Integrated Driver Modeling in the
ACT-R Cognitive Architecture

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Introduction

As an extremely complex dynamic task that people perform successfully on an everyday basis, driving offers a significant challenge for computational modeling. Modeling of driving and driver behavior has, roughly speaking, assumed one of two forms. On the one hand, some driver modeling has aimed to produce rigorous computational mechanisms that drive as “perfectly” as possible, maintaining a central lane position and a safe distance from any obstacles. For instance, CMU?? (Pomerleau & Jochem, 1996). Such models are typically evaluated using performance metrics in comparison with an “ideal” driver, and might be used as part of specific practical applications such as intelligent cruise control or automated steering. On the other hand, some driver modeling has aimed to produce rigorous models that mimic no-so-perfect human behavior as much as possible. Just as humans exhibit variability and errors in their behavior due to their cognitive, perceptual, and motor limitations, such computational models also try to exhibit such behavior. These models are evaluated not with respect to an ideal driver, but rather with respect to real human drivers — in other words, by examining not how well the models drive, but how well they match human driver behavior.

Our approach to driver modeling, like many of the approaches described in this book, falls in the latter group of computational models. Specifically, our approach centers on the development of driver models in the framework of a cognitive architecture (see, e.g., VanLehn, 1991). A cognitive architecture is a general framework for specifying computational behavioral models of human cognition performance (see John & Altmann, 1999). The architecture embodies both the abilities and constraints of the human system — for instance, abilities such as memory storage and recall, learning, perception, and motor action; and constraints such as memory decay, foveal vs. peripheral visual encoding, and limited motor speeds. As such, a cognitive architecture helps to ensure that cognitive models developed in the framework are rigorous and psychologically valid, thus abiding by all the limitations of the human system. The chosen
framework for our driver model is the ACT-R cognitive architecture (Anderson & Lebiere, 1998), a production-system architecture founded on chunks of declarative knowledge and production rules that operate on these chunks. We will discuss the particular advantages of the ACT-R architecture in the course of this chapter; however, it is important to note that many of the central themes and ideas remain the same for models developed in any cognitive architecture, such as Aasman’s driver model (this volume) developed in the Soar architecture (Laird, Newell, & Rosenbloom, 1987; Newell, 1990).

This chapter provides an overview of our recent theoretical and application-oriented work with the ACT-R driver model. First, we begin with a more thorough description of the driver model and the ACT-R architecture framework in which it is built. Second, we discuss how the model has been validated with human empirical data across a number of measures — for instance, steering profiles and eye movements during curve negotiation and lane changing. Third, we summarize recent work using the ACT-R driver model to predict driver distraction from visual, motor, and even cognitive tasks.

The ACT-R Driver Model

The ACT-R driver model (Salvucci, Boer, & Liu, 2001) is a computational model of driver behavior implemented in the ACT-R cognitive architecture (Anderson & Lebiere, 1998). The current driver model is intended to represent behavior specifically in the context of a driving on a multilane highway (or parkway, thruway, etc.) with other vehicles. Highway driving is a common driving scenario that accounts for a large percentage of vehicle miles — for instance, highway driving accounted for 72.1% of vehicle miles in the United States in 2000 (Federal Highway Administration, 2001). While we hope to extend the model to other common contexts (e.g., city driving) in the near future, the highway-driving context has enabled us to explore a number of interesting specific subtasks (e.g., lane changing) and general subtasks (e.g., monitoring for situation awareness) that will generalize well to other contexts.
The driver model includes three main components. The first component, *control*, manages all aspects of lower-level perception of the external world and mapping of specific perceptual variables to manipulation of vehicle controls (e.g., steering, acceleration, braking). The second component, *monitoring*, maintains awareness of the current situation by periodically perceiving and encoding the surrounding environment. The third component, *decision making*, handles any non-lower-level decisions — e.g., lane changes — based on knowledge of the current environment. All three components are implemented in the ACT-R architecture to take advantage of both the architecture’s built-in features and human-like limitations that result in a more psychologically-plausible model of driver behavior. We first provide a brief description of the ACT-R architecture and then describe each of the core components of the driver model as implemented in this architecture.

**The ACT-R Cognitive Architecture**

The ACT-R cognitive architecture (and all cognitive architectures) is simultaneously a rigorous theory of human cognition and a working framework in which to build computational models of human behavior. ACT-R posits two separate but interacting knowledge stores. The first type of knowledge, *declarative knowledge*, comprises *chunks*, or small logical units, of symbolic information. Declarative chunks can encode simple facts (e.g., Philadelphia is in Pennsylvania), current goals (e.g., try to change lanes), even ephemeral situational information (e.g., there is a car to my left). Chunks are also associated with “subsymbolic” parameters that encode continuous-valued properties of each chunk — for instance, chunk *activation* as a representation of the ease with which the chunk can be recalled. In addition, learning mechanisms can affect these subsymbolic parameters— for instance, chunk activation decays over time to mimic forgetting but also increases as the chunk is recalled more often.

The second type of knowledge, *procedural knowledge*, comprises *production rules* (or simply productions) representing procedural skills that manipulate declarative knowledge as well as the environment. Each production rule is essentially a condition-action rule that generates the
specified actions if the specified conditions are satisfied. Rule conditions specify the current goal and often retrieve a chunk from declarative memory, provided that the chunk exists and can be retrieved given its current activation value. When all conditions match and the rule “fires”, rule actions can add to or alter declarative memory, set a new current goal, and/or issue perceptual or motor commands (e.g., find a particular visual object or type a key). Like declarative chunks, production rules are associated with subsymbolic parameters that affect their behavior — for example, “conflict resolution” parameters that determine which rule fires given several possible matches. And also like declarative parameters, parameters for procedural knowledge can adapt over time given different choices and situations.

