DEVELOPMENT OF A STRATEGY MODEL OF THE DRIVER

by

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

The ever expanding population of drivers on our nation's highways has led to a legitimate interest, among researchers and engineers, in the automobile as a control system, its safety, and its limitations. As a better understanding of the driver-automobile system is acquired, highway safety can be improved through better equipment design and more concentrated human operator training. An increased understanding will also aid in evaluating the automobile as a means of transportation and estimating the boundaries within which it can be expected to operate.

One of the most elusive and yet the most essential components in the driver-automobile system is the driver. Because of man's stochastic nature and complex character he is extremely hard to study. However, it is also true that a conventional automobile cannot by itself maintain lane position indefinitely or perform other desired manuevers, except by chance. The driver-vehicle system, then, is dependent upon the driver to provide closed-loop control. Hence, no matter how difficult it is to understand the driver as a control element, his importance in the driver-vehicle system warrants the attempts made in that direction.

It is the aim of this study to examine driver control characteristics as related to driving and, through modeling techniques, to gain some understanding of the driver strategy used in automobile directional control. More specifically, a model of drivers performing the lane-keeping task will be postulated and experimentally tested.

LITERATURE REVIEW

To date, relatively little research has been performed dealing with dynamic modeling of automobile drivers.

Sheridan (1966) proposed three mathematical models for obstacle avoidance based upon notions of constrained preview and nonuniform importance of input. The first model employs an extension of linear convolution; the second model uses an iterative fast-time prediction in parallel with continuous real-time control; and the third model involves a repetitively updated computation of optimal control strategy over the previewed input. The accuracy of each model is limited by the fact that all three involve linear approximations of the driver's control function. Hence, they do not account for any nonlinearities in the driver's response.

An optimization technique developed by Wierwille (1965) was employed by Wierwille, Gagne, and Knight (1967) to model individual operators in the driving task. The technique provided a mathematical procedure for minimizing the mean-squared error (over time) between the driver's output and the model output by iteratively adjusting the model parameters. Wierwille, et al. (1967) then derived a general transfer function for a typical driver based upon the individual models. This modeling technique, although it incorporates error minimization, does not reflect the nonlinearities characteristic of real drivers.

Operators of vehicular systems were described by McRuer and Weir (1969) using a "crossover model". The model was based upon the crossover frequencies of the various loops in a vehicular control system. Using classical control system theory, the model parameters could then be determined. This model, again, is a linear one based upon servo-type modeling techniques.

The above three examples treat the driver as a linear "black box" with concern given only to the loop-closure aspects of the driver-vehicle system. The authors did not investigate or attempt to explain to any appreciable degree the internal strategy employed by the driver in controlling the vehicle. The models used are control theory models and are limited in their ability to accurately describe the nonlinear characteristics of the responses so apparent in real drivers (Wierwille, et al., 1967).

However, one driver modeling study, performed by Kroll (1971), did incorporate a nonlinear model of driver behavior in a formulation aimed at hypothesizing a closed-loop control mechanism suitable for use in the investigation of driver behavior in emergency and precollision situations. Its main emphasis was in modeling situations that were near the limits of vehicle and driver control. Kroll's model presents plausible steering response data, but a detailed experimental comparison with drivers is not presented.

There has been substantial work done in the area of nonlinear and time-varying dynamic models of human operators in the more general area of manual control systems. Probably the earliest work done in the area was an investigation of the time-varying dynamics of human operators by Sheridan (1960). His work was followed by that of Snyder (1964), who examined the nonlinear characteristics of a closed-loop manual control system for compensatory tracking. Later Wierwille and Gagne (1966) investigated linear time-varying, nonlinear time-varying and nonlinear constant coefficient models of human operator dynamics in one- and two-axis tracking systems.

Miller and Elkind (1967) worked with adaptive models of trained human controllers for compensatory velocity control systems.

A surge model was proposed by Costello (1968). This was a dual-mode device containing a linear constant-coefficient model and a second-order controller model. The size of the system's error and its derivative determined the mode within which the model functioned.

In contrast, little work has been done in the area of nonlinear driver modeling, and the internal strategy the driver uses is not understood at present. Previous models have been primarily linear and have described external control system characteristics.

BACKGROUND

It has already been mentioned that driver control behavior is elusive to grasp and understand. Yet, there is reason to believe that the process of driving, say lane-keeping in particular, is a relatively easy task to perform. Senders and Kristofferson (1967) established that driving has a low attentional demand. Large numbers of people are able to successfully drive an automobile with very little training. Indeed, adolescents can be taught the lane-keeping task in a short time. If lane-keeping is a relatively easy task, then perhaps with the right model, driver strategy can be understood.

To aid in the development of such a strategy model it would be helpful to examine first some known characteristics of the human operator as they relate to manual control systems.

One characteristic of human operators is a delay or lag between the time he senses an error in the system output and the time that a corrective action is taken (Birmingham and Taylor, 1954). The "response time" is made up of basically two components -- processing time and transmission time (neuromuscular lag). Processing time is the time needed to decide what corrective action should be taken, whereas, transmission time is the time necessary to initiate that action. The human operator "response time" is an important variable to be considered in manual control systems because it introduces lag into the system and thus affects system stability, the system stability decreasing as lag increases. An effective human operator model, then, should in some way take human response time into consideration.

Another characteristic of human operators is that they tend to compensate for their own lag or response time by "second-guessing" the system's output. In other words, as Wierwille (1964) and Sheridan (1966) point out, trackers use some type of preview control, where possible. The amount of preview that is exercised affects the system's stability. Up to a point, the more preview that is used, the more stable will be the system.

Also inherent in human operators is a finite threshold to input amplitudes. Two possible reasons for the existence of thresholds are the inability of human operators to perceive system errors below a certain level and the lack of concern by human operators about system errors until they reach some level of amplitude. The operator, then, either cannot perceive small errors or he chooses to neglect them. It has been found that as these thresholds decrease the human operator becomes more responsive and thus keeps tighter control of the tracking system (Wierwille, et al., 1967).

Neither must it be forgotten that the human operator exhibits both time-varying and nonlinear behavior. Physiological traits vary among individuals and within individuals over time. A good human operator model should be general enough to allow for these variations. The nonlinear behavior of human operators is an area of little known research. It is suspected, however, that human operator thresholds account in part for these nonlinearities.

An examination of the automobile as a control system should also aid in defining the constraints placed on the driver as a control element. Since this study deals with driver steering control, main consideration should be given to the vehicle lateral-directional dynamics, including, for example, roll angle (ϕ), yaw angle (ψ), and lateral position (y). In general, a driver only indirectly controls vehicle roll. He does so by maintaining the vehicle on the highway, thereby producing acceptable amounts of vehicle roll. On the other hand, the driver, by movement of the steering wheel, controls lateral position and yaw angle in order to maintain correct position and orientation relative to the highway. Consequently, it can be hypothesized that the system variables of interest in vehicle lateral control are primarily yaw angle and lateral position.

It is clear that lateral position provides an indication of the vehicle's present status relative to some given reference. However, due to the nature of the driving task, this reference is not a fixed parameter and can vary over time and from driver to driver (Mourant and Rockwell, 1970). The driver might choose to use the center line as a reference at one time, the right-hand edge of the road at another time, or some point between these two lines. He is free to choose his own reference and change it at will, provided he maintains proper vehicle path.

The nature of automobile dynamics is such that yaw angle is approximately proportional to the derivative of lateral position and gives the vehicle's heading angle with respect to a tangent to the road. Hence, yaw angle may provide some assessment of the vehicle's future trajectory.

The automobile's open-loop transfer function can be obtained by using a linearized approximation of the vehicle equations of motion. The stylized transfer functions of yaw and lateral position for the open-loop automobile may be simplified to the following form for use in a driving simulator:

$$\frac{Y(s)}{\Delta(s)} = \frac{k(s + a)}{s^2(s^2 + bs + c)} \tag{1}$$

for lateral position in response to steering, and:

$$\frac{\Psi(s)}{\Delta(s)} = \frac{kk_1(s + a)}{s(s^2 + bs + c)} \tag{2}$$

for yaw angle in response to steering. In these equations s is the Laplace transform independent variable.

In summary, the following characteristics should be included in a dynamic model of the driver: driver delay, compensation for delay, thresholds, some aspect of time-varying and nonlinear behavior, inputs of yaw angle and lateral position, compatability with automobile transfer function dynamics, and steering as an output.

PROCEDURE

The experimental procedure used in this study differs substantially from that used in other modeling studies, and therefore requires explanation. A combination of analytical and experimental techniques was necessary to arrive at the final models (one for each subject). The basic procedure for determining the final models consisted of the following steps:

(1) A class of models was postualted based on the known characteristics of human operators as discussed in the last section.

(2) The relationships among various parameters of the model-vehicle system were examined by analytic techniques of approximation.

(3) A controlled experiment was performed in a high-quality moving-base driving simulator. Time histories of several man-vehicle responses were recorded for human subjects driving the simulator.

(4) The recorded responses from the simulation were statistically analyzed to yield driver-vehicle performance measures for each subject. These measures were used directly to specify some of the parameters of the model (for each subject). They were also used to provide a means of comparing each final model with its corresponding subject.

(5) The remaining model parameters were obtained by operating each model on line in the simulation (replacing the driver with the model) and adjusting the remaining model parameters until all measures were approximately matched to the corresponding driver responses.

(6) Finally, qualitative checks were made on the detailed character of the time histories of corresponding model and driver.

This thesis will follow the above steps in explaining the details of the study.

Model Specification

Specifying the model consists of selecting the appropriate class of models and examining the analytical relationships inherent in the model class.

There are a number of control models that will provide closed-loop stability for the driver-vehicle system. However, not all of them reflect the driver's steering characteristics. As mentioned earlier, there is reason to believe that a simple control strategy can provide an accurate representation of the driver. Based on that hypothesis and the known human operator characteristics described earlier, the following model form or class is proposed for describing the driver's steering response

$$\delta(t) = \delta_H(t) + \delta_L(t) \tag{3}$$

where: $\delta(t)$ = the total steering response

$\delta_H(t)$ = the portion of the steering response that is unrelated to yaw and lateral position

$\delta_L(t)$ = The steering response that is related to yaw and lateral position and is given by:

$$\delta_L(t) = \int_0^\infty \frac{1}{\tau} e^{-\frac{\lambda}{\tau}} \delta_{L_0}(t - \lambda)\, d\lambda \tag{4}$$

where:

$$\delta_{L_0}(t) = \begin{cases} 0; \text{ for } |y(t) - y_m(t)| < y_o \\ \quad \text{and } |\psi(t)| < \psi_o \\ -k_y(y(t) - y_m(t)); \text{ for} \\ \quad |y(t) - y_m(t)| \geq y_o \\ \quad \text{and } |\psi(t)| < \psi_o \\ -k_\psi \psi(t); \text{ for } |\psi(t)| \geq \psi_o \\ \quad \text{and } |y(t) - y_m(t)| < y_o \\ -k_y(y(t) - y_m(t)) - k_\psi \psi(t); \\ \quad \text{elsewhere} \end{cases} \tag{5}$$

and where: $\delta_{L_0}(t)$ = the steering response prior to the filtering,

τ = the time constant of the lag filter,

k_y = gain of the response to a lateral position error,

k_ψ = gain of the response to a yaw angle error,

y_o = threshold for lateral position errors,

ψ_o = threshold for yaw angle errors, and

$y_m(t)$ = chosen reference for lateral road position

According to this model, the automobile driver uses lateral position errors and yaw deviation errors as criteria for controlling the automobile. The driver evaluates the size of the lateral position error as a function of time. When it exceeds a chosen threshold (y_o) he takes corrective action. This action consists of multiplying the lateral position error by a constant (k_y) and inputting the negative of the adjusted error signal back into the automobile system, by use of the steering wheel. Yaw deviation errors are processed in a similar manner.

