Fluctuations in Alertness and Sustained Attention: Predicting Driver Performance

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Abstract

Fatigue has been implicated in an alarming number of motor vehicle accidents, costing billions of dollars and thousands of lives. Unfortunately, the ability to predict performance impairments in complex task domains like driving is limited by a gap in our understanding of the explanatory mechanisms. In this paper, we describe an attempt to generate *a priori* predictions of degradations in driver performance due to sleep deprivation. We accomplish this by integrating an existing account of the effect of sleep loss and circadian rhythms on sustained attention performance with a validated model of driver behavior. Although quantitative empirical data for validation are lacking, the predicted results across four days of sleep deprivation match qualitative trends published in the literature, and illustrate the potential for making useful predictions of performance in naturalistic task contexts that are relevant to real applied problems.

Keywords: Driver Behavior; Fatigue; Computational Model; Sustained Attention; Sleep Deprivation.

Introduction

Accidents on roadways in the United States account for a distressingly high number of fatalities and substantial cost on an annual basis (Horne & Reyner, 1999; Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006; NTSB, 1995; Pack et al., 1995). According to a National Highway Transportation Safety Administration report, nearly 25% of these accidents can be wholly or partially attributed to the effects of drowsiness or fatigue on driver attention, judgment, and/or performance (NTSB, 1995).

The alarmingly high cost of fatigue in the context of driving has been one motivation for studies to better understand changes in cognitive performance stemming from extended time awake (sleep deprivation), insufficient sleep (sleep restriction), and being awake at times of the day when the body is predisposed to sleep (circadian desynchrony; Dijk, Duffy, & Czeisler, 1992; Van Dongen & Dinges, 2005a; 2005b). This research has succeeded in identifying characteristic consequences of fatigue on cognitive performance. However, there remain significant limitations in the capacity to make valid predictions about performance in novel task contexts based on a history of time awake and circadian rhythms (Dinges, 2004; Van Dongen, 2004).

Our computational modeling research has been targeted at addressing some of these current limitations in predictive validity. Much of this research addresses significant theoretical challenges associated with understanding the link between cognitive processes and fluctuations in overall cognitive arousal, or alertness (e.g., Gunzelmann, Gross, Gluck, & Dinges, 2009; Gunzelmann, Gluck, Kershner, Van Dongen, & Dinges, 2007). However, we are also addressing the issue of how these theoretical insights can be used to make a priori quantitative performance predictions in novel, naturalistic task contexts, based upon the mechanisms and parameters that have been identified (e.g., Gunzelmann, Byrne, Gluck, & Moore, 2009; Gunzelmann & Gluck, in press)

In the research presented here, we evaluate the capacity to make predictions about degradations in driver performance associated with an extended period of total sleep deprivation. We discuss the implications of our research in the context of potential applications of a predictive capacity in the domain of driving. In the next sections, we describe our model of driving behavior, our theoretical mechanisms for fatigue, and how they are integrated to allow for the generation of quantitative predictions of behavior. We then compare the model's predictions with qualitative trends in the empirical literature, demonstrating that the a priori predicted trend in the integrated model are aligned with those published results.

Driver Model

The first component of our exploration of driving and fatigue is the ACT-R driver model (Salvucci, 2006), a

computational model of driver performance developed in the ACT-R cognitive architecture (Anderson, 2007; Anderson et al., 2004), which serves as a psychological theory and simultaneously a computational framework for specifying and simulating human behavior models. The driver model is based on a control law of steering behavior (Salvucci & Gray, 2004) that visually encodes two salient points on the roadway: a near point in the lane center immediately in front of the vehicle; and a far point such as the vanishing point on a straight road, the tangent point on a curved road, or the lead vehicle when present. The control law describes how steering can be realized by keeping the far point stable while keeping the near point both stable and centered in the current lane.