One critical advantage of a cognitive architecture for driving (or any other complex task, for that matter) is the incorporation of built-in features that mimic human-like abilities. For instance, ACT-R has built-in perceptual and motor mechanisms (Byrne, 2001; Byrne & Anderson, 2001) that allow ACT-R models to interact with external simulations. These mechanisms can perceive changes in the environment and can manipulate the environment using code modules that interface with the actual simulation. Also, ACT-R has the ability to parallelize these processes such that, for example, the perceptual module can look at a new item while the motor module performs a physical movement. Of note, this allows ACT-R models to run in simulation — often in real time — and predict exactly those data and measures that are collected from human drivers (e.g., steering wheel, throttle, and brake positions; turn signals; eye movements; etc.). The prediction of real-world measures greatly facilitates model validation through direct comparison with human data.

At the same time, ACT-R places certain limitations and constraints on models that mimic those constraints of the human system. One of the most important constraints for the driver model is that, although perceptual and motor processes can run in parallel with cognition, the cognitive processor itself is serial and, in essence, can only “think” one thing at a time. This cognitive processor is responsible for collecting all information from perceptual modules and issuing all motor commands, and thus serves as a central bottleneck for behavior. This fact is
critical to our approach to applications to driver distraction: when the driver attempts to perform a secondary task such as dialing a phone, the cognitive processor must interleave this secondary task with the primary driving task. This approach can account not only for interference from primarily perception- and motor-oriented secondary tasks, but even primarily cognitive secondary tasks, since the latter would interfere with the cognitive processor’s ability to manage the primary task.

Model Components

As mentioned, the ACT-R driver model has three primary components: control, monitoring, and decision making. Each component is implemented essentially as an ACT-R goal and an associated set of production rules that implement this goal. The three components are integrated to run in ACT-R’s serial cognitive processor as a tight loop of small cognitive (and related) operations. This section describes each component in detail, and the following section describes how the three components are integrated into a working model that interacts with a driving simulation.

< INSERT FIGURE 1 HERE >

Control

The control component of the driver model manages all perception of low-level visual cues and manipulation of vehicle controls for steering and acceleration / braking. The control process centers on a two-level model (see Donges, 1978; Land & Horwood, 1995) based on the perception of two salient visual points. First, the near point represents the vehicle’s current lane position, used to judge how closely the vehicle is to the center of the roadway. The near point is characterized as a point in the center of the lane at a distance equivalent to a time headway of one-half second. Second, the far point indicates the curvature of the upcoming roadway, used to
judge what the driver should soon execute — in a somewhat predictive manner — to remain in the current lane. The far point is characterized as the nearest one of three possible targets: (1) the vanishing point of a straight upcoming roadway, (2) the tangent point of an upcoming curve (Land & Lee, 1994), or (3) a lead car. Together, the near and far point provide nicely complementary pieces of information that allow for adjustment to the lane center at the current position (using the near point) and for predictive compensation at a near-future position (using the far point).

The perception segment of the control process involves the encoding of the near and far points through ACT-R’s perceptual mechanisms. The model moves its visual attention first to the near point, then to the far point, noting the visual angles $\theta_{\text{near}}$ and $\theta_{\text{far}}$ of the two points (respectively). The actual far point is chosen from the various possible far points (vanishing point, tangent point, and lead car) by moving attention from the near point up to the closest far point. (Note that the tangent and vanishing point are mutually exclusive, but each can co-exist with a lead car.) Depending on the type of the far point, the model computes several secondary parameters. When the far point is a lead car, the model calculates the time headway $THW_{\text{car}}$ to the lead car as needed for speed control. Also, assuming the far point has remained the same from the last cycle of the main control loop, the model also calculates differences for the above values from the last cycle, in particular $\Delta \theta_{\text{near}}, \Delta \theta_{\text{far}}, \Delta THW_{\text{car}},$ and $\Delta t$ (given the time of the last cycle).

The motor-manipulation segment of the control process uses the above perceptual variables to update the steering and accelerator (speed) controls by some incremental value. The model strives for the most simple but effective method of control, and to this end, utilizes a variation of a basic PID (proportional-integral-derivative) controller for both steering and acceleration control. The equations for computing changes in steering and acceleration are as follows:

$$\Delta \text{steer} = c_1(\Delta \theta_{\text{far}}) + c_2(\Delta \theta_{\text{near}}) + c_3(\Delta \theta_{\text{near}}) \Delta t$$
\[ \Delta \text{acc} = c_4(\Delta \text{THW}_{\text{car}}) + c_5(\text{THW}_{\text{car}} - \text{THW}_{\text{follow}}) \Delta t \]

The steering equation essentially attempts to impose three constraints: a steady far point (\( \Delta q_{\text{far}} = 0 \)), a steady near point (\( \Delta q_{\text{near}} = 0 \)), and a near point at the center of the lane (\( q_{\text{near}} = 0 \)). Similarly, the acceleration equation attempts to impose two constraints: a steady time headway (\( \Delta \text{THW}_{\text{car}} = 0 \)), and a time headway approximately equal to a desired time headway for following a lead vehicle (\( \text{THW}_{\text{car}} = \text{THW}_{\text{follow}} \)). The value for acceleration actually manipulates two controls: a positive value translates to depression of the throttle / accelerator, and a negative value translates to depression of the brake pedal. The absolute value of acceleration is limited to \( \text{acc}_{\text{max}} \) to represent a desired maximum acceleration (or deceleration).