The evaluation and decision processes associated with the above error corrections require a finite amount of time. This processing time is represented by the lag time τ in the model.

Furthermore, according to the model, drivers exhibit a make-work steering characteristic ($\delta_H(t)$) (Greenshields, 1970). Some random steering responses, unassociated with the task at hand, would then be evident in modeled steering responses.

Figure 1 shows a block diagram of this model. The parameter definitions will be more completely specified below.

If this is an adequate model, it should be possible to represent an individual driver by specifying k_y, k_ψ, y_o, ψ_o, τ and $y_m(t)$.

Evaluation of Driver-Model Parameters

Now that a class of models has been chosen for investigation it is necessary to evaluate the model parameters as they relate to the

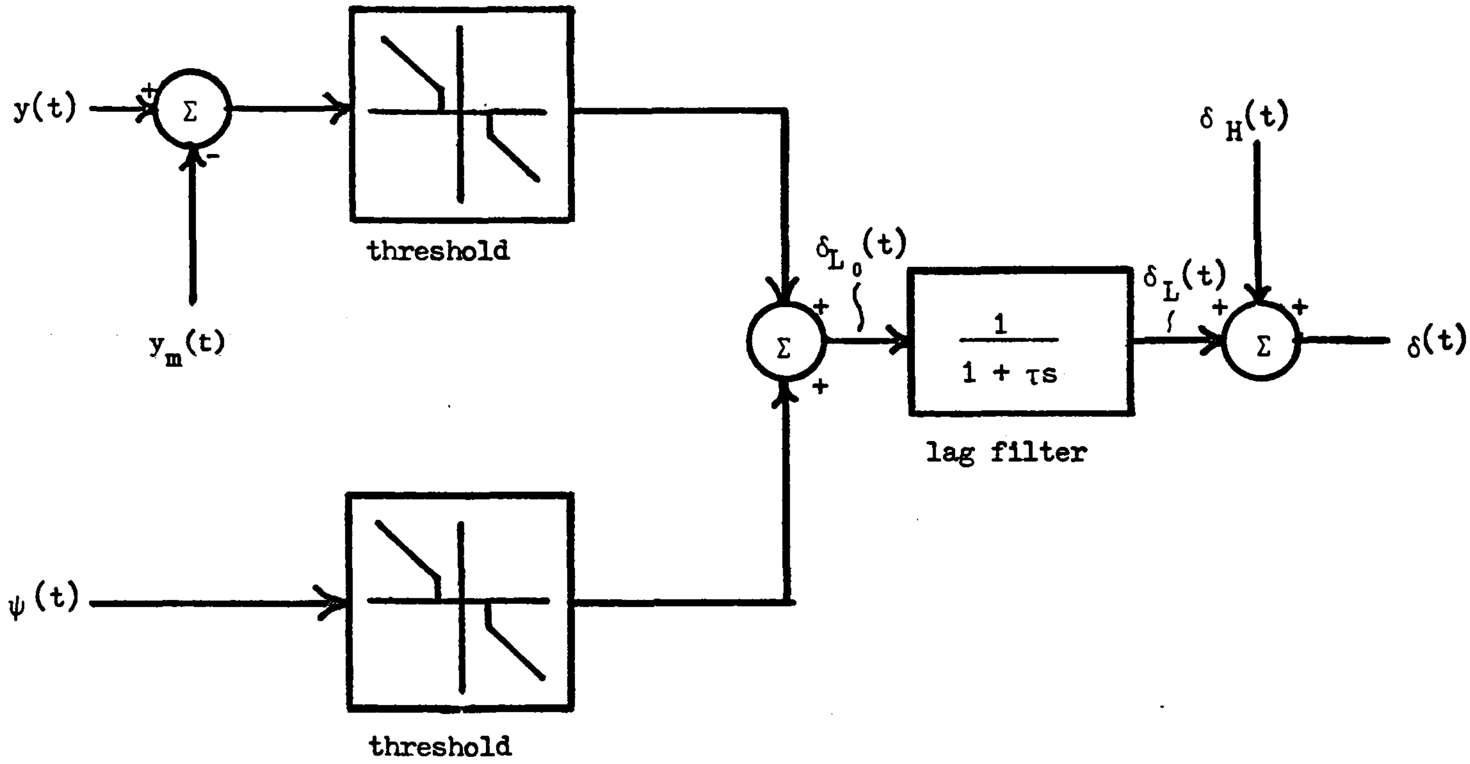

FIGURE 1. Nonlinear Gain Model of the Driver

automobile system.

To aid in the evaluation of the model, the closed-loop stability of the model-vehicle system should first be examined. The model may be temporarily simplified so that a stability analysis can be performed more readily. For the moment, let $\delta_H(t)$, y_o, ψ_o, τ, and $y_m(t)$ equal zero; then the model becomes:

$$\delta(t) = -k_y y(t) - k_\psi \psi(t) \tag{6}$$

The vehicle dynamics might be temporarily replaced by the following simple transfer functions

$$\frac{Y(s)}{\Delta(s)} = \frac{k}{s^2} \tag{7}$$

$$\frac{\psi(s)}{\Delta(s)} = \frac{kk_1}{s} \tag{8}$$

Figure 2 shows the block diagram for this simplified system. Using these two sets of approximations, the system's closed-loop transfer function for lateral position as related to disturbance input becomes:

$$\frac{Y(s)}{N(s)} = \frac{k}{s^2 + kk_1k_\psi s + kk_y}, \tag{9}$$

where the natural frequency, w_n, $= \sqrt{kk_y}$ and where the damping, ζ is

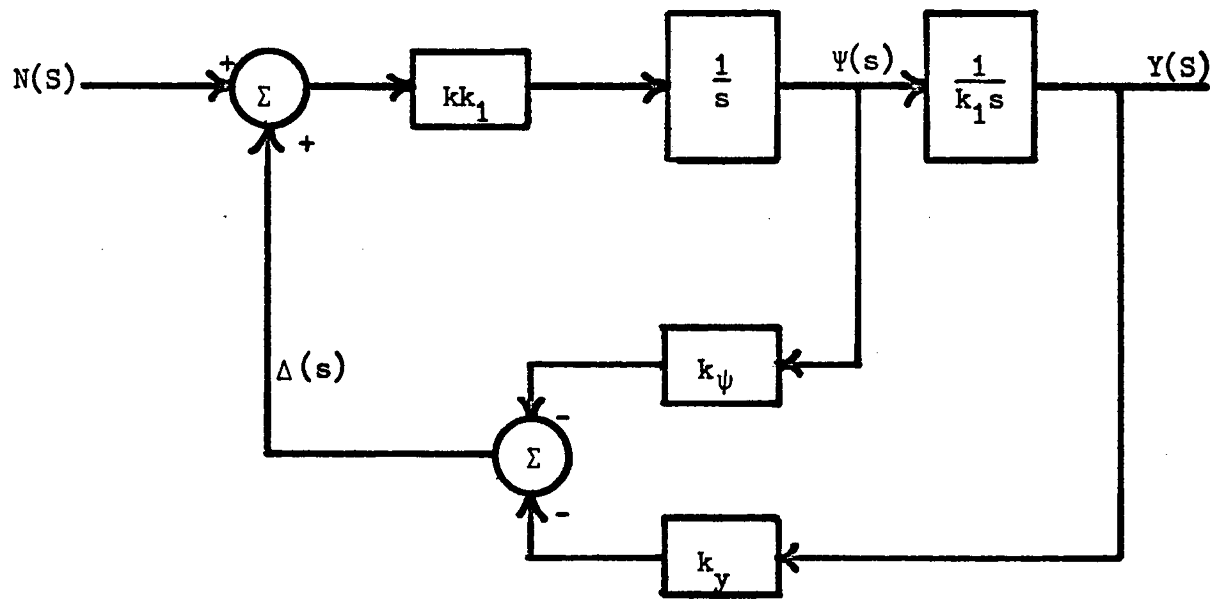

FIGURE 2. Elementary Model of the Driver-Vehicle System

$\frac{k_1\sqrt{K}\,k_\psi}{2\sqrt{k_y}}$.

The closed-loop system stability can be evaluated by examining ζ. As the value of ζ increases from zero to one, the system becomes more stable. Therefore, the system stability will increase as $\frac{k_\psi}{\sqrt{k_y}}$ increases. By adjusting k_y and k_ψ it should then be possible to vary the system stability.

Some criteria then is needed for adjusting k_y and k_ψ, in an attempt to match the stability characteristics of real drivers. If one assumes that the system's forcing function is a random disturbance, n(t), then a statistical approach can be used for approximating k_y and k_ψ. From the configuration of the system, y(t), $\psi(t)$ and $\delta_L(t)$ are functions of n(t). Thus, y(t), $\psi(t)$ and $\delta_L(t)$ are also random variables. Returning now to the complete model as defined in equations (4) and (5), it should be possible to specify k_y and k_ψ.

For $|y(t) - y_m(t)| < y_o$ and $|\psi(t)| < \psi_o$, $\delta_{L_0}(t)$ equals zero. Thus, k_y and k_ψ can take any value when $|y(t) - y_m(t)| < y_o$ and $|\psi(t)| < \psi_o$. Also, if $|y(t) - y_m(t)| \geq y_o$ and $|\psi(t)| < \psi_o$ then

$$\delta_{L_0}(t) = -k_y(y(t) - y_m(t)) \qquad (10)$$

which implies that:

$$\sigma_{\delta_L}^{\,2} = k_y^{\,2}\sigma_y^{\,2} \qquad (\text{for } y_m(t) = 0) \qquad (11)$$

where $\sigma_x^{\,2}$ is the variance of x(t).

Finally,

$$k_y = \frac{\sigma_{\delta_L}}{\sigma_y} . \tag{12}$$

Similarly, for $|\psi(t)| \geq \psi_o$ and $|y(t) - y_m(t)| < y_o$:

$$k_\psi = \frac{\sigma_{\delta_L}}{\sigma_\psi} . \tag{13}$$

Finally, when $|\psi(t)| \geq \psi_o$ and $|y(t) - y_m(t)| \geq y_o$:

$$\delta_{L_0}(t) = -k_y y(t) - k_\psi \psi(t) \tag{14}$$
$$(\text{for } y_m(t) = 0)$$

Using regression analysis in conjunction with equation (14), it can be shown that:

$$k_y = b_{y\delta_L} = \rho_{\delta_L y} \frac{\sigma_{\delta_L}}{\sigma_y} , \tag{15}$$

and similarly:

$$k_\psi = \rho_{\delta_L \psi} \frac{\sigma_{\delta_L}}{\sigma_\psi} , \tag{16}$$

where: ρ_{xy} is the correlation coefficient for x and y.

It has been found, based on preliminary experiments in this laboratory, with the model, that the lateral position error and the yaw angle error are rarely above their respective thresholds at the same time (given that y_o and ψ_o are different than zero). Hence, the model analysis can be simplified by letting:

$$k_y = \frac{\sigma_{\delta_L}}{\sigma_y} \tag{17}$$

and:

$$k_\psi = \frac{\sigma_{\delta_L}}{\sigma_\psi} \tag{18}$$

for the entire model. This choice of parameters should cause inaccuracies only when both lateral position and yaw angle are simultaneously above their respective thresholds, a rare occurance.

It can also be shown that, as y_o and ψ_o are adjusted, the effective gain of the driver model changes. To keep the overall system gain at a constant level, a correction factor should be included to compensate for the effects of changes in the lateral position and yaw thresholds. A derivation of the compensation technique will be carried out for $y(t)$. A similar derivation holds for $\psi(t)$.

