43

Coupling Perception, Action, Intention, and Value: A Control Theoretic Approach to Driving Performance

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Abstract

The Problem. Driving is a prototypical example of a closed-loop control problem. This chapter presents a tutorial introduction to the logic of closed-loop systems and the implications for theory and research on driver performance. The human-vehicle system is parsed into three coupled components: (1) the problem constraints; (2) the observer constraints; and (3) the control constraints. We hope to illustrate the importance of each component to a full appreciation of the closed-loop dynamic and to consider how the coupling across these components will determine the emergent stability of the human-vehicle systems. We hope that this tutorial will help to provide common ground between behavioral scientists and engineers, so that each can better appreciate how the human factor, the vehicle, and the driving ecology interact to shape system performance. We hope that this will provide a theoretical context for interdisciplinary driver research using simulators. ***Role of Driving Simulators***. There is a growing appreciation among those who study human performance that context matters. Thus, increasingly it becomes important to be able to evaluate performance under conditions that are representative of natural life experiences. Driving simulators provide a unique bridge between the complexity of natural environments and the demands for controlled observation in order to test hypotheses about human performance. This is equally important for addressing practical issues associated with training and design, as well as for basic issues associated with understanding adaptive cognitive systems.

43.1 Introduction

This chapter is designed to illustrate how a control theoretic approach might inform research on driving performance and simulation. In doing this, the focus will not be on specific control theoretic models, but on the motivation and rationale behind the models and the implications for research programs utilizing simulation to evaluate and improve driving performance. We believe that the driving problem in particular, and human-vehicle systems in general, are important instances where a closed-loop system architecture; is required for deep understanding of the relations among component behavioral elements. Frankly, we believe that this generalization can be made to most of the field of human performance and cognition (e.g., Flach, Dekker, & Stappers, 2008). The closed-loop architecture captures the mutually causal relationships between perception and action as well as emergent systemic properties such as stability and varieties of convergence toward behavioral goals.

This chapter will first consider three components of any control problem: 1) the *problem specification*; 2) the *observer problem*; and 3) the *control problem*. An additional section will consider

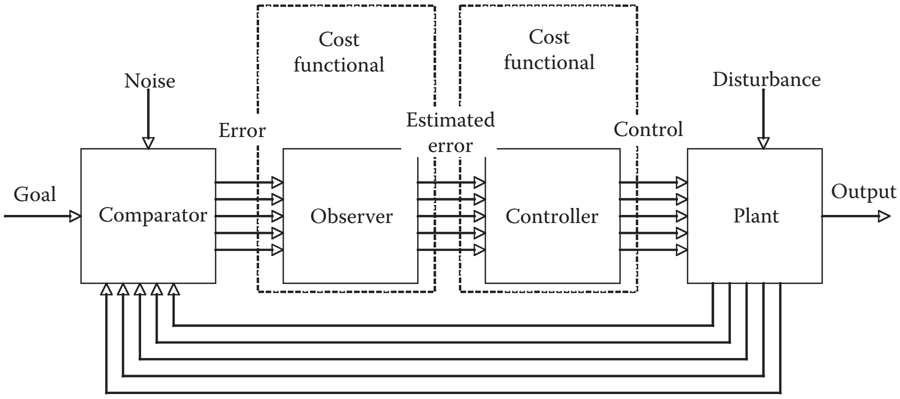

FIGURE 43.1 This abstract model illustrates a generic control system.

what Weinberg and Weinberg (1979) call the *Fundamental Regulator Paradox.* The final section will summarize key points and suggest how the control theoretic orientation might contribute toward a general approach to human-machine systems.

Figure 43.1 provides an abstract view of a generic control system. It is abstract in that the components do not necessarily correspond to any single mechanism or object. Rather, these components reflect logical aspects of a control problem (e.g., to move through a problem space from an initial state to a goal state) and of the system that might solve this problem (e.g., operations that determine movement in the space). To a certain extent, two of the boxes in Figure 43.1 represent constraints of the control problem (the Plant and the Comparator) and two of the boxes represent means for solving this problem (the Observer and the Controller).

The plant represents the dynamic process that is to be controlled. In the case of driving, this would typically be the vehicle dynamics. It is typical to describe this process in terms of state variables. The state variables reflect the condition of the system at any specific time t, such that knowledge of this state, together with knowledge of the input (control actions and disturbances) from t forward, is sufficient to predict the performance (output) of the system from t forward. For example, for a simple inertial system the state variables could be position and velocity. Thus, if you know position and velocity at time t and the forces acting on the body from t forward, then it is possible to specify the path of the body from time t forward.

Figure 43.1 shows multiple feedback paths from the plant to the comparator. Each path represents a measure of a state variable of the plant. Typically, there would be at least one measure for each state variable. The comparator represents comparisons between the current states of the plant and the goal states. To the extent that all measures are in a common metric, the comparator can be visualized as a subtraction to yield an error measure (i.e., the difference between the current state and the target state). For example, the target state might be the center of the lane on a curving road; the relevant states would be the vehicle's position and heading angle; and the errors would be the lateral position error (center of lane—vehicle position) and the heading angle error (road lane angle—vehicle heading angle).

The role of the observer is to estimate error at time $t + \Delta$ from the potentially noisy observations at time t (and perhaps earlier times). Note that the observer function involves both estimation and prediction. Figure 43.2 (upper labels) illustrates the estimation process. The observation process typically involves weighting and integrating information over time. For example, the estimate for any particular state variable may correspond to a weighted function of all observations at time t and of previous estimates. Again, consider the simple inertial system, position at $t + \Delta$ might be estimated as a weighted function of the position and velocity observed at time t and previous estimates of these quantities. In a designed observer the weightings would be chosen to reflect knowledge about the process being observed. That is, there is at least an implicit internal model of the plant guiding the observation process. See Jagacinski and Flach (2003, Chapter 18) for some examples of simple observers.

The observation process in Figure 43.1 is shown in the context of a "cost functional". The point of this is to make it clear that the observation process will typically require a trade-off among multiple criteria or preferences. This trade-off is seen in Signal Detection Theory in terms of the choice of a decision criterion (β). The decision criterion can be chosen to maximize the expected

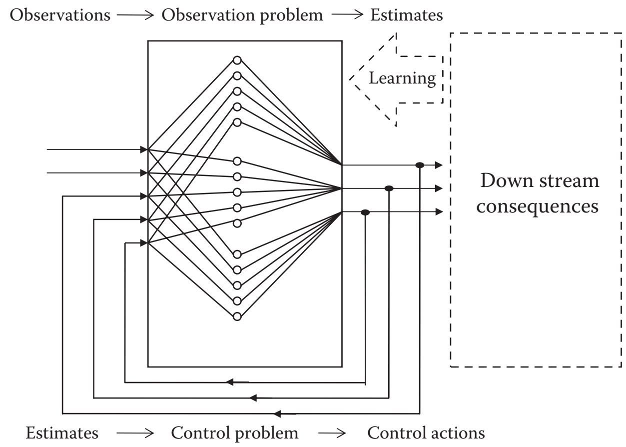

FIGURE 43.2 This figure illustrates observation (upper labels) and/or control (lower labels) as a process of weighting and possibly integrating information. The small open circles represent gains or multiplicative weightings of the various signals. The convergence of lines to a single point represents a summation of signals. This figure highlights parallels between the observation and control problems.

value associated with a specific payoff matrix (e.g.,value of hits and correct negatives and costs of misses and false alarms). In filtering, on the other hand, the trade-off is typically reflected in the gain of the filter (Jagacinski & Flach, 2003). This can be thought of as the relative weight given to the current observation relative to the expectation based on the integration of previous observations and/or an internal model. If the gains on new observations are high, the filter will be biased in favor of the current observation. This system would be very sensitive to a changing signal, but would also have a tendency to chase the noise. If the gains on new observations are low, the filter will be biased in favor of the expectation. This system would be more effective at filtering out noise, but would be sluggish to respond to real changes in the signal. Ideal Observer Theory provides analytical tools for specifying an optimal value for the filter gains, given a specific set of criteria (e.g., Gelb, 1974). Thus, the major point of the observer cost functional box in Figure 43.1 is to emphasize that evaluation of an observation process (i.e., determining whether it is optimal or satisfactory) involves consideration of an extrinsic payoff matrix or cost functional regarding the importance of new observations and prior estimates.

Like the observation process, the control process can also be envisioned as a weighting process based on some, at least implicit, model of the process (Figure 43.2, lower labels). In the case of control, the inputs are the state estimates coming from the observer process and the outputs would be control actions (i.e., manipulations of the control surfaces). In general, the weights can be thought to reflect the gains or sensitivities to the various estimated errors. As with the observation process, there typically will be optimal gains. If the gains are below optimal levels, the control system will be slow to eliminate error (i.e., it will be sluggish). However, if the gains are very much above optimal levels, then the control system can become unstable. That is, rather than reducing error, the control actions will tend to increase error (e.g., pilot induced oscillations—see National Research Council, 1997). If there are effective time-delays in the observer, controller, or the controlled process (e.g., the vehicle dynamics), then there will always be a stability limit on the gains. Choosing the right gains for the controller also requires consideration of a cost functional or payoff matrix. Typically, in control systems one is balancing the cost of control action (or effort) versus the cost of error. For example, the Optimal Control Model of the human tracker typically uses the velocity of control action as a measure of effort. The model assumes that the human is minimizing the integral of mean-squared error and mean-squared control velocity (Kleinman, Baron, & Levison, 1971). Optimal control theory provides analytic tools for specifying the optimal values for control gains (e.g., Kirk, 1970).

