The Virtual Driver: Integrating Physical and Cognitive Human Models to Simulate Driving with a Secondary In-Vehicle Task

by

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To my parents

Acknowledgments

Writing a dissertation is a daunting business. Putting a pen to paper (or fingers to a keyboard, as the case may be) and organizing all the knowledge gained during four years of study can be positively terrifying. And sanity-straining. Luckily, mine is still nearly as intact as when I began the process, and there are a great many people who deserve a great deal of thanks for that.

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ABSTRACT

The Virtual Driver: Integrating Physical and Cognitive Human Models to Simulate Driving with a Secondary In-Vehicle Task

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Models of human behavior provide insight into people's choices and actions and form the basis of engineering tools for predicting performance and improving interface design. Most human models are either cognitive, focusing on the information processing underlying the decisions made when performing a task, or physical, representing postures and motions used to perform the task. In general, cognitive models contain a highly simplified representation of the physical aspects of a task and are best suited for analysis of tasks with only minor motor components. Physical models require a person experienced with the task and the software to enter detailed information about how and when movements should be made, a process that can be costly, time consuming, and inaccurate. Many tasks have both cognitive and physical components, which may interact in ways that could not be predicted using a cognitive or physical model alone.

This research proposes a solution by combining a cognitive model, the Queuing Network – Model Human Processor, and a physical model, the Human Motion Simulation (HUMOSIM) Framework, to produce an integrated cognitive-physical human model that makes it possible to study complex human-machine interactions. The physical task environment is defined using the HUMOSIM Framework, which communicates relevant information such as movement times and difficulty to the QN-MHP. Action choice and movement sequencing are performed in the QN-MHP. The integrated model's more natural movements, generated by motor commands from the QN-MHP, and more realistic cognitive decisions, made using physical information from the HUMOSIM Framework, make it useful for evaluating different designs for tasks, spaces, systems, and jobs.

The Virtual Driver is the application of the integrated model to driving with an in-vehicle task. A driving simulator experiment was used to tune and evaluate the integrated model. Increasing the visual and physical difficulty of the in-vehicle task affected the resource-sharing strategies drivers used and resulted in deterioration in driving and in-vehicle task performance, especially for shorter drivers.

The Virtual Driver replicates basic driving, in-vehicle task, and resource-sharing behaviors and provides a new way to study driver distraction. The model has applicability to interface design and predictions about staffing requirements and performance.

Chapter 1

Introduction

Motivation

Models of human behavior provide insight into people's choices and actions and form the basis of engineering tools for predicting performance and improving interface design. Most human models are either cognitive, focusing on the information processing underlying the decisions made when performing a task, or physical, representing postures and motions used to perform the task.

In general, cognitive models contain a highly simplified representation of the physical aspects of a task and are best suited for analysis of tasks with only minor motor components. Physical models require a person experienced with the task and the software to enter detailed information about how the movements should be made, a process that can be costly, time consuming, and inaccurate. Many tasks have both cognitive and physical components, which may interact in ways that could not be predicted using a cognitive or physical model alone.

This research addresses the divide between cognitive and physical human models by integrating a cognitive human model with a physical human model. This new combined model uses the advantages of each type of model to overcome the weaknesses of the other. The capabilities of the new integrated model are evaluated by using it to model a task scenario with both cognitive and physical components: driving while performing a secondary in-vehicle task.

Driver distraction is a topic that is increasingly prevalent in the news media. Stories of pedestrians, bicyclists, and motor vehicle operators injured or killed by inattentive drivers can be found on a daily basis. The rapidly changing systems available for use in vehicles make it difficult to study and predict their effects on drivers. Driving simulator studies are expensive and time-consuming, and the results are not always comparable to real driving.

Previous research has addressed this problem by developing models of human cognition that attempt to predict driving performance and how humans will decide to perform a secondary task while driving. However, most models of driving only simulate the cognitive aspects of the task, while in-vehicle tasks can have significant physical components.

The proposed solution, the Virtual Driver, combines a cognitive human model with a physical human model, which can represent how a person would interact with his or her physical task environment. The resulting integrated human model can be used to evaluate interfaces for in-vehicle designs and to represent complex interactions between a driver and the real world.

Significance and Contribution to Current Knowledge

Digital Human Modeling

Software models of the human body and mind provide a means for representing how a human may perform tasks and interact with the environment. They also aid in understanding mechanisms underlying human behavior. These digital human models are useful for interface and workstation design and for predicting task performance and staffing requirements. They can be used to estimate the consequences of performing tasks in a given work environment to determine if people are likely to become injured or overwhelmed by the task requirements. Simulations using human models are much less resource-intensive than building and testing a physical workstation. This makes them very useful in the iterative design process, as a large number of workstations with minor differences can be tested to find the optimal design.

Currently, human models may be divided into two categories: cognitive and physical. Cognitive models focus on the cognitive processing underlying the decisions made when performing a task. Physical models represent postures and the physical motions used to perform the task.

Cognitive models can simulate how a person might decide to perform a task, including timing of motor commands. However, motor representations in these models are generally limited to empirical timing models. Factors affecting the actual movement time and difficulty, such as the distance to be moved, physical characteristics of the person, and properties of the environment, such as obstacles, are generally not represented. As a result, cognitive models are currently most useful for analysis of tasks with only minor motor components.