If one assumes that $y(t)$ is normally distributed, $\delta_{L_0}(t)$ can be mapped into $y(t)$ as shown in Figure 3. Examining the probability density functions, one obtains

$$p_Y(y) = \frac{1}{\sqrt{2\pi}\,\sigma_y} e^{-\frac{y^2}{2\sigma_y^2}} \tag{19}$$

and:

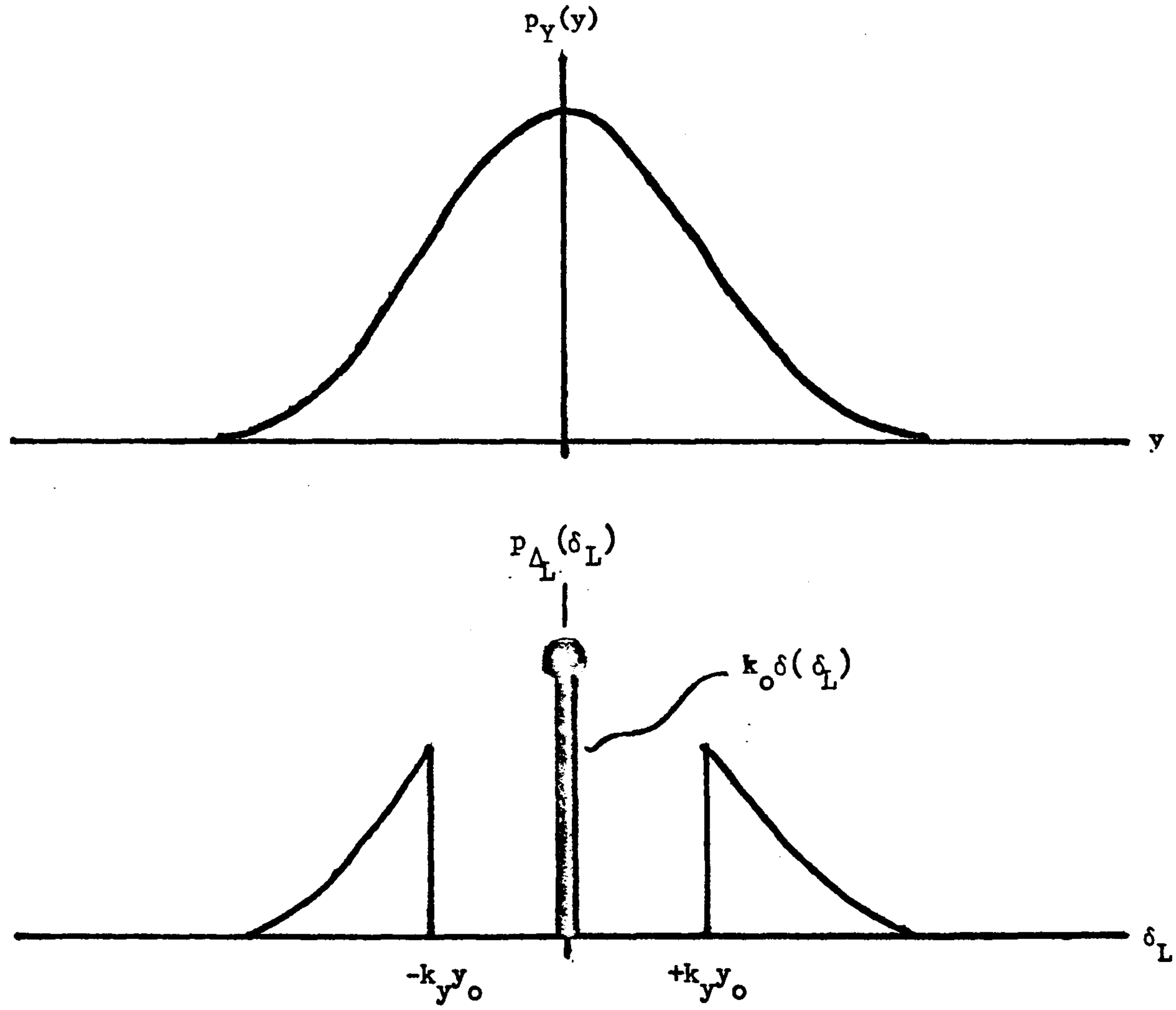

FIGURE 3. Mapping of Lateral Position Distribution into Steering Position Distribution

$$p_{\Delta_L}(\delta_L) = \begin{cases} k_o\delta(\delta_L); \text{ for} \\ \quad -k_y y_o \le \delta_L \le k_y y_o \\ \\ \dfrac{1}{\sqrt{2\pi}\,\sigma_{\delta_L}} e^{-\frac{1}{2}\frac{\delta_L^2}{\sigma_{\delta_L}^2}} ; \text{ elsewhere} \end{cases} \tag{20}$$

$$\text{where: } k_o = \int_{-y_o}^{y_o} \frac{1}{\sqrt{2\pi}\,\sigma_y} e^{-\frac{1}{2}\frac{y^2}{\sigma_y^2}} dy.$$

It should be noted that $p_{\Delta_L}(\delta_L)$ contains both a continuous and a "point mass" or discrete portion. For simplicity, the delta function, $\delta(x)$, has been used to specify the point mass. Rearranging (17) yields

$$\sigma_{\delta_L} = k_y \sigma_y . \tag{21}$$

From the definition of the second moment of a probability density function,

$$E(\Delta_L^2) = \sigma_{\delta_L}^2 = \int_{-\infty}^{\infty} \delta_L^2 p_{\Delta_L}(\delta_L)\, d\delta_L , \tag{22}$$

where it is assumed that δ_L has zero mean.

Which implies that:

$$\sigma_{\delta_L}^2 = 2\int_{k_y y_o}^{\infty} \delta_L^2 \frac{1}{\sqrt{2\pi}\, k\sigma_y} e^{-\frac{1}{2}\frac{\delta_L^2}{k_y^2\sigma_y^2}} d\delta_L \tag{23}$$

which yields:

$$k_y^2 = \frac{\sigma_{\delta_L}^2}{.8\sigma_y y_o e^{-\frac{1}{2}\frac{y_o^2}{\sigma_y^2}} + 2\sigma_y^2\left(1 - F\left(\frac{y_o}{\sigma_y}\right)\right)} \tag{24}$$

where: $F(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{t^2}{2}} dt$

and letting:

$$R = \frac{y_o}{\sigma_y} \tag{25}$$

gives:

$$k_y = \frac{\sigma_{\delta_L}}{\sigma_y}\left[.8Re^{-\frac{R^2}{2}} + 2(1 - F(R))\right]^{-\frac{1}{2}} \tag{26}$$

As y_o is increased k_y must be adjusted to keep a consistent system gain. Figure 4 illustrates the functional correction factor as a function of R.

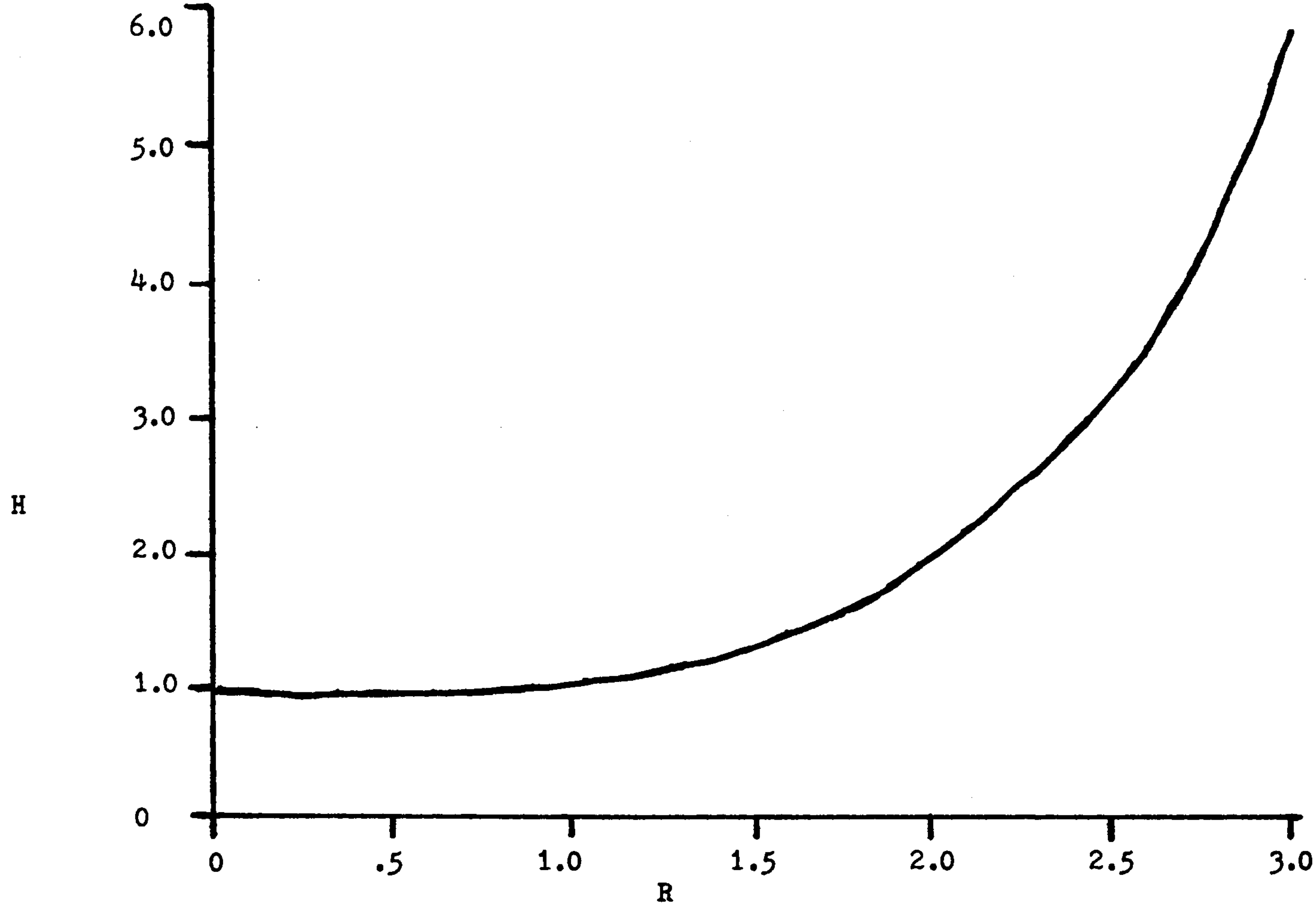

FIGURE 4. H as a function of R $(H = k_y \frac{\sigma_y}{\sigma_{\delta_L}})$

Experimental Analysis of Human Driving Behavior

To specify further the model and to provide a basis for later statistical verification, human driver responses were obtained and analyzed.

Apparatus. This research employed the V.P.I. & S.U. computer-generated display driving simulator. A full description of the apparatus appears in Wierwille (1973) and in McLane and Wierwille (1975). The simulator possesses a display system consisting of a computer-generated roadway display, a closed-circuit television system and a lens system which makes the image appear at about 30 feet. The display system accepts roll, yaw, lateral position, velocity, and wind disturbances as inputs. It then produces roadway and field images that are geometrically correct and are exit-pupil free to the seated driver (see Figure 5). The simulator also provides three axes of physical motion (roll, yaw, and lateral position) plus sound and vibration cues. Figure 6 shows a block diagram of the simulator. The physical arrangement of the system components can be seen in Figure 7.

The driving simulator has been in operation for approximately three years and has provided plausible and reasonable results for a number of studies. The simulator provides a strong illusion of driving and handles reasonably well. It has never produced nausea, unlike certain other driving simulators (Barrett, Nelson, and Kerber, 1965; Breda, Kirkpatrick, and Shaffer, 1972). Consequently, this simulator is believed to be valid for dynamic studies which can then be performed in an economical and controlled environment.