Typically, novice drivers show high degrees of effort and a tendency to weave within their lane. This behavior could be modeled as high gains on either the observer (i.e., tracking the noise) or the controller (i.e., over-correcting or pilot-induced oscillations). With the development of more proficiency, driving seems to take much less effort and drivers become better at tracking within their lane. This progression could be modeled as tuning toward or discovering more "optimal" gains for the observer or the controller, or both. This might be described as tuning of the internal control model.

Note that in the design of automatic control systems, an internal model together with the cost functional or payoff matrix guides the choices of the designers (e.g., the gain settings for the observer and the controller), but it is not always an explicit component of the control system. For biological systems, however, which are essentially "self-designing" or "self-organizing", some degree of knowledge/experience with the action, information, and value constraints will be fundamental components of the system. Thus, for researchers who are trying to model and/or explain skill development, this component needs to be more explicit. Much of the empirical research on control theoretic models has finessed the issue of these experiential and value constraints by exclusively modeling only well-trained and skilled operators. In essence, these skilled operators have become tuned to the task demands and their internal models and cost functions can be assumed to result in near-optimal weightings of the

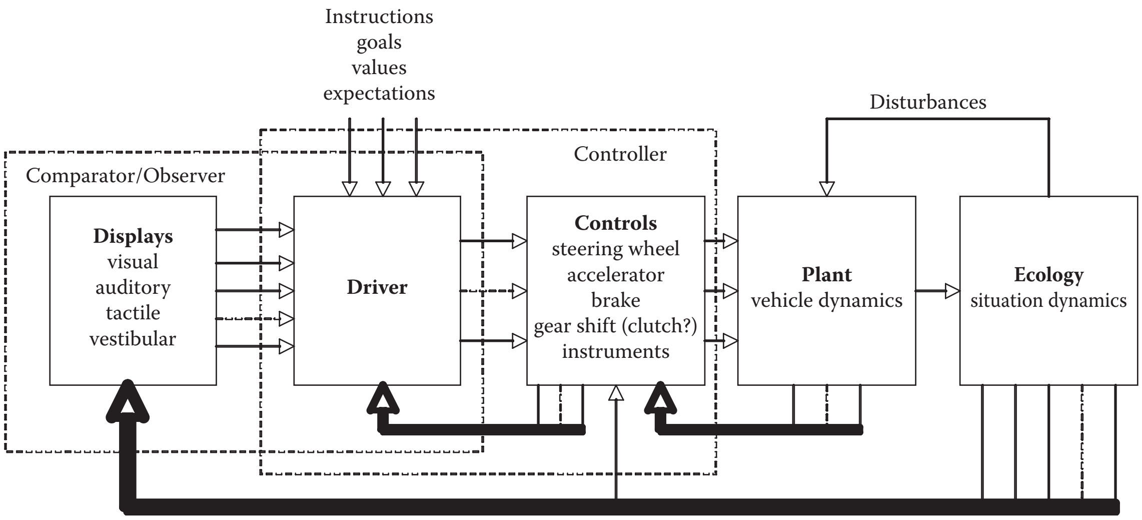

FIGURE 43.3 This figure shows the components of the human/vehicle control system.

relevant task criteria (e.g., see Kleinman et al. 1971; or Pew & Barron, 1978). A major obstacle to applying optimal control theory to modeling novices is an inability to specify this knowledge and/or the cost functional. This will be explored in a later section in the context of the regulator.

Figure 43.3 provides a more detailed illustration of control in the context of driving. Figure 43.3 parses the control system to reflect the individual physical components of the system. Note that the human, as a component of both the observer and the controller, is at the heart of the control problem solution. This suggests that the attunement or skill level of the human will be critical to the effectiveness of the overall control solution. Figure 43.3 also includes a box to reflect the ecology. Classically, control problems are framed in terms of the vehicle being controlled. However, in framing the larger problem of driving safety, and particularly in considering the use of simulation, it may be very important to explicitly consider the ecology as part of the total system. This ecology reflects the driving surfaces, information displays (e.g., traffic signals), and obstacles (including pedestrians and other vehicles). In a simulator, this ecology must be explicitly specified. This specification will have important implications for how well performance in the simulator will generalize to natural driving contexts.

Figure 43.3 will be examined more carefully in the following sections as we delve deeper into four aspects of a control theoretic approach: the problem specification, the observer problem, the control problem, and the adaptive control problem.

43.2 The Problem Specification: The Situation Demands

Kirk (1970) cites the old adage that "a problem well put is a problem half solved." This certainly is consistent with the experiences of early workers in artificial intelligence. For example, Newell and Simon (1972) made the following observation:

> It would be perfectly possible for the psychologist to follow the route of the economist: to construct a theory of concept formation that depended on no characteristic of the subject other than his being motivated to perform well. It would be a theory of how perfectly rational man would behave in that task environment—hence, not a psychological theory but a theory of the structure of the task environment. (p. 54)

In this sense, a control model is in essence a theory of the task environment or the situation demands. Ashby (1956) states this in terms of his *Law of Requisite Variety,* noting that only variety in the controller can reduce variety due to the environment (i.e., the disturbances). In other words, if the control has too few degrees of freedom, there may be aspects of the environment that cannot be reached or disturbances that cannot be attenuated. "A regulator must be 'like' the environment it regulates," was cited from p. 206 of Weinberg and Weinberg (1979) formalize this as the Parallel Principle:

> A regulator must be "like" the environment it regulates. (p. 206)

From a research perspective, the idea of problem specification or situation demands is related to ecological validity (i.e., the degree to which the research context is representative of the natural phenomena of interest). In the context of simulation, this issue is typically framed in terms of fidelity. It might be valuable to consider three aspects of fidelity:

1. *Vehicle fidelity*—to what extent do the control dynamics of the simulation correspond to the dynamics of the vehicle? (e.g., *Handbook* Chapters 8, 9, & 10)
2. *Situation fidelity*—to what extent do the scenarios and tasks presented in the simulation represent situations that would be encountered in natural driving contexts? (e.g., Chapters 16, 17, 18, & 19)
3. *Experiential fidelity*—to what extent do the experiences of the driver in the simulator correspond with experiences in natural driving contexts? (e.g., Chapters 11, 12, 13, & 14)

These three aspects of fidelity are addressed in greater depth in earlier chapters, as noted above. For this chapter we simply want to emphasize that in using simulation as a research tool for modeling or predicting driving performance, it is important to realize that the generality of models and predictions will be impacted by how well the simulation represents the problem. If the model of the vehicle is inaccurate, the situation contexts naïve, and/or the experience of the participants is biased by demand characteristics, then the generality of any models or predictions based on performance in that simulation will be suspect. Similarly, if the simulation is being used for training, then the degree of positive transfer to natural environments will depend to a large extent on how well the simulation represents the control problems of the natural environment.

Thus, the first step to effective modeling of human performance is to clearly specify the nature of the problem that the human is being asked to solve. Again, we quote Newell and Simon (1972):

> … we shall often distinguish two aspects of the theory of problem solving as (1) demands of the task environment and (2) psychology of the subject. These shorthand expressions should never seduce the reader into thinking that as a psychologist he should be interested only in the psychology of the subject. The two aspects are in fact like figure and ground—although which is which depends on the momentary viewpoint. (p. 55).

Neisser (1987) made the case even more explicitly when he wrote:

> If we do not have a good account of the information that perceivers are actually using, our hypothetical models of their 'information processing' are almost sure to be wrong. If we do have an account, however, such models may turn out to be almost unnecessary. (p. 11)

If care is taken to ensure that the problems presented to participants in the simulator are good (ecologically valid) representations of the driving problem, then the control models of this performance can be important elements in an ecological approach to human performance. However, if the simulator is used to recreate abstract control problems (e.g., stationary compensatory tracking, simple discrete decision tasks), then the simulator can become simply a demonstration device that reifies well-known principles of information and control systems using humans. In a task designed to be accomplished by a simple servomechanism, the well-trained and well-motivated human can be expected to behave much like a simple servomechanism. A million such studies do not "prove" the relevance of control theory for modeling everyday human performance. They simply confirm the internal consistency of control theory.

Thus, we would propose an inverse to the Weinbergs' Parallel Principle as cited above. *We propose that to build an accurate model of a regulator (or control system), one must begin with an accurate model of the environmental relationships it regulates*.

43.3 The Observer Problem: The Awareness Demands

In classical models of vehicle control, the state variables are typically specified in terms of Euclidean distances and their derivatives consistent with Newtonian models of motion. In these models, both goals and state variables are presumed to be measured in common units. Thus, negative feedback is accomplished by the subtraction of a measure of the current state of the system from a goal or target state for that variable. This approach fits well with classical approaches to "space" perception that assume that the function of perception is to construct an internal analog of the world consistent with the "truth" as reflected in the models associated with Newtonian physics and Euclidean space. Thus, a classical psychophysics program focuses on the perception of (e.g., thresholds and differential sensitivity to) Euclidean distances (e.g., depth) and their derivatives (e.g., velocity). In both views, the functional feedback channels are defined in terms of Euclidean dimensions.

However, for a number of reasons, many people are beginning to suspect that for biological systems the observation problem is either far more complex or far simpler, depending on your perspective. One piece of evidence that suggests this is research using a paradigm of "blind walking" (e.g., Loomis, Da Silva, Fuijita, & Fukusima, 1992). In this task, people are shown a position on the ground in front of them and are then asked to close their eyes and walk to the position. Although classical research on depth-perception shows systematic biases in human judgments of depth, when people are asked to walk to a position visually specified in front of them without visual feedback (blind), they show no systematic biases. Thus, while classical psychophysical research suggests a flawed internal model of depth, when tested in an action context, humans prove surprisingly capable. While judgment of depth seems difficult for humans, control of action relative to depth seems fairly simple.