In a highway environment, the majority of low-level control arises in the context of lane keeping and curve negotiation. However, one other common subtask that frequently occurs in highway driving is that of lane changing. Interestingly, the basic equations stated above, particularly that for steering control, generalize in a completely straightforward manner to lane changing: when the driver enacts a lane change, she simply begins to use the near and far points of the destination lane rather than the current lane. This change has the immediate effect of creating a large \( \Delta q_{\text{near}} \), thus initiating a large steering motion in the direction of the destination lane. However, this effect is tempered by the compensation of the \( \Delta q_{\text{far}} \) and \( \Delta q_{\text{near}} \) terms in the equation, which attempt to maintain a steady transition and prevent the vehicle from swinging wildly into the other lane. This compensation limits the maximum rate at which the driver should steer, but in addition, some drivers may wish to steer even less rigorously for safety precautions; thus, the model also incorporates a parameter \( \Delta q_{\text{near, max}} \) that puts a threshold on the \( \Delta q_{\text{near}} \) to induce even steadier steering. As we will see in the upcoming section on model validation, this process of lane changing produces a smooth transition into the destination lane that nicely mirrors the behavior of human drivers.
Monitoring

The monitoring component of the driver model handles the continual maintenance of situation awareness. For this model in the highway driving environment, situation awareness centers critically on awareness of the position of other vehicles around the driver’s vehicle. Monitoring is currently based on a random-sampling model that, with some probability $P_{\text{monitor}}$, checks one of four areas — namely, either the left or right lane, and either forward or backward (i.e., in the mirror). The model assumes that forward checks are three times as likely as backward checks due to the relative ease of checking lanes in front of the driver. When the model decides to monitor a particular lane and direction, it moves visual attention to that area and determines whether there is any vehicle present. If so, the model notes the vehicle’s current position in ACT-R declarative knowledge, and also computes the vehicle’s relative velocity if that vehicle has been previously encoded. Thus, declarative knowledge continually maintains the awareness of surrounding vehicles. Note that because of memory decay mechanisms in ACT-R, the chunks that encode vehicle position and velocity decay rapidly and may be forgotten when not refreshed often, thus providing predictions (albeit yet untested predictions) about mistaken estimation of surroundings and potentially hazardous lane changes.

Decision Making

The decision-making component of the driver model uses the information gathered during control and monitoring to determine whether any higher-level decisions must be made. In the highway environment, the most common decision-making opportunity arises in the determination of whether and when to execute a lane change. The decision of whether to change lanes depends on the driver’s current lane, since drivers (at least in the United States) attempt to stay in the right lane during normal driving and use the left lane for passing only (ideally). If the driver vehicle is in the right lane, the model checks for a safe temporal distance from a lead vehicle as measured by the current time headway to this vehicle; if the lead-car time headway drops below a desired time headway $THW_{\text{pass}}$, the model decides to change lanes to pass the vehicle. If the
driver vehicle is in the left lane, the model checks instead that there is no lead vehicle within \( THW_{\text{pass}} \), thus indicating that the passing lane is clear and the model decides to change lanes to return to the right lane.

Even after the model decides to change lanes, it must still determine when to initiate the maneuver at an appropriate, safe time. First, the model monitors the destination lane both front and back to check for the presence of another vehicle and update its mental model of the environment. Also, the model attempts to recall from declarative knowledge the nearest vehicle to the driver’s vehicle; because there is a blind spot in which the driver cannot see a nearby vehicle, this process relies on previous monitoring to note nearby vehicles. (Nevertheless, as discussed earlier, recall may fail if the encoding chunk has decayed over time, resulting in potentially dangerous lane-change situations that also occur for human drivers.) If no vehicles found in either the visual checking or the mental recall are within a safe distance \( D_{\text{safe}} \) from the driver vehicle, the model initiates the execution of the lane change; otherwise, the model immediately aborts the maneuver. As described earlier, the execution of the lane change corresponds simply to the use of the near and far points of the destination lane rather than the current lane. The lane-change maneuver continues until the vehicle reaches the center of the destination lane such that \( q_{\text{near}} \approx 0 \).

**Model Integration**

*Component Integration and Multitasking*

The integration of the three core model components requires some method of multitasking in performing each of the three respective subtasks. Because of its implementation in the ACT-R cognitive architecture, the model is constrained to a serial cognitive processor that cannot perform all three tasks at once but rather must interleave the tasks serially. To this end, the model contains a single, tight main loop that performs an incremental step of each subtask — namely, control, monitoring, and decision making (in that order). For control, this incremental step
involves a single instantiation of the perception of visual control features and execution of manual processes; for monitoring, the step involves (with some probability) the check of a single vehicle in a particular lane and direction; and for decision making, the step involves a single decision whether or not to initiate a lane change.

The serialization of the three model subtasks is critical to its ability to predict realistic driver performance that incorporates human-like constraints and limitations. Because even this tight loop requires some time to execute (very roughly, on the order of 100-500 ms or more), the driver model does not produce perfect performance even on a straight roadway with no other secondary tasks, just as human drivers would also not produce perfect performance. In addition, if the driver attempts to perform secondary tasks as well as the primary driving task, these tasks will further interrupt the main loop and may potentially worsen performance; this observation forms the basic premise of our approach to predicting driver distraction, as discussed later in this chapter. Ideally, we would like to add arbitrary secondary tasks to the primary component tasks and allow a rigorous theory of multitasking to arbitrate the execution of the tasks using some notion of prioritized task scheduling. However, currently, the ACT-R cognitive architecture does not incorporate such a model (although these efforts are underway; e.g., Lee & Taatgen, 2002). Nevertheless, the driver model’s somewhat naïve account of task scheduling has proven adequate for the purposes of validating the basic model and demonstrating its feasibility for integration into practical applications such as predicting driver distraction.