In contrast, human figure models can show the movements that might be used to accomplish a task in a computer representation of the task environment. This can help to identify the physical challenges and risk of injury related to that task. A major limitation with physical modeling is the need for a person experienced with the task and the software to enter detailed information about how the movements should be made. Thus, using physical modeling for job analyses can be costly, time consuming, and possibly inaccurate.

Many of the limitations of the two modeling approaches may be overcome by integrating two separate models to develop a combined cognitive-physical model, with the capabilities of both models. Providing the cognitive model with physical information would allow the cognitive model to behave in a more realistic way. Similarly, providing the physical model with cognitive information would increase the realism of the model's movements, because the physical model could get timing and positioning information from the cognitive model, rather than relying on the software user to make the decisions.

Thus, a combined cognitive-physical human model would provide a more realistic representation of human actions and decisions, making it useful for designing tasks, spaces, systems, and jobs. A combined model would be especially useful in tasks that have significant cognitive and physical components.

A few groups have begun to address the need for a combined cognitive-physical model (Zhang, 2003; Badler et al., 2005; Raschke et al., 2005). Recent developments and improvements in both cognitive and physical modeling architecture have improved the opportunities for productive integration between the two types of models (Tsimhoni & Reed, 2007).

An important example of a task with both cognitive and physical components is driving while performing a secondary task using an in-vehicle system. With the increasing numbers of systems for in-vehicle tasks being installed in motor vehicles, it is more difficult to put a given system in the ideal location. Therefore, drivers may have to perform difficult reaches while looking away from the road for significant periods of time to complete an in-vehicle task. To determine the effects of system design and placement on driver safety, it is important to have a way to accurately model the cognitive and physical challenges of using an in-vehicle system..

Driver Distraction

The magnitude of the impact of driver distraction on road safety has prompted considerable attention. Wang and colleagues (1996) used the 1995 Crashworthiness Data System to estimate that 25.6% of all passenger vehicle tow away crashes involved driver inattention; this included 13.3% that involved distraction, 9.7% that were categorized as "looked but did not see", and 2.6% that had drowsiness as a factor. However, the 100-Car Naturalistic Driving Study found that driver distraction was involved in almost 80% of all crashes and 65% of all near-crashes (Dingus et al., 2006). In addition, Hendricks and colleagues (2001) reported that driver distraction and inattention were the leading cause of vehicle crashes in the United States.

More recently, in police-reported crashes in 2008 with at least one form of driver distraction listed on the crash report, 5,870 people were killed and approximately 515,000 were injured (Ascone et al., 2009). The problem may be underrepresented in these numbers, because identification of driver distraction and its role in a crash can be difficult for law enforcement. According to data from the Fatality Analysis Reporting System (FARS) and the General Estimates System (GES), driver distraction was involved in 16% of all fatal crashes and 21% of all injury crashes in 2008.

A variety of secondary task activities can be classified as driver distractions. These include dialing a cell phone, talking on a cell phone, texting, eating, drinking, conversing with passengers, and interacting with in-vehicle technologies (Ascone et al., 2009).

The level of sophistication of various types of in-vehicle technology has increased more rapidly than both the understanding of the effects of these cognitive distraction and the presence of legislation that might regulate the use of these devices and diminish their risks. Some models of driving and driver distraction have been proposed, but these have various limitations, and recent calls have been made for better models of driver distraction (e.g. US DOT Distracted Driving Summit, 9/30/09).

An accurate model of the human driver in a realistic vehicle cab environment could be used to assess the risks that distractions pose and make it possible to examine potential interventions while using fewer resources than experimental studies would require. Ultimately, such a model could serve to reduce traffic injuries and fatalities.

A human driver model could simulate the average driver on the road, but it would also be useful for modeling the demands of certain occupations that rely heavily on motorized vehicles. Civilian truck drivers often are required to use in-vehicle computers to enter and receive information (Figure 1.1). Law enforcement officers also utilize in-vehicle devices such as displays and radios.

Figure 1.1. A truck driver operates the in-vehicle computer he uses to correspond with dispatchers and receive routes and assignments (Richtel, 2009).

In-vehicle information systems are also heavily used in military applications. Military drivers may face substantial cognitive and physical demands, which could be difficult or dangerous to duplicate in a test environment. A human driver model could be used to make predictions about performance and consequent staffing requirements based on physical factors such as device position and restrictive clothing.

Thesis Statement

The goal of this research was to improve the simulation of complex tasks by integrating a cognitive human model, the Queuing Network – Model Human Processor

(QN-MHP) (Liu et al., 2006), with a physical human model, the Human Motion Simulation (HUMOSIM) Ergonomics Framework (Reed et al., 2006). The combined model, referred to as the Virtual Driver, makes it possible to explore the interactions between cognitive and physical task demands. The new model could also be a useful tool in the future for the design of systems and workplaces, allowing users to perform proactive ergonomic assessments on virtual workspaces. The specific aims for this project were as follows.

Specific Aim 1: Conduct a driving simulator experiment and analyze the results to determine the behavioral strategies used to perform a secondary task while driving, given different task environments. Movement organization, glance duration, and resource sharing strategies all varied based on the physical task demands.

Specific Aim 2: Integrate the cognitive QN-MHP human model with the physical HUMOSIM Framework to produce a combined cognitive-physical human model. The QN-MHP and HUMOSIM Framework work together to direct the actions of a human model in performing a set task. The HUMOSIM Framework provides information about the physical state and capabilities of the human and environment; the QN-MHP uses this, along with information internal to the cognitive model, to make decisions about resource allocation and movement timing. This integration makes it possible for the combined model to accomplish multiple, goal-directed tasks.