Gibson and Crooks (1938) were the first to imagine that the states relevant for controlling human locomotion may be different than the classical states suggested by Newtonian models. They introduced the construct of a "safe field of travel". It should be clear that in describing the safe field of travel, Gibson and Crooks are making a statement about the dimensions of the driver's state space. They define this space as "the field of possible paths which the car may take unimpeded" (p. 120). That this field is relevant to the observation problem, and that it is different from classical Newtonian measures of motion, is made clear in the following statement about the minimum stopping zone: "The driver's awareness of how fast he is going does not consist of any estimate in miles per hour; instead, he is aware, among other things, of this distance within which he could stop" (p. 123).

Thus, Gibson and Crooks (1938) are suggesting that animals do not construct an internal model of a Euclidean space. Rather, people "see" the environment relative to action capabilities (e.g., minimum stopping distance) and consequences (e.g., imminence of collision). The concept of safe field of travel was a precursor of Gibson's (1979/1984) more general construct of "affordance". The idea of direct perception of affordances can be understood in control theoretic terms as the idea that there is no need for an internal model of Euclidean space to mediate between the observation and control processes. To the extent that there is an internal model, an ecological approach suggests that the model is framed in the language of perception and action, not the language of classical physics.

While the paper by Gibson and Crooks is important to help people imagine how the states of motion for humans may be different from the classical physical dimensions, they did not provide any suggestions about how this information might be fed back for observation. However, Gibson, Olum and Rosenblatt (1955) laid the foundation for modeling structure in optical flow fields that would provide a way to directly measure the states specified by Gibson and Crooks. The connections and the implications for control of animal locomotion were first described in Gibson (1958), where he provided explicit recipes for how motion can be controlled via structure in optical flow. For example, here is Gibson's postulate about steering:

> The center of the flow pattern during forward movement of the animal is the direction of movement. More exactly, the part of the structure of the array from which the flow radiates corresponds to that part of the solid environment toward which he is moving. If the direction of his movement changes, the center of flow shifts across the array, that is, the flow becomes centered on another element of the array corresponding to another part of the solid environment. … To aim locomotion at an object is to keep the center of flow of the optic array as close as possible to the form which the object projects. (p. 155)

The first empirical demonstrations of the plausibility of direct coupling of action to optical structures were inspired by Lee's (1976) analysis of the optical control of braking. Lee (1976) showed how a control system based on optical variables could work. Lee focused on the optical variable *tau* and its derivative *tau-dot*. *Tau* is the ratio of projected optical size of an object (i.e., optical angle) to the expansion rate (i.e., looming or rate of change of optical angle). Since Lee's analysis, a large amount of empirical data has been published that is consistent with the idea that collision actions (e.g., braking to avoid collisions, or swinging a bat to create collisions) are directly contingent on a *tau* criterion (e.g., Hecht & Salvelsbergh, 2004). That is, people (and other animals) tend to initiate action (braking or bat swing) at a constant value of *tau*, independent of distance, speed, and object size.

More recently, Flach, Smith, Stanard and Dittman (2004) have suggested that the observation process may involve measuring and weighting optical angle (θ) and optical expansion rate ($\dot{\theta}$) as independent observables as illustrated in Figure 43.4. Additionally, this model provides a better fit to performance early in practice, where people appear to give disproportionate weight to expansion rate. This model is consistent with errors observed in many of the empirical studies of collision control. Research consistently shows that when object size is manipulated, people tend to respond early to the largest objects; and that when object speed is manipulated, people tend to respond early to the slowest objects (e.g. Smith, Flach, Dittman, & Stanard, 2001). Both these trends can be accounted for by a disproportional weight on expansion rate (relative to the fixed proportional weighting assumed in Lee's original model). Note that our model and Lee's model both assume a linear function of angle and expansion rate. However, Lee's model assumes a zero intercept (a one-parameter line, allowing only the slope to vary), and our model loosens this constraint (a two-parameter line, allowing both the intercept and slope to vary).

It is important to note that with practice in the control of collisions, people tend toward a proportional weighting of angle and expansion rate as predicted by Lee's early model. Thus, our model is not a contradiction of Lee, but rather a refinement that allows Lee's intuitions to be extended over a wider range of skill levels. The major conflict with Lee's original hypothesis is that there is no need to include *tau-dot* as a feedback variable.

In addition to feedback of optical angle and expansion rate ($\dot{\theta}$). Figure 43.4 also shows feedback of global optical flow rate (GOFR), which is a function of the overall (e.g., average) angular speed of ground textural elements. Whereas, θ and $\dot{\theta}$ specify relative rates associated with a looming obstacle (e.g., a stopped or slowing lead vehicle), GOFR specifies the observer's speed relative to the ground surfaces and fixed objects on that surface. GOFR for a flat ground plane is directly proportional to movement speed and inversely proportional to the distance of the eyes above the surface (i.e., eye height). Since eye height is constant in most driving situations, GOFR can be a reliable source of information about the surface speed of the vehicle (i.e., speed as measured by a speedometer). However, changes in eye height associated with changing vehicle sizes (e.g., going from a sports car to a large SUV) might create some negative transfer (e.g., Owen, 1984).

Another potential source of information for vehicle speed is edge rate (Denton, 1980). For regularly spaced textures, such as the lane markers on a highway, the rate at which these texture elements pass through a fixed field of view will be proportional to vehicle speed. There is a growing literature exploring the various optical structures and the role that they play for the perception and control of self-motion (e.g., Fajen, 2005; Flach & Warren, 1995; Warren & Wertheim, 1990). This work is consistent with Gibson's (1979/1984) concept of ecological optics. The essential idea is that structure in dynamic perspective resulting from a moving point of observation, can specify states of self-motion and that animals can use this information to skillfully control that motion.

Note that the various optical variables together span the same space as the classical state variables (distance and speed). And they do so in a way that there are common components associated with the classical variables—for controlling inertial systems these common components might be the "signal". Additionally, each variable has sources of variability associated with other

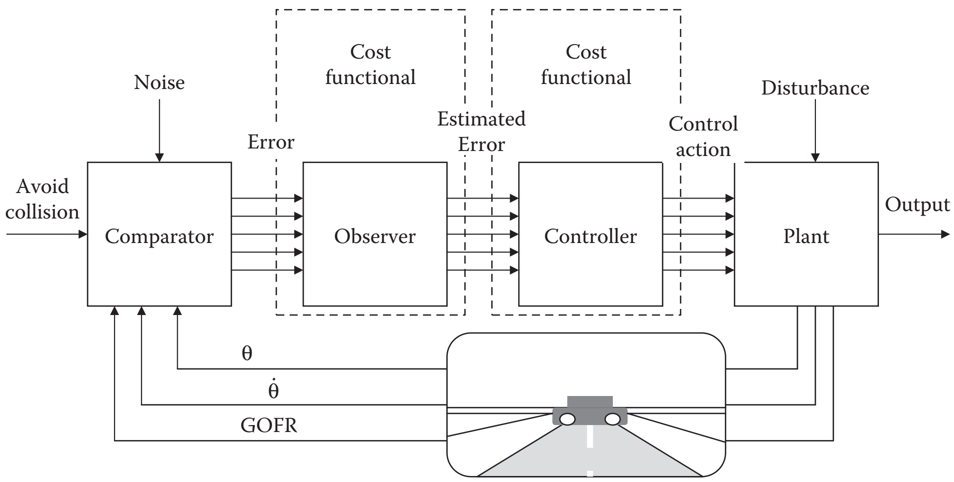

FIGURE 43.4 It is important to consider the possibility that input to the comparator and observer processes may be direct input of perceptual primitives (e.g., optical angles and angular rates), rather than Newtonian primitives (i.e., Euclidean distances and derivatives).

properties that might be considered "noise" with regard to the problem of controlling motion (e.g., object size and distribution of optical texture on surfaces).

Although the emphasis here has been on ecological optics, we believe that Gibson's (1958) intuitions about dynamic optical perspective and animal motion can be generalized to other modalities (e.g., auditory, vestibular, and tactile). We believe that an important step in modeling the observer components in any biological control system is to consider the possible sources of information feedback and their relations to the states of motion. In general, we expect that skilled drivers will learn to take advantage of all or most of the information available to them. Thus, knowledge of the limits of this information will provide valuable intuitions about the limits of human performance. Also, knowledge of how information is specified in natural contexts can suggest more effective ways to configure information in engineered displays. For example, Smith (2002) observed faster driver responses for forward collision warning (FCW) displays that featured a looming stimulus (an expanding vehicle angle) when compared with displays that featured only a unidimensional scale presentation. The data from these driving simulator studies led Delphi to select the "looming" display for the large-scale field operational test (ACAS FOT) that evaluated both adaptive cruise control (ACC) and FCW.

These assumptions suggest both unique opportunities and challenges for the use of simulators in research and training. Driving simulators provide a unique opportunity to control and manipulate information structures such as optical flow fields and to measure the implications for driving performance. This general program of research has been called "active psychophysics" (Warren & McMillan, 1984). In the active psychophysics research programs on visual control of locomotion, the independent variables are typically motivated by ecological optics, while the tasks (e.g., tracking), the measures (e.g., frequency response), and analyses (e.g., Fourier or Bode analysis) are motivated by control theory (e.g., Jagacinski & Flach, 2003, Chapter 22).

An important challenge in the use of simulators to study and to train drivers is that it is important to represent the natural information constraints as well as possible. Inferences about and transfer to natural situations will generally be constrained by the level of perceptual fidelity that is possible, as noted earlier. One of the benefits of ecological optics is that it has increased our capacity to analytically specify optical fidelity beyond the engineering or simple psychophysical constraints (e.g., screen resolution, frame rate). However, it is clear that there are some aspects of optical fidelity that are difficult to simulate, such as the unfolding of nested texture that is associated with approach to an object in natural situations. For example, from a distance a cornfield appears as a single element of texture, but as an observer gets closer, the field disappears as a texture unit and individual stalks of corn become the texture elements. Other modalities can provide even greater challenges (e.g., vestibular fidelity and spatial audio fidelity). Thus, when the risks allow, instrumented cars operating on test tracks or in natural environments can be a valuable supplement to research using simulators.

