Modeling Effects of Age in Complex Tasks: A Case Study in Driving

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Abstract

While computational cognitive modeling has made great strides in addressing complex dynamic tasks, the modeling of individual differences in complex tasks remains a largely unexplored area of research. In this paper we present a straightforward approach to modeling individual differences, specifically age-related cognitive differences, in complex tasks, and illustrate the application of this approach in the domain of driving. We borrow ideas from rigorous work in the EPIC cognitive architecture (Meyer et al., 2001) and extend them to the ACT-R architecture (Anderson et al., in press) and a recently-developed ACT-R driver model (Salvucci, Boer, & Liu, 2001) to model the effects of age on driver behavior. We describe two validation studies that demonstrate how this approach accounts for two important age-related effects on driver performance, namely effects on lateral stability and brake response during both normal driving and driving while performing a secondary task.

Introduction

Computational architectures and cognitive modeling have in recent years begun to account for increasingly complex and dynamic tasks, in domains such as piloting combat aircrafts (Jones et al., 1999) and controlling air traffic (Lee & Anderson, 2001). While such models have captured many aspects of human cognition and performance in these tasks, one aspect of complex tasks, namely individual differences, remains a largely unexplored area of research. The modeling community has seen several rigorous studies of individual differences in the context of cognitive architectures, perhaps most notably the work of Meyer et al. (2001) in the EPIC cognitive architecture (Meyer & Kieras, 1997) and that of Lovett, Daily, and Reder (2000) in the ACT-R architecture (Anderson et al., in press). However, due to their emphasis on specific sources of individual differences, these studies focused on relatively short laboratory tasks in controlled environments rather than more complex continuous tasks in dynamic environments.

Our goal in this paper is to generalize ideas from existing work on individual differences in simpler tasks to account for individual differences in complex dynamic tasks. We illustrate our approach in the domain of driving, a complex task that people perform on daily basis. There now exist several so-called “integrated driver models” (e.g., Aasman, 1995; Levison & Cramer, 1995) that attempt to combine the lower-level aspects of driving (e.g., steering control) with the higher-level aspects of the task (e.g., decision making, navigational planning). In particular, Salvucci, Boer, and Liu (2001) have developed and refined an ACT-R driver model that predicts many aspects of driver control, situational awareness, and decision making during common highway driving. However, to date, no integrated models of driving, including the ACT-R driver model, have accounted rigorously for any individual differences in driver behavior and performance.

This paper builds on previous work by presenting an account of individual differences, specifically age-related differences, in the complex task of driving. Not surprisingly, age plays a significant role in driver differences, often couched in broad terms as differences between younger drivers (roughly 20-30 years of age) and older drivers (roughly 60-70 years of age). Our approach borrows recent results of Meyer et al. (2001), who explored models of age-related individual differences in the context of the EPIC cognitive architecture. Age effects on driving offer a particularly interesting challenge to computational cognitive modeling: on the one hand, some studies have found that older drivers exhibit performance equal to that of younger drivers for certain combinations of driving and/or secondary tasks; on the other hand, other studies have found that older drivers sometimes experience extremely reduced performance, particularly in the presence of secondary tasks (e.g., using a cell phone). Thus, the effects of age are far from trivial and must be taken in the fuller context of both the complex behavior necessary for driving and also the complex interaction between the driver and the “artifact” (i.e., vehicle, road, etc.) through which the driver’s behavior is externalized.

In the next section of the paper, we describe our basic approach and its instantiation in the ACT-R cognitive architecture. We then present two modeling studies that validate our approach for complementary tasks and aspects of behavior, namely drivers’ ability to maintain lateral stability on the road and drivers’ ability to respond (i.e., brake) to sudden external stimuli. While our work in this paper emphasizes driver behavior and the ACT-R cognitive architecture, the fundamental ideas generalize well to other complex task domains and other modeling frameworks. Thus, our ultimate goal is to explore the interaction between basic individual differences and their downstream effects on performance in complex dynamic task environments.