**Parameter Estimation**

As driving is an extremely complex task that involves significant individual differences, it is reasonable that any model of driver behavior involve a number of domain-specific parameters, some of which vary among individual drivers. At this stage of development for the ACT-R driver model, having not yet tackled the problem of individual differences, and we use a single set of estimated values for all model parameters (with an eye for future individual differences in these parameters). The parameter estimation process is described in Salvucci, Boer, and Liu (2001).
The constants $c_i$ in the steering and speed control equations required the most effort, since they had an extreme impact on the ability of the model to drive successfully. To estimate these constants, we ran through several iterations of setting them to reasonable values, observing the model driving in the simulated highway environment (e.g., making sure the driver vehicle handled curves satisfactorily and stayed on the roadway), and revising their values accordingly. As a final check, we ran one trial of the model validation described later and ensured that the predicted measures were at least within reason. We used a similar process to estimate $\alpha_{\text{near}, \text{max}}$, focusing especially on the durations of lane changes and the speed with which the human drivers chose to execute the maneuvers. The final group of parameters — $THW_{\text{follow}}$, $THW_{\text{pass}}$, $D_{\text{safe}}$, $acc_{\text{max}}$, and $P_{\text{monitor}}$ — were preset to reasonable values based primarily on further informal observation of model driving as well as approximations from available empirical literature. The final estimated parameter values were: $THW_{\text{follow}} = 1 \, \text{s}$, $THW_{\text{pass}} = 2 \, \text{s}$, $D_{\text{safe}} = 30 \, \text{m}$, $acc_{\text{max}} = .8$, $P_{\text{monitor}} = .33$; $\alpha_{\text{near}, \text{max}} = .5$; $c_1 = 20$, $c_2 = 10$, $c_3 = 5$, $c_4 = 3$, $c_5 = 1$.

**Integration with Simulation Environment**

One of the primary goals of the ACT-R driver model is to facilitate rigorous evaluation and validation by having the model drive in the same environment as human drivers. The environment used for the driver model and the validation subjects is a multilane highway environment integrated with a fixed-base driving simulator.\footnote{The original driving simulator was located at Nissan Cambridge Basic Research in Cambridge, MA, USA. Using equipment and software from this simulator, we are now developing a new small-scale driving simulator at Drexel University with fully updated hardware platforms.} The environment incorporates a rigorous physical vehicle model as well as automated vehicles that simulate realistic traffic around the driver. When a human driver navigates this environment in the driving simulator, the system generates a lengthy protocol that includes vehicle control data (e.g., steering wheel and throttle...}
position), driver gaze (eye-movement) data, and environment information (e.g., location of all vehicles). The ACT-R driver model has its own fully equivalent simulation that differs only in that the complex graphics generation has been removed. When the driver model navigates this environment, the system generates exactly the same protocol as the original simulation system — for instance, the model turns a virtual steering wheel to control lateral position, and also focuses its virtual eyes on various components of the visual field (including the near and far points and other vehicles). In fact, the model protocol can be immediately replayed in the original simulator with no modification. Thus, not only can we examine the qualitative nature of the model’s behavior, but we can also generate direct quantitative comparisons of the model’s and humans’ behavior, greatly facilitating the quantitative evaluation and validation of the model with empirical data.

**Model Validation**

Given that the goal of the ACT-R model is to accurately represent driver behavior, we wish to demonstrate how well it corresponds to real human behavior. This is no small endeavor: just as no single method, measure, or metric will suffice for understanding human driver behavior, no single one will suffice to validate that the model indeed corresponds well to human drivers. Nevertheless, we can validate the most critical parts of a driver model by focusing on key scenarios and analyzing the most important observable data involved in these scenarios. To this end, we now examine how the ACT-R model fits several aspects of driver data from two scenarios in particular, namely lane keeping and lane changing — the two basic scenarios that arise in normal highway driving. In particular, we focus our examination on three specific measures: vehicle lane position, steering wheel angle, and driver gaze focus (as a surrogate for the location of driver visual attention). The model validation discussed in this section represents an integration of empirical and modeling results from Salvucci, Boer, and Liu (2001); Salvucci, Liu, and Boer (2001), and Salvucci and Liu (2002).
Data Collection

The computational nature of the ACT-R driver model, combined with its ability to interact with the same simulation environment as human drivers, greatly facilitates the collection and comparison of human and driver data. Human data from 11 drivers were collected in the previously-mentioned fixed-base driving simulator (Salvucci, Boer, & Liu, 2001). Model data were collected by running three model simulations in the same environment; note that the model produces some variability (though at present not nearly as much as human drivers), thus a few simulation runs are desirable to achieve stable results. Because the human and model simulation protocols are identical in form, we analyze each set in the same manner to generate directly comparable measures of driver behavior and performance.