The equations of motion are solved on an EAI TR-48 analog computer.

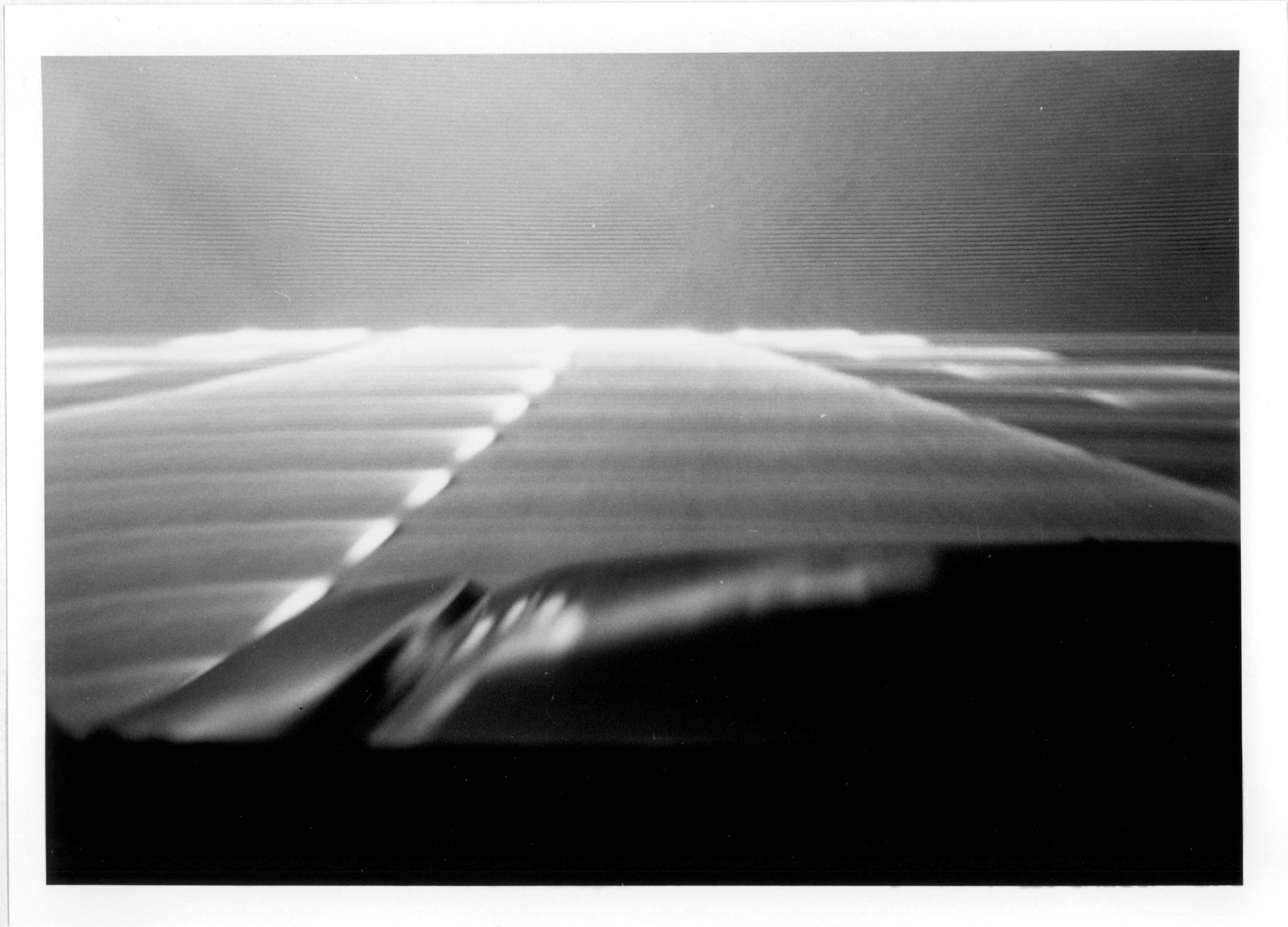

Figure 5. Computer Generated Roadway Display

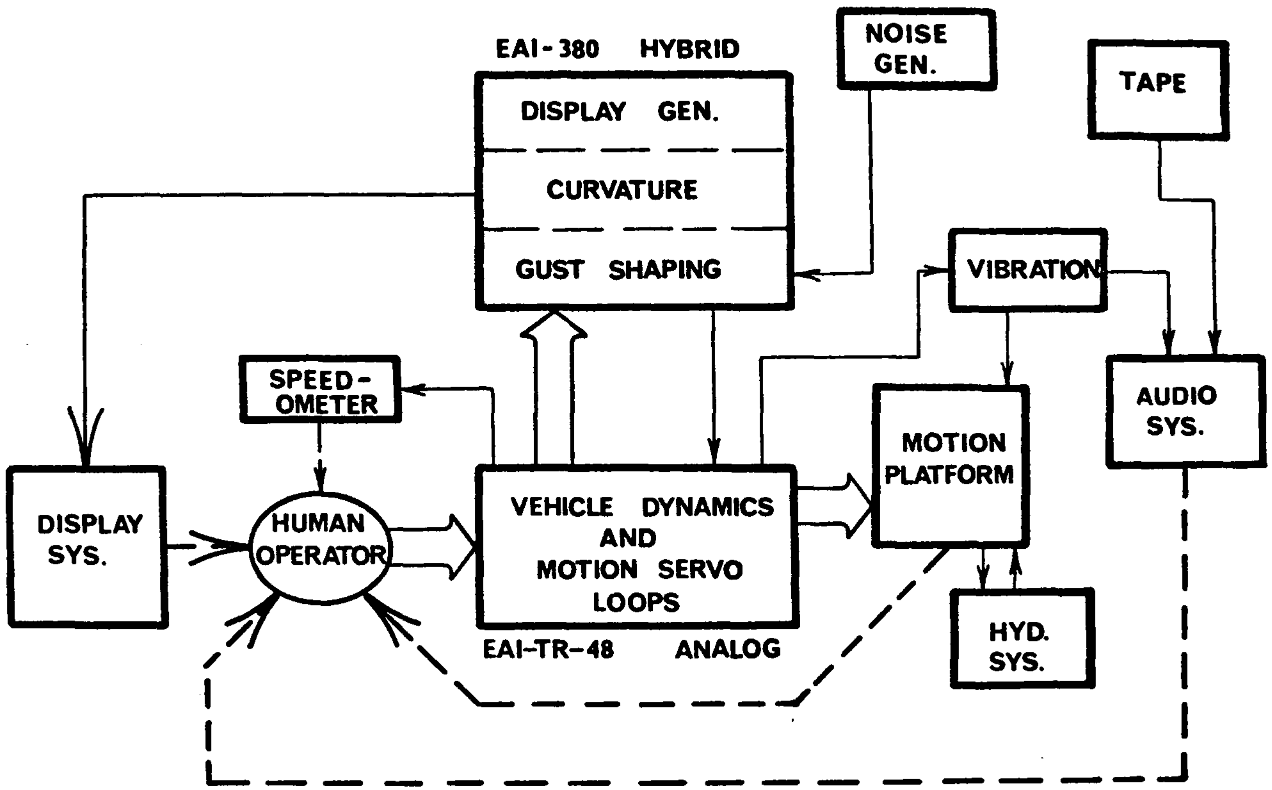

Figure 6. Simulator Block Diagram

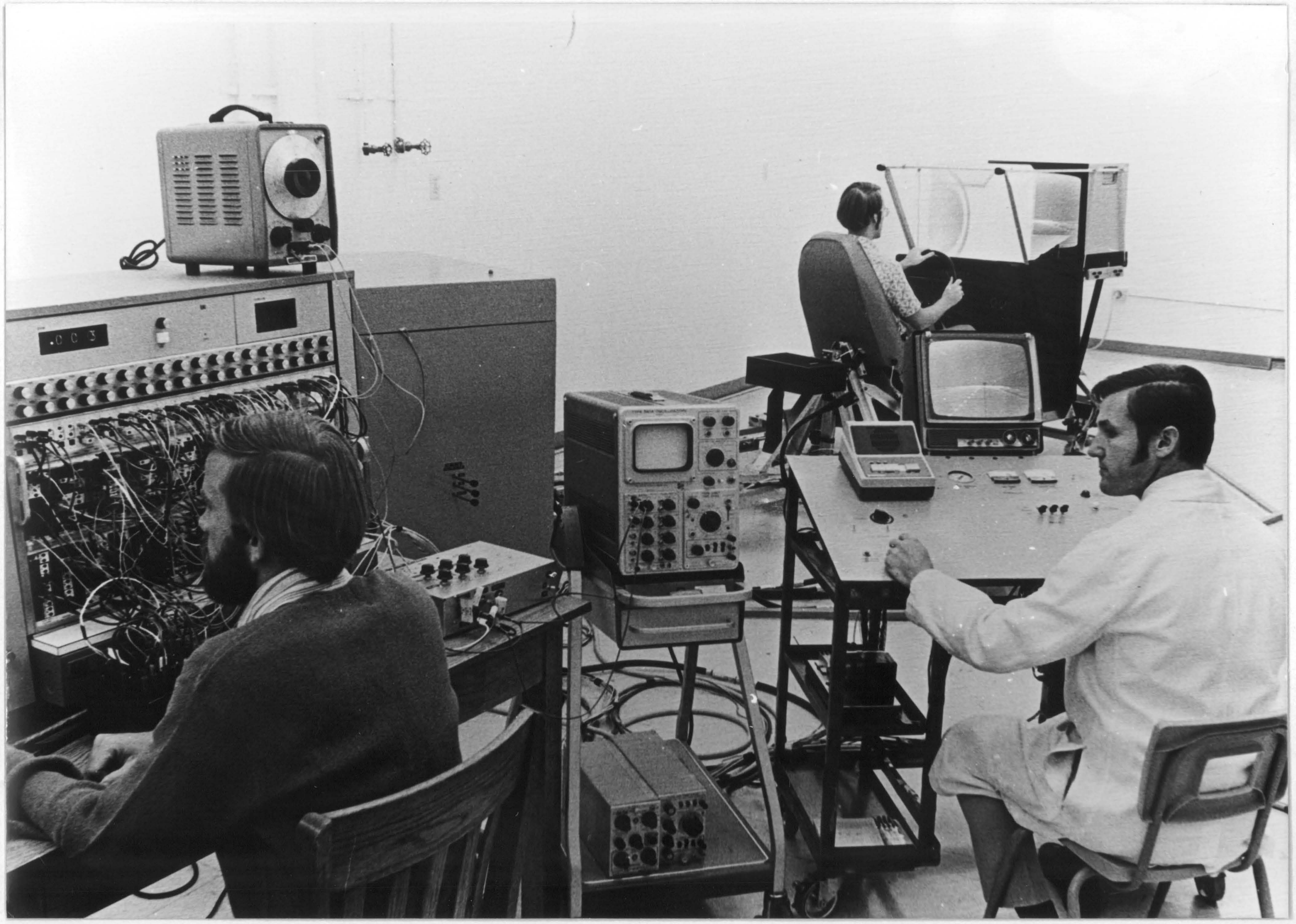

Figure 7. Physical Arrangement of System Components (Picture of Simulator Area)

Roll, yaw, and lateral position are obtained as a function of steering position and velocity. The equations are velocity dependent -- although that is of little consequence for this study, because all tests were performed at a constant speed of 55 mph. Once in operation, the driver has complete closed-loop control of the simulator. Equation (27) shows the open-loop transfer function of lateral position as a function of steering for this particular study, assuming that velocity (u) is constant.

$$\frac{Y(s)}{\Delta(s)} = \frac{1.96\ u\ (2s + 21)}{s^2(s^2 + 1.6s + 7)} \tag{27}$$

The transfer function for yaw is similar to that for lateral position except that it is multiplied by 1.17s. The simulated roll characteristics are approximated using a second-order system ($w_n = 6$, $\zeta = 0.5$) having been set to model a conventional late-model sedan.