Specific Aim 3: Add representations of more complex motor behavior to the combined cognitive-physical model. A review of the motor control literature was conducted to identify a suite of properties and theories that should be included in the combined model. Additions to the model included proprioceptive sensory input, feedforward control, and motor programs.

Specific Aim 4: Use the combined cognitive-physical model to simulate changes in dual task performance strategies during driving while performing a secondary in-vehicle task. Task performance varies based on the cognitive and physical difficulty of the task. Knowledge of the physical environment and awareness of personal cognitive and physical capabilities influence the strategies people use to perform a task. The goal was to model the task strategy using one set of rules; individual differences, such as stature and level of risk taking, were used as inputs to the combined model.

Dissertation Outline

Chapter 2 presents some relevant background on human performance and modeling that will be important to understanding the Virtual Driver. Chapter 3 describes the driving simulator experiment that was performed to obtain the data used to tune and evaluate the Virtual Driver. Chapter 4 presents the conceptual model of the Virtual Driver. It describes how the interaction between the cognitive and physical models was represented. Chapter 5 details the technical modeling work that was performed to integrate the QN-MHP and the HUMOSIM Framework. The work performed to model the driving simulator experiment is presented, along with the results that were obtained. Chapter 6 consists of a review of the significant findings, a discussion of the implications of the results, a summary of the limitations, and suggestions for future work.

Chapter 2

Background on Human Performance Modeling

Introduction

Human performance modeling integrates ideas and results from many fields. This chapter will outline the concepts that are most important to the development of the Virtual Driver. The first part of the chapter will present relevant theories of motor control, multitask performance, and resource allocation. Next, there will be a discussion of current cognitive and physical human models. Finally, existing models of driving and driver distraction will be discussed, including their capabilities and limitations.

Relevant Physiology

An understanding of certain concepts related to motor control is useful when considering human task performance. In order to accurately simulate human behavior, a model of human physical and cognitive performance should be able to represent a number of these concepts. The concepts that appear to be most relevant to the model integration are feedforward and feedback control, noise in motor commands, internal models, motor programs, and motor memory.

Proprioception is the sense of the relative location and orientation of body parts, providing information about one's own movement (Schmidt & Lee, 1999). Feedback loops frequently use proprioception. By comparing actual position with an internal mental model of the intended position, it is possible to adjust a movement to achieve the desired outcome. The use of feedback in motor control creates a closed-loop system, which frequently involves conscious decision making (Schmidt & Lee, 1999). In contrast, feedforward control is a characteristic of an open-loop system. Feedforward control is essential in movements that must be executed more quickly than would be possible using only feedback control, such as when playing a musical instrument or competing in sports. Many movements have both open-loop and closed-loop components.

Harris and Wolpert (1998) linked variability and movement planning by noting that larger motor commands require greater neural activity, which results in larger variability, because signal noise grows with the signal magnitude. Greater noise will decrease movement accuracy, so there is an accuracy cost with faster movements.

Humans appear to have an internal model that simulates the dynamic behavior of the body (Wolpert & Flanagan, 2001). The internal model is learned and updated through experience by comparing the predicted and actual outcomes of a motor command. Motor prediction is useful in sensorimotor control because it enables state estimation, which allows for faster movements than using sensory feedback alone.

There are two varieties of internal model: inverse and forward (Wolpert et al., 1995). Inverse models estimate the motor command that caused a particular state transition. Forward models mimic the causal flow of a process by predicting its next state and are essential to solving four fundamental problems in computational motor control. First, forward models estimate the outcome of an action during rapid movements when feedback control would be too slow. Second, forward models also anticipate and cancel reafference, the sensory effects of movement, using the efference copy of a motor command. Third, forward models permit motor learning by transforming errors between desired and actual sensory outcome into errors in motor command and by predicting action outcome without actually performing the action, which teaches selection between possible actions via mental practice. Finally, forward models can be used for state estimation, in which the model's prediction of the next state is combined with a reafferent sensory correction.

Motor programs are often thought of as a prestructured set of central commands that are capable of carrying out movement in an open-loop fashion (Schmidt & Lee, 1999). There are three main categories of evidence for the existence of motor programs. First, because feedback processing is relatively slow, rapid movements will be completed before a feedback correction could be applied. Second, reaction time increases with movement complexity, which suggests that movements are planned in advance. Finally, deafferation studies have shown that movement is possible even when there is no feedback from the moving limb, implying some central mechanism is involved in movement organization and control.

There are two main problems with the traditional view of motor programs (Schmidt & Lee, 1999). Because of context-conditioned variability, it would be necessary to have a very large number of motor programs in order for humans to perform all the activities they are capable of. Such a design for the motor control system is neither simple nor elegant, and it is unlikely the system evolved in this way. In addition, humans are capable of performing new actions accurately the first time. If people had to develop a motor program for each action, they would likely need to practice an action before it could be performed accurately. A proposal that addresses these arguments is that of generalized motor programs. According to this hypothesis, a motor program for a particular class of actions is stored in memory. Parameters in the motor program can be adjusted so that a unique pattern of movement will result when the program is executed.

Motor memory is the memory for movement or motor information (Schmidt & Lee, 1999). Skills involving motor memory are acquired via motor learning. Motor memory may include information about a tool's purpose in addition to information about how to use it (Shadmehr & Krakauer, 2008).