Lane Keeping

The most common component of highway driving (and most driving for that matter) is lane keeping, or simply steering down the center (or near the center) of a lane. Under informal observation, the ACT-R driver model can clearly negotiate down the center of its current lane and maintain a reasonable central position in the lane. However, because the driver model obeys the human-like constraints of the ACT-R architecture, it does not driver perfectly and does deviate somewhat from the lane center. Aggregate analysis of the model data revealed an average model lane deviation of 0.06 m, measured as the RMS (root-mean-squared) error from lane center; a similar analysis of the human data revealed an human-driver average lane deviation of 0.12; the model thus correctly exhibits some error in performance, although its error is approximately half that of human drivers. We will return to the issue of lane-keeping lane deviations in our discussion of the prediction of driver distraction in the next section.

One very interesting subset of the lane-keeping task involves curve negotiation — that is, steering into and through a curved section of roadway. Figures 2 and 3 show aggregate time-course plots of the drivers negotiating right and left curves, respectively. The construction of
these plots requires some explanation. First, we extracted the sections of the protocols that corresponded with entering and exiting and curve, as noted by the roadway at the vehicle’s current position; the roadway used in data collection had curved segments of different lengths and curvatures, but all segments had a constant curvature throughout the segment. Next, we divided each segment into ten equal-sized units, and also extended these units out to before and after the actual curved road segment. Finally, we aggregated all protocols by averaging together all the values within each segment. The time units in the plots represent 0.5 s on average of aggregate data.

Figures 2 and 3 show the time-course plots for the human data (solid line) and model data (dotted line) for both lane position and steering wheel angle. In Figure 2, we see that when entering right-hand curves, both the humans and the model began steering before entering the curve and steadily decreased steering wheel angle well into entering the curve. After holding a fairly constant wheel angle during the curve, both the humans and the model steadily turned the wheel back to center, starting before the actual curve end and completing the maneuver in the following straight segment. Interestingly, the model tended to “hug” the right side (i.e., the near side) of the road during the curve, as did the human drivers; this fact is especially interesting given that we had not designed the model to hug the near side, and thus this prediction emerged from the original simple steering mechanism. In Figure 3, we see much the same pattern for left-hand curves, with steady steering changes before and after the entrance and exit of the curved segments. The one difference between the two plots occurs in the fact that the human drivers did not hug the near side for left-hand curves as they did for right-hand curves, while the model hugged the near side for both curves. The most likely explanation for this behavior is that left-hand curves present more danger in highway environments, since either the passing lane or
oncoming traffic can be present to the left of the driver vehicle. The driver model currently has no sense of danger on either side, and thus produces the same behavior for both curve directions.

Another measure by which we can examine lane-keeping behavior is the distribution of driver gaze to various parts of the visual environment — that is, the distribution of where drivers look as they drive. While we expect that drivers generally maintain gaze in front of their vehicle at a far point or lead car, we also expect occasional gazes to other areas of the environment for purposes of monitoring and situation awareness (and potentially other reasons, even boredom). Figure 4 shows the dwell ratios for the human and model data, expressed as the ratio of time spent looking at one of several salient visual areas: the current lane’s lead car, near point, far point, or other cars (in front); the other lane’s lead car, near point, far point, or other cars (in front); and the rear-view mirror. Perhaps not surprisingly, the human drivers spent the most time looking at the far objects in their own lane, namely the lead car and the far point (i.e., the vanishing point or tangent point). The model also predicted this majority of gaze dwell time on far objects, albeit with an overprediction of dwell ratio for the far point. The model produced an overall nice fit with the other data points as well, particularly in that (1) both humans and model look at the lead car in the other lane for the same amount of time, and (2) both humans and model rarely look at the near point for either lane. The latter point is another emergent prediction of the driver model, arising from the fact that the model gathers very little information from the near point (only the visual angle on the x axis) and thus can often acquire this information peripherally without actually fixating the near point directly.

Lane Changing

The second common scenario in highway driving is that of lane changing. As we did for lane keeping, we can examine the three basic measures of lane position, steering wheel angle, and
gaze dwell ratios to elucidate and compare the behavior of the driver model and human drivers. Figures 5 and 6 show aggregate time-course plots for all lane changes in the human and model protocols. These plots were generated in the same manner as those for curve negotiation, except that the boundaries of the protocol segments were dictated not by roadway curvatures but by verbal protocols: both human drivers and the model produced a verbal utterance when (1) they formed the intention to change lanes, and (2) they completed this goal and reverted back to lane keeping. Again, the protocol segments were broken into ten units, extended before and after the actual lane-change segment, and averaged together to form the aggregate plots. In addition, two additional data points were added — one before and one after the time-course plot — to represent the average values of the respective measures during lane keeping before and after the span of the time-course plot. Again, one unit in the plot is approximately equivalent to 0.5 s of real time.

< INSERT FIGURE 5 HERE >

< INSERT FIGURE 6 HERE >

Figure 5 shows the time-course plots for lane changes to the left-hand lane, which, on American roadways, indicates a passing maneuver. The first plot in the figure shows, not surprisingly, the vehicle’s steady movement from the center of the right lane to the center of the left lane. The second plot shows the steering profile during the lane change. The initiation of lane change steering begins immediately after the intention to begin a lane change, and shows a fairly steep peak soon into the lane change even before the vehicle has moved a significant distance from the original lane center. The steering profile swings the opposite direction as the vehicle moves into the destination lane, reaching a slightly lower peak than the first, indicating a smoother adjustment back to center to steady the vehicle in the new lane. The model’s profile nicely resembles the human drivers’ profile, particularly the sharper steering at the start and steadier adjustment at the end of the lane change. Figure 6 shows the time-course plots for lane
changes to the right-hand lane, that is, the return to the normal-traffic lane after passing. The lane-position and steering profiles are, for the most part, identical to those for the lane changes to the left-hand lane except in the opposite direction. Again, the model produces the basic profiles and the slower steering adjustment at the end of the lane change.