Experimental measures. To date no known work has been done in statistical verification of human operator models. Before attempting such an endeaver it is appropriate to examine the driving situation and determine an appropriate method of classifying drivers and measuring system performance. For this particular study it was decided that three driver-vehicle system parameters -- steering position, yaw angle, and lateral position -- might provide the necessary information for fitting and evaluating the driver model. As mentioned earlier, the parameters of interest are random variables. This would tend to indicate that some type of statistical verification or validation technique might be appropriate. Also, based on past experience, it was decided that matching driver-vehicle system stability and response characteristics might provide an adequate basis for model fitting and evaluation. Hence, some measure of system stability should be determined. One possible measure is the variance of each parameter of interest. If the system becomes less stable with respect to a given parameter, the variance of that parameter tends to increase. Time estimates of the mean-square values (variances) of steering position, yaw, and lateral position were then used as comparative measures.

Data collection. To obtain measures of human performance for the model fitting and evaluation phase of this study, 10 subjects were chosen at random from the population of drivers at the university. Each subject had from 3 to 8 years of driving experience. All subjects were paid for their participation in the study. Each subject was asked to drive the simulator as he would an automobile in a normal highway driving situation, maintaining a speed of 55 mph and his normal right-lane road position. Appendix A shows the written instructions for each subject. Randomly generated lateral wind gusts were introduced as a system input.

Each experimental session consisted of segments of straight and curved roadway, and lateral wind gusts. (The entire session lasted approximately 15 minutes.) The last five minutes of each run was a segment of straight roadway with lateral wind gusts ($n(t)$). Performance measures were obtained during this final portion of each run and recorded on both a Sanborn model 350 eight-channel chart recorder and a Sanborn model 2000 seven-channel FM tape recorder. Four measures were recorded for each subject -- steering response, lateral position, yaw angle, and lateral gust input. The FM tape recordings were later used in processing the subject data.

Data analysis. The next step necessary for fitting the model was an analysis of the subject time histories and specification of the data of importance. The analysis was performed entirely on an EAI-380 hybrid computer using the FM tape recordings as inputs. The use of this system made it possible to process the data continuously rather than employ a sampled data process. The first step in the analysis was to divide the steering response into a low- and a high-pass component using a filter whose transfer function was:

$$G(s) = \frac{1}{1 + s} \tag{28}$$

It was then possible to obtain, simultaneously, estimated mean-square values for the total steering response, the low-pass steering component, the high-pass steering component, the vehicle's yaw deviation, and the vehicle's lateral position with respect to fixed references. Equation (29) gives the formula used for obtaining these estimates:

$$MS(x) = \frac{\int_o^T x^2 \, dt}{T} \tag{29}$$

Each estimate was obtained for the final 250 second segment of the subject's run ($T = 250$). Table 1 shows the results of this analysis.

TABLE 1

Estimated Mean Square Values

Subject	Steering (deg^2) Total	Steering (deg^2) Low-Pass	Steering (deg^2) High-Pass	Lat (ft^2)	Yaw (deg^2)
1	0.1351	0.0799	0.0552	0.3429	0.0787
2	0.3161	0.1998	0.1163	0.3517	0.1191
3	0.2421	0.1727	0.0693	0.5510	0.1312
4	0.7861	0.5006	0.2855	0.6859	0.2362
5	0.3854	0.2432	0.1422	0.2843	0.1333
6	0.2491	0.1810	0.0682	0.6507	0.1555
7	0.2421	0.1610	0.0812	0.5041	0.1191
8	0.3326	0.2103	0.1222	0.4367	0.1474
9	0.2456	0.1727	0.0729	0.4983	0.1292
10	0.2280	0.1445	0.0834	0.4631	0.0848

Model Fitting

The nature of the model under study made it possible to use analog computer technology to represent the model. As mentioned earlier, the automobile equations of motion were simulated on an EAI TR-48 analog computer. Thus, an electronic analog of the driver model was compatible with the experimental apparatus. The strategy model (equations 4 and 5) was programmed on two Comdyna model 808 analog signal processors used together. Figure 1 shows the block diagram of the model. The system's yaw and lateral translation signals could be taken from the TR-48, in electrical form, and inputted directly to the model. Similarly, the steering signal from the model could be directly linked to the steering input of the vehicle equations of motion, closing the lateral directional control loop. The velocity of the simulated vehicle was set to 55 mph by replacing the simulator's accelerator pedal input with one of the TR-48's potentiometer inputs. Thus, the performance of the "simulated driver" could be evaluated under experimental conditions similar to those experienced by the test subjects.

Analysis of the model's performance was carried out in a manner similar to that performed for the subject's. Using the relationship demonstrated in equation (29), estimates of the mean-square values for steering, yaw, and lateral position were obtained.

Furthermore, it seemed reasonable to believe, because of the model's versatility, that adjusting the open parameters -- k_y, k_ψ, $\delta_H(t)$, y_o, ψ_o, and $y_m(t)$ -- could allow the model to be matched to a population of drivers on a driver-by-driver basis. Hence, if the values of k_y, k_ψ, $\delta_H(t)$, y_o, ψ_o, $y_m(t)$, and τ could be determined for a particular driver, and if the model approximately describes his behavior, incorporating those parameters in the model should cause a high degree of correspondence between the driver's performance and the model's performance. The task, then, of fitting the model becomes one of determining estimates of k_y, k_ψ, $\delta_H(t)$, y_o, ψ_o, $y_m(t)$, and τ for the subjects of interest.

In the strategy model shown in Figure 1, $\delta_{L_0}(t)$ is lag filtered to produce $\delta_L(t)$. The lag represents the combined recognition and initiation lags of the driver. In general, the lag time constant would vary with time and would be different for each driver. However, the effects of this variability are probably not substantial. Hence, to simplify the fitting of the model, it was decided to hold the driver lag constant. A value of $\tau = 0.5$ second produces rise characteristics similar to nominal driver rise characteristics; consequently, this value was specified for the model.

Formulas for estimating k_y and k_ψ have already been derived and are given in equations (12) and (13). Using the data presented in Table 1, an estimate of k_y and k_ψ can be determined for each subject. Table 2 gives a compilation of these estimates.

The variable $\delta_H(t)$ could be thought of as a random steering response, used by the driver to keep the steering system in a dynamic mode. The high-pass portion of the driver's steering response does not appear to have a substantial effect on the other driver-vehicle parameters. Hence, the high-pass portion, as filtered, could be approximated with an uncorrelated noise generator output whose

TABLE 2

Estimated Values of k_y and k_ψ from the Subject Data (in Table 1)

Subject	$k_y \left(\frac{deg}{ft.}\right)$	$k_\psi \left(\frac{deg}{deg}\right)$
1	.48	1.00
2	.75	1.30
3	.56	1.15
4	.85	1.46
5	.92	1.35
6	.53	1.08
7	.57	1.16
8	.69	1.19
9	.59	1.16
10	.56	1.31

character is approximately the same as the high-pass steering response and whose amplitude is the same. Such a variable should be an adequate estimate of the driver's high-pass response. A random function whose bandwidth ranged from one to two and one-half radians per second was used.

The problem of approximating driver thresholds (y_o and ψ_o) for lateral position and yaw errors is a complex one. Because of the simultaneous presentation of lateral position and yaw, it is difficult to determine which of the two signals evokes a particular driver response. To circumvent the problem of estimating driver thresholds it was decided to specify k_y, k_ψ and $\delta_H(t)$, and then adjust y_o and ψ_o by trial-and-error (remembering the effect of each on system stability) until the estimated mean square of $\delta_L(t)$ (for the model) approximately matched the estimated mean square of the low-pass steering component of the modeled driver. Hence, each model was fitted to its corresponding driver in two phases:

Phase (1). With y_o and ψ_o equal to zero and k_y, k_ψ, and $\delta_H(t)$ specified, the model was run and estimated mean-square values were obtained for $\delta_L(t)$, $\delta(t)$, $y(t)$ and $\psi(t)$.

Phase (2). y_o and ψ_o were increased (with k_y and k_ψ being increased by the relation given in Figure 4) until the estimated mean square of $\delta_L(t)$ for the model approximated that of the subject's low-pass steering component.

The variable $y_m(t)$ is a driver parameter that allows for changes in reference over time. If $y_m(t)$ and $y(t)$ are assumed independent of one another, then

$$MS\left[y_T(t)\right] = MS\left[y(t)\right] + MS\left[y_m(t)\right] , \tag{30}$$

where $y_T(t)$ is the total lateral position signal.

The difference between the estimated mean square of the driver's lateral position signal and the estimated mean square of the model's lateral position signal could be used to approximate the estimated mean square of $y_m(t)$. (Here it is assumed that the estimated mean square of the model's signal is less than that of the corresponding driver.)

In summary, Table 3 shows the model-automobile system outputs for Phase 1. Table 4 shows the values of the parameters for the final models. Table 5 gives the corresponding system measures for the final models.

Results

It now becomes necessary to evaluate the model's effectiveness in describing human performance. This evaluation can be carried out two ways. One is a statistical comparison of driver-vehicle and model-vehicle performance data. The second is a qualitative comparison of the actual time histories of human and model responses.

As mentioned earlier, the system performance measures of prime interest are the mean square values of steering, yaw, and lateral

TABLE 3

Estimated Mean Squares for Phase 1 Model

	Steering (deg^2)				
Model	Total	Low-Pass	High-Pass	Lat (ft^2)	Yaw (deg^2)
1	0.1563	0.1011	0.0552	0.3312	0.1292
2	0.3666	0.2503	0.1163	0.2169	0.1857
3	0.2068	0.1375	0.0693	0.1817	0.1312
4	0.6087	0.3232	0.2855	0.2140	0.2019
5	0.4712	0.3290	0.1422	0.2638	0.2362
6	0.2116	0.1434	0.0682	0.2052	0.1373
7	0.2210	0.1398	0.0812	0.1905	0.1393
8	0.3361	0.2139	0.1222	0.2374	0.1878
9	0.2174	0.1445	0.0729	0.1993	0.1474
10	0.2150	0.1316	0.0834	0.1553	0.1272

TABLE 4

Input Parameters for Phase 2 Model

M#	k_y $\left(\frac{deg}{ft.}\right)$	k_ψ $\left(\frac{deg}{ft.}\right)$	y_o(ft)	ψ_o(deg)	MS(δ_{HP})(deg^2)	MS(y_m)(ft^2)
1	.54	1.13	.59	.28	0.0552	0.1847
2	.84	1.31	.59	.07	0.1163	0.1378
3	.61	1.06	.67	.36	0.0693	0.2990
4	.83	2.01	.17	.73	0.2855	0.2579
5	1.10	1.35	.64	.07	0.1422	0.0762
6	.54	1.28	.48	.47	0.0682	0.3136
7	.63	1.29	.71	.35	0.0812	0.2521
8	.72	1.20	.40	0	0.1222	0.2228
9	.61	1.28	.67	.36	0.0729	0.2462
10	.56	1.30	0	0	0.0834	0.2990

TABLE 5

Estimated Mean Squares for Phase 2 Models

	Steering (deg^2)			
M#	Total	Low-Pass	Lat (ft^2)	Yaw (deg^2)
1	0.1293	0.0729	0.3429	0.0888
2	0.3196	0.2033	0.3517	0.1635
3	0.2515	0.1821	0.5510	0.1514
4	0.7462	0.4606	0.6859	0.3230
5	0.3843	0.2421	0.2843	0.1817
6	0.2197	0.1516	0.5602	0.1675
7	0.2374	0.1563	0.5041	0.1413
8	0.3232	0.2009	0.4367	0.1656
9	0.2550	0.1821	0.4983	0.1514
10	0.2150	0.1316	0.4631	0.1272

position. However, to overcome the squaring of errors associated with these measures and to provide more accurate estimates of true modeling errors, root-mean-square estimates (RMS) of steering, yaw, and lateral position have been used for this comparative analysis. Regression analysis techniques were used as a means of implementing this comparative analysis. Using the square roots of the values presented in Table 1 and Table 5, two linear regression parameters, the slope (b) of the regression line and the correlation coefficient (r), were calculated as measures of the similarity between drivers and models, with respect to steering RMS, yaw RMS, and lateral position RMS. The slope is a measure of correspondance between the two populations and the correlation coefficient is a relative measure of relative accuracy. These two quantities are given by equations (31) and (32).

$$b_{xy} = \frac{\sigma_{xy}}{\sigma_x^2} \tag{31}$$

$$r_{xy} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \tag{32}$$

Table 6 is a summary of the slopes and correlation coefficients relating subject and model performance measures. A significant relationship exists ($p < .010$) between the subject and model populations.