In our view, identifying the potential sources of information is a pre-requisite to studying the unique limitations associated with human information processing. Again, consider the Neisser quote, cited earlier. However, it should be clear that the observer problem involves many considerations above and beyond the ecological analysis of information sources. In addition to general psychophysical limits, it should be clear that the ability to utilize potential information will be constrained by experience (e.g., Gibson, 1969) and by situational demands. For example, a growing safety concern is the proliferation of electronic media (e.g., cell phones and MP3 players) with the potential to distract drivers (Caird, Willness, Steel, & Scialfa, 2008; Chisholm, Caird, & Lockhart, 2007; Strayer & Johnston, 2001). Also, while many control models assume continuous feedback and proportional control, it is likely that, due to the spatial distribution of information (e.g., windows, side mirrors, rear-view mirrors, dashboard) and the presence of distractions, the human driver is more likely to function as a discrete control device (intermittently sampling information and using discrete stereotypic/automatic control responses over short time periods, e.g., see Senders, 1964).

The main point for this section is that the problem of how humans and other animals solve the observer problem may be more complex than assumed by classical models. Researchers should not assume that the dimensions which are conventionally used in physical models of space and motion are the feedback dimensions for biological control systems. Thus, it is dangerous to uncritically generalize from engineering analyses and engineered control solutions to biological systems. Nevertheless, the methodologies and logic of control theory as reflected in "active psychophysics" will play an important role in exploring biological control systems to identify the information that is available to specify the relevant states of motion.

43.4 The Control Problem: The Action Demands

Given that the driver can solve the estimation problem so that there are good estimates of the states of motion relative to a slowing line of traffic or relative to a winding road, how does the driver translate these estimates into appropriate actions? That is, at what point should the driver release the accelerator? At what point should the driver initiate braking? How hard should the driver press the brake? How much should the driver turn the wheel? The control problem involves choosing actions that bring the system closer to the goal states. In other words, the controller (driver) needs to choose the action that best nulls the error.

The overall control problem can be parsed into two subproblems which we will call the *degrees of freedom problem* (Bernstein, 1967) and the *gain problem*. The *degrees of freedom problem* is associated with the numbers of possibilities. This can mean that there may be many different actions (or means) that lead to the same goal (or ends), but also can mean that there are many paths to failure. Since there are many possibilities—the control problem can be very complex—which approach is best? This is well-illustrated by the problem of the golf swing (e.g.,

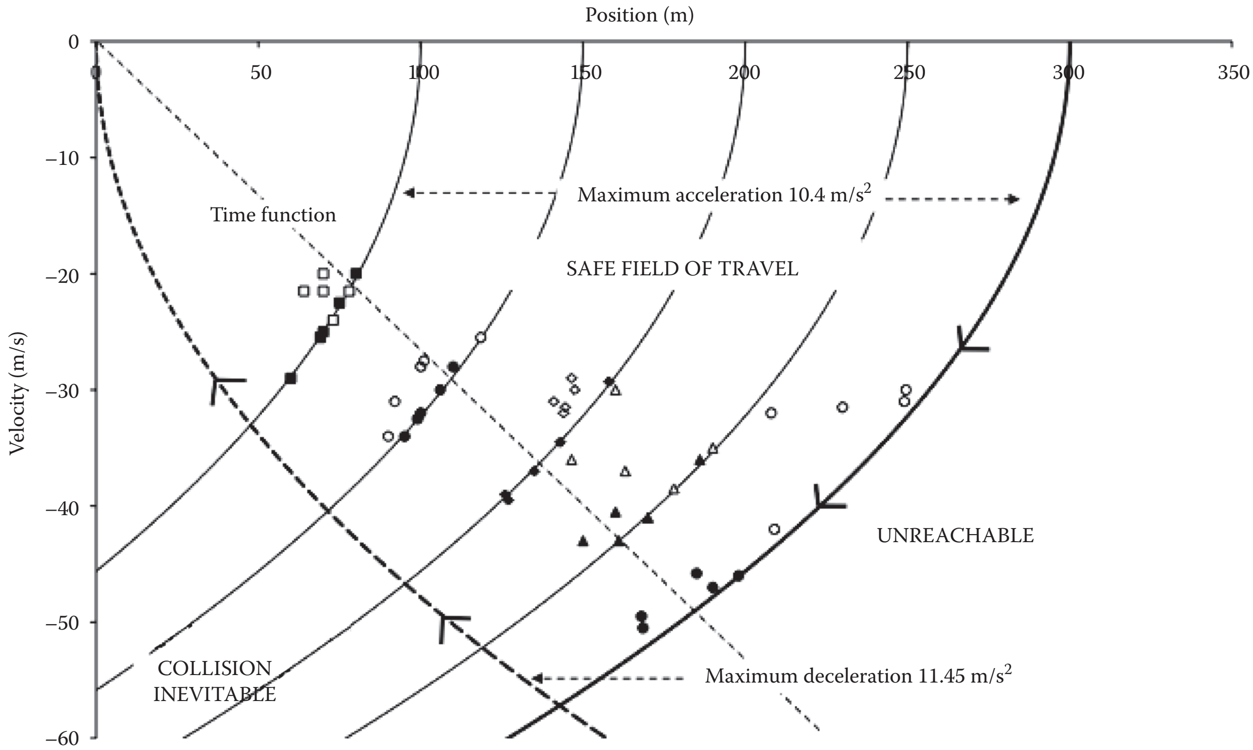

FIGURE 43.5 A state-space (position × velocity) for a braking control task employed by McKenna (2004) is illustrated. The data indicate the motion state of the vehicle when the driver released the accelerator in order to stop in front of an obstacle at the zero position (left boundary of the state space). The open symbols show performance in the first block of trials. The filled symbols show performance in the twenty-fifth block of trials. Five trials from each block are shown for each of five starting positions.

Cochran & Stobbs, 1968). The human body has many degrees of freedom as a result of the various joints involved in the golf swing. Of all the possible combinations, only a very few will yield the results desired by the golfer. Thus, a golfer seeking to eliminate a persistent slice has many possibilities to consider. Is it my head position or my stance, or my right elbow, or my grip, or some combination of these? Vehicle control systems tend to be relatively low degree of freedom systems; that is, the options are limited. If the traffic in front of you is slowing, you have two basic options to avoid a collision, to brake or to change lanes to pass the slowed traffic. Thus, we will focus on the gain problem.

The *gain problem* typically involves the timing and the magnitude of action relative to the state observations. This applies both for proportional control where the gain determines the magnitude of a proportional response and to discrete control actions where the gain may reflect the amplitude of a stereotypic response pattern (e.g., a bang-bang control). For example, given that you choose to brake (because there is no room to pass), at what point do you initiate the braking, and how hard do you press the brake? Note that while the ratio of visual angle-to-expansion rate may specify the time-to-collision, it does not specify the right time-to-brake. The right time-to-brake depends not only on the optics, but also on the state of the braking system (and perhaps the road). With poor brakes or slippery surfaces, it would be prudent to begin braking much earlier than with better brakes or drier surfaces. This is another facet of Gibson's (1979/1984) affordance construct. The information has to be seen relative to the action capabilities. Many of the limits on the field of safe travel are limits on the control dynamics. In control theory, these limits are often visualized as boundaries in state space. Figure 43.5 is an example where presenting human performance data relative to control boundaries in a state space can provide insight into skill development.

The data in Figure 43.5 show the performance for one subject in an experiment conducted by McKenna (2004). The experiment was conducted using a desktop computer simulation. The simulation started with the car positioned on a road at one of five distances from an obstacle (at the zero position (left boundary) of the state space). The task was to drive from the initial stopped position to a stopped position just in front of the obstacle. Participants were asked to do this as quickly as possible while avoiding collisions with the obstacle. The data show the state of motion (position and velocity) when the driver released the accelerator. The open symbols show performance early in training (Block 1) and the filled symbols show performance late in training (Block 25). Each block involved 25 trials, five at each of five initial distances (in meters) from the obstacle (100 [squares], 150 [circles], 200 [diamonds], 250 [triangles], and 300 [circles]).

The first thing to note in Figure 43.5 is the dimension of the space. The dimensions in this case reflect the two state variables (position and velocity) for motion of an inertial system.

The quadratic curves represent control limits for each of the five starting positions. The curves extending from the initial vehicle positions to the left (i.e., toward the velocity axis) show maximum acceleration curves for the simulation; that is, the acceleration that would result from full deflection of the accelerator pedal. The dashed curve extending to the origin from the right shows the maximum deceleration for the simulation (i.e., the deceleration that would result from full deflection of the brake pedal).

The state space, together with the control limits, provides one way to analytically represent constraints within the field of travel. We will focus on the darkened curve for the farthest position (300 m). However, the same logic can be applied to the curves associated with any of the five initial conditions. The region enclosed by the acceleration curve and the two coordinate axes represents the field of possible travel. It is possible for the driver to reach any state inside this region. The region below and to the right of this curve represents the states that are unreachable in the simulation. Given that the car is constrained to only move forward and there is a constraint on maximum acceleration, there is no possible way to reach states in that region. The fastest path to the position of the collision object (vertical axis) is along the maximum acceleration path. However, this path leads to a collision at high velocity (over 60 m/s).

The region enclosed by the maximum acceleration curve, the dashed maximum deceleration curve, and the horizontal coordinate axis represents the safe portion of the possible field of travel. From within this region it will be possible to stop prior to collision. The region below the dashed deceleration curve represents collision conditions. That is, for all combinations of position and speed in this region, it is impossible to reach zero velocity prior to reaching zero distance—a collision is inevitable. If a driver enters this region, he/she has "overdriven his/her brakes". Thus, this region is outside the safe field of travel.

