Measurement of Behavior and Performance in Driving Simulation

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Abstract

Driving simulation includes many elements that must be implemented to produce a useful research, assessment or training tool. Given that the physical attributes and cueing environment are appropriate for a given application, performance measurement becomes a critical simulation element. Performance measures can be crucial to research objectives. Performance measurement is central to tracking and documenting training progress. Performance measurement can also provide criteria for diagnostic assessment procedures concerning driver capability, qualification and certification. This paper will review various categories of measurements, and give examples of typical results. The objective is to lay the ground work for a fairly broad view of the measurement of driver behavior and driver/vehicle performance in driving simulators. The general thesis of this paper is that performance measurement can be structured and clarified by conceptual, qualitative and quantitative models of the driving task.

Introduction

Driving performance measurement can be broken down into several categories. Simple global measures include accidents, tickets, speed limit exceedances, lane and speed deviations, turn indicator usage, etc. This category can also include various measures of driver steering, throttle and brake control actions and associated vehicle responses including body axis accelerations and velocities. These measures can be collected during entire simulator runs, and can be subdivided into sections of driving scenarios where road geometry, vehicle and pedestrian interactions, traffic control devices and other task demands make them particularly relevant. Various algorithms can be applied to these measures including distributions and moments (e.g. mean and standard deviation), power spectra, and more modern procedures such as wavelet analysis which can quantify time variations.

More powerful measurement paradigms can be defined where independent variables are closely controlled and the measurement algorithm quantifies the relationship between dependent variables (i. e., driver response) and independent variables. For example time series analysis methods can quantify the relationship between stimulus and response variables. Fourier analysis procedures have been used to carry out stimulus/response relationships, such as steering response to wind gusts and roadway curvature, and speed response to varying road grade or lead vehicle speed variations. These methods allow the analysis of driver time delay in responding to stimulus inputs, and the correlation of driver response to the stimulus input. Driver response can also be measured in response to more discrete stimuli such as a traffic signals or conflicts with vehicles and pedestrians. These situations can involve steering and/or speed control responses, and can be analyzed in terms of driver decision making and response time. This paper will review various modeling and measurement paradigms and algorithms, and give example simulation results and associated field test measurements.

Background

The measurement of human operator behavior including driving has been pursued for more that half a century, and finds its roots in the general problem of modeling the human operator, e.g. (1, 2). The early work dealt with the stable feedback control of vehicle dynamics in general, and a special conference, the Annual Conference on Manual Control, was held for over two decades and was devoted to the behavior and modeling of the human operator, e.g. (3, 4). Figure 1 generally illustrates the driving task. This conceptual model portrays several issues associated with modeling and measuring performance of the driving task. The driver controls a vehicle, and this feedback process must be stable in a closed loop sense. Theories of linear feedback control have been applied to this problem, and a range of models have been proposed, e.g. (5), that deal with stability either structurally, such as classical stability analysis (6, 7) or algorithmically with procedures such as optimal control (8-10). These two approaches raise the general issue of the computational procedures used in driver measurement, which can involve typical data analysis, and modern techniques such as wavelets, e.g. (11). Higher level characteristics can be ascribed to the human operator, e.g. (12, 13), and in fact cognitive functions such as risk perception, decision making and

situation awareness factor strongly into the driver's reaction to environmental inputs such as traffic, traffic control devices, and hazards in general.

Generally, driver models and measurements can be broadly categorized according to control, guidance and navigation functions. Control concerns psychomotor functions that stabilize vehicle path and speed against various aerodynamic and road disturbances. Guidance involves perceptual and psychomotor functions coordinated to follow delineated pathways, adhere to implied speed profiles, interact with traffic and avoid hazards. Navigation involves higher level cognitive functions applied to path and route selection and decisions regarding higher level traffic interactions (e.g., avoiding congestion). A generic model for guidance and control functions is illustrated in Figure 2. This model allows for the human operator to respond to disturbances and commands and can apply broadly to the guidance and control of aeronautical, marine and land vehicles, e.g. (14). The driver operates in both compensatory and pursuit modes. The compensatory mode relates to nulling out errors such as lane or speed deviations. Pursuit behavior arises when the human can perceive commands independently of errors, for example road curvature (15). An additional feedback has been added to Figure 2 to account for the driver's perception and response to vehicle motions and steering torque. Through vestibular and proprioceptive feedbacks the human operator can also respond to vehicle motions and control system forces that may be important in limit performance maneuvering, e.g. (1).