The driver model that uses this control law relies on a fundamental component of the ACT-R architecture – the production system that represents central cognition. Central cognition in ACT-R operates through a series of conflict resolution cycles to produce cognitive processing and behavior. During each cycle the subset of productions whose conditions match the current system state is identified. The "system state" is represented by the contents of a set of buffers that provide limited-bandwidth communication between central cognition and peripheral information processing modules such as perception and motor action. Within this set of matching productions, the one with the highest "utility value" is selected and its actions are executed, provided that it exceeds the ACT-R "utility threshold" parameter. The default duration for these cycles is 50 ms.

The driver model uses successive iterations of four ACT-R production rules to represent the control law of steering behavior. Specifically, these four rules comprise a *control update cycle* during which the model (1) encodes the near point, (2) encodes the far point, (3) updates steering and acceleration according to the control law, and (4) checks the vehicle's current stability as measured by the lateral velocity and position of the near and far points. If the vehicle is not yet stable, the model immediately initiates another control update; otherwise, the model waits approximately 500 ms to initiate the next control update.

The driver model has been shown to account well for driver behavior with respect to curve negotiation and lane changing (Salvucci, 2006). The most critical aspect of the model for our purposes here is the execution time for a control update cycle: A single cycle requires approximately 200-250 ms, including 50 ms for each production rule firing (as dictated by ACT-R theory) plus some additional time for visual encoding. The update cycle time can increase, however, when attention is divided between driving and some secondary task, thus resulting in degradations in driver performance. For example, recent work has shown how dialing a phone (Salvucci, 2001; Salvucci & Taatgen, 2008) and rehearsing a memorized list of numbers (Salvucci & Beltowska, 2008) affects the driver model's performance; in both cases, concurrent execution of the secondary task interferes with processing of the driving task, thereby increasing the update cycle time and degrading performance (measured by, e.g., lateral deviation from lane center or brake response time to an external event). As we will describe, proposed mechanisms for fatigue in ACT-R can also prolong or delay the update cycle, leading to similar degradations in driver performance.

Mechanisms for Fatigue

The driver model provides a validated basis for making predictions about driver behavior. In independent research, efforts have been made to identify mechanisms within ACT-R to account for the impact of sleep loss and circadian rhythms on cognitive processing. In some of this research, we have focused on central cognitive mechanisms associated with the production execution cycle (Gunzelmann, Gross, et al., 2009). To account for changes associated with decreased alertness, we have integrated mechanisms in ACT-R that create opportunities for brief breakdowns in cognitive processing called *microlapses.*. In addition, we proposed a secondary process to represent the influence of explicit effort, which decreases the likelihood of a microlapse but also increases the probability of using lower-cost, less effective strategies in pursuit of achieving the goal.

The mechanisms in the fatigue model are based on the theoretical perspective that fluctuations in overall alertness or arousal can be associated with changes in utility values for selecting and executing production rules in ACT-R's central production system. Utility values are decreased, which increases the likelihood that no action will be taken on a given cycle. This situation leads to a microlapse, which is formally defined as a gap in cognitive processing lasting for the duration of one cognitive cycle (approximately 50 ms).

To account for the potential benefits of increased effort, a second parameter is manipulated – the utility threshold – which sets the minimum utility value required for a production to fire. Decreasing the utility threshold instantiates greater *effort* by making it more likely that some production will successfully fire. However, this manipulation also increases the probability that a suboptimal action (a production with a low utility) will be executed instead (see Gunzelmann, Gross, et al., 2009).

To evaluate the validity of our account, we compared the model's performance to human data on a sustained attention task across 88 hrs of total sleep deprivation. The model captured the important features of the human data, including explanations for small increases in the median of appropriately fast responses and increasing probabilities of false starts, slowed responses (lapses), and complete failures to respond (sleep attacks). The task, model, and results are described in detail in Gunzelmann, Gross, et al. (2009).

Integration

The mechanisms for fatigue instantiate a theory of changes in central cognitive processing resulting from fluctuations in alertness attributable to sleep loss and circadian rhythms.