Relevant Psychology

Several concepts in psychology and human factors are important to human performance modeling, including theories of cognitive resources, multiple task performance, measurements of cognitive workload, and resource allocation while driving. Multiple task performance refers to when an individual performs two or more tasks in a short period of time, often concurrently. Two important theories related to multiple task performance are outlined below.

Resource theory (Kahneman, 1973) is based on the idea that humans have a limited number of the resources needed to carry out a task. When the difficulty of a single task increases, more resources will be used in order to complete that task. If a person is working on two tasks and the difficulty of one increases, there will be a decrement in the dual-task divided attention.

Multiple resource theory (Wickens, 1992a) adds another level of complexity to the treatment of multiple task performance. This principle states that there are three different dimensions of processing, each of which defines two specialized resources.

Specifically, processing code has separate types of resources for stimuli that are spatial or analog and stimuli that are verbal or linguistic; processing modality has one type of resource for visual inputs and manual responses and another type for auditory inputs and vocal responses; processing stage has a type of resource for perceptual and cognitive processing and another type for response or motor processing. The dimensions are illustrated below (Figure 2.1).

According to resource theory, two tasks will show greater interference effects if one or both tasks is difficult. However, multiple resource theory claims that the interference between two tasks will increase if the tasks compete for similar resources within a dimension. Therefore, it is necessary to consider both the resource demand of each task and the structural similarity between the tasks in order to predict the degree of dual-task interference.

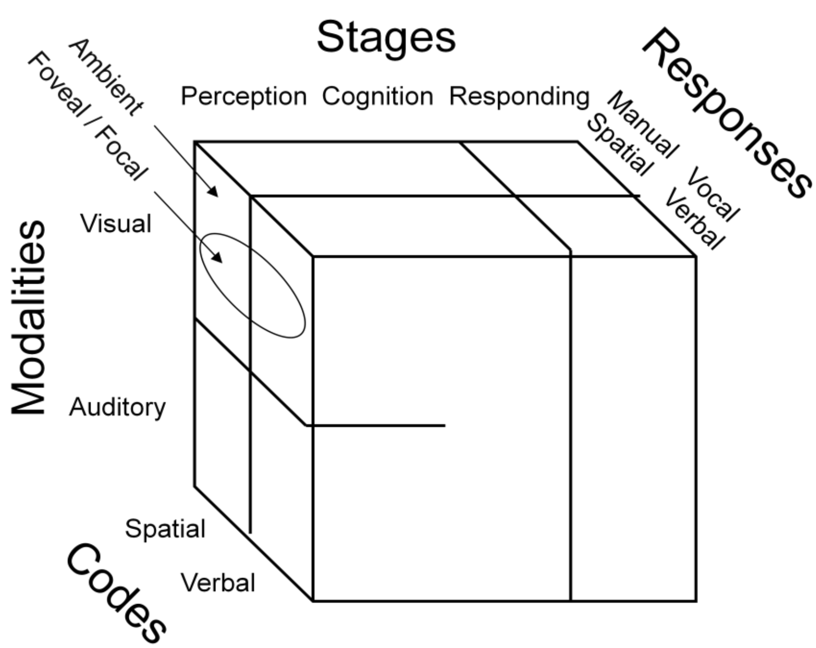


Figure 2.1: An illustration of the dimensions in multiple resource theory (Wickens, 2002; Wickens, 2008).

Researchers have investigated the use of several techniques for measuring operator cognitive workload (Wierwille & Williges, 1978; Lysaht, 1989) and driver workload (Hicks & Wierwille, 1979; Hulse et al., 1989; Green et al., 1993). Five categories of workload measurement have been proposed. 1) Primary task measurement includes factors such as measurement of steering performance as indicated by lane variation (Lansdown et al., 2002; Blanco et al., 2006). 2) For secondary task measurement, researchers introduce an additional task for the driver to work on and measure the performance on that task (Wierwille et al., 1977; Kantowitz, 1995; Stanton et al., 1997; Young & Stanton, 2007). 3) Physiological measures include heart rate variability (Jahn et al., 2003). 4) Subjective measures are obtained by querying the subject directly after the task to obtain a rating of difficulty and perceived workload (Hart & Staveland, 1988; Reid & Nygren, 1988). 5) Visual occlusion involves blocking the driver's view of the road for a certain amount of time or until the driver requests a view of the road, which can yield important information about relative workload in different driving and secondary task scenarios (Senders et al., 1967; Hicks & Wierwille, 1979; Mourant & Ge, 1997).

Tsimhoni (2003) identified four key constructs that affect time-sharing of visual resources while driving and performing an in-vehicle task. 1) Time pressure to look back to the road increases with more demanding roads. This may cause drivers to partition in-vehicle tasks into smaller chunks and to perform the tasks with greater efficiency. 2) Interference of concurrent driving can result in an increase in the time needed to complete the secondary task, compared to a stationary condition. 3) Postponed processing and planning ahead while looking away from the in-vehicle task could reduce the time needed to perform the task, but only if the glances away from the task are long enough. 4) The cost of partitioning the in-vehicle task into chunks could result in a degradation of performance on the in-vehicle task.

Other researchers have investigated the effects on driver workload of a variety of secondary tasks. The in-vehicle tasks studied include digit repetition (Wierwille et al., 1977), reading (Kantowitz, 1995; Ranney et al., 2001), and performing navigation tasks (Burns et al., 2005).