Continuous Control of Steering and Speed

The human operator's compensatory behavior is designed to minimize error and also to maintain control stability. This behavior can be somewhat complicated, including anticipatory and smoothing compensation for vehicle dynamics characteristics. If we consider the combined behavior of the human operator and vehicle, however, compensatory behavior in manual control systems has been compactly characterized by two parameters, a gain or crossover frequency (ω_c) and a time delay (τ_e) (16). In Laplace transform terms, the open loop transfer function in the Figure 2 compensatory loop can be expressed as: $Y_n \bullet Y_c = \omega_c e^{-\tau_c s} / s$.

In the crossover model characterization of manual control system dynamic behavior, crossover frequency is a measure of the system (driver/vehicle) bandwidth, and the product of crossover frequency and time delay is a measure of system damping: Crossover Frequency (bandwidth) = ω_c and Phase Margin (system damping) = $\phi_m = \pi / 2 - \omega_c (\text{rad} / \text{sec}) \times \tau_c (\text{sec})$. System

damping decreases with decreasing Phase Margin, and when Phase Margin goes much below unity, the system response is oscillatory. When Phase Margin goes to zero, the system becomes unstable. A well known unstable phenomenon occurs in aeronautical (pilot/vehicle) systems, e.g. (17), and has its equivalent in driving when tire saturation causes unstable control of vehicle yawing.

The above crossover model has been applied to measurements for the steering control task in simulators and test vehicles (18) and also to test vehicle measurements for a headway (longitudinal) control task (19). Crossover model parameters from these steering and headway control studies are summarized in Figure 3. These measurements clearly distinguish the low bandwidth longitudinal control from higher bandwidth steering control and between fixed base simulator and moving base test vehicle steering control. Here we see that there is almost an order of magnitude difference in the bandwidths and equivalent time delays between the headway control and steering control. The low bandwidths in headway control are basically due to longitudinal vehicle dynamics, including available engine power, and the driver's perceptual response of headway. Driver headway time delay is also larger for the open road

measurements where the car following task is less well defined and more variable. For steering control we see that fixed base simulator bandwidth is about half of that found in a real test vehicle. This effect is due to the motion and steering force feedback cues that the driver perceived in the real vehicle which allows for higher bandwidth control of the vehicle.

Figure 3. Crossover Model Behavior



Measurement applied to original

time histories can be carried out with Fourier analysis techniques, e.g. (6, 15, 16, 18, 19). This approach has been used in simulation studies to characterize the behavior of cognitively impaired drivers (20, 21). For pursuit control, the driver must have some preview of the required path. This behavior has been studied in person-in-the-loop driving simulations (22, 23), and driver models have been developed from the experimental data that include steering actions directly proportional to roadway curvature. These models account for driver perception of road curvature some distance ahead of the vehicle, and have been characterized as incorporating a `look ahead' distance or headway time (distance divided by velocity), e.g. (24).

Emergency Control

In real world conditions with various complexities in the roadway environment, there is some question about whether a driver will decide to steer and or brake in a given emergency encounter. A simple model for this decision process has been considered based on a rather simple kinematic analysis (25) of the task portrayed in Figure 4. This kinematic model considers maximum steering or braking maneuvering times as follows given the variables defined in Figure 4 where



Distance - T_RUo $x_m = T_m U_o$

Reaction Time

x is longitudinal distance, y is lateral distance and t is time. Consider Steering at Constant Lateral Acceleration:

$$y = a_y t^2 / 2$$
 and $t = T_m = \frac{x_0}{U_0} - T_R$; then $y_0 = \frac{a_y (x_0 - T_R U_0)^2}{2U_0}$ and $T_m = \sqrt{2y_0 / a_y}$. For

<u>Braking at Constant Longitudinal Acceleration</u>, given that $x_0 = T_R U_0 + a_x t^2 / 2$ and $t = \frac{U_0}{t}$,

 $x_0 = U_0(T_R + U_0/2a_x)$ and $T_m = U_0/2a_x$. The results of this model are illustrated in then Figure 5. Here we see that, given the maneuvering assumptions in the model, at low speeds the driver can safely stop or steer. At higher speeds

the stopping distances are long enough that the driver can only safety steer.

Figure 5. Steer versus Brake Decisions Based on Kinematic Analysis.