Meanwhile, the model of driver behavior provides a validated account of mechanisms and processes involved in skilled driving. Importantly the ACT-R driver model relies on procedural knowledge for successful performance, including staying within its lane. As a result, an opportunity exists to bring together an existing model of driver behavior with an existing account of fatigue to explore the implications of fatigue on driving behavior. This opportunity represents an important step in the evolution of computational architectural accounts of cognitive phenomena, and illustrates the potential utility of unified theories that integrate theoretical insights from various domains of psychological research.

The integration of the driver model and fatigue mechanisms was a straightforward process. The implementation of the driver model was altered to run on a high-performance computer but was not changed with respect to its core behavior. The driver model is similar to the sustained attention model in that neither makes extensive use of declarative memory, simplifying the account by eliminating the need to consider potential influences of fatigue on declarative knowledge access (e.g., Gunzelmann et al., 2007). The fatigue mechanisms were taken directly from Gunzelmann, Gross, et al. (2009) and applied to the driver model. Thus, our procedural fatigue mechanisms alone provide the moderating effects in the driving model.

The actual effects of the fatigue mechanisms center on the production selection and execution phases of the production cycle in ACT-R. Proportional scaling of utility values during the selection phase of the driver model creates situations where the matching production with the highest utility fails to exceed the utility threshold. Thus, no production is executed on that cycle, producing a microlapse as described above. This is the key component in our theoretical account of performance declines associated with fatigue because it provides an account, based upon a single mechanism, of phenomena in the sleep research community that have been associated with *cognitive lapses* and *cognitive slowing* (e.g., Dinges & Kribbs, 1991). Parameter manipulations associated with fluctuations in alertness influence the frequency of microlapses, and microlapses lead to the performance changes exhibited by "tired" models.

In cases when a microlapse occurs with no other ongoing processes in any of ACT-R's information processing modules, the microlapse is accompanied by additional attenuation of utility values. The noise component of the utility values allows subsequent conflict resolutions to potentially match a production and continue model execution. However, this does not always occur, and as each successive decline in alertness further reduces the possibility of utilities rising about the threshold, a model can quickly spiral into a state analogous to sleep. In the model described in Gunzelmann, Gross, et al. (2009), this mechanism is critical in capturing the most substantial breakdowns in cognitive processing (i.e., sleep attacks).

In the sustained attention task, long periods of time go by – as long as 10 seconds – where the model is simply waiting for a stimulus event. In contrast, the processing in the driver model incorporates a constant monitoring behavior, which leads to cognitive processing in modules outside central cognition throughout the task. Peripheral processing does not affect the occurrence of microlapses, but does prevent any progressive declines in utility values over the course of a 10-minute driving session. The implication is that our model currently does not capture changes in performance that may be expected over the course of a 10-minute driving episode (i.e., time on task effects). However, our focus is on making truly *a priori* predictions, and so we leave them unchanged in the model runs described below.

In the next section, we evaluate the impact of our fatigue mechanisms on the driver model. Recall that the driver model realizes the continuous control law through four key productions. It is in this control update cycle that the fatigue mechanisms are most influential, since microlapses increase the overall update cycle time. As will be shown, even brief delays in cognitive activity can amount to significant and potentially devastating behavioral impacts.

Model Evaluation

To evaluate the model, its behavior was assessed in the context of a driving scenario described in Salvucci and Taatgen (2008). In the task, the driver steered down a single-lane highway, keeping the vehicle as centered as possible in the roadway. The vehicle moved at a constant speed that was not controlled by the driver, thus focusing the task particularly on lateral control. One key measure of performance in the task is *lateral deviation*: the root-mean-squared error between the lane center and the vehicle's lateral position within the lane. The baseline driver model navigating this environment exhibits an average lateral deviation of approximately 15 cm across a 10-minute driving scenario (see Salvucci & Taatgen, 2008).