The path along the edge of the safe field of travel, moving from the initial position along the maximum-acceleration curve until it intersects with the maximum-deceleration curve and then following the deceleration curve to the origin, represents the minimum-time path through the state space that satisfies the goal of stopping prior to collision. That is, any other path through the safe field of travel will take longer to travel to the same position. This path would be achieved through a bang-bang style of control—full acceleration to the point of intercepting the maximum-deceleration curve, then full braking to the point of zero velocity.

This driver from McKenna's (2004) study tended to converge toward a bang-bang style of control with practice. By the twenty-fifth block he/she tended to move along the maximum-acceleration curve, releasing the accelerator prior to intersecting the maximum-deceleration curve. The dashed line extending from the origin represents a *tau-like* function (constant time-to-collision, assuming a constant velocity of motion) fit to the data for Block 25. In fact, when computed based on optical state variables (visual angle and expansion rate) a linear function consistent with a *tau* strategy accounted for 80% of the performance variance for Block 1 and 89% of the variance for Block 25. Using the physical states (position and velocity) less variance is accounted for (approximately 42% of the variance). Thus, this particular driver appears to be using a bang-bang style of control and the switch from acceleration to braking seems to be triggered by a criterion that is consistent with Lee's optical *tau* function.

If you observe the progression from Block 1 (open symbols) to Block 25 (filled symbols), it suggests that the driver is learning or tuning to the control limits. That is, the point of accelerator release tends to be closer to the edge of the field of safe travel in the later block. This is consistent with the task instructions to get to the target as quickly as possible. One might hypothesize that the driver is learning to "see" his action capabilities in terms of the optical variable *tau*. He is beginning to "see" the optimal time to release the accelerator and initiate hard braking for the dynamic constraints (braking limits) of the simulation. Or it might be said that the driver is developing an accurate internal model of the simulation dynamics (e.g., Jagacinski & Miller, 1978).

Figure 43.5 and the associated experiment by McKenna (2004) illustrate one facet of the field of travel (or affordances): the action constraints or control limits. However, a potentially important facet of the natural field of travel is not well-represented in either the diagram or the experiment. That is the consequences which are associated with the actions. In the simulation, while the participants were instructed to avoid collisions, the actual consequences of stopping a little too early or a little too late were essentially the same. In the natural driving environment this is not the case. The consequences of braking too late are dramatically different (a collision with the potential for costly damage to the vehicle and the driver), than the consequences of braking too early (need for corrective action and increased time to target).

Another important consequence of action in natural driving conditions that was not experienced by the participants in McKenna's study was g-force. With the desktop simulation, the task was purely visual (kinematic), whereas in the natural diving situation there is a kinetic (g-force) component. It would be unusual to see drivers adopt a bang-bang style of control to accomplish tasks similar to those in McKenna's study (e.g., pulling into a parking spot against a building). If a driver did adopt this strategy, his/her passengers would not be happy. Figure 43.6 provides another hypothetical model of the safe field of travel with respect to braking. The boundaries of the field of travel represent acceptable levels of g-force. Normal braking typically results in forces on the order of 0.3 g and hard braking results in forces on the order of 0.6 g. A driver who was concerned about his/her own comfort (and that of their passengers) would typically strive to keep within the comfort zone region of state space. They would try to avoid hard accelerations and situations that might require hard braking.

Thus, in the driver's control solution, it is important to consider both attunement to the control limits (action constraints) and the value criteria reflected in the cost functional that the driver is attempting to satisfy (consequences). Again, the choice of control magnitude (i.e., gain) in solving the control problem depends both on the dynamics of the vehicle (e.g., the status of

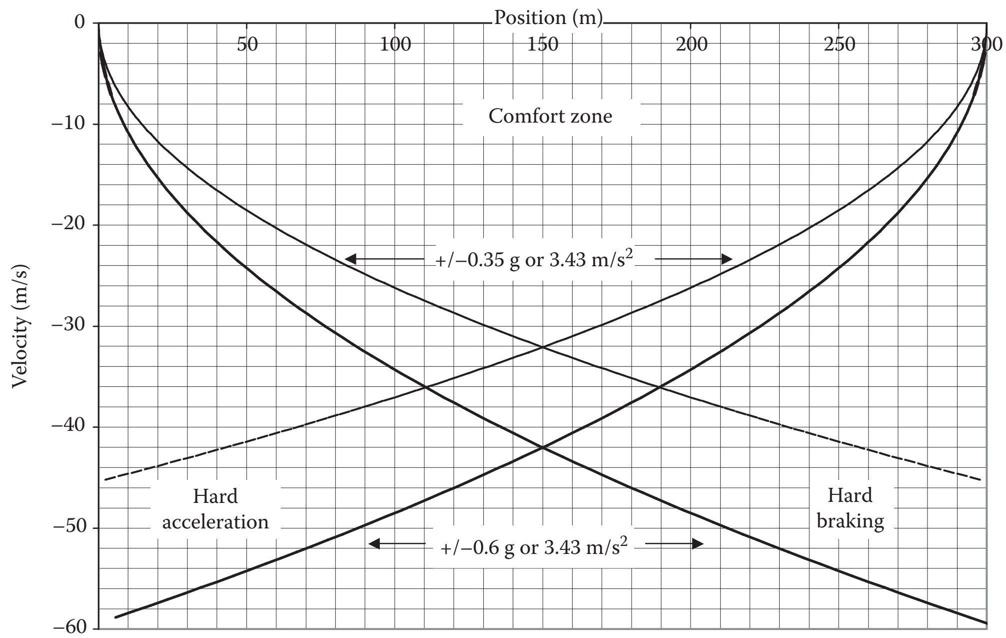

FIGURE 43.6 This figure illustrates a hypothetical model of the comfort zone for accelerating and braking in which the limits are specified in terms of g-forces. The zero position (left boundary) of this state space represents a potential collision object or obstacle, and the axes represent position (distance from this obstacle) and velocity toward the obstacle.

the brakes) and the criteria for successful control as typically reflected in a cost functional. Note that the cost functional is not typically represented in control diagrams. However, this function is an important consideration to the engineer who is choosing the control gains or the control algorithms.

A major point for this section is the need to consider both the constraints on action and the value or cost constraints that guide the choice from among the options for action. These constraints are not typically represented in control diagrams. However, they are critical to the logic for choosing one control solution relative to another. We suggest that state spaces showing the action and comfort/success boundaries can be an important tool for researchers who are interested in understanding the logic of biological control systems. In this context, the normative models for optimal control are used to partition the state or problem space into qualitative regions that provide clear benchmarks for evaluating and interpreting the behaviors of biological control systems.

It is also important to note any potential differences between the constraints in the simulator environment and constraints in the environments to which either training is intended to transfer, or to which models are intended to generalize. Thus, for example, the lack of g-forces in a simulator may lead to very different control behavior in that context (e.g., more aggressive bang-bang strategies).

43.5 The Fundamental Regulator Paradox

> The task of a regulator is to eliminate variation, but this variation is the ultimate source of information about the quality of work. Therefore, the better job a regulator does, the less information it gets about how to improve. (Weinberg & Weinberg, 1979, p. 250)

This quote is Weinberg and Weinberg's definition of the Regulator Paradox. It is interesting, in the context of this book that they go on to illustrate this paradox with a driving example:

> This lesson is easiest to see in terms of an experience common to anyone who has ever driven on an icy road. The driver is trying to keep the car from skidding. To know how much steering is required, she must have some inkling of the road's slickness. But if she succeeds in completely preventing skids, she has no idea how slippery the road is.
>
> Good drivers, experienced on icy roads, will intentionally test the steering from time to time by 'jiggling' to cause a small amount of skidding. By this technique, they intentionally sacrifice the perfect regulation they know they cannot attain in any case. In return, they receive information that will enable them to do a more reliable, though less perfect job. . .
>
> Without the jiggling . . . the driver . . . doesn't have any way of knowing if success comes from skill, or from the momentarily benign environmental conditions. The jiggling … tactic is an investment in model improvement. Not only does it refine the model of the transitory environment, but also, even more important, it refines the model of the system's own regulatory ability . . . (p. 251).

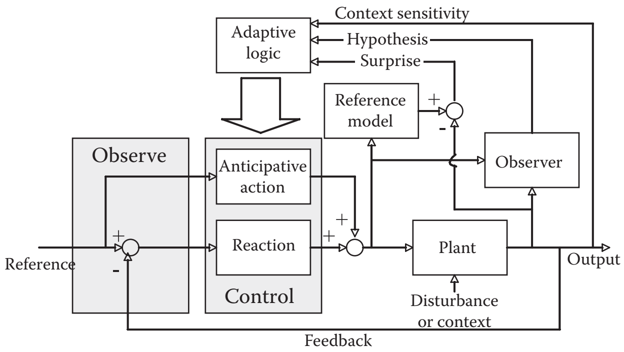

FIGURE 43.7 Three styles of outer-loop adjustments are shown as possible components in an adaptive control process.

Simple automatic control systems are typically designed off-line. That is, the jiggling needed to build a "model" of the control problem is done by the designer, not by the control system. In the off-line design of simple control systems, engineers have found it to be convenient to treat the observer and controller processes independently. Thus, engineers and engineering courses often focus on one of these problems (ideal observers or optimal controllers) independent of the other. However, biological systems typically design their control solutions through trial and error. That is, they have to tune their control solutions while actively engaged in solving the control problem. This is generally referred to as the problem of adaptive control. It requires a kind of meta-cognition in which drivers monitor system performance and adjust their effective *control laws* in order to improve performance (i.e., satisfy some value index). This adjustment could be a change of goals, priorities, and values. It could involve shifts of attention or attunement of the observation process to monitor states that are discovered to be relevant. It can also involve changing the mapping from state to control. In other words, while simple, automatic systems are designed by an extrinsic agent, biological control systems are self-organizing.

