive in order to apply the Kalman estimation procedure.

In treating Problem 2 the following approaches were considered:

1. The application of conventional least-squares and weighted least squares theory following the approaches of Kalman[(5)] and the later work of Steiglitz

and Mc Bride[6]. These techniques yield an iterative estimate of the discrete transfer function representation of the closed loop system the the form

$$\frac{N(z)}{D(z)} = \frac{a_o + a_1 z^{-1} + \ldots + a_{n-1} z^{n-1}}{1 + b_1 z^{-1} + \ldots + b_n z^{-n}}$$

Here $z^{-1} = e^{-zT}$ where T is the interval of sampling at the input and output of the measurement configuration (Figure 2) and does not directly refer to the internal sampling interval (T_x) of the closed loop system. Further

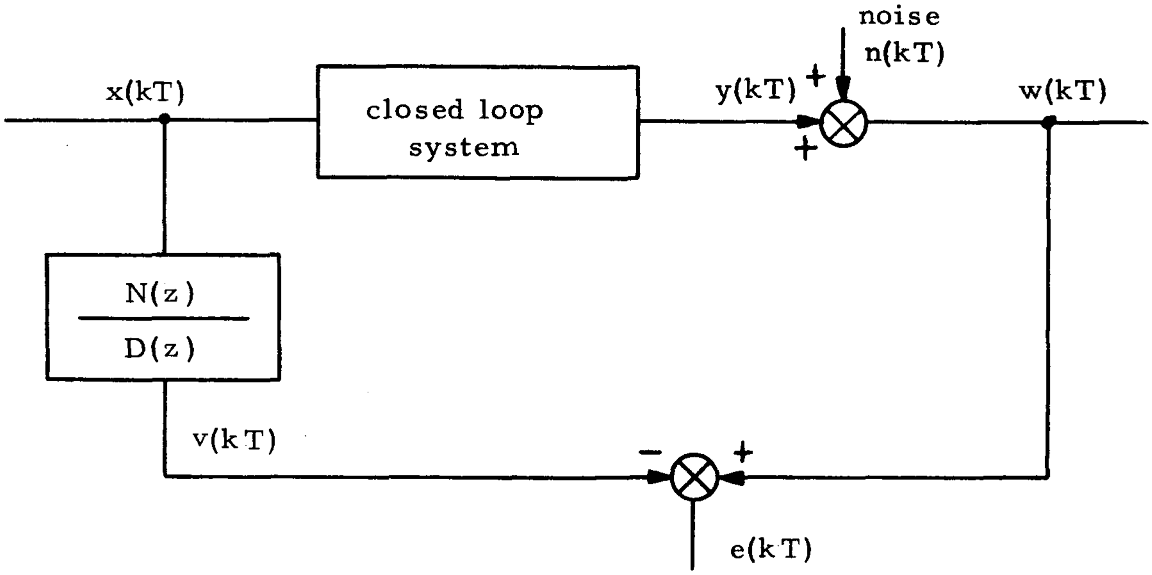

Figure 2

work would be necessary to establish whether T_x could be derived. Only a small amount of time was spent with this scheme because of the comparative promise of stochastic approximation which is discussed below.

2. The technique of stochastic approximation appears attractive for solving Problem 2. Literature search disclosed a considerable body of purely analytical work, but only a few engineering application. Of these, the work of Sakrison[7] can be used directly. It is a multiparameter Kiefer-Wolfowitz

stochastic gradient technique[8] and provided that the iteration process is such that the measurement noise term approaches zero (along with a few easily-met conditions on the cost function) then convergence is no worse than mean square; i. e. if P_n is the n-th estimate of the parameter vector,

$$\lim_{n \to \infty} E \left[\|P_n - \bar{P}\|^2 \right] = 0$$

where $\bar{P}$ is the true value of the system parameter vector. The overall advantage of this method is that it is quite straight forward to compute the Kiefer-Wolfowitz algorithm for the iterative correction to the parameter vector.

Programming of the equations for stochastic approximation of a simple 1st order system (under Problem 2) has been completed. Only the sampling interval will be varied. Later, other parameters will be varied as well.

The IBM CSMP 1130 Program for digital simulation of continuous systems is currently being used in the basic arrangement of Figure 1. Work is also beginning in an attempt to develop a general stochastic approximation treatment for the case of noisy parameters and observation noise.

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IV. MODIFICATION TO THE DATA ACQUISITION STATION

Personnel: M. J. Merritt

The IBM 1710 digital computer described in previous reports has been replaced by an IBM 360 model 44 digital computer. The new IBM 360 computer is almost a thousand times faster and has eight times more memory than the IBM 1710 system and will allow for greater freedom in the design of experiments than was possible previously. Unfortunately, the two systems are sufficiently different that an entirely new interface system and software program are required.

The interface system contains all of the communication between the analog and digital computers:

a) analog to digital converters

b) digital to analog converters

c) digital outputs

d) digital inputs

e) analog mode control

f) cross-bar control for address selection and sot setting

An interface system has been designed and constructed under support from other sources and checkout is in progress.

The operating system and monitor provided with the 360 system are very complex and some difficulty was encountered in operating the ADC's and DAC's at the speeds required for the human pilot and the modeling experiments planned. Many of the difficulties have been overcome by modifying the operating system so that direct control of the converters can be obtained. A comprehensive software package which will allow high speed processing of ADC and DAC data as well as discrete data is being developed under a contract with IBM. The resultant software package will also be available to FORTRAN users and will be essential in our future manual control experiments.

V. ADAPTATION OF IBM 1130 CONTINUOUS SYSTEM MODELING PROGRAM (CSMP) TO THE IBM 360 MODEL 44.

Personnel: M. J. Merritt

The Continuous System Modeling Program (CSMP) is a block structured digital simulation language. Many of the block elements are identical in function to the components of an analog computer; summers, inverters, integrators, potentiometers, etc. Since the computations are carried out digitally, no amplitude scaling or time scaling is necessary. The program as supplied by the SHARE Library was written for an IBM 1130 computer. The program was modified to meet the requirements of the 360 system and was subsequently loaded on a disk file. Both test and production programs have been run successfully and the program is considered fully operational. Current research using stochastic approximation to identify unknown sampling intervals in human pilot models is being performed entirely using CSMP, at a large savings in computer time and increase in reliability as compared to purely analog methods.