Some of the most interesting studies recently on driving and multitasking have examined the use of cellular telephones while driving. Strayer and Johnston (2001) observed significant interference with simulated driving performance from a word-generation task using a cell phone, even though they found no disruption from listening to a radio broadcast or a book on tape or from performing a continuous shadowing task using a handheld phone, indicating that the decreased performance was not due to holding the phone, listening, or speaking. They also noted that drivers were significantly less likely to detect traffic signals during unconstrained conversation using either a handheld or a hands-free phone.

Cooper and Strayer (2008) found that those who reported greater familiarity with cell phones performed no better when driving and conversing on a hands-free phone than those who were less experienced with cell phones. In addition, practice sessions had no effect on performance deficits due to cell phone use while driving.

Perhaps most disturbing of all, Strayer and colleagues (2003; 2006) observed that impairments associated with using a cell phone can be as profound as those caused by driving while drunk. Use of handheld phones and hands-free phones caused delays in braking responses and increased rates of traffic accidents while driving in a simulator.

Physical Modeling of Human Performance

Physical models of human performance attempt to represent the way in which a human interacts with his or her physical environment. Physical models can be very useful in understanding and demonstrating the importance of appropriately configured workspaces in a cost-efficient manner. It is possible to model a proposed workstation digitally, then insert a digital human into the workspace. By manipulating the human within the space, one can identify possible problems with the workspace design that would prohibit a person from performing a job safely or effectively.

The HUMOSIM Framework

The HUMOSIM Ergonomics Framework (Figure 2.2) is an approach to organizing digital human simulation for ergonomics analysis that is independent of any particular human modeling system (Reed et al., 2006). The HUMOSIM Framework was developed to address the inaccuracies of posture and motion and the inefficient use of time when performing manual manipulation of figures for simulations.

An interconnected, hierarchical set of posture and motion modules that control certain aspects of human motor behavior make up the Framework. The modules, which use basic forward-kinematics control and public-domain numerical algorithms, are responsible for simulating activities such as gaze, upper-extremity motion, and transition stepping. Most human movements can be performed in many ways, using different combinations of motion at various joints. Empirical models based on laboratory data are used to resolve this redundancy in the human kinematic linkage. The modules that are most important to the research proposed here are those for gaze, upper-extremity, hand, and torso motion prediction.

Limitations to the HUMOSIM Framework

The HUMOSIM Framework lacks a model of human information acquisition and processing. It makes no attempt to simulate the decision making that occurs as a human interacts with the information environment. Due to these limitations, it can be time consuming to simulate complicated activities. In addition, inaccuracies may arise when users attempt to simulate human behavior, and it is not possible to predict how a human would interact with an environment that is novel to the user commanding the software.