Besides lane-position and steering profiles, the time-course plots show gaze dwell ratios over time during the lane change. Each plot includes dwell ratios for three different visual areas: the start lane of the lane change, the end lane, and the rear-view mirror. The dwell ratio plot in Figure 5 for a passing lane change shows an interesting pattern. A short time before the lane change, drivers shifted more gaze time to the rear-view mirror at the expense of the start-lane visual locations (including the lead car and far point). Presumably these gazes indicate that the drivers were searching for surrounding vehicles and checking behind their vehicles for enough space to make a lane change. Immediately after the initiation of the lane change, drivers dropped their gaze time to the rear-view mirror and began shifting gaze time to the end lane. The model reproduced the basic dwell-ratio profile exhibited by humans; however, there are slight discrepancies in that the model shifted slightly more gaze time to the end lane and slight more abruptly than did the human drivers. The dwell ratio plot in Figure 6 exhibits the complementary pattern: again drivers used the rear-view mirror before starting the change and gradually shifted more gazes to the destination lane, converging on the final ratio by the end of the lane change. Again, the model reproduces the basic profile, albeit shifting its gaze moreso at the initiation of the lane change rather than some time before initiation. Thus, not only did the model capture the critical gaze time distributions during curve negotiation and lane keeping, it also captured the gaze distributions before and during lane changes.

**Validation Summary**

In this section we have summarized several aspects of human driver behavior in a highway environment that are currently captured by the ACT-R driver model. But while our focus has been on the comparison of basic quantitative measures, it is important to note that
model validation can come in at least other forms as well. First, informal observation of the model’s behavior can be immensely useful in producing a “first-cut” driver model that generally behaves like human drivers; we are very astute observers of our own and others’ driving behavior, and simply watching the model navigate a roadway can provide an immediate sense of any flaws or major discrepancies in normal behavior. Second, practical application of the model for real-world uses can provide rigorous validation in its own right, showing that the model’s theory can generalize to practice in a straightforward way. In the next section we attempt to accomplish exactly this, testing how well the ACT-R driver model generalizes to predicting driver distraction from secondary tasks.

Sample Application: Predicting Driver Distraction

A theoretical, computational driver model such as the ACT-R driver model of can tell us a great deal about driver behavior and, in explaining some of the intricacies and limitations of human drivers, can be used to inform future development of vehicles specifically and the transportation environment more generally. Although the contributions of such model are typically more theoretical and indirect, it is especially nice when such a model can serve as the basis for a real-world practical tool that designers and engineers can utilize in a very direct way. This section describes such an application of the ACT-R driver model to the difficult problem of predicting driver distraction. Driver distraction has become a hotbed issue (e.g., Alm & Nilsson, 1994, 1995; Brookhuis, De Vries, & De Waard, 1991; McKnight & McKnight, 1993; Reed & Green, 1999; Redelmeier & Tibshirani, 1997) as a common and increasingly dire problem affecting drivers and vehicle manufacturers alike. While driver distraction can arise in a large variety of ways — e.g., seeing a captivating billboard, noticing a friend on the street, honking from other motorists — we generally limit the scope of the term to distraction arising from over-attention to in-vehicle devices — e.g., cellular phones, navigation devices, and climate controllers, just to name a few. Driver distraction is one of the leading causes of vehicle crashes (e.g., see Federal Highway
Administration, 2001, for year 2000 data for the United States) and this problem will only become increasingly dire as powerful in-vehicle devices become increasingly prevalent.

This section provides an overview of three studies that apply the ACT-R driver model to predicting driver distraction. The first two studies involved driver distraction from cell-phone dialing — Study 1 examining the effects of dialing on steering performance, and Study 2 examining these effects on steering and speed control in a more complex environment. Study 3, on the other hand, examined the effects of a (primarily) cognitive task on performance, showing that the predicted effects are not limited only to perceptual-motor phenomena. Each of these studies utilized an integrated-model approach (see in particular Salvucci, 2001) in which the ACT-R driver model was combined with a model for a secondary task to produce simulations in which both tasks (driving and the secondary task) are performed together. However, due to ACT-R serial cognitive processor, the model cannot perform the tasks simultaneously and instead must interleave small incremental units of each task together in a serial stream. Each of the following studies demonstrates how the integrated-model approach can predict when and how secondary tasks can affect primary driving performance.

**Study 1: Cell-phone Dialing**

The first study (Salvucci, 2001) represents our initial attempt to apply the integrated-model approach for one of today’s most highly publicized secondary tasks: using a cellular telephone, or “cell phone.” In the study, drivers were asked to steer down a single-lane roadway at a computer-controlled constant speed, and thus needed only keep the car centered laterally in the lane. At the same time, drivers were occasionally asked to dial a memorized seven-digit phone number using one of two modalities: voice dialing by speech input, and manual dialing by standard keypad-typing input. The length of phone numbers were also varied: “speed dialing” represented a single keypress or spoken phrase that dialed a pre-entered number directly, and full dialing represented typing or speaking the full phone number. Thus, the study involved four conditions: *full-manual* (e.g., typing “5551212”), *speed-manual* (e.g., typing “3” to dial 555-
Validation and demonstration of the integrated-model approach began with the development of an ACT-R model for each of the phone-dialing tasks. Because the study and approach centered on \textit{a priori} predictions with no parameter manipulation, these models were direct straightforward translations of the tasks including only the necessary sequence of motor processes (e.g., typing a digit), perceptual processes (e.g., look at the phone), and cognitive processes (e.g., recall the number). Each model was then integrated with the ACT-R driver model, and the resulting integrated model, in a series of simulations, generated three behavioral protocols for each model. At the same time, an empirical study was conducted to collect data from 11 human drivers in a fixed-base driving simulator. It is important to note that the models navigated the exact same environment as the human drivers and generated protocols identical to those generated by humans, including such data as steering, pedal positions, environmental data, and even gaze (eye-movement) data. This fact greatly facilitated direct comparison of the models’ behavior with that of the human drivers.