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Modeling Age Effects in Driving

The various types of age-related differences that might arise in driving can be categorized broadly in terms of "hardware" and "software" differences (Meyer et al., 2001). Hardware differences arise from fundamental changes to the human system — for instance, a slowdown in cognitive processing, visual processing, or motor movement. Software differences arise in modifications or differences in the strategies used to accomplish tasks — for instance, intentionally slowing down and backing away from a lead vehicle when talking on the phone. In this paper, we focus on hardware differences, specifically differences in cognitive processing. While there is no doubt that both hardware and software differences play a role in effects on driver performance, we wish to explore to what extent modeling of basic hardware differences can account for critical effects on performance found in recent driver studies.

The ACT-R Cognitive Architecture

The ACT-R cognitive architecture (specifically version 5.0: Anderson et al., in press; see also Anderson & Lebiere, 1998) is a production-system cognitive architecture based on two types of knowledge stores, declarative and procedural. Declarative knowledge embodies "chunks" of symbolic information including factual ('3+4=7'), perceptual ('car 10 m in front'), and goal-related ('driving to the grocery store') information. Procedural knowledge operates through condition-action "production rules" that evaluate the current state of declarative knowledge (e.g., 'if my goal is to pass the lead car') and enact changes on memory and/or the environment accordingly (e.g., 'check that there is sufficient room in the left lane'). Each production rule firing (instantiation and execution) requires 50 ms of cognitive "effort" time, in addition to any time needed to wait for conditions to be met, such as the completion of a memory retrieval. Overall, the ACT-R architecture has a number of built-in functions that enable human-like behavior (e.g., interaction of memory and perceptual-motor processes) as well as built-in limitations on behavior (e.g., forgetting declarative chunks after a period of inactivity). An in-depth discussion of the architecture is beyond the scope of this paper; interested readers may wish to consult Anderson et al. (in press) for more information.

ACT-R and Age Effects

To model age effects, specifically hardware-related effects on cognitive processing, we base our approach on recent work by Meyer et al. (2001). Meyer et al. found that one of the most robust differences between younger and older people arose in the speed of cognitive processing. In particular, they found that, in the context of their EPIC architecture (Meyer & Kieras, 1997), the time for a production-rule firing increases from 50 ms for a younger person to 56.5 ms for an older person — a 13% increase. They offer several pieces of evidence to back their claim. First, for the initial claim of a 50 ms firing time, they argue that this value has a neurological correlate in the average period between zero crossings in the brain's alpha rhythm for younger adults, which has a positive relationship with mean simple response time (see Callaway & Yeager, 1960; Surwillo, 1963; and Woodruff, 1975, as cited by Meyer et al.). For older adults, they argue that mean zero-crossing periods for alpha rhythms is about 10-15% higher for subjects with an age close to 70 when compared to young adults; older subjects' mean simple response times also show a 10-15% increase (see Cerella, 1985; Somberg & Salthouse, 1982, as cited by Meyer et al.). These data lead the authors to conclude that the mean cognitive processor time increases by 13% for older adults and that this is a robust finding independent of task.

The work of Meyer et al. has a straightforward interpretation in the ACT-R architecture. ACT-R, like EPIC, uses a 50 ms cycle time for production rules. To model an older person, we simply incorporate the same cycle-time increase as Meyer et al. — namely, we increase the cycle time for production rules (called "effort" times in ACT-R) by 13%. As we will show, this change impacts performance in non-trivial ways: instead of a 13% impact on performance across measures, the change produces no effects for some measures and large effects for others depending on the emergent interactions between model and task.

In this paper, we focus in particular on the effects of cognitive cycle time and ignore potential changes in the timing of perceptual and motor processes. Meyer et al. also explored how perceptual and motor processes are affected by age; however, the mapping of their results to the ACT-R architecture is not as straightforward as the mapping for cognitive cycle time, and thus we leave this for future work. Nevertheless, we demonstrate in this paper that at least some significant aspects of age-related individual differences in driving can be successfully accounted for simply by incorporating basic differences in cognitive processing.

