Multitasking while driving: central bottleneck or problem state interference?

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Introduction

In the context of driving, man-machine systems have recently been envisioned to adapt to the driver's cognitive state to mitigate accident risk as a result of cognitive failure (Hancock et al., 2013). A crucial step in this direction is to understand how different tasks affect the mental capacity of the drivers. Previous research by Scheunemann et al. (2019) demonstrated that visuospatial demands and working memory not only affect driving performance but show interactions, which complicate accurate predictions of the driver's mental state. Scheunemann et al. (2019) have proposed that the interaction between the two cognitive concepts could be due to a common resource at a task-unspecific level or a task-specific level.

Understanding *how* these tasks affect cognitive load and where they show interactions while driving requires a comprehensive understanding of the underlying computational mechanisms of the task (Kriegeskorte & Douglas, 2018), which is why we developed two ACT-R models based on the driving model by Salvucci (2006): one implementing a bottleneck merely at the central processing unit, the other additionally implementing a bottleneck at the problem state. We use these models to explain where common resources can cause interactions between different kinds of cognitive load in a simple driving-simulator experiment.

Methods

The models used in this study was a modification of the ACT-R driving model by Salvucci (2006), re-implemented in Java[1].

The models performed a highway driving task, while navigating through concurring traffic following the experimental design by Unni et al. (2017). The road layout changed between a three-lane highway with 3.5m lane-widths and a two-lane construction site with 2.5m lane-widths.

At the same time, the models performed a modified n-back task involving speed signs, which occurred every 20s on the right side of the road. Depending on the n-back level (ranging from 0 to 4) the model had to drive according to the speed that was presented *n* signs back. Thus, the 0-back condition translates to common highway driving.

To interleave both tasks, the models used threaded cognition (Salvucci & Taatgen, 2008) that dictates which task is pursued based on available resources.

Central Bottleneck Model

Based on the work by Salvucci & Beltowska (2008), we did not explicitly model an interaction between the tasks in the central bottleneck model but hypothesized that the model would predict human driving behavior by a contention for the central processing unit of ACT-R. As only one production rule can be initiated at the same time, performing the n-back task simultaneously can cause a delay in the execution of production rules of the driving loop causing fewer steering updates (purple dashed box with diagonal lines in Figure 1).

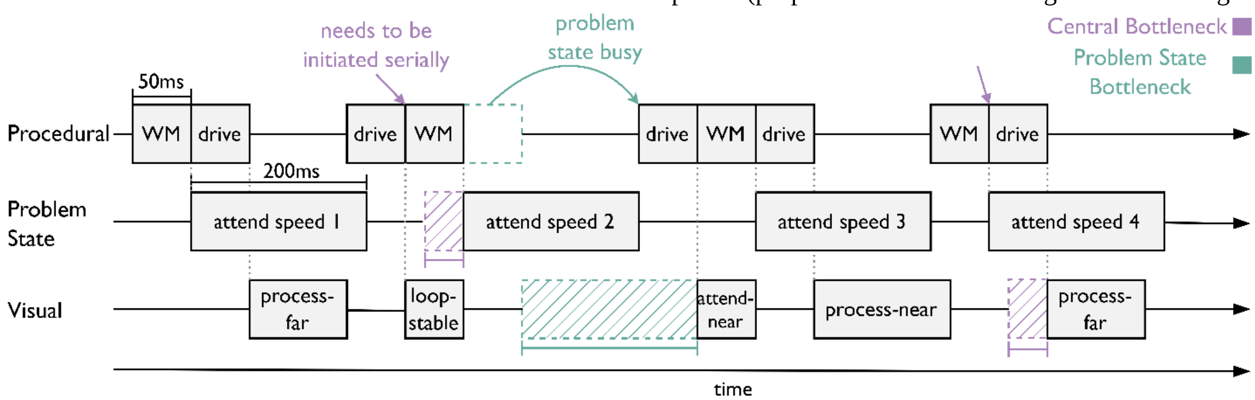


Figure 1: Demonstration of the two bottlenecks. The figure starts when a new sign appears and the correct speed is being recalled. The driving loop is ongoing, and a new iteration is initiated by attending the near point ("attend-near"). Boxes with diagonal lines signify the delay period due to the specific bottlenecks.