To produce predictions of driver behavior and performance, we used parameter values for the fatigue mechanisms that were estimated in our research on sustained attention (e.g., see Gunzelmann, Gross, et al., 2009). Specifically, the model for that research was able to account for human sustained attention performance at 2 hour intervals across 88 hours of total sleep deprivation. As an initial assessment of the driver model, we used the parameter values from sessions occurring shortly after participants awakened on the baseline day of the study, and from sessions occurring after 24, 48, and 72 hrs of total sleep deprivation (0800 on each of 4 consecutive days). The model was run 200 times using each of those parameter sets, leading to reliable measures of central tendency in the performance measures as well as evidence regarding the variability in fatigue effects across 10 minute driving sessions.

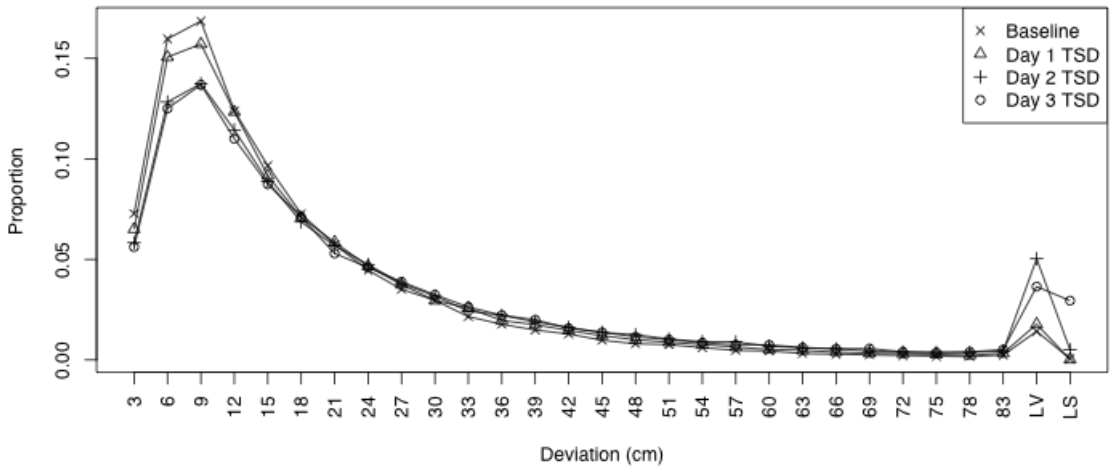

Figure 1: Proportion of 1-second samples of lateral deviation falling into each of the specified bins. The last two categories represent instances where (1) the vehicle is partway out of the proper lane (a lane violation, "LV"), and (2) the vehicle's deviation is more than a full lane width off (a lane switch, "LS"). Separate lines represent 0, 24, 48, and 72 hours of total sleep deprivation (TSD).

To assess the performance, the lateral deviation of the model was recorded for each second during each model run. Figure 1 shows a histogram of these deviation values as a function of degree of sleep deprivation (0, 24, 48, and 72 hrs). Perhaps surprisingly, the distributions are not radically different. Note however, that on the left side of the distribution the proportion of lower deviation values (3-12 cm) decreases with increasing sleep deprivation. The overall trend is toward an increasingly skewed distribution, where performance is basically normal most of the time, but diverges more often and to a greater extent as sleep deprivation increases. This pattern of results matches the data from the sustained attention task that we have used in developing the mechanisms applied to the driver model in this paper (see Gunzelmann, Gross, et al., 2009).

While the distributions in the larger deviations (21-80 cm) are not very different, clear differences emerge in the categories representing the largest deviations. Lane violations ("LV" in the figure) represent points when some portion of the vehicle had crossed the lane line (i.e., the vehicle overlapped the adjacent lane). The proportions of lane violations more than double for Days 2 and 3 of sleep deprivation as compared to the baseline day or a single night without sleep. The final category, lane shifts ("LS" in the figure), represent points during which the vehicle has moved an entire lane's width laterally — clearly a substantial degree of driver performance error. Whereas the Baseline and Day 1 conditions exhibit no lane shifts, there appear a small number of lane shifts in Day 2, and in Day 3, 3% of all lateral deviation values sampled are in this category. This means that 3% of the time, the model is driving completely out of its intended lane (possibly off the road or possibly into oncoming traffic).