A t-test can be performed to compare the central tendencies of these populations. Although a definite relationship exists, it is

TABLE 6

Summary of Slopes (b) and Correlation Coefficients (r) Relating Model and Subject Performance Measures

Statistic	RMS($\delta(t)$)	RMS($y(t)$)**	RMS($\psi(t)$)
b	0.99*	1.00*	0.78*
r	0.99	1.00	0.95

* $p < .010$

**RMS($y_T(t)$) of each model was matched to the RMS($y(t)$) of its corresponding subject by adjusting $y_m(t)$. Hence, a nearly perfect relationship resulted.

possible for a nearly constant bias to cause differences in the two populations.

There is no significant difference between the central tendencies of subjects and models for steering at the α = .20 level and for lateral position at the α = .20 level. There is, however, a significant difference between the central tendencies of subjects and models for yaw (at the α = .01 level). It is felt, that, as better estimates of model input parameters are obtained, this difference will diminish.

It is also important for a model of the driver to reflect the driver's response characteristics. Adjustment of the spectral characteristics of $\delta_H(t)$ allowed for the adjustment of the model's steering response characteristics with little effect on the rest of the model. Hence, the model's response characteristics could be matched to subject response characteristics, without affecting other system measures. This was accomplished by selectively adding independently generated random waveforms to produce a composite signal that was similar in shape and character to the driver response being modeled. (This was done by trial-and-error.) The total signal amplitude was then adjusted until its estimated mean square approximated that of the driver.

Figures 8 thru 13 show a random selection of subject responses and their corresponding model responses. Visual examination of subject and model time histories indicates that some relationship exists between the spectral characteristics of each subject and its corresponding model.