[1] https://www.cs.drexel.edu/~salvucci/cog/act-r/

For the driving part of the model, we updated the Salvucci (2006) model to implement a low-control loop and a high-control loop. The high-control loop is identical to Salvucci (2006), which continuously negotiates a new steering angle using a near and far point at the center of the road. However, the low-control loop does not update the steering angle but merely checks if the car is in a safe position on the road. The safety margin is based on the distance to the lane edges and was parameterized for a good model fit. If the car is in an unsafe position, it transitions back to the high-control loop to steer back to a safe position on the lane. The safety margin is identical in both driving conditions. Because the construction site is narrower than the normal highway, the car spends less time in a safe position on the road and enters the high-control loop and consequently updates the steering angle more often.

The n-back task is modeled via a sequential recall. When a speed sign is encountered it is stored in declarative memory together with a unique episodic marker indicating when the speed sign was observed. In addition, the chunk contains a reference to the speed sign encountered directly before. Thus, the memorized list of speed signs can be described as a linked list going backwards in time. As each rehearsal may potentially interfere with driving due to a competition for resources, the number of times the model rehearses has a direct effect on the driving performance and, thus, has been adjusted to fit the model. To follow the correct speed, the target speed is held in a chunk in the problem state. During recall this chunk is updated according to the n-back task.

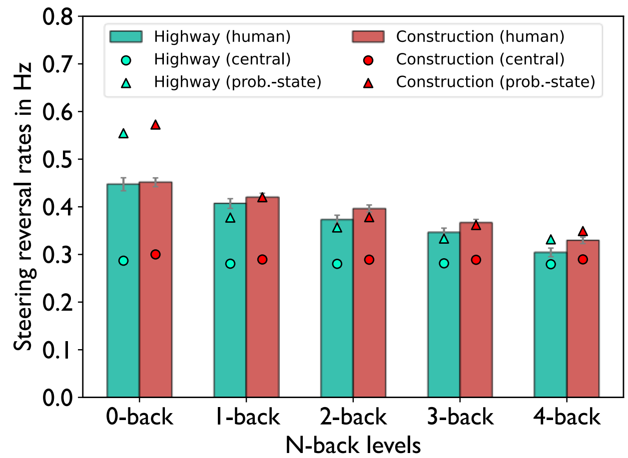
Problem State Bottleneck Model

In the problem state bottleneck model, we revised the parameters regarding the control law and implemented a restriction to the start of each iteration of the driving control loop, which starts with the "attend-near" production such that it could only be initiated if the problem state is not busy (green arrow indicates the delay in Figure 1), which it is for 200ms after creating a new chunk in the buffer. This restriction can delay the execution of the driving loop (green dashed box with diagonal lines in Figure 1) and acts as a second bottleneck in the model.

For the revision of the n-back model we categorized the target speed as control information and stored it in the goal buffer chunk of the driving goal. In the recall or rehearsal process, the model goes through the speed signs backwards in time. While doing so, each of the signs is held in the problem state and released when the previous sign is recalled. Thus, the chunks encoding the speed signs are constantly replaced in the recall and rehearsal process resulting in a heavy use of the problem state in the process. Upon reaching the target sign, the problem state is cleared before a new rehearsal starts. In this time window, the problem state is not occupied.

Human data

The experimental data, which was used to validate the model was recorded using the same simulation the model was driving in. Twenty-five participants completed a block for each pairing of n-back condition and visuospatial condition twice for a total of 20 blocks.



Results

As can be seen in Figure 2, the central bottleneck model underestimates the steering reversal rate in total compared to human behavior, which results in a lower number of steering reversals overall. Additionally, the decrease of steering reversal rate (SRR) over n-back level is only marginal in the model and significantly higher in human participants.

In the problem state bottleneck model, we observe a better fit to human data. This is evident for the SRRs across all conditions, but also for the effect of decreasing SRRs as n-back difficulty increases.

In addition, the central bottleneck model captures the effect of narrower lane width in the construction condition, resulting in a higher number of steering reversals, which can be seen in human participants. Importantly, the revised model is able to show the same effect of decreasing SRRs while still showing differences in SRRs between n-back levels.

Discussion

The ACT-R models are able to show how both tasks compete for available resources on either a task-unspecific level or task-specific level. In the central bottleneck model, the driving behavior is mainly influenced by a contention for the central processing unit simulating a bottleneck at a task-unspecific resource. This model demonstrates that a central bottleneck is insufficient to account for human behavior regarding the influence of the secondary task. The implementation of a bottleneck for the problem state shows that both the driving task and n-back task require this resource indicating a bottleneck at a task-specific resource.

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