To better understand the nature of this performance in terms of the driver model and fatigue mechanisms, Figure 2 shows a histogram of update times for the driver model in each condition — that is, the amount of time needed for the model to complete its four-production control update cycle. As was the case for lateral deviation, the distributions shift with increasing sleep deprivation such that update times reflecting cycles that are not interrupted (200-300 ms) become less frequent and longer update times become more prevalent. The increase in update times arises because production rules are more likely to fall below threshold under the influence of fatigue mechanisms, thus missing an opportunity to fire during a conflict resolution cycle.

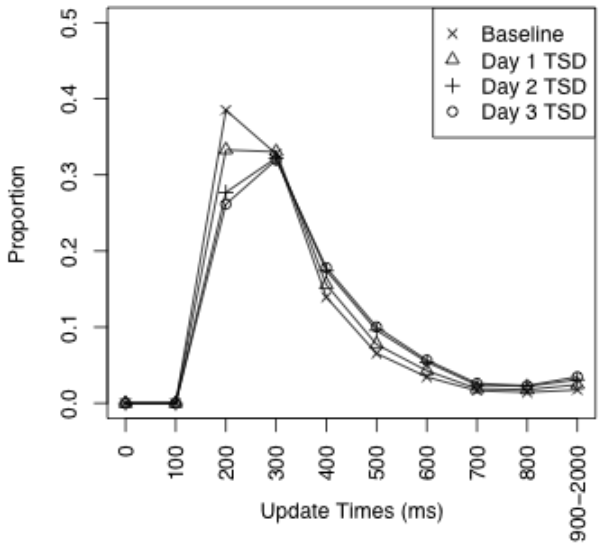

Figure 2: Distribution of model update times as a function of number of days of total sleep deprivation (TSD).

Comparison to Human Performance

To evaluate the model predictions in the context of actual human driver performance, we compared the model's performance to published results from a study of fatigued driving (Peters, Kloeppel, & Alicandri, 1999). Peters et al. (1999) measured lane violations during conditions of restricted sleep and sleep deprivation. Figure 3 compares the pattern of results from Peters et al. (1999) to the data from our model. The data from Peters et al. (1999) are frequency counts of lane violations, while the data from the ACT-R model reflect proportions of 1-second samples of lane deviation that exceeded the threshold for a lane violation. Though these measures are slightly different, they are closely related, and the pattern of results is identical (r=.99).

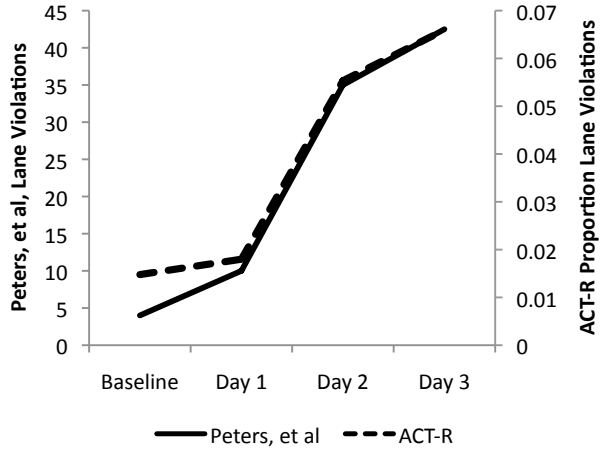

Figure 3: Lane violations from Peters et al. (1999) compared to the proportion of lane deviation samples classified as lane deviations or lane shifts in the model.