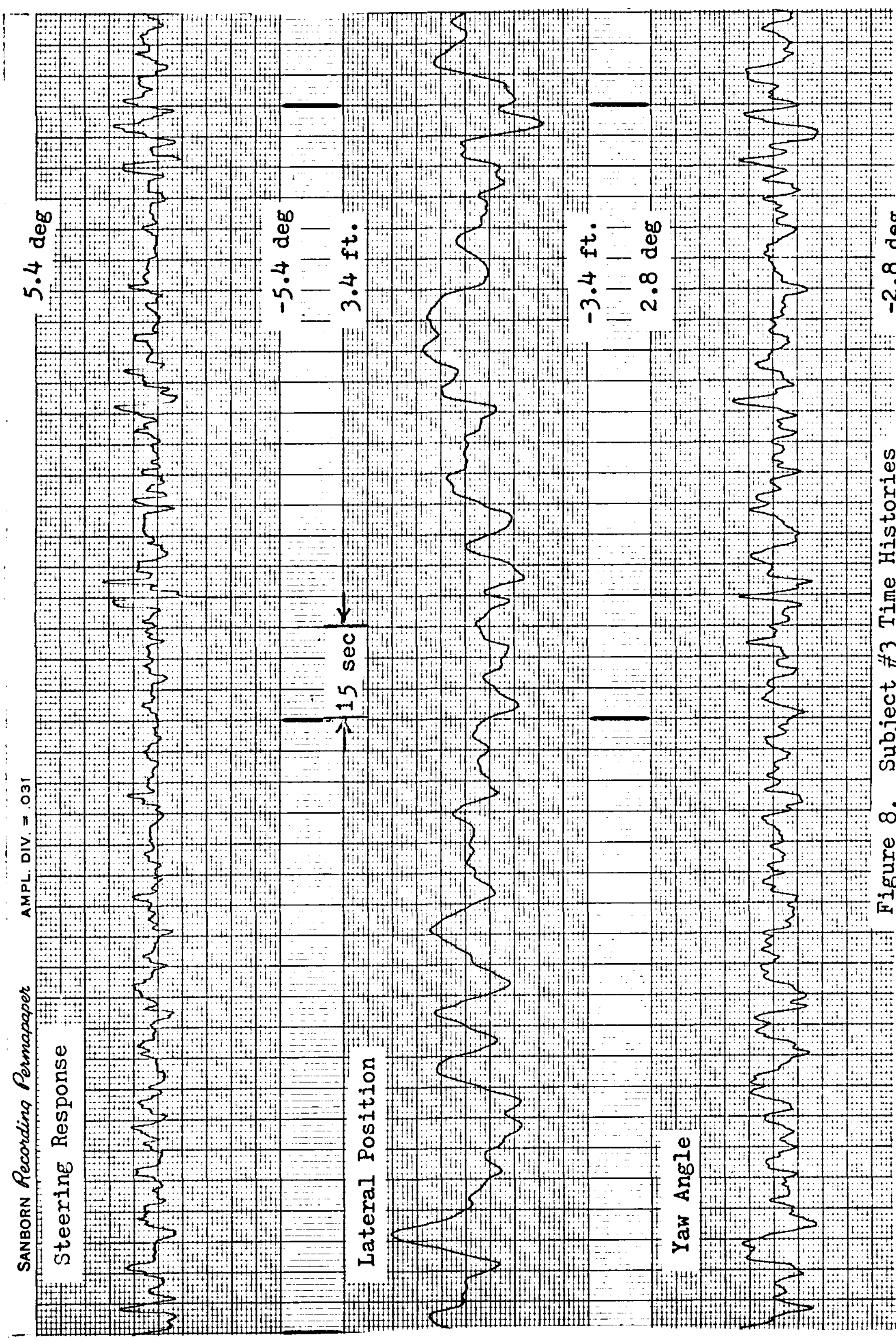

Figure 8. Subject #3 Time Histories

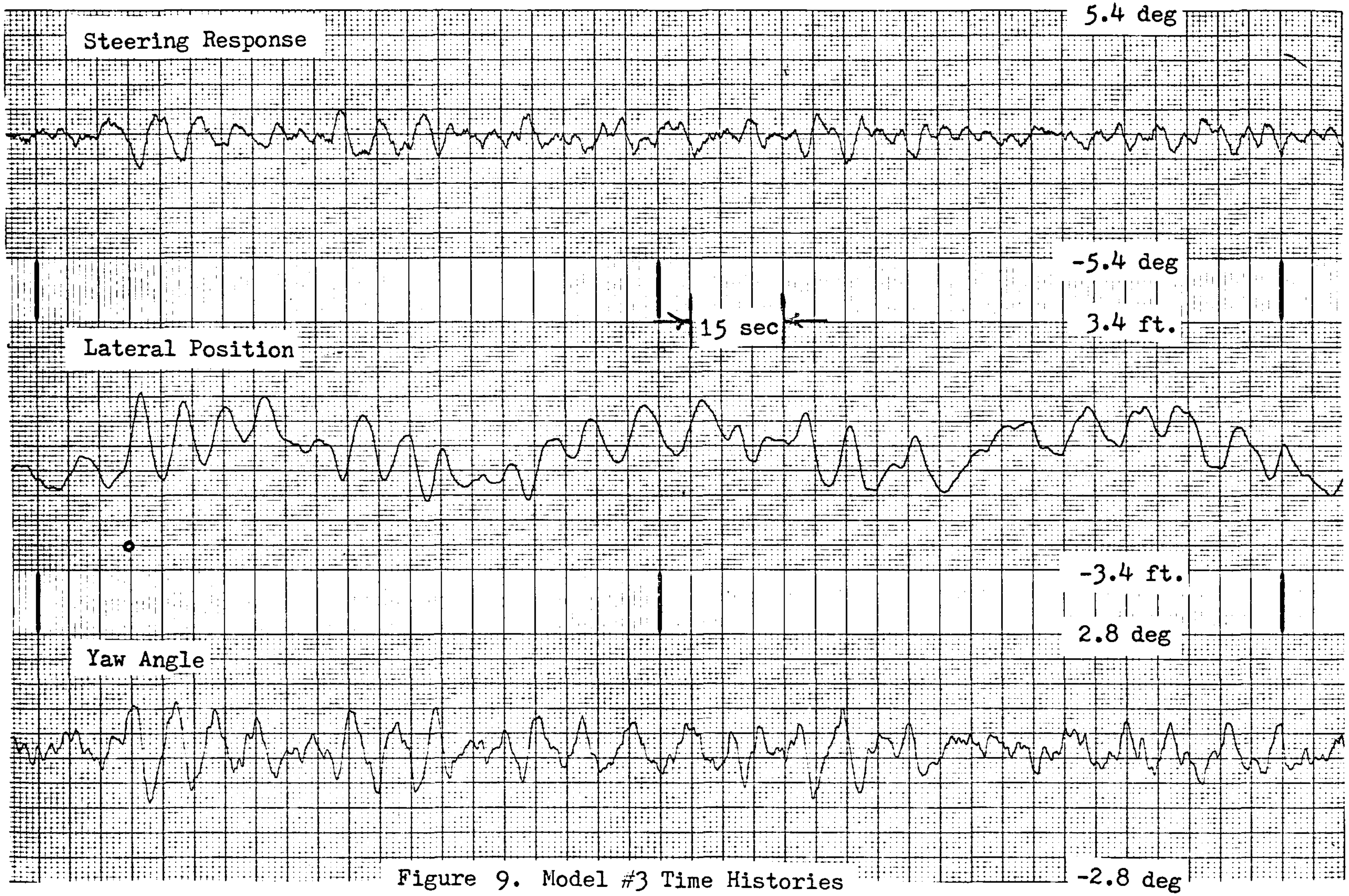

Figure 9. Model #3 Time Histories

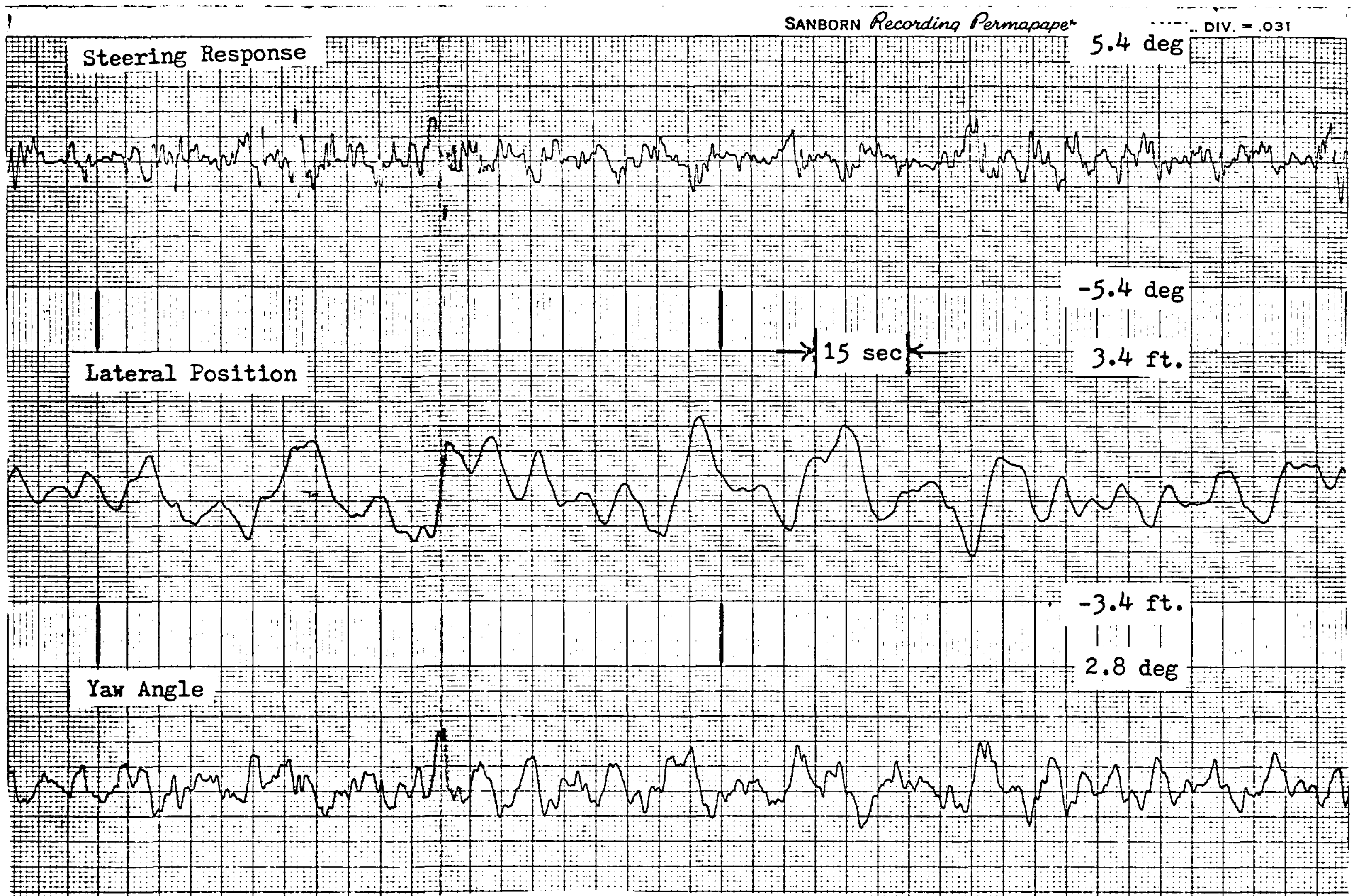

Figure 10. Subject #7 Time Histories

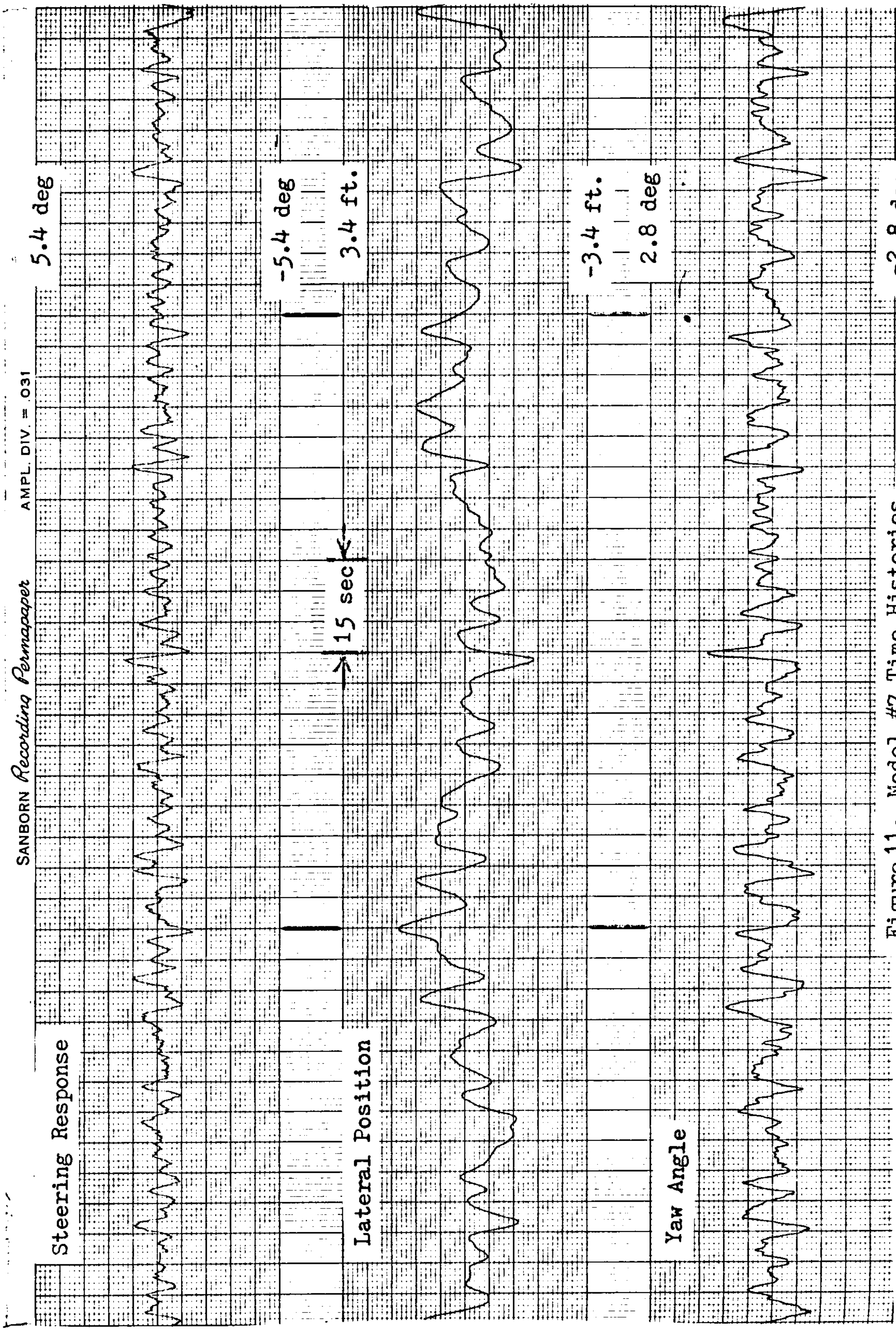

Figure 11. Model #7 Time Histories

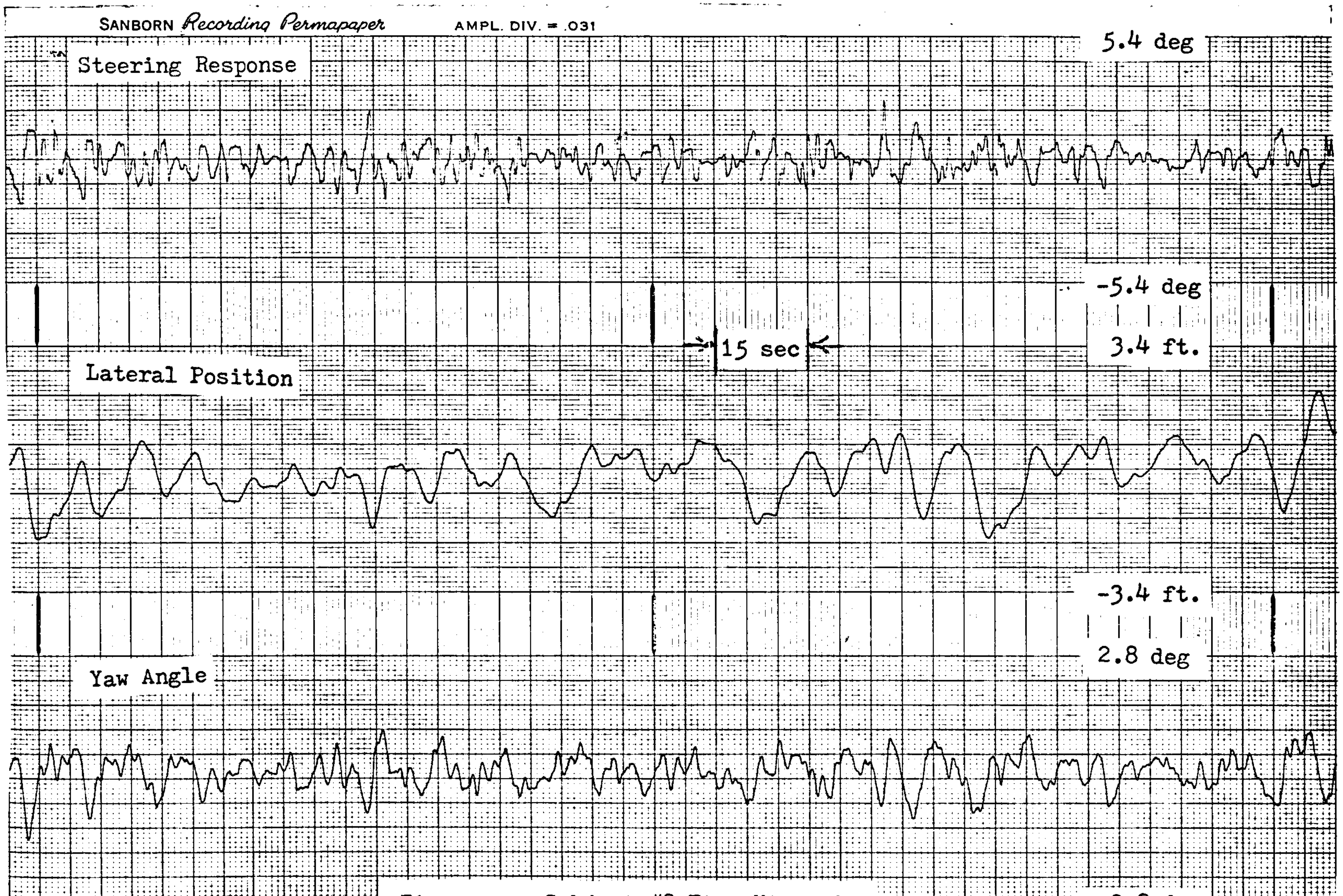

Figure 12. Subject #8 Time Histories

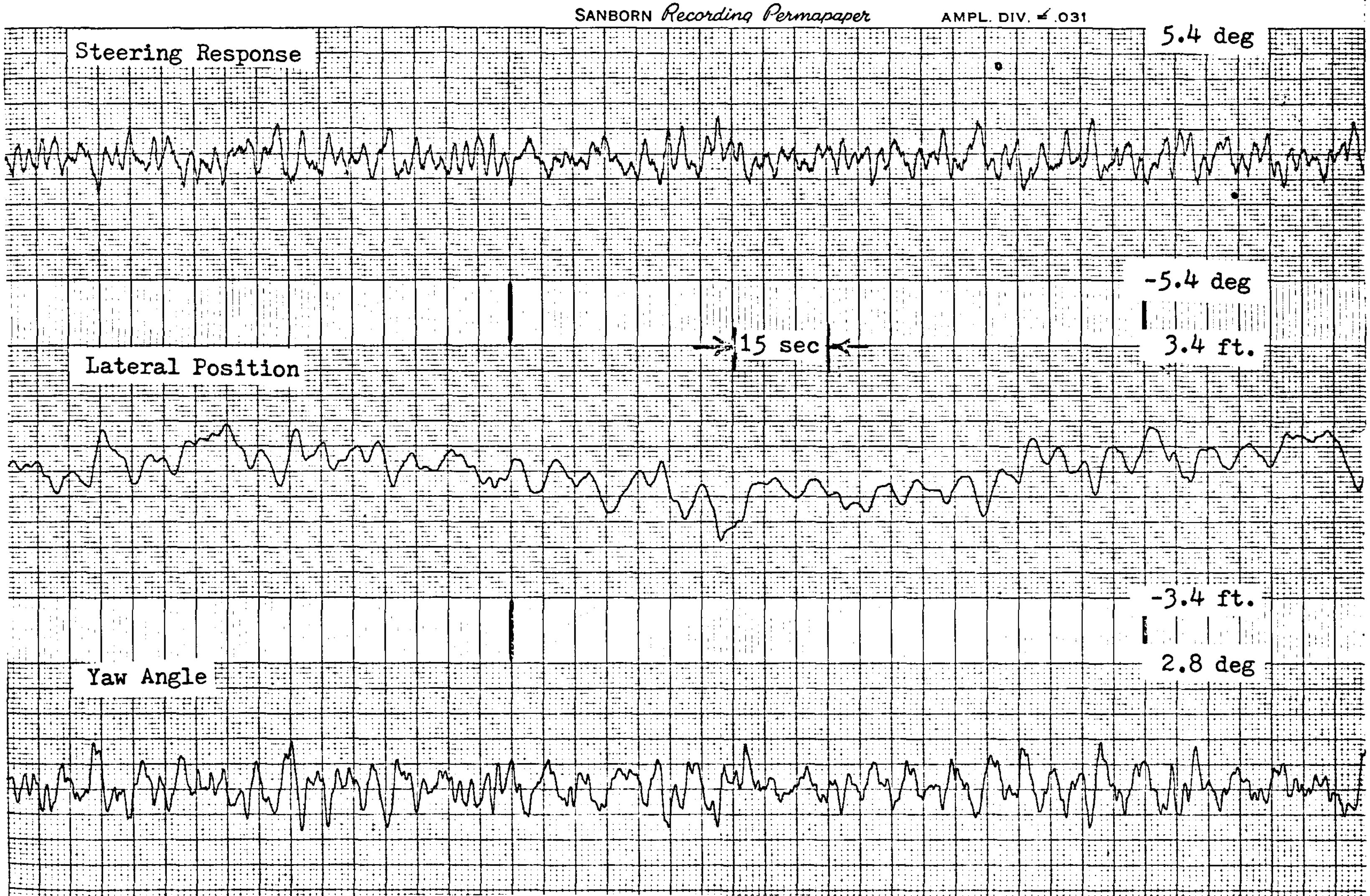

Figure 13. Model #8 Time Histories

DISCUSSION AND RECOMMENDATIONS

On the basis of comparative results, the modeling procedure presented has been successful. Driver control characteristics have been examined and a strategy model has been developed to describe them. Through the use of analytical and experimental techniques, models were specified for several drivers. These models were then experimentally tested and shown to provide effective descriptions of the drivers under study.

However, it should not be concluded that the models, as specified, would predict driver behavior for some other interval of time or driving situation than the one under study. The objective of this study was not to establish predictive validity of the models but to show that a driver's behavior over a given period of time and in a given situation could be reproduced by use of the model. It is felt that the basic class of models presented will provide an adequate basis for a general description of driver behavior, but a more detailed understanding of the driver parameters necessary to specify the model would be needed before any attempts could be made in developing predictive models.

The success of the procedure might be linked to the versatility of the proposed model and the use of fundamental behavioral concepts in developing the model. The versatility has been demonstrated by the ability to model ten different subjects. Furthermore, fundamental behavioral concepts provided a basis for developing a set of models that approximately describe driver behavior.

There is some indication, based on study results that drivers exhibit a "make-work" characteristic (Greenshields, 1970). The existence of this phenomonon might be demonstrated by recognizing that a driver can use far less steering activity than he normally does (if he tries) without causing a noticeable degradation in system performance. The fact that there is a "make-work" driver characteristic could explain why driver control strategies have been so elusive in the past. The true control behavior might have been masked by the unrelated "make-work" response. Further work in this area might provide a better description of this "make-work" behavior and an analysis determining if there is some driver-vehicle parameter to which it is related.

The results also tend to substantiate the original hypothesis that the driving task is relatively easy, and could be described with a simple control model. This means that complex driver models, as presented in the past, might not be necessary as tools for investigating driver behavior. Such implications could also be carried over to the more general area of human operator modeling. Possibly simple human operator strategy models would be appropriate for describing human response behavior in several types of control systems.

There are several potential applications of this modeling approach. One use might be in the analysis of man-vehicle systems. (Emphasis in this thesis has been on model development, rather than on stability analysis.) By replacing the driver with an appropriate model, it should be possible to investigate alternatives in vehicle dynamics and determine what effects they have on system stability. Furthermore, unstable system behavior (in existing designs) might be explained and traced to the cause, thus providing a technique for improving driver-vehicle system performance. Various road and wind conditions could be studied to determine their effects on the automobile system and driver performance. The nature of the model presented lends itself to computer analysis, making it possible to investigate alternatives in nonreal time.

Before the above analyses are performed, investigation of the adaptability of drivers versus the adaptability of the model should be carried out. This investigation could determine whether changes in control system dynamics have similar effects on drivers and the model. Such a study would establish the range of system dynamics over which this particular model is applicable.

Another possible application of the model is in driver research. Many areas of interest are not presently investigated because they would present hazardous or high-risk situations to the subjects. If the model or some adaptation of it were proven appropriate in describing driver behavior in such situations, then model populations could be used instead of driver populations in these investigations.

The need for modeling driver populations in studies such as these gives rise to another area of investigation. If a sample of driver parameters could be obtained for the population of interest, it should be possible to determine parameter distributions and subsequently develop random parameter generators. Then by drawing samples from these generators one could, theoretically, derive models of representative members of the driver population of interest. A prior investigation should be carried out to determine the degree of correlation between various driver parameters for use in developing the parameter generators.

In conclusion, the modeling technique presented in this thesis appears to be a profitable approach to investigations of driver behavior. It provides a model that matches driver-vehicle system stability and response characteristics, and better describes driver behavior than previous linear approaches.

REFERENCES

Barrett, G. V., Nelson, D. D., and Kerber, H.E. Human Factors evaluation of a driving simulator, Final Report. Contract No. PH 108-64-168, Goodyear Aerospace Corporation, 1965.

Birmingham, H. P. and Taylor, F. V. A design philosophy for man-machine control systems. Proceedings of the Institute of Radio Engineers, 1954, 1748-1758.