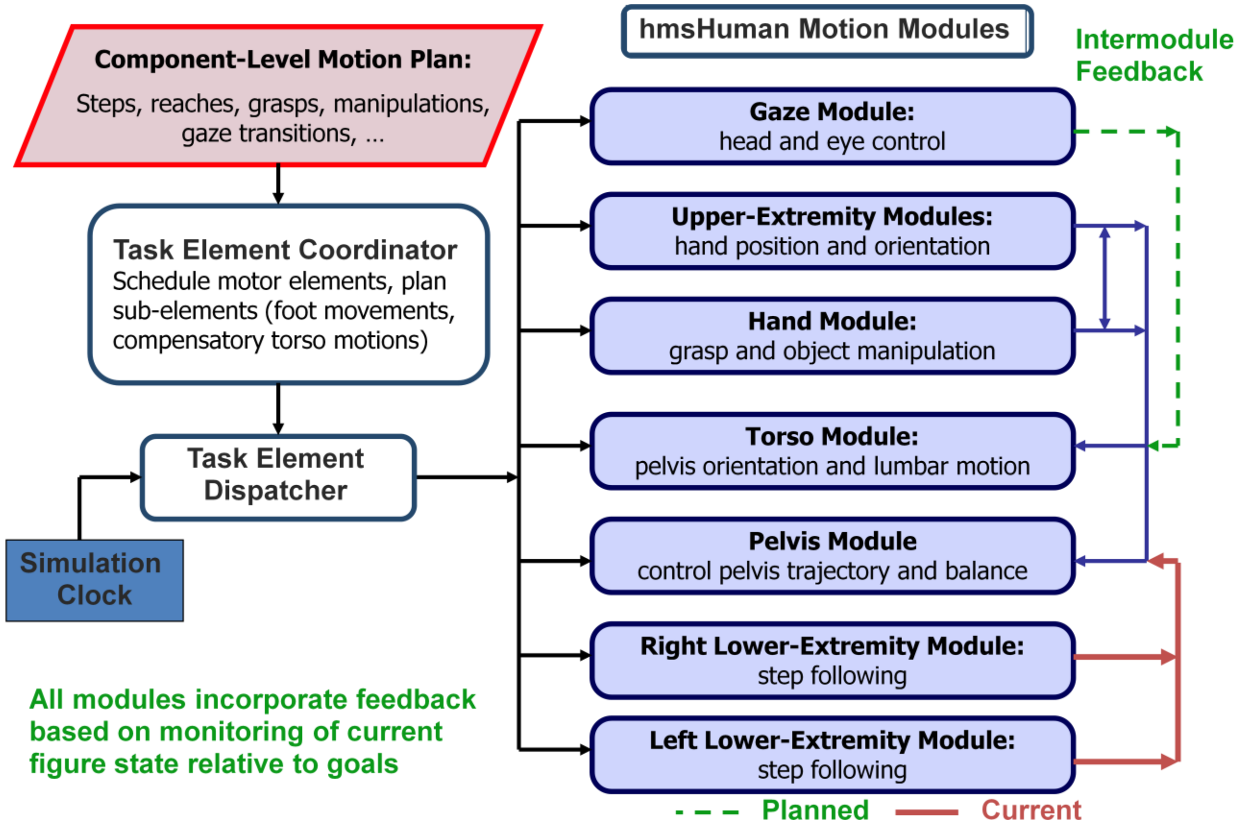


Figure 2.2. HUMOSIM Ergonomics Framework (Center for Ergonomics, University of Michigan, 2008).

Cognitive Modeling of Human Performance

Cognitive models of the human mind attempt to predict the decisions people will make in particular situations and the timing within which they will act. To truly count as cognitive modeling, the model should explain the mechanisms behind actions and decisions, and it should model the mechanisms in a task-independent way.

In modeling, it is always necessary to make some assumptions. To have a psychologically-relevant cognitive model, these assumptions must be psychologically-grounded. For such a model, there must be explicit statements about which part of the mind is responsible for various tasks and there must be support from the existing psychological research. These requirements constrain a model to be human. Similarly, a biologically-relevant model would have biologically-grounded assumptions. At this point in time, the most biologically-accurate models have biological inspiration only. Fully functional models with biological foundation do not yet exist.

Most early engineering models of human cognition were very limited in scope. Pew and Baron (1983) noted the importance of including human performance elements in the representation of complex human-machine systems. Other early cognitive models were limited by their assumptions about human information processing. The human operator simulator (Lane et al., 1980) was developed in an attempt to predict the behavior of an individual operator in a system context. However, it used the common assumption that an operator can only do one thing at a time, the single-channel processing assumption. Models that use this assumption are relatively simple to implement, and there is still some psychological support for these models, though they cannot explain all aspects of human cognitive performance. Liu and Wickens (1992) provide a discussion of single-channel models.

An alternative to the single-channel assumption is the limited capacity assumption. Models using this assumption can process information for concurrent tasks in parallel as long as the total processing load does not exceed the limited capacity. One example is the multiple-resource limited capacity theory proposed by Wickens (1980; 2002) and discussed in greater detail above. According to this model, two tasks can coexist without interference if they rely on separate resources.

Based on the psychological support for both single-channel models and limited capacity models, Liu (1996; 1997) developed an integrated computational framework. The resulting model combines the single-channel and the multiple-resource models.

In 1973, Allen Newell famously commented on the current state of psychology research and called for the development of unified theories of cognition (UTC), arguing that decomposing the cognitive system into many elements may cause one to miss important links and interactions among elements (Newell, 1973). Since then, several important models and cognitive architectures that fit with Newell's goal of UTC have been developed. These include the Model Human Processor (MHP) and the GOMS family of models (Card et al., 1983; Card et al., 1986; John & Kieras, 1996), ACT-R (Anderson & Libiere, 1998), SOAR (Newell, 1990; Laird et al., 1987), and EPIC (Meyer & Kieras, 1997a; Meyer & Kieras, 1997b).

Model Human Processor (MHP)

The Model Human Processor (MHP) is a psychologically-relevant cognitive human model, specifying where in the mind something occurs and providing explicit support from the psychological literature (Card et al., 1983; Card et al., 1986). The MHP divides the human mind into three components, perceptual, cognitive, and motor, each with a processor and memory.

GOMS and CPM-GOMS

Where MHP is a cognitive model, GOMS, which stands for Goals, Operators, Methods, and Selection rules, is a methodology to apply that model (John & Kieras, 1996). GOMS was proposed at the same time as MHP and is important for representing complex information processing.

CPM-GOMS is part of the MHP/GOMS family of models. and uses the symbolic approach to cognitive modeling. CPM-GOMS is an engineering tool, rather than a new way of understanding psychology or engineering. Unlike the production system models, CPM-GOMS is in sequence form, not program-form.

Though it has no concurrent processing, CPM-GOMS is capable of modeling overlapping activities. In CPM-GOMS, operations can be performed in parallel, unlike in ACT-R. Multiple active goals can be represented in CPM-GOMS. The operators that accomplish two goals are interleaved. Depending on the goals, this may represent a very high level of skill in the simulated person.

Adaptive Control of Thought – Rational (ACT-R)

The predecessor of ACT-R, ACT, was the first unified theory of cognition (Newell, 1990). ACT-R, which uses a serial cognitive processor, makes a distinction between declarative knowledge (chunks) and procedural knowledge (production rules). The architecture consists of three modules: declarative memory, procedural memory, and a goal stack.

In terms of representing multitask performance, ACT-R is a fixed-attention architecture, which means that at any given point, it is focused on a single goal and a single production fires. It can be used to predict behavior and test new hypotheses. ACT-

R has perceptual-motor modules, which are responsible for representing the interface between the modeled human and the simulation of the real world. The most well-developed perceptual-motor modules in ACT-R are the visual and the manual modules.