Data has been analyzed that relates to the above kinematic analysis. Test track data was obtained under conditions where the driver was asked maneuver at the last possible moment before running into a lead vehicle by either braking (26) or steering (27). This data has been subsequently analyzed using regression analysis (28) to determine when the driver decides to maneuver in



Given that

terms of the range and range rate (R, \dot{R}) to a lead vehicle. The general formula for the regression analysis can be expressed as $R = a\dot{R}^2 + b\dot{R} + c$. By dividing through the above formula by range rate, \dot{R} , we obtain the equivalent of the time to collision or maneuver time plus driver reaction time illustrated in Figure 5: $T_R + T_m = a\dot{R} + b + c/\dot{R}$.

In the above form of the equation the b coefficient is the equivalent to the total maneuvering time in the (25) analysis for mid range rate levels, and the a and c coefficients give some range rate dependency. The regression analysis from (28) is summarized in Table 1 where range and range rate were expressed in meters and meters/sec respectively and range rate was expressed as negative (i.e. decreasing range). The steering analysis was linear while the braking analysis included the \dot{R}^2 term. According to the authors (28) the above results demonstrate that "drivers initiate last-second braking maneuvers at generally longer distances than last-second steering maneuvers to avoid a lead vehicle ahead in their lane of travel."

This is consistent with the kinematic analysis summarized in Figures 4 and 5. It can also be shown that reaction plus maneuvering times for braking are shorter than for steering in the hard maneuvering scenarios when range rate is below 14 meters/second (about 43 feet/second). The *b* coefficients in Table 1 are consistent with driver decision/reaction times on the order of one second or greater and the *a* coefficients indicate that the decision/reaction time increases with increasing range rate. Perception reaction times can easily be greater than 1 second as discussed in (29) and decisions made in response to the onset of yellow traffic lights have also been investigated (30, 31).

Table 1. Analysis of Stopping and Steering Behavior Relative to a Lead Vehicle.							
Case		Regression Analysis					
Maneuver	Intensity	a	b	С	r^2		
Braking-Lead Vehicle Stopped	Normal	0.05	-3.92	5.0	0.98		
	Hard	0.11	-1.05	5.0	0.99		
Braking-Lead Vehicle Moving	Normal	0.14	-2.54	11.0	0.96		
	Hard	0.13	-1.21	7.5	0.99		
Steering-Lead Vehicle Stopped	Normal	NA	-4.08	5.0	0.99		
	Hard	NA	-2.54	5.0	0.98		
Steering-Lead Vehicle Moving	Normal	NA	-3.82	4.42	0.95		
	Hard	NA	-2.56	2.25	0.98		
NA: Not applicable, the steering analysis was linear							

Combined Steering and Speed Control

The stimuli that motivate general driver steering and braking behavior may not be as apparent or direct in their influence as more constrained tasks. This is somewhat typified by car following behavior that exhibits significant between subject variation, e.g. (19). A range of stimuli influence driver behavior in general driving, for example warning or advisory signs, traffic, pedestrians and other obstacles, road profile, etc. Speed selection during path following in the absence of traffic is somewhat arbitrary, and is one of the least well-understood elements of driver behavior and modeling. Much of the detail in modeling and measuring the driver's closed loop feedback process for controlling speed and lane position has been described above. Now we consider combined steering and speed modeling efforts applied to relatively free driving behavior.

The assumptions in the above modeling work have been tested against data obtained in two onroad studies (32). The assumptions that were supported were that the driver will flatten curves, and that a linear control model is adequate for describing steering behavior. Not supported were assumptions regarding consistent preferred lateral acceleration in horizontal curves, and consistent preferred longitudinal decelerations and accelerations during curve approach and exit respectively. Driver speed profiles in negotiating curves have been a long term interest of behavioral scientists and highway and traffic engineers, e.g. (33, 34). Based on analysis of driver speed behavior on 135 rural two-lane highways, a regression relationship has been developed (35) between driver 85^{th} percentile speed (*V*85, km/hour) and the independent variables of degree of curvature (*D* degrees), length of curve (*L*, meters), and total deflection angle of curve (*I*, degrees): V85 = 102.45 - 1.57D + 0.0037L - 0.10I. There is also some discussion in (35) about accounting for tangent speeds on approaches to curves. This formula and similar relationships developed in the traffic engineering literature could be incorporated into the decision process for modeling and measuring driver speed selection. A thorough survey of the traffic engineering literature is probably warranted to get useful information for the driver model speed and steering decision processes.