Figure 43.7 adds outer loops to the control diagram to reflect the meta-cognitive processes associated with evaluation and adaptation. The different loops are analogous to some of the tactics that have been used by control systems designers to solve the adaptive control problem. These tactics include *gain scheduling*, *model reference adaptive control*, and *self-tuning*. In each case, the simple controller is augmented by an outer-loop that monitors and adjusts inner-loop performance. *Gain scheduling* reflects a kind of context sensitivity. This control system monitors some aspect of the control context and it chooses one of several pre-stored control algorithms that best fits the context. For example, in aviation systems, the control system chooses different gains for different ranges of altitude. In a driving context, a driver may choose a different style of control for driving in different road conditions (e.g., dry, wet, snowy, or icy).

A second tactic is *model reference adaptive control*. With this tactic, the actual response of the vehicle is compared to an "internal model" or expectation of what the "normal" response should be. For example, a driver may have expectations about how brakes should respond. When the expectations are not met (i.e., the driver is surprised), the control process is adjusted in a direction intended to bring the actual response into closer alignment with the expected normal response. For example, if the response to braking is less deceleration than expected due to poor brakes or surface conditions, the driver might increase the braking force, until the deceleration matches expectations.

A third tactic for monitoring and adapting control processes is *self-tuning*. With this tactic, the input-output relations are being continuously observed to directly or indirectly (i.e., via revisions to an internal model of the plant) adjust the controller. This continuous process is typically supported by active tests (e.g., exploratory actions) of hypotheses about the plant. For example, after driving through high water a driver might tap the brakes to see if the braking dynamics have changed. The jiggling in the Weinbergs' example above illustrates a technique called dithering, where continuous small amplitude, high-frequency movements are made together with normal control actions. The small amplitude movements are designed to have minimum impact on the target response (e.g., lane maintenance), while providing continuous information about changes in the plant dynamic (e.g., road slickness).

In the self-organization process, the coupling of observation, control, and adaptation may be much more intimate than suggested by the partitioning of the observation and control problems as suggested by Figure 43.1, Figure 43.2, and Figure 43.7. Whereas, observation, control, and adaptation tend to be separable operations in engineered systems, in biological systems these processes are more likely to be tightly coupled processes. That is, every action may function to simultaneously reduce error in service of control and to generate information in service of observation of both the situation and the self. Gibson (1963) recognized this coupling with the terms *performatory action* (control function) and *exploratory action* (observer function). Figure 43.8 represents our attempt to make this intimate coupling salient.

The circles in Figure 43.8 represent three sets of constraints similar to those of Peirce's triadic model of semiotics [see Hawthorne, Weiss and Burks (Eds.) 1931–1966] and Neisser's (1976) perception-action cycle. Beginning from the left, reading the non-italicized labels, Figure 43.8 illustrates a feedback control process in which intentions originating from experience are compared with consequences being fed back from situations as represented in an information medium. The differences resulting from this comparison (i.e., errors) can be reduced either through performatory actions on the situation or through change of the intention. Simultaneously, an observation process is also happening in which *expectations* are compared with *results* stimulated by *exploratory actions*. The comparison can result in *surprise*, which can lead to both change in expectations and further exploration. Any action (e.g., depressing the brake) will have both performatory (e.g., decelerating the car) and exploratory (e.g., updating expectations about brake dynamics or road surfaces) implications. These actions can change beliefs (experiential constraints) as well as the physical circumstances of those beliefs (situational constraints). The link that allows the simultaneous coordination of control and observation is the informational constraints.

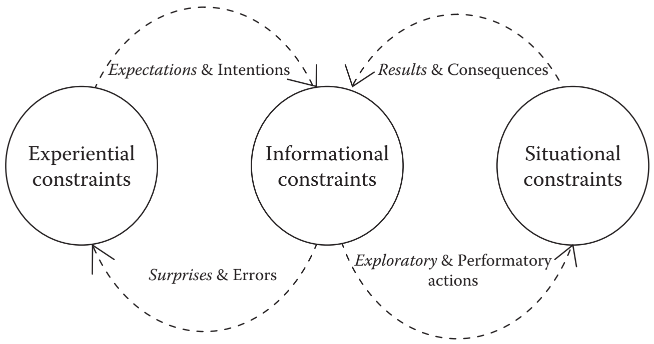

FIGURE 43.8 This diagram attempts to represent the intimate coupling between control (action) and observation (perception), where these processes are operating in parallel.

The adaptive processes associated with parallel control and observation reflects a process of "learning by doing" that is consistent in many ways with Peirce's concept of *abduction*. Peirce introduced abduction as a pragmatic alternative to classical logical models of human thinking (i.e., deduction and induction). An abductive process is driven by surprise. In such a system, belief is tentative. It reflects hypotheses about situations. These hypotheses are tested, not in terms of abstract truth or normative logical processes, but in terms of success (i.e., the consequences of acting on them). Beliefs that lead to successful actions are maintained, while beliefs that lead to unsuccessful actions are revised and modified. In an abductive system, beliefs are shaping actions, while simultaneously being shaped by the consequences of those actions.

The simplicity of Figure 43.8 compared to Figure 43.1, Figure 43.2, and Figure 43.7 is deceiving. In the earlier diagrams the complexity is parsed in a logical way that reflects the modular organization of designed systems and of the associated academic disciplines. It would be nice if we could divide the system so that the psychologist could model the human, while the mechanical and automotive engineers modeled the vehicle, the computer scientists and electrical engineers modeled the information displays, and the civil engineers modeled the highway environments. It would be nice if we could neatly separate the control problem from the observer problem in ways that were compatible with the normative models of control and observation. Unfortunately, the coupling of perception and action (observation and control, performance and exploration) are both richer and more complex than suggested by many of the normative control models or designed control systems. As Juarrero (2002) notes:

> … complex adaptive systems are typically characterized by … feedback processes in which the product of the process is necessary for the process itself. Contrary to Aristotle, this circular type of causality is a form of self-cause. Second, when parts interact to produce wholes, and the resulting distributed wholes in turn affect the behavior of their parts, interlevel causality is at work. Interactions among certain dynamical processes can create a systems-level organization with new properties that are not the simple sum of the components that constitute the higher level. In turn, the overall dynamics of the emergent distributed system not only determine which parts will be allowed into the system: the global dynamics also regulate and constrain the behavior of the lower level components. (p. 5–6)

Thus, we are suggesting caution when using engineered control systems as models for adaptive human-in-the-loop systems. We strongly believe that intuitions from working with simple closed-loop systems and the methodologies of control engineering will be essential for unpacking the complexity of biological control systems. However, when simple control systems are used as a metaphor, we fear that they can hide as much as they reveal. The result can sometimes be a trivialization of the phenomena, rather than a deepening understanding. We believe that simulators can be critical components in research programs that have the goal of converging on that deeper understanding. They allow simultaneous measurement at multiple levels of detail under controlled conditions. For example, in evaluating steering behavior as a function of risk and optical flow information (e.g., comparing performance on the open road versus performance in a construction zone with an elevated cement barrier on one edge of the lane) it may be that gross measures of lane excursions or tracking error may show no performance differences. However, time histories of the steering activity or of the car path may show differential properties (e.g., more high-frequency power in the barrier condition) that would suggest subtle changes in control strategy (e.g., higher gain).

43.6 Control Theory: More Than Meets the Eye

It is important to differentiate between control theory, as a guide to research and design, and the specific analytic tools and solutions that have been motivated by this approach. As systems become very complex, the application of many of the analytic tools may be of limited value or may be completely infeasible, and any specific engineered control mechanism is likely to be a relatively weak metaphor. Nevertheless, we feel that the intuitions of control theory can be an important guide. In fact, the theory is very important even where the analytic tools and simple metaphors fail. At this point, a mindless application of the tools will not be useful and theoretically informed judgment and hypothesis (i.e., abduction) become essential. For those interested in the analytic techniques themselves, we recommend Jagacinski and Flach (2003) as a tutorial introduction to these techniques and the qualitative insights they provide for dynamic behavior.

We hope it is becoming clear at this point that many of the constraints that shape the solutions to control and observation problems are not well-represented in the block diagram images used to illustrate control mechanisms. It is important to differentiate between the control problem and the control mechanism. For any control problem there will be many potential mechanisms that might yield satisfactory or stable performance. For example, a cost functional reflects constraints on the control problem, but

TABLE 43.1 Control Problem Constraints Organized According to Level of Abstraction

Rasmussen's Levels (Rasmussen, 1986)	Control System Constraints
Functional Purpose	Goals or forcing functions; resources; cost functions or value systems.
Abstract Function	The physical (e.g., laws of motion), information (e.g., ecological optics), and regulatory (e.g., speed limits) constraints that guide the choice of state space dimensions.
General Function	This reflects the general functional organization as reflected in block diagrams of generic functions such as Figure 43.1.
Physical Function	This level reflects the allocation of function among different physical systems (e.g., which functions are accomplished by humans as illustrated in Figure 43.3 or possibly the different modalities of information).
Physical Form	This level considers the physical details (e.g., the layout of controls and displays and or the detailed geometry of information sources such as in an optical flow field).

it is not an explicit component of the control mechanism. Thus, there is a need for some way, other than the diagram of a control mechanism, to summarize the problem constraints. This fact is an important motivation for Rasmussen's (1986) Abstraction Hierarchy. The Abstraction Hierarchy is a nested hierarchy of means-ends relations that are used to model the problem space for a complex control system.