ACT-R has two main downsides. In order to model multiple tasks, the modeler must write code to interleave production rules into a serial program. In addition, it borrows models from other programs rather than having its own, incorporating an EPIC-like perceptual-motor system and impasse resolution from Soar. The greatest strength of the ACT-R model is the way it implements long term declarative memory storage and retrieval, which is unique.

Computational modeling of driving has been performed using ACT-R (Salvucci, 2006). An integrated driver model that focuses on the components processes of control, monitoring, and decision-making is capable of accounting for steering profiles, lateral position profiles, and gaze distributions of drivers. Though useful for predicting driver behavior and distraction in a cognitive environment, the driver model in ACT-R has no good representation of the physical environment.

Soar

As a production system based model, Soar lacks a mathematical framework for representing its overall architecture, but it is well-suited to generating a person's actions during a specific task scenario (Newell, 1990; Laird et al., 1987). In general, Soar follows the philosophy that the number of distinct architectural mechanisms should be limited. One of the great strengths of Soar is its ability to perform impasse resolution, referred to as "chunking", and to learn from novel situations.

Soar has several limitations. Many of its assumptions are not consistent with the human mind, so the model is not psychologically relevant. This makes it less useful for describing and learning about the behavior of people in given situations. Soar uses serial, rather than parallel operators. It also has minimal declarative memory and assumes that working memory cannot be understood independently of learning and long-term memory. Though it is capable of simulating multitasking, Soar has no sophisticated theories of human multitask performance. When driving, people frequently engage in a variety of tasks, such as steering, maintaining a safe headway, and operating in-vehicle controls.

Because of its limited theories of multitask performance, Soar is not useful for driver interface design.

EPIC

EPIC is a psychology and engineering model that is similar in spirit to the MHP (Meyer & Kieras, 1997a; Meyer & Kieras, 1997b). It is based on production rules and incorporates recent theoretical and empirical results of human performance. EPIC has interconnected software modules for perceptual and motor processors, along with a cognitive processor with a production rule interpreter, working memory, long term memory, and production memory.

EPIC is a generative model and can produce actions in simulated real time. Unlike Soar, EPIC allows concurrent, parallel processing at the cognitive stage. A drawback to EPIC is that is requires executive processes to interactively control task processes. This is not a realistic representation of the human mind, in which there is no executive process overseeing behavior.

The Queuing Network – Model Human Processor (QN-MHP)

Mathematical models based on queuing networks integrate models of response time (Liu, 1996) and multitask performance (Liu, 1997). The Queuing Network – Model Human Processor (QN-MHP) is a computational model that bridges mathematical models of queuing networks and symbolic models of cognition. It is a task-independent cognitive architecture that represents information processing as a queuing network, based on research findings in neuroscience and psychology (Bear et al., 2001; Faw, 2003; Roland, 1993; Smith & Jonides, 1998).

Research has shown that neural pathways connect major brain areas with certain information processing functions (Smith & Jonides, 1998; Faw, 2003). In the QN-MHP, these brain areas are represented as servers in a queuing network, and neural pathways are treated as routes. Information processed in the brain is coded in spike trains (Rieke, 1997), which are processed by brain regions. These spike trains are represented as entities in the QN-MHP.

Entities in the QN-MHP travel along routes between servers. They may move through the network and undergo processing serially or in parallel. The entities may be processed immediately upon arriving at a server or may wait in a queue until the server finishes processing a previous entity.

The QN-MHP may be divided into three subnetworks: perceptual, cognitive, and motor (Figure 2.3). Entities representing information enter the QN-MHP via the perceptual subnetwork, where they undergo initial processing. The entities then move to the cognitive subnetwork for additional processing. If a motor response is required, the entities progress to the motor subnetwork.

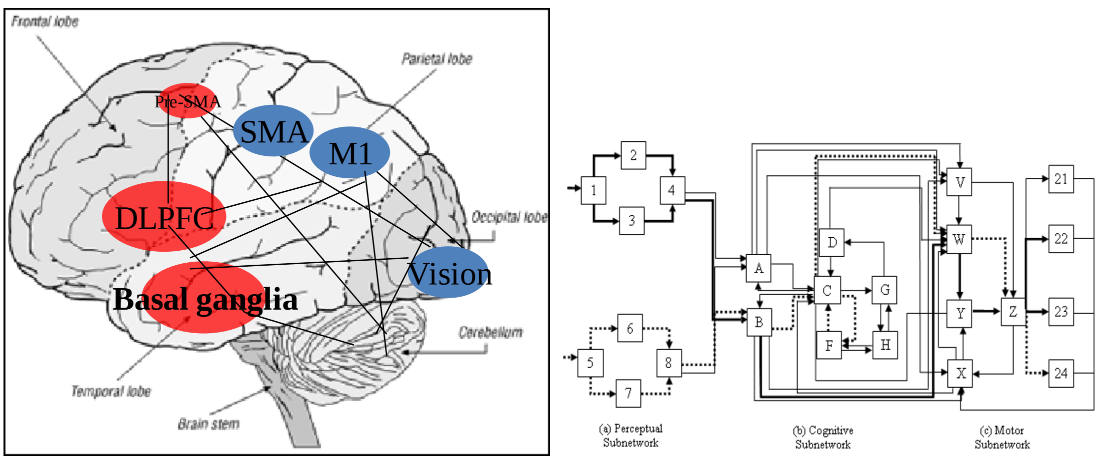


Figure 2.3: The brain, with regions that are represented in the QN-MHP highlighted, and the QN-MHP (adapted from Liu, 1996).