Analysis of the data from 11 drivers centered on two \textit{a priori} predictions. The first set of predictions were the model and human dialing times — that is, the mean times needed to dial the entire phone number in each condition. Figure 7 shows two types of dialing times for model and human drivers: a “baseline” time for dialing along (i.e., without driving), and a “driving” time for dialing while driving. Overall the baseline model predictions closely correspond to the human dialing times for the various tasks: full dialing required more time (not surprisingly). Interestingly, the model predicted only a small increase in dialing time while driving, and the human data supported this prediction. Thus, both quantitatively and qualitatively, the model predictions are quite good. The most serious discrepancy between model and data occurred in that the model predicted much less variability that human drivers exhibited.

< INSERT FIGURE 7 HERE >
The second set of predictions involves the lateral deviations from the lane center during each of the dialing tasks as well as during normal driving (i.e., with no secondary task). In this simple driving task, lateral deviations measured (to a large extent) the amount of attention given to the primary driving task as opposed to the secondary task. Figure 8 shows that even during normal driving with no secondary task, neither the model nor human drivers steered perfectly, although the model predicted approximately half the lateral deviation exhibited by the human drivers. For both human and model data, the manual-dialing lateral deviations were significantly higher than the baseline (normal driving) deviations. (The lateral deviation for the speed-manual model was small but still statistically significantly different). On the other hand, the voice-dialing deviations were not significantly differences from the baseline values, again for both human and model. Thus, the models nicely predicted the rank-order of secondary tasks with respect to their tendency to induce errors in steering performance.

< INSERT FIGURE 8 HERE >

**Study 2: Cell-phone Dialing Revisited**

The first study represented a successful initial attempt at applying the integrated-model approach and ACT-R driver model to cell-phone dialing. However, there were two significant limitations of the study: the driving task handled speed control automatically and limited driver input to steering only, and the dialing tasks used a non-working cell phone keypad (with mock dialing and voice recognition). The second study (Salvucci & Macuga, 2002) addressed each of these two limitations. First, the driving task involved a more realistic construction-zone environment that required drivers to follow a randomly accelerating and decelerating lead car while steering down a curvy roadway. Second, the dialing tasks utilized a real cellular phone as well as four dialing methods built into the phone: *manual* for standard typing, *voice* for speech-
controlled entry, *speed* for a manual shortcut key, and *menu* for navigation of a vertical menu of numbers. Once again, ACT-R models of each dialing task were developed in a simple, straightforward way, and then integrated with the ACT-R driver model to generate behavioral protocols. The final analysis included three model protocols as well as seven protocols from human drivers navigating in a fixed-base driving simulation.

This second study, like the first study, examined dialing times and lateral deviations and confirmed the first study’s results with respect to these measures. In addition, the second study looked at two new measures. The first measure, speed deviation, was analogous to lateral deviation but in the longitudinal direction — it measured the mean speed deviation between the driver’s car and the (accelerating and decelerating) lead car. Figure 9 shows the speed deviations for the model and human data for each dialing condition as well as the “none” (no dialing) condition. As for lateral deviation, the model predictions correspond well to the human data and predict the rank order of the various conditions. The model even predicts the (somewhat anomalous) fact that speed deviations in the “none” condition were not the lowest of all conditions.

< INSERT FIGURE 9 HERE >

The second measure, phone gaze time, measured how long drivers looked at the phone while dialing. The basic expectation was that tasks that require less manual typing would generally require less gaze time. Notably, the model rigorously predicts eye movements along with the all the standard control data, and thus we can compare its gaze times directly to those of human drivers (as measured by an eye tracker). Yet again we see a close fit between model and data: the model not only predicts the rank order of the conditions but also provides a good quantitative fit as well. This result suggests that for the given cell-phone dialing tasks, there is a direct link between the amount of visual attention to a secondary task and the amount of degradation in driver performance (lateral and longitudinal) due to the secondary task.
Study 3: Cognitive Distraction

The first two studies nicely demonstrated that the integrated-model approach nicely predicts how driver distraction from cell-phone dialing affects driver performance across several important measures. However, the approach is not limited to primarily perceptual-motor tasks such as cell-phone dialing; in fact, any cognitive workload can potentially produce driver distraction, and can also potentially (though not necessarily) have noticeable effects on driver performance. The third study (Salvucci, 2002) demonstrates how the integrated-model approach also predicts effects of “cognitive distraction” from primarily cognitive secondary tasks. The study is based on driving and tasks investigated by Alm and Nilsson (1995). In their study, drivers followed a lead car at a set distraction and then reacted to the sudden braking of this car at given intervals. The secondary task involved a “sentence-span” task in which drivers heard blocks of five sentences and performed two tasks with these sentences: (1) judge and state the sensibility of each sentence (e.g., “The boy brushed his teeth” is sensible, while “The train bought a newspaper” is not) immediately after hearing the sentence; and (2) remembering and reporting the last word in each sentence in order (e.g., “teeth”, “newspaper”, etc.) after hearing all five sentences. Thus, the secondary task involved minimal perceptual-motor components but instead involved a fairly significant, intense cognitive component. We developed two straightforward ACT-R models of the sentence-span task, identical except with respect to how often they ceded control back to the driver model: the Single-Step (SS) model ceded control after each single production firing, while the Group-Step (GS) model ceded control only after a logical group of firings (see Salvucci, 2002, for details). Both models were run in in a simulated task as similar to Alm and Nilsson’s as possible, and the models’ predictions were compared directly to the results reported by Alm and Nilsson (1995).