Table 43.1 is an attempt to map the levels in the Abstraction Hierarchy to constraints of control problems. The left column shows Rasmussen's levels, and the right column is our view of how these levels are reflected in control theoretical terms. At the highest level, *Functional Purpose*, the focus is on the goals and resources associated with the control problem. The priorities that specify how goals are traded-off against each other (e.g., lane maintenance might compete with obstacle avoidance) or how the goals are traded-off against resources (e.g., precision versus effort) are reflected in cost functions. Note that the cost functions or value constraints that are guiding a biological control system will not always be obvious or clearly specified. Thus, in analyzing the control problem, one should consider what the effective cost functional might be. Normative models (e.g., the optimal control model) might be very useful to provide benchmarks associated with specific cost functions (e.g., the quadratic cost functional or a minimal time solution). However, in using the abstraction hierarchy as a component in a formative program of work analysis as described by Vicente (1999), the goal would be to consider possible or plausible cost functions. What are the goals and resources? What range of trade-offs would be reasonable or likely? How might different training, display, or control innovations impact the priorities or trade-offs (e.g., reduce the resource costs or workload)?

At the second level, *Abstract Function*, attention turns to the space of possibilities in its broadest sense. This space should obviously include the goal states and the potential paths of movement through the problem space. The dimensions of this space should reflect the states of the problem, reflecting physical, information, resource, and regulatory constraints on motion in that space. In other words, the dimensions of this space should reflect any variable that might be required to specify functional distance from a goal or that might be needed to differentiate various paths to the goal. For example, for a vehicle control task the state space should at least include functions of position and velocity for each axis of motion. The space might also take into account information constraints. For example, Smith et al. (2001) found that using an optical state space (visual angle and expansion rate) helped in identifying the decision rules for a collision control task. This space reflects the joint constraints of the inertial properties of motion and the optics of flow fields. Again, this space is not a property of the control mechanism, but a property of the problem context.

At the third level of the Abstraction Hierarchy, *General Function,* the classical functional flow diagram such as reflected in Figure 43.1 provides a useful way to visualize the constraints associated with the partitioning of function and flow of information. At this stage, consideration is given to the demands created by the problem and the general types of processes that might meet those demands. Classically, this has been the focus for information-processing models inspired by the Cybernetic Hypothesis (Weiner, 1948). While this level of abstraction offers its own insights into the dynamic constraints associated with specific system architectures (e.g., open- versus closed-loop dynamics), these insights are often missed because of tendencies to emphasize open-loop, causal relations between pairs of stages, rather than the more global constraints (e.g., stability limits) of the overall system organization (e.g., closed-loop dynamics). As Jagacinski and Flach (2003) have noted, the information-processing modelers have often included closed-loops in their diagrams, but have rarely addressed the circular flow of mutual causality that such diagrams imply.

At the fourth level of the Abstraction Hierarchy, *Physical Function*, consideration is given to the particular types of systems that might satisfy the functions identified at the General Function level. For example, considerations of whether braking is accomplished by a human driver or by an automated braking system become important. Choices at this level can have important implications for considerations at all the other stages. In modeling an automated braking system, the dimensions of the state space (the Abstract Function level) should reflect the dimensions assumed in the design of the automated system (e.g., functions of distance and velocity). However, in modeling manual braking, it may be important to consider optical constraints in addition to the inertial constraints in choosing the dimensions of the state space. Individual differences among drivers may be an important consideration here, since the driver is the physical system that satisfies important control functions. What should the performance criteria be for deciding whether a person is capable of functioning safely? Can simulators be used to test driver capabilities? For example, Caird, Chisholm, Edwards and Creaser (2007) examined how age impacts perceptual reaction time relative to the response to a yellow light.

At the lowest level of abstraction, *Physical Form*, the physical details of specific systems become important to the success of the control system. A significant example of the importance of such details for control solutions is the case of unintended accelerations (Schmidt, 1989). A physical detail such as the rotation of the head over the right shoulder while initiating a backing-up maneuver may bias the foot trajectory to the right, away from the brake and toward the accelerator. This physical detail can be the difference between an action that satisfies the intention and one that leads to potentially catastrophic failure. As an aside, unintended accelerations can be an example where at least for a brief time, human drivers function as effectively open-loop, automatic systems that are unable to make use of the error feedback indicating that they are depressing the accelerator while intending to brake.

The key point is that a research program to understand driving *must* consider multiple levels of abstraction as represented in Rasmussen's Abstraction Hierarchy. It is important to differentiate between the use of a specific control system as a metaphor for human performance, and a serious program to identify the constraints shaping driver performance. Understanding the system as a control system means to understand the loose couplings across these different levels of constraints, for example, to differentiate when drivers are functioning as a closed-loop system (e.g., adjusting on the basis of feedback) and when drivers are functioning open-loop (e.g., applying automatic routines that have been reinforced by consistent experiences).

It is important to appreciate that no single level of abstraction is privileged (e.g., as ultimate cause or as ground truth) with respect to the others; and that each level has the potential to significantly affect the emergent behaviors of the total system. Also, different forms of representation (e.g., block diagrams or state spaces) may be better for different levels of abstraction. As with the levels, no single representation is sufficient. Each representation reveals some facets of the problem and hides others.

Simulators can be critical tools for exploring the couplings across levels of abstraction. The simulation can allow researchers to manipulate any of the five levels of abstraction and to measure the implications at all other levels. For example:

- The level of Functional Purpose can be manipulated through instructions and payoff matrices.
- The level of Abstract Function can be manipulated through adjusting the vehicle/surface dynamics or information constraints.
- The levels of General Function and Physical Function can be manipulated by controlling access to certain types of information or by constraining/automating or uncoupling some of the functions (e.g., occluding the speedometer to force the person to estimate speed from optic flow).
- The Physical Form (e.g., position of the pedals) can be directly manipulated.

In many human social technical systems (e.g., nuclear power plants, air traffic control, or high performance aircraft) the simulator may be the only context where such manipulations and measurements are feasible. In driving, instrumented cars can also provide access to multiple levels of measurement and opportunities to sample across many contexts that reflect important differences associated with various levels of abstraction.

The US Department of Transportation has funded field operation tests (FOT's) to investigate the human interaction with emerging active-safety technologies (e.g., forward collision warning and lane departure warnings). These studies have cost tens of millions of dollars, and in collecting driver behavior for hundreds of thousands of miles, have contributed greatly to our understanding of driver acceptance of active safety systems. However, despite the grand scale of these field operational tests, they still provide an insufficient basis to make solid conclusions about the ability of active safety systems to minimize collisions. Although on global or national scales automotive crashes occur far too frequently and have the potential to produce devastating consequences for the people involved, on the scale of any given mile of travel, the chances of collision are low. Police-reported crashes in the United States occur on average only two times every million miles or once every 32 years of driving (derived from NHTSA, 2006; or see Evans, 1991). The approach of waiting for collisions to occur naturally, although extremely informative (see Dingus et al., 2006), is clearly impractical for most research applications and research time-scales.

For the purposes of human subject testing, test tracks represent a compromise in many respects between driving simulator research and on-road testing. However, test tracks are also "simulations" in that the situations faced may be quite distinct from those in natural driving contexts (e.g., limited traffic). Because of the level of control, test track research may provide an opportunity to examine collision minimization more efficiently than field testing. In some circumstances, methods can be developed on the test track where the driver believes that they are at risk when in reality there is actually little risk to the driver. One of the difficulties with human subject research on test tracks is that drivers may not feel as completely at ease as they might in a well-designed driving simulator test or in the field. The need to communicate with traffic control and other vehicles, the responsibility of driving in a novel environment, and the accompanying experimenter can sometimes overwhelm participants, preventing them from relaxing or adopting realistic driving behaviors. As a result, it may be quite difficult to distract drivers to a large extent. Test-track research is also usually less efficient than driving simulator research and often involves logistical issues that can become expensive and time-consuming. Nevertheless, test track research can be a valuable tool for validating driving simulator testing, conducting system-verification tests, and for rapidly educating subjects about the system capabilities. Due to the respective advantages and disadvantages of the three venues (field, test-track, and driving simulation), a recent ongoing government-sponsored program utilized a combination of venues; an efficient between-subject driving simulator methodology to focus on collision minimization, field-testing to focus on driver acceptance, and test-track work to rapidly expose drivers to the system prior to field testing (Smith, Bakowski, & Witt, 2007). In this context, control theory may help to identify the long threads that connect levels of abstraction that, in turn, allows integration of insights obtained across many different research venues.

In conclusion, we argue that it is very clear that driving is a control problem. That is, behaviors are being adapted at multiple time scales to satisfy various intentions. As such, the intuitions of control theory will be invaluable for a research program aimed at driver performance, training systems design, or highway safety. However, it is important not to confuse control theory with any specific control mechanism. Control theory provides tools for a search for explanations of how drivers might behave. It is not the answer; but it can provide important intuitions for unpacking the very complex dynamics of an adaptive, self-organizing biological control system. Control theory is not the end, but one means for attacking this very important and interesting phenomena of driving.

Key Points

- The human-vehicle and the human-simulator systems are complex control systems.
- Control theory can provide an important framework when using simulators for performance evaluation to meet the applied goals of performance evaluation and training design.
- Control theory can provide an important framework for integrating simulators into basic research programs to evaluate humans as adaptive cognitive systems.

Keywords: Control Theory, Optimal Control Model, Regulator Problem, Observer

Key Readings

Ashby, W. R. (1956). *An introduction to cybernetics.* London: Chapman & Hall.

Gibson, J. J. (1958). Visually controlled locomotion and visual orientation in animals. *British Journal of Psychology, 49*, 182–194. Reprinted in Reed, E., & Jones, R. (Eds.). (1982). *Reasons for Realism* (pp. 148–163). Hillsdale, NJ: Lawrence Erlbaum Associates.