Decision Making

There are a variety of circumstances where the driver is confronted with choosing between alternative courses of action and has to make a decision under time pressure. These situations might include deciding whether to stop or go at a signal when confronted with a yellow light or choosing a gap when turning across oncoming traffic, merging onto an expressway or lane changing. Consider a signal light task that was simulated in both a fixedbase simulator and an instrumented vehicle on a closed course (36). The signal light timing was controlled similarly in both the simulator and field studies. When the driver was approaching the intersection, the signal light was initially green, and at a random-appearing time later, the signal turned yellow confronting the driver with a decision to either stop or go. Because drivers were motivated to minimize driving time with rewards, there was a strong motivation to go. However, there were also penalties for running a red light, so driver decisions were made in the face of rewards and penalties (37). The yellow light interval was a constant 3 seconds, and the timing of the light changing from green to yellow was controlled as a function of time to the intersection (distance divided by speed) so that regardless of approach speed the drivers were faced with perceiving a time interval and deciding whether they could legally and safely go or whether they should stop. Five signal timings were randomly presented during drives: One set to require a sure stop (early yellow) and another a sure go (long green). The remaining three timings ranged from a probable stop to a probable go, with the yellow light onset timing ranging from 2.0 to 3.4 seconds to go to the intersection as summarized in Table 2.

Table 2. Time-to-Go Intersection Timings for Signal Light Decision Making Task							
Qualitative	Simu	lation	Field Test				
Probability of	T_{I} (sec)	Number of	T_{I} (sec)	Number of			
Going		Encounters		Encounters			
1. Sure Go	0.0	1-2	0.0	2			
2. High	2.2	8	2.8	9			
3. Medium	2.8	8	3.3	8			
4. Low	3.4	8	4.2	9			
5. Sure Stop	5.5	1-2	7	2			

Subjects were instructed to behave as they normally would in a driving situation with a reasonable motivation for timely progress and a desire to avoid tickets and accidents. A monetary incentive structure was also provided as a tangible and quantifiable motivation for performance (37). Objective and subjective performance measures were taken. The action taken (stop or go) at each signal timing presentation was recorded along with whether a given encounter was a success (getting through on the yellow light) or a failure (running a red light).

Figure 6 shows some results for both simulation and field test trials. Here we see that in the simulator trials when drivers were 2.2 seconds from the intersection that all decided to go and were all successful. When they were 2.8 seconds from the intersection only about 75-80% of the drivers decided to go and were all successful. For the 3.4 second timing drivers only had a marginal chance of making the signal if they accelerated, and on the order of 20-40% tried to go and were largely unsuccessful (i.e. ran the red light). In the test track experiment the yellow onset time-to-go to the intersection timings (T_I) were increased to achieve more marginal decision situations. For the field test data in Figure 6 we see that performance was similar to the simulation data for the 2.8 second time interval. Longer time intervals reduced the percentage of drivers going, and reduced the probability of failure given a go.



The effect of penalty level was also explored in the field test experiment. Results are plotted in Figure 7. Here probability of going is plotted as a function of the drivers' subjective probability of failing given a go decision. This data illustrates two effects. First we see that drivers in jeopardy of \$4 tickets were less willing to go than the \$1 ticket group. Secondly, the operating functions of the two groups are almost equal, with the high penalty group being slightly

Figure 7. Effect of Penalties on Signal Decisions.



more conservative (less willing to go for a given perceived probability of failure). Thus, the level of penalty for failure has a definite effect on decision making, and thus is an important element in risk taking and risk acceptance research. In other words, behavior will vary depending on the consequences of performance, and thus tangible and objective penalties are an important consideration in experimental designs and measurement paradigms.

Concluding Remarks

Performance measurement paradigms for driver behavior are fairly well developed in several fields of engineering and behavioral science. Computational algorithms for various performance measures are available and can be easily implemented in driving simulators. Implementation in driving simulators will depend on providing for relevant independent and Independent variables need to be controlled through scenario dependent variables. development, particularly in tasks involving interaction with other vehicles and pedestrians and traffic control devices where timing is critical. Event based measures are important as well as measures of speed and accuracy throughout complex driving scenarios, e.g. (38). Modeling the kinematic relationships in event based tasks is important to understand constraints on driver and vehicle performance. Modeling driver behavior can be an important adjunct to measurements in order to reveal important dependent variables and to properly interpret results in various tasks. Proper control of independent variables and appropriate calculation of dependent variables will significantly advance the application of driving simulator research, assessment, training and prototyping.

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