The study explored two measures in detail. The first measure, brake reaction time, measured the elapsed time between the sudden braking of the lead car and the driver’s first depression of the brake pedal. Figure 10 shows the model results with no task, with the SS
model performing the secondary task, and with the GS model performing the task. Both models predicted a significant effect of secondary task on brake reaction time, as the task reaction times were significantly greater than the no-task reaction time. Figure 10 also shows Alm and Nilsson’s (1995) empirical results, which showed the same significant effect of task on brake reaction time.

< INSERT FIGURE 10 HERE >

The second measure explored in the study, lateral deviation, measured the deviations from lane center as in the cell-phone studies. Figure 11 shows the model predictions: While the SS model showed no significant difference from the no-task condition, the GS model did exhibit a significant difference from the no-task condition. Alm and Nilsson’s (1995) did not report actual lane deviations in their published results, but they did note that statistical analyses revealed no significant effect of the secondary task on lateral deviations. Thus, the SS model correctly predicted the lack of an effect on lateral deviation — somewhat surprisingly, given that it did (correctly) predict a significant effect on brake reaction time. The GS model failed to fit the empirical data, emphasizing the fact that how the integrated model performs multitasking of the primary and secondary tasks can have a large impact on downstream predictions.

< INSERT FIGURE 11 HERE >

**Application Summary**

These three studies demonstrate both the validity and usefulness of the integrated-model approach in predicting the effects of driver distraction on driver performance. In addition, these studies offer several major contributions to the modeling community as a whole. First, they emphasize model re-use as a critical component to the methodology: While the secondary task
models are (necessarily) developed for each different secondary task, the approach centers on re-use of the basic computational model of driver behavior. Second, they demonstrate that the driver model in particular, and cognitive architectures more generally, nicely generalize to complex, dynamic domains that involve a wide variety of cognitive, perceptual, and motor processes. Third, the studies demonstrate the great potential of cognitive architectures and cognitive modeling for producing real-world tools that can help test and evaluation new in-vehicle interfaces and, consequently, can help improve the performance and safety of all drivers.

**Conclusion**

Computational cognitive modeling is quickly maturing to address increasingly complex phenomena at an increasingly high level of rigor. The ACT-R driver model presented here, as well as the variety of models presented in this book, have begun to demonstrate the ability not only to account for numerous aspects of real-world data but also to provide useful insights and tools for real-world applications. Accurate models of human behavior that incorporate the abilities and limitations of the human system are essential to the ability to successfully explain, recognize, and predict real-world phenomena. Recent efforts in modeling driver behavior along with a host of other domains have shown that the modeling community is quickly rising to accept and tackle these challenges.
References


Figures

Figure 1. Overview of the ACT-R driver model. (Reproduced from Salvucci, Boer, & Liu, 2001.)

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Drive

Control
- Perceive control variables
  - Update steering, acceleration/braking

Monitor
- Note other car in random lane
  - With probability $P_{monitor}$

Decide
- If lead car is too close
  - Look at or recall car in other lane in front
    - Look at or recall car in other lane in back
      - Decide to change lanes if clear

Note other car in random lane
- With probability $P_{monitor}$
```
Figure 2. Curve negotiation for right curves, including human data (solid) and model data (dashed). (Adapted from Salvucci, Boer, & Liu, 2001.)
Figure 3. Curve negotiation for left curves, including human data (solid) and model data (dashed). (Adapted from Salvucci, Boer, & Liu, 2001.)
Figure 4. Gaze dwell ratios on different visual targets, including human data (solid) and model data (dashed). (Adapted from Salvucci, Boer, & Liu, 2001.)
Figure 5. Lane position, steer angle, and gaze dwell ratios for right-to-left lane changes, including human data (solid) and model data (dashed). (Adapted from Salvucci, Boer, & Liu, 2001.)
Figure 6. Lane position, steer angle, and gaze dwell ratios for left-to-right lane changes, including human data (solid) and model data (dashed). (Adapted from Salvucci, Boer, & Liu, 2001.)
Figure 7. Mean dialing times for each interface while not driving (baseline) and while driving for (a) the integrated model and (b) the empirical data. (Reproduced from Salvucci, 2001.)
Figure 8. Mean lateral deviations without dialing and while dialing each interface for (a) the integrated model and (b) the empirical data. (Reproduced from Salvucci, 2001.)
Figure 9. Results for the model simulations (left) and human drivers (right) for speed deviation and gaze time per dialing trial. Note that some adjacent graphs are plotted on different scales to best display the overall patterns. (Adapted from Salvucci & Macuga, 2002.)
Figure 10. Brake reaction times for (a) model simulations and (b) empirical data. (Reproduced from Salvucci, 2002.)
Figure 11. Lateral deviation for model simulations. (Reproduced from Salvucci, 2002.)