Jagacinski, R. J., & Flach, J. M. (2003). *Control theory for humans.* Mahwah, NJ: Lawrence Erlbaum Associates.

References

Ashby, W. R. (1956). *An introduction to cybernetics.* London: Chapman & Hall.

Bernstein, N. (1967). *Coordination and regulation of movement.* New York: Pergamon Press.

Brunswik, E. (1956). *Perception and the representative design of psychological experiments.* Berkley, CA: University of California Press. AU: Please provide citation.

Caird, J. K., Chisholm, S. L., Edwards, C. J., & Creaser, J. I. (2007). The effect of yellow light onset time on older and younger drivers' perception response time (PRT) and intersection behavior. *Transportation Research Part F: Traffic Psychology and Behavior, 10,* 383–396.

Caird, J. K., Willness, C. R. Steel, P., & Scialfa, C. (2008). A meta-analysis of the effects of cell phones on driver performance, *Accident Analysis & Prevention, 40*(4), 1282–1293. doi:10.1016/j.aap.2008.01.009

Chisholm, S. L., Caird, J. K., & Lochhart, J. (2007). The effects of practice with MP3 players on driving performance. *Accident Analysis & Prevention, 40*(2), 704–713. doi:10.1016/j.aap.2007.09.014

Cochran, A., & Stobbs, J. (1968). *The search for the perfect swing.* Philadelphia, PA: J. B. Lippincott.

Denton, G. G. (1980). The influence of pattern on perceived speed. *Perception, 9*, 393–402.

Dingus, T. A., Klauer, S. G., Neale, V. L., Petersen, A., Lee, S. E., Sudweeks, J, . . . Knipling, R. R. (2006). *The 100-car naturalistic driving study: Phase II – Results of the 100-car field experiment* (NHTSA DTNH22-00-C-07007). US Department of Transportation, National Highway Traffic Safety Administration. Retrieved from http://www-nrd.nhtsa.dot.gov/departments/nrd-13/driver-distraction/PDF/100CarMain.pdf

Evans, L. (1991). *Traffic safety and the driver*. New York: Van Nostrand Reinhold.

Fajen, B. R. (2005). Calibration, information, and control strategies for braking to avoid collision. *Journal of Experimental Psychology: Human Perception and Performance, 31*(3), 480–501.

Flach, J. M., Dekker, S., & Stappers, P. J. (2008). Playing twenty questions with nature (The surprise version): Reflections on the dynamics of experience. *Theoretical Issues in Ergonomics Science 9*(2), 125–145.

Flach, J. M., Smith, M. R. H., Stanard, T., & Dittman, S. M. (2004). Collisions: Getting them under control. In H. Hecht & G. J. P. Salvelsbergh (Eds.), *Time-to-contact*. (pp. 67–91). Amsterdam: Elsevier Science.

Flach, J. M., & Warren, R. (1995). Low-altitude flight. In P. Hancock, J. Flach, J. Caird, & K. Vicente (Eds.), *Local applications of the ecological approach to human-machine systems* (pp. 65–103). Hillsdale, NJ: Lawrence Erlbaum Associates.

Gelb, A. (Ed.). (1974). *Applied optimal estimation.* Cambridge, MA: MIT Press.

Gibson, E. J. (1969). *Principles of perceptual learning and development.* New York: Appleton-Century-Crofts.

Gibson, J. J. (1958). Visually controlled locomotion and visual orientation in animals. *British Journal of Psychology, 49*, 182–194. Reprinted in Reed, E., & Jones, R. (Eds.). (1982). *Reasons for Realism* (pp. 148–163). Hillsdale, NJ: Lawrence Erlbaum Associates.

Gibson, J. J. (1963). The useful dimensions of sensitivity. *American Psychologist, 18*, 1–15.

Gibson, J. J. (1979/1984). *The ecological approach to visual perception.* Hillsdale, NJ: Erlbaum.

Gibson, J. J., & Crooks, L. E. (1938). A theoretical field-analysis of automobile driving. *American Journal of Psychology, 51*, 435–471. Reprinted in Reed, E., & Jones, R. (Eds.). (1982). *Reasons for Realism* (pp. 119–147). Hillsdale, NJ: Lawrence Erlbaum Associates.

Gibson, J. J., Olum, P., & Rosenblatt, F. (1955). Parallax and perspective during landings. *American Journal of Psychology*, *68*, 372–385.

Hawthorne, C., Weiss, P., & Burks, A. (Eds.). (1931–1966). *Collected papers of Charles Sanders Peirce.* 8 volumes. Cambridge, MA: Harvard University Press.

Hecht, H., & Salvelsbergh, G. J. P. (Eds.). (2004). *Time-to-contact*. Amsterdam: Elsevier Science.

Jagacinski, R. J., & Flach, J. M. (2003). *Control theory for humans.* Mahwah, NJ: Lawrence Erlbaum Associates.

Jagacinski, R. J., & Miller, R. A. (1978). Describing the human operator's internal model of a dynamic system. *Human Factors, 20*, 425–433.

Juarrero, A. (2002). *Dynamics in action. Intentional behavior as a complex system.* Cambridge, MA: MIT Press.

Kirk, D. E. (1970). *Optimal control theory.* Englewood Cliffs, NJ: Prentice-Hall.

Kleinman, D. L., Baron, S., & Levison, W. H. (1971). A control theoretic approach to manned-vehicle systems analysis. *IEEE Transaction on Automatic Control, AC-16*, 824–832.

Lee, D. N. (1976). A theory of visual control of braking based on information about time-to-collision. *Perception*, *5*, 437–459.

Loomis, J. M., Da Silva, J. A., Fujita, N., & Fukusima, S. S. (1992). Visual space perception and visually directed action. *Journal of Experimental Psychology: Human Perception and Performance, 18*, 906–921.

McKenna, B. P. (2004). *Role of optical angle and expansion rate in a braking action.* Unpublished Masters Thesis. Wright State University, Dayton, OH.

National Highway Transportation Safety Administration (NHTSA). (2006). *Traffic Safety Facts* (Rep. DOT HS 810 623). Washington, DC: US Department of Transportation. Retrieved from http://www-nrd.nhtsa.dot.gov/Pubs/810623.pdf

National Research Council. (1997). *Aviation safety and pilot control: Understanding and preventing unfavorable pilot-vehicle interactions.* Washington, DC: National Academy Press.

AU: Please check year mismatch

Neisser, U. (1989). From direct perception to conceptual structure. In U. Neisser (Ed.), *Concepts and conceptual development: Ecological and intellectual factors in categorization* (p. 11–24). Cambridge, MA: Cambridge University Press.

Newell, A., & Simon, H. A. (1972). *Human problem solving.* Englewood Cliffs, NJ: Prentice-Hall.

Owen, D. H. (1984). *Optical flow and texture variables useful in detecting decelerating and accelerating self-motion* (AFRHL-TP-84-4, AD-1248 718). Williams Air Force Base, AZ: Operations Training Division, Air Force Research Laboratory.

Pew, R. W., & Baron, S. (1978). The components of an information processing theory of skilled performance based on an optimal control perspective. In G. E. Stelmach (Ed.), *Information processing in motor control and learning.* Cambridge, MA: MIT Press.

Rasmussen, J. (1986). *Information processing and human-machine interaction: An approach to cognitive engineering*. New York: North-Holland.

Schmidt, R. A. (1989). Unintended acceleration: A review of human factors contributions. *Human Factors, 31*(3), 345–364.

Senders, J. (1964). The human operator as a monitor and controller of multidegree of freedom systems. *IEEE Transactions on Human Factors in Electronics, HFE-5*, 2–6.

Smith, M. R. H. (2002). *Automotive Collision Avoidance System field operational test.* Warning cue implementation summary report. US Department of Transportation, Federal Highway Administration. Retrieved from: http://www.its-docs.fhwa.dot.gov//JPODOCS/REPTS_TE/13674.pdf

Smith, M. R. H., Flach, J. M., Dittman, S. M., & Stanard, T. (2001). Monocular optical constraints on collision control. *Journal of Experimental Psychology: Human Perception, and Performance,* 27, 395–410.

Smith, M. R. H., Bakowski, D. L., & Witt, G. J. (2007). *The utilization of different testing venues for the evaluation of safety ad acceptance in the SAVE-IT program.* Proceedings of the Driving Simulation Conference North America. Iowa City, IA. Available from: http://www.dsc-na.org/

Strayer, D. L., & Johnston, W. A. (2001). Driven to distraction: Dual task studies of simulated driving and conversing on a cellular phone. *Psychological Science, 12*(6), 462–466.

Vicente, K. J. (1999). *Cognitive work analysis.* Mahwah, NJ: Lawrence Erlbaum Associates.

Warren, R. (1982). *Optical transformation during movement: Review of the optical concomitants of egomotion* (Final Tech. Rep. for Grant N. AFOSR-81-0108). Columbus, OH: Ohio State University. Also appears as Tech. Rep. AFOSR-TR-82-1028, Bolling Air Force Base, DC: Air Force Office of Scientific Research. (NTIS no. AD-A122 275).

AU: Please provide citation

Warren, R., & McMillan, G. R. (1984). *Altitude control using action-demanding interactive displays: Toward an active psychophysics.* Proceedings of the 1984 IMAGE III Conference (pp. 37–51). Phoenix, AZ: Air Force Human Resources Laboratory.

Warren, R., & Wertheim, A. (Eds.). (1990). *Perception & control of self-motion*. Hillsdale, NJ: Erlbaum.

Weiner, N. (1948). *Cybernetics or control and communication in the animal and machine.* Cambridge, MA: The MIT Press.

Wienberg, G. M., & Wienberg. D. (1979). *On the design of stable systems.* New York: John Wiley & Sons.

AU: Please provide citation