Driving and Age Effects

Modeling the effects of age on driver performances centers on our use of the ACT-R integrated driver model (Salvucci, Boer, & Liu, 2001). The driver model, as mentioned, incorporates both the lower-level aspects of vehicle control with the higher-level aspects of driver situational awareness and decision making. The model can navigate a variety of highway environments, the most common being a multi-lane highway with automated traffic and realistic vehicle dynamics, as pictured in Figure 1. While driving, the model interacts with the simulated environment through a virtual steering wheel and pedals, producing behavioral protocols completely analogous to those of human drivers in the simulator — recording, for example, steering and pedal depression over time along with eye movements to visual regions. The model has been validated with respect to various aspects of basic driver behavior, such as curve negotiation and lane changing (e.g., Salvucci, Boer, & Liu, 2001), and also with respect to effects of secondary tasks on performance (e.g., Salvucci, 2001).

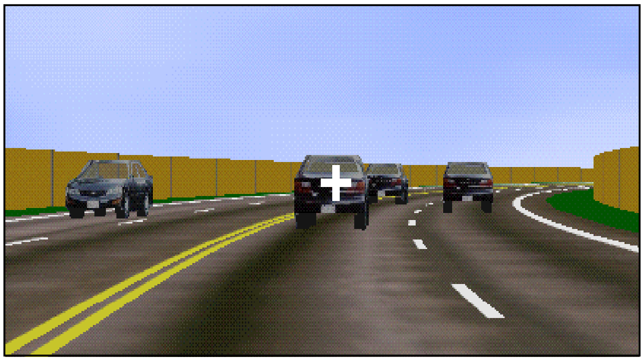

Figure 1: Sample driving simulation environment.

To model the effects of age on driver behavior, we incorporate the 13% cycle-time increase into the driver model. The increase affects all production rules across the model — most importantly, slowing down the iterating control cycle that handles the updates for steering and speed control. As mentioned, this has non-trivial downstream effects on performance rather than a simple 13% effect across measures of performance. The next two studies demonstrate how such a small change at the "hardware" level can result in very interesting emergent behavioral predictions.

Study 1: Age Effects on Lateral Stability

Our first validation study addresses effects of age on drivers' ability to maintain lateral stability — that is, side-to-side stability as measured by lateral velocity. Reed & Green (1999) compared the performance of younger and older human drivers in a simulator and on the road while executing a secondary task (dialing phone numbers). We focus our analysis on their simulator data, comparing the performance of their drivers to the predictions of the driver model in a simulator with the same task.

Human Data

In Reed and Green's (1999) study, drivers navigated a simulated straight road at a constant speed of roughly 60 mph and were occasionally cued verbally to perform a secondary task, namely dialing an 11-digit phone number (including '1' and an area code: e.g., '1-215-555-1212'). On cue, drivers picked up the phone, dialed the 11-digit number presented on a card located at the center console, and pressed a "Call" button to initiate the call. The driver then received a voice confirmation that the number was dialed correctly, and finally the driver pressed "End" to end the call. Reed and Green collected data from a total of twelve drivers, six of whom were older than 60 years of age, six of whom were between the ages of 20 and 30. They measured lateral stability as the mean lateral (side-to-side) velocity of the vehicle both during the secondary task and during normal driving.

Model Simulations

The model for the Reed and Green task was derived in a straightforward manner. The ACT-R driver model was integrated with a task environment analogous to that in the Reed and Green study — that is, a simulated one-lane straight road. The one difference in the model's task environment from that of Reed and Green arose in speed control: because the model has no speedometer with which to monitor speed, the model was given a lead vehicle driving at a constant speed, which it used to monitor its own speed. The model was then extended to include a model for the secondary task of phone dialing. This secondary-task model derived directly from a similar previous model of dialing (Salvucci et al., 2004) specified in the ACT-Simple framework (Salvucci & Lee, 2003), which is essentially a shorthand notation for standard ACT-R production rules. The model, shown in Table 1, differed from the previous model only in that it dialed the prefix "1" before the area code and phone number and that it looked at the cue card for the number rather than recalling it from memory. The "pop" marking in the table denotes commands after which the dialing model passed control to the driving task. Because the control characteristics of the Reed and Green simulator (e.g., steering force feedback) differed from those of the simulator used to validate the original driver model, three parameters[1] of the model that control overall steering were adjusted to produce the best fit in the results below. However, it should be noted that the model immediately produced the desired qualitative fit — this estimation only improved the quantitative fit. The younger and older driver models differed only in the 13% increase in cognitive cycle time for the older driver model. The model data reported below represents roughly 4-5 minutes of driving in which the model performed eight secondary-task trials with a 20 s delay between task trials.

Table 1: Secondary-task model for Study 1.

```
(move-hand device pop)
(think pop)
(press-button key1 pop)
(look-at device pop)
(think pop)
(press-button key2)
(press-button key1)
(press-button key5 pop)
(look-at device pop)
(think pop)
(press-button key8)
(press-button key6)
(press-button key7 pop)
(look-at device pop)
(think pop)
(press-button key5)
(press-button key3)
(press-button key0)
(press-button key9 pop)
(think pop)
(press-button send pop)
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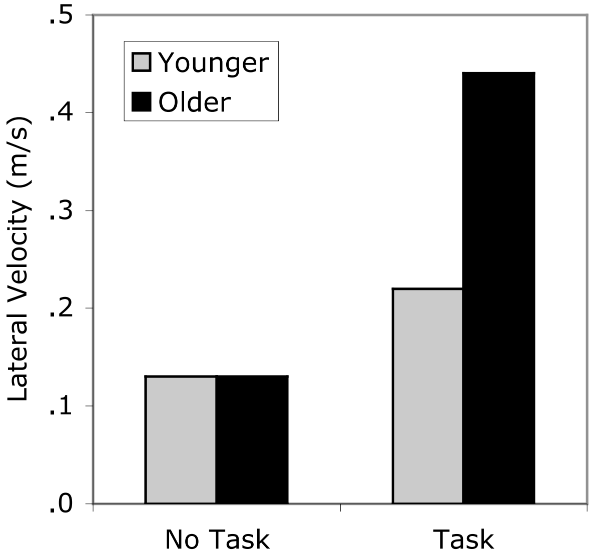
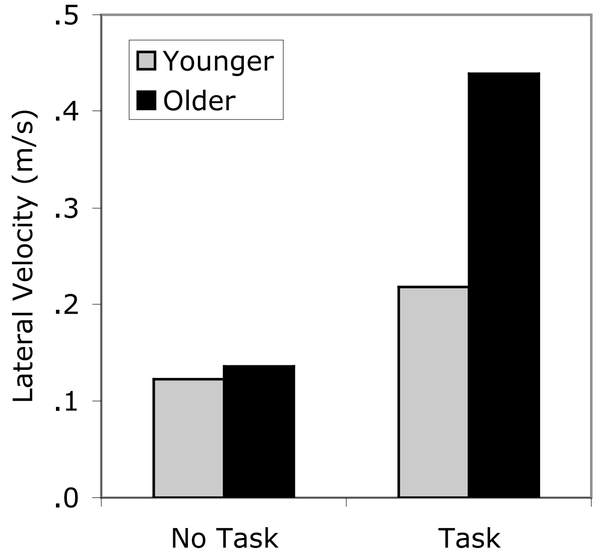
[1] $k_{far} = 13$, $k_{near} = 5.6$, $k_I = 1$



(a) Human



(b) Model

Figure 2: Lateral velocity, (a) human drivers (Reed & Green, 1999) and (b) model predictions.

Results

Figure 2(a) shows the lateral-velocity results taken from the human drivers in the Reed and Green study. In the No-Task condition, the younger and older drivers performed equally and there were no effects of age. In the Task condition, while the performance of both younger and older drivers degraded significantly, the performance of the older drivers was affected far more dramatically, with older drivers exhibiting a mean lateral velocity of .44 m/s and younger drivers a mean lateral velocity of .22 m/s in this condition.

Figure 2(b) shows the models' predictions for the same conditions, R=.99. The models, like human drivers, exhibit no age effect in the No-Task condition. Here the 13% cycle-time increase is not large enough to affect the downstream performance with respect to lateral velocity, effectively adding only tens of milliseconds to the overall control-cycle time: while the younger model updates control every 200 ms, the older model updates every 226 ms, and the extra 26 ms does not affect overall steering performance. However, also like human drivers, the model exhibits differential effects of age and task on performance. The younger model exhibits reduced performance because of less time devoted to control, as we have observed in previous studies (e.g., Salvucci, 2001). The older model exhibits an even greater degradation because of occasional, somewhat severe steering corrections: in situations where the younger model may not update control for, say, 1 s, the 13% increase for the older model would exceed 100 ms — enough time for the vehicle to travel roughly 2.7 m at the given speed and move significantly off-center in the lane. The model, seeing the large offset from lane center, performs a hard steering correction and generates a large lateral velocity. In fact, the younger model also experiences such corrections; however, the corrections are both more frequent and more severe for the older model.

Study 2: Age Effects on Brake Response

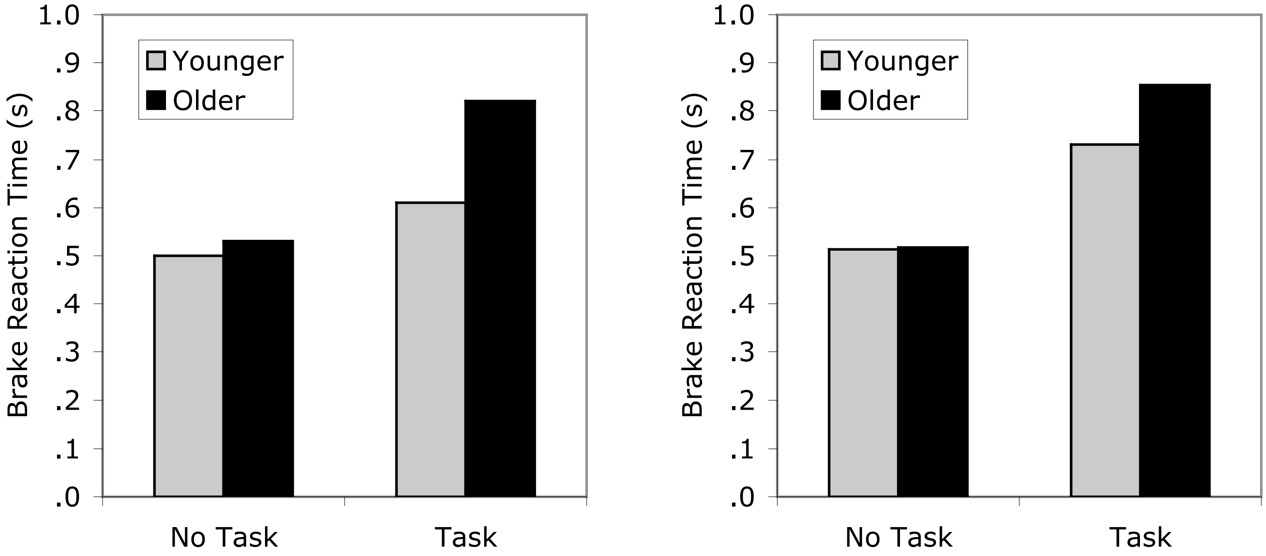
Our second validation study addresses effects of age on drivers' ability to respond to sudden external events via braking. Hancock *et al.* (2003) ran an empirical study on younger and older drivers to investigate differential effects of cell-phone distraction on braking performance. We now examine their task and results and show how the same driver model can account for this very different aspect of driver behavior and performance.

Human Data

In Hancock *et al.*'s (2003) study, drivers drove down a test track at approximately 25 mph toward an intersection with a stoplight. During some trials, the driver was cued by tone to perform a secondary task: they looked at a digit on mounted screen and pressed a key to indicate whether or not this digit corresponded to the first digit of a previously-memorized number. Also during these trials, the stoplight turned red 0.5-1 s after the onset of the secondary task, causing the driver to brake in response. During other trials, the driver only responded to the red stoplight without a secondary task. Hancock et al. collected data from 36 drivers — 19 between the ages of 25 and 36, and 16 between the ages of 55 and 65. Overall, they measured brake response time with and without the task as the time delay between the onset of the red stoplight and the initial depression of the brake.

Model Simulations

To model the Hancock et al. task, we took the model from the Reed and Green task and modified only the task components of the model. The driver model does not currently have the ability to encode and monitor stoplights, and thus we modified the environment such that the lead



(a) Human

(b) Model

Figure 3: Brake reaction time, (a) human drivers (Hancock et al., 2003), and (b) model predictions.

vehicle's brake lights would turn red 0.5-1 s after the onset of the secondary task, keeping the basic temporal structure of the Hancock et al. task. The secondary-task model was derived by modifying the Reed and Green task model to type only 1 keypress as opposed to 11; the task model is shown in Table 2. All parameter values were taken directly from the model in Study 1. However, we had to modify one braking-related parameter because of the nature of this task: the standard driver model requires 500 ms to move its foot from accelerator to brake, but because of the emergency nature of this task, we instead used a time of 310 ms — recently reported by Lee et al. (2002) as the minimum time for this movement — and eliminated motor preparation time due to the drivers' pre-preparation of the movement as they approached the intersection. Again, the younger and older driver models differed only in the 13% increase in cognitive cycle time for the older driver model. The model data below includes roughly 5 minutes of driving in which the model performed 16 secondary-task trials with a 10 s delay between task trials.

Table 2: Secondary-task model for Study 2.

```
(move-hand device pop)
(look-at device pop)
(think pop)
(press-button key5 pop)
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Results

Figure 3(a) shows the results for the human drivers. We see a similar pattern emerge in this study as we saw in Study 1. First, younger and older drivers showed no significant difference in the No-Task condition. Second, the secondary task significantly degraded the performance of both groups in the Task condition. Third, the task has a greater effect on the older drivers than the younger drivers. We should note that, although the graphs for Studies 1 and 2 are visually similar, they show very different aspects of behavior; the similarity is rather surprising given that one study examines lateral stability while the other emphasizes response time for longitudinal (braking) behavior.

Figure 3(b) shows the results for the model simulations, R=.94. As in Study 1, the models nicely account for the human drivers' behavior. The younger and older models show equivalent braking response times in the No-Task condition. Again, the slightly longer control update cycle for the older model is not enough to produce a significant effect. At the same time, the models show large effects of task in the Task condition, and the older model shows a significantly larger effect than the younger model. As in Study 1, the 13% cycle-time increase for the secondary task model increases pauses in control by 100 ms or more, thus producing an effect of roughly this size between the younger and older models. One might expect that the age effect for brake response might be heavily tied to differences in motor-movement speeds (from accelerator to brake), and given that the interaction effect in the human data is slightly larger than that for the model, this could indeed be one factor. Nevertheless, these results show that differences in cognitive processing are also a major component of this interaction and accounts for critical aspects of the human data.

General Discussion

In this paper we present a straightforward method of accounting for age-related differences in driver performance, focusing on "hardware" differences in cognitive processing time. While the idea of slowing processing time by 13%

for older people seems simple enough, it should be noted that the resulting predictions are far from trivial. Indeed, one might at first expect the slowdown to result in analogous performance decrements — for instance, a 13% degradation in lateral velocity and braking response. However, for complex dynamic tasks, this situation is much more complicated: the model's behavior is filtered through both the perceptual-motor processes and the vehicle dynamics, resulting in predictions that can only be generated and tested through "embodied" cognitive models that interact directly with realistic task environments. The two validation studies show that the ACT-R driver model, in the context of such a realistic environment, successfully accounts for these complex interactions in the driving domain, namely for both the lack of effects (in the No-Task condition) and larger-than-expected effects (in the Task condition) for lateral and longitudinal measures.

This work also illustrates one of the important advantages to working in the context of a cognitive architecture — namely, the sharing and re-use of ideas and model implementations within an architecture and even across different architectures. Not only does the work of Meyer et al. (2001) have large implications for their own EPIC architecture (Meyer & Kieras, 1997), the work translates well to other architectures such as ACT-R. In addition, this type of foundational work has immediate implications for all models developed in the architectures; for instance, other ACT-R models of complex dynamic tasks (or any tasks general) could incorporate the 13% cycle-time increase to immediately derive age-related predictions, enabling comparison to human data for a host of new measures. Such work would nicely complement recent work on other aspects of individual differences, such as differences in working memory (Lovett, Daily, & Reder, 2000). These studies of individual differences bring to light the predictive power inherent in cognitive architectures and help to make further strides toward Newell's (1990) vision of more "unified theories of cognition."

Acknowledgments

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