Breda, W. M., Kirkpatrick, M., and Shaffer, C. L. A study of route guidance techniques, Final Report. Contract No. DOT-FH-11-7708, North American Rockwell, 1972.

Costello, R. G. The surge model of the well-trained human operator in simple manual control. Institute of Electrical and Electronic Engineers Transactions on Man-Machine Systems, 1968, MMS-9, 2-9.

Greenshields, B. D. Traffic and highway research and how it may be improved. Science, 1970, 168, 674-678.

Kroll, C. V. Preview-predictor model of driver behavior in emergency situations. Highway Research Record, 1971, 364, 16-26.

McLane, R. C. and Wierwille, W. W. The influence of visual and motion cues on driver performance in a simulator. Human Factors, 1975.

McRuer, D. T. and Weir, D. H. Theory of manual vehicular control. Institute of Electrical and Electronic Engineers Transactions on Man-Machine Systems, 1969, MMS-10, 257-291.

Miller, D. C. and Elkind, J. I. The adaptive response of the human controller to sudden changes in controlled process dynamics. Institute of Electrical and Electronic Engineers Transactions on Human Factors in Electronics, 1967, HFE-8, 218-222.

Miller, I. and Freund, J. E. Probability and statistics for engineers. Englewood Cliffs, New Jersey: Prentice-Hall, Inc., 1965.

Mourant, R. R. and Rockwell, T. H. Mapping eye-movement patterns to the visual scene in driving: an exploratory study. Human Factors, 1970, 12, 80-87.

Senders, J. W. and Kristofferson, A. B. The attentional demand of automobile driving. Highway Research Record, 1967, 195, 15-33.

Sheridan, T. B. Time variable dynamics of human operator systems. Report No. ARCRC-TA-60-169, M.I.T. Dynamic Analysis and Control Lab., 1960.

Sheridan, T. B. Three models of preview control. Institute of Electrical and Electronic Engineers Transactions on Human Factors in Electronics, 1966, HFE-7, 91-102.

Snyder, D. L. A nonlinear study of compensatory manual control systems. Institute of Electrical and Electronic Engineers Transactions on Human Factors in Electronics, 1964, HFE-5, 25-28.

Wierwille, W. W. Improvement of human operator's tracking performance by means of optimum filtering and prediction. Institute of Electrical and Electronic Engineers Transactions on Human Factors in Electronics, 1964, HFE-5, 20-24.

Wierwille, W. W. Theory for optimal deterministic characterization of time-varying human operator dynamics. Institute of Electrical and Electronic Engineers Transactions on Human Factors in Electronics, 1965, HFE-6, 63-61.

Wierwille, W. W. A part-task driving simulator for teaching and research. Computers in Education Division of American Society of Engineering Transactions, 1973, 12, 193-203.

Wierwille, W. W. and Gagne, G. A. Nonlinear and time-varying dynamical models of human operators in manual control systems. Human Factors, 1966, 8, 97-120.

Wierwille, W. W., Gagne, G. A., and Knight, J. R. An experimental study of human operator models and closed-loop analysis methods for high-speed automobile driving. Institute of Electrical and Electronic Engineers Transactions on Human Factors in Electronics, 1967, HFE-8, 187-201.

APPENDIX A: Written Instructions Given to Each Subject

Instructions

The purpose of this experiment is to obtain a better understanding of normal driving behavior.

You will be seated in the driver's seat of an automotive mock-up. You will be presented with a visual display consisting of a moving, geometrical roadway simulation, and a dashboard speedometer. During operation of the simulator, you will experience simulated vehicle motions corresponding to the driving conditions and your control maneuvers. Your control of the simulator's speed and road position will be by means of a standard steering wheel and accelerator pedal as in a normal automobile. After being seated on the platform you will be given instructions by, and may communicate with the experimenter via the dash mounted (upper right) speaker/microphone.

The total experiment will take approximately 15 minutes to complete. A 1-minute practice session is incorporated at the beginning of the run, followed by a 15-minute data session.

During the run, you will be asked to perform two tasks:

1) maintain a speed of 55 mph, and

2) maintain a normal right-lane highway driving position.

Please Keep in mind that you are at all times to drive as you normally would on a highway.

The experimental procedure will be as follows:

1. Be seated in driver's seat; adjust seat position and fasten safety belt.
2. Become familiar with controls, speaker/microphones, and emergency motion cut-off button.

   NOTE: Activation (1 push) of the emergency motion cut-off button halts all motion of the simulator platform. If at any time during the experiment you sincerely feel that continued simulator operation would not be agreeable with you, please verbally notify the experimenter and depress (once) the emergency motion cut-off button. You may leave the platform (to the left only) if and only if all platform motion has stopped.
3. Communications checkout and questions.

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DEVELOPMENT OF

A STRATEGY MODEL

OF THE DRIVER

by

James M. Carson

(ABSTRACT)

Based upon vehicle constraints and known human operator characteristics, a class of strategy models was postulated for describing driver behavior in the lane-keeping task. To verify the appropriateness of this class of models, 10 student subjects were chosen to be modeled. Each subject performed the lane-keeping task in a highway driving simulator for five minutes. Each subject's time histories of steering, lateral position, and yaw angle provided a basis for estimating the driver parameters necessary to specify an appropriate model of the subject. Ten driver models were then programmed to describe the 10 subjects, respectively. Each model was run over the same course, and experienced the same conditions as its corresponding subject. Regression analysis provided a means of comparing subject and model responses. The models developed were found to be effective in describing the responses of the 10 subjects, respectively.