Task Strategy in the QN-MHP

An important use for the QN-MHP is in studying how humans plan and perform tasks. Humans may perform actions in ways that differ in both physical movement and timing. Some of these differences may be due to people optimizing for time, effort, or posture, including biomechanical stresses on the body. Other differences are likely random.

The QN-MHP can provide accurate predictions of human behavior when performing certain tasks. The predictions include total task time, glance behavior, and perceived cognitive load while performing the task (Feyen, 2002; Tsimhoni, 2004; Lim, 2007; Wu, 2007).

The division of attention when humans perform two or more tasks simultaneously may affect the strategy used for each task. The concept of multiple resources (Wickens, 1992a), discussed previously, is important for understanding multiple task performance. In the QN-MHP, different types of entities represent information acquired via different modalities. For example, one type of entity represent visual information, while another represents auditory information. The decrease in interference between tasks due to training can also be modeled using the QN-MHP (Wu, 2007).

Limitations to the QN-MHP

The QN-MHP has no explicit representation of the geometry of the human or the environment. Therefore, it cannot simulate the physical interaction between a person and the task environment directly. The model, which is implemented in ProModel (ProModel Solutions, Version 2001), obtains information about the physical environment from a Microsoft Excel (2007) spreadsheet. Because of the limitations of ProModel, it is difficult to change the environment once the task begins, which is necessary to simulate changes the human makes in the task space.

The limited physical representation of the human makes it difficult to simulate complicated motions. For example, the current version of the model contains no representation of the torso, so it is assumed that all reaches are performed with the hand and arm alone. In addition, the model currently cannot simulate small differences in how people perform motions, such as pressing a button with the wrist in an awkward posture, which could lead to injury, as opposed to pressing the button with the wrist in a neutral posture. These functions are important for realistic simulation of a task and evaluation of the impact of performing the task on the human.

Previous Studies Using the QN-MHP

The QN-MHP has been used to generate human behavior in real time in a variety of situations. These include simple and choice reaction time (Feyen, 2002), transcription typing (Wu & Liu, 2004a), psychological refractory periods (Wu & Liu, 2004b), visual search (Lim & Liu, 2004), driver workload (Wu & Liu, 2007), and driver performance (Liu et al., 2006). In addition, the QN-MHP can account for brain imaging data in a transcription typing task (Wu & Liu, 2008).

The most relevant experiment to the current research is a study of driving while performing a secondary task (Liu et al., 2006). The authors used the QN-MHP to model an experiment in which subjects drove in a driving simulator while performing a secondary task involving map reading. The model was able to accurately predict metrics of driving and task performance, performed both individually and simultaneously. One limitation was that the experiment and driving model both used cruise-controlled speed, which is not as realistic as requiring the driver to perform longitudinal control of the vehicle.

Models of Driving and Driver Distraction

Many studies on driving behavior have been performed in an attempt to predict and model how human drivers respond to the surrounding traffic. The results have influenced roadway designs, traffic rules, and vehicle interfaces. Computational cognitive driving models can make quantitative predictions about scenarios that have never occurred. They can simulate real time driver performance and predict possible interferences with in-vehicle tasks.

In a comprehensive review of modeling the human driver, Macadam (2003) discussed the characteristics of the human driver, including physical limitations and attributes. In terms of physical limitations, humans exhibit time delays in reacting to stimuli, these stimuli must exceed certain thresholds in order to be detected, and humans have more difficulty controlling higher-order systems. Some attributes that help to balance these limitations are the abilities of humans to look ahead and preview information, adapt to altered operating conditions, and develop an input-output understanding ("internal model") of the vehicle being controlled.

This section will present an overview of various driving models, including models for lateral control and longitudinal control. It will also give a brief discussion of models of driving while multitasking.

Lateral Control

Steering a vehicle is referred to as lateral control. This driving behavior is important for lane keeping, to maintain control of a vehicle while going around curves, and to avoid hazards in the road.

There are several recent examples of lateral control models of driving (Levison, 1998; Prokop, 2001; Savkoor & Ausejo, 2000). These models incorporate many of the elements Macadam identified as essential to modeling a human driver, including a provision for a transport time delay, the use of preview to sense upcoming lateral control requirements, and the presence of an internal vehicle model (Macadam, 2003).

An earlier lateral control model for linear or quasi-linear closed-loop steering applications was the UMTRI driver model (Macadam, 1981; Macadam, 1988). This was later expanded into a model capable of handling nonlinear, near-limit operating conditions, the GM/UMTRI driver model (Macadam, 2001). The model contains a simplified nonlinear approximation of the external controlled vehicle and can project an estimated vehicle response into the future. It accounts for the driver's perception of the desired path input and has an adjustable driver preview feature to enhance maneuverability and stability. The GM/UMTRI model uses the inputs and knowledge of the vehicle dynamics to calculate a steering control response that minimizes an integral of path errors over the preview time interval. A transport delay, accompanied by optional neuromuscular filtering treatments and noise, is applied to this response, and the resulting output is the driver steering control response that controls the external vehicle.

The steering model used in the QN-MHP combines several concepts, including a hierarchical task structure, the presence of focal and ambient visual systems, and the ability to perform concurrent cognitive processing. The steering model is discussed in greater detail in the fourth chapter.

Longitudinal Control

Longitudinal control refers to when the driver adjusts the speed of the vehicle to meet certain