The Peters et al. experiment protocol was slightly different than the strict total sleep deprivation protocol assumed in our model predictions. Participants in Peters et al. (1999) were allowed four hours of sleep on the first night, between the Baseline Day and Day 1, whereas the parameters in the model assume total sleep deprivation. This could have some impact on the quantitative results, but the overall pattern would be similar in either case. The pattern is similar for both the human data and the model: only a slight performance decrement in Day 1, but a much larger decrement in Days 2 and 3. While the above caveat concerning the experiment protocol differences should be noted, these results suggest that the integration of the driver and fatigue models indeed captures an important aspect of fatigued driver behavior.

Conclusions and Future Directions

The model described in this paper exhibits declines in performance when mechanisms are implemented to represent the deleterious effects of sleep loss on central cognitive functioning. The foundation is a validated model of skilled driver behavior (Salvucci, 2006). That model is augmented with a set of mechanisms that account for changes in central cognitive processing that result from increased levels of fatigue associated with time awake and circadian rhythms (Gunzelmann, Gross, et al., 2009).

The primary contribution of this research is the demonstration that it is possible to make truly a priori predictions regarding the effects of extended wakefulness on performance in complex, dynamic tasks. The qualitative changes in the model's performance are identical to the performance changes observed in human participants attempting to drive after extended periods of partial or total sleep deprivation. The results go beyond intuitive notions regarding degradations in cognitive processing and performance as time awake increases by providing quantitative estimates about the actual impact of those changes on performance in the driving task.

Of course, qualitative comparisons of overall performance falls short of the rigorous evaluation of the model that we would like to perform. However, the current research effort represents a critical step in the process of using computational cognitive modeling to make predictions about human cognition and behavior in naturalistic task contexts. The modular design of ACT-R facilitates this convergence of research efforts by providing an infrastructure that allows new theoretical components (like the account of fatigue) to be added seamlessly to the architecture. Once added, these new components, or modules, influence the model's behavior to the extent that the proper conditions arise to activate the mechanisms. In this case, the mechanisms for fatigue have a substantial impact on model behavior. Importantly, the impact appears to be in line with human data on a similar task in the research literature.

A major goal of research on fatigue is to develop an understanding of the impact of sleep loss that is useful in making predictions regarding the consequences for performance in applied settings. At the outset, we cited the enormous cost of fatigue – both in dollars and lives – on highways in the United States. A better understanding of the relationship between fluctuations in alertness and changes in observable human behavior has the potential to greatly reduce this cost, potentially saving thousands of lives. Moreover, driving is not the only area where the potential benefits exist. In many applied settings, lack of sleep and circadian desynchrony may lead to disastrous consequences (e.g., Caldwell, Caldwell, Brown, & Smith, 2004; Dinges, 1995). Accurate predictions of the consequences of fatigue could help to avert some of these potential tragedies.

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References

Anderson, J. R. (2007). *How Can the Mind Exist in a Physical Universe?* Oxford University Press.

Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., & Qin, Y. (2004). An integrated theory of the mind. *Psychological Review, 111*, 1036-1060.

Caldwell, J. A., Caldwell, J. L., Brown, D. L., & Smith, J. K. (2004). The effects of 37 hours of continuous wakefulness on the physiological arousal, cognitive performance, self-reported mood, and simulator flight performance of F-117A pilots. *Military Psychology, 16(3)*, 163-181.

Dijk, D-J., Duffy, J. F., & Czeisler, C. A. (1992). Circadian and sleep/wake dependent aspects of subjective alertness and cognitive performance. *Journal of Sleep Research, 1*, 112-117.

Dinges, D. F. (2004). Critical research issues in development of biomathematical models of fatigue and performance. Aviation, Space, and Environmental Medicine, 75(3), A181-A191.

Dinges, D. F. (1995). An overview of sleepiness and accidents. *Journal of Sleep Research, 4(2)*, 4-11.

Dinges, D. F., & Kribbs, N. B. (1991). Performing while sleepy: effects of experimentally-induced sleepiness. In Monk, T.H. (Ed.) *Sleep, sleepiness and performance* (pp. 97-128). Chichester: John Wiley & Sons.

Gunzelmann, G., Byrne, M. D., Gluck, K. A., & Moore, L. R. (2009). Implications of Computational Cognitive Modeling for Understanding Fatigue. *Human Factors, 51(2)*.

Gunzelmann, G., & Gluck, K. A. (in press). An Integrative Approach to Understanding and Predicting the Consequences of Fatigue on Cognitive Performance. *Cognitive Technology*.

Gunzelmann, G., Gluck, K. A., Kershner, J., Van Dongen, H. P. A., & Dinges, D. F. (2007). Understanding decrements in knowledge access resulting from increased fatigue. In D. S. McNamara and J. G. Trafton (Eds.), *Proceedings of the Twenty-Ninth Annual Meeting of the Cognitive Science Society* (pp. 329-334). Austin, TX: Cognitive Science Society.

Gunzelmann, G., Gross, J. B., Gluck, K. A., & Dinges, D. F. (2009). Sleep deprivation and sustained attention performance: Integrating mathematical and cognitive modeling. *Cognitive Science*.

Horne, J., & Reyner, L. (1999). Vehicle accidents related to sleep: A review. *Occupational and Environmental Medicine, 56*, 289-294.

Klauer, S.G., Dingus, T. A., Neale, V. L., Sudweeks, J.D., & Ramsey, D.J. (2006). The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data. *Technical Report #DOT HS 810 594*. Washington, DC: National Highway Traffic Safety Administration.

Mallis, M., Mejdal, S., Nguyen, T., & Dinges, D. (2004). Summary of the key features of seven biomathematical models of human fatigue and performance. *Aviation, Space, and Environmental Medicine, 75(3)*, A4-A14.

National Transportation Safety Board (1995). Factors that affect fatigue in heavy truck accidents (volume 1). NTSB Safety Study: *Report no. NTSB//SS-95/01 (PB95-9170012)*. Washington, DC: NTSB.

Pack, A. I., Pack, A. M., Rodgman, E., Cucchiara, A., Dinges, D. F., & Schwab, C. W. (1995). Characteristics of crashes attributed to the driver having fallen asleep. *Accident Analysis & Prevention, 27(6)*, 769-775.

Peters, R.D., Kloeppel, E., & Alicandri, E. (1999). Effects of partial and total sleep deprivation on driving performance. *Publication No. FHWA-RD-94-046*, Washington, DC: Federal Highway Administration, US Department of Transportation.

Salvucci, D. D. (2001). An integrated model of eye movements and visual encoding. *Cognitive Systems Research*, *1*, 201-220.

Salvucci, D. D. (2006). Modeling driver behavior in a cognitive architecture. *Human Factors*, *48*, 362-380.

Salvucci, D. D., & Beltowska, J. (2008). Effects of memory rehearsal on driver performance: Experiment and theoretical account. *Human Factors*, *50*, 834–844.

Salvucci, D. D., & Gray, R. (2004). A two-point visual control model of steering. *Perception*, *33*, 1233-1248.

Salvucci, D. D., & Taatgen, N. A. (2008). Threaded cognition: An integrated theory of concurrent multitasking. *Psychological Review*, *115*, 101-130.

Van Dongen, H. P. A. (2004). Comparison of mathematical model predictions to experimental data of fatigue and performance. Aviation, Space, and Environmental Medicine, 75(3), A15-A36.

Van Dongen, H. P. A., & Dinges, D. F. (2005a). Circadian rhythms in sleepiness, alertness, and performance. In M. H. Kryger, T. Roth, & W. C. Dement (Eds.), *Principles and practice of sleep medicine, 4th ed.* (pp. 435-443). Philadelphia, PA: Elsevier Saunders.

Van Dongen, H. P. A., & Dinges, D.F. (2005b). Sleep, circadian rhythms, and psychomotor vigilance. *Clinical Sports Medicine, 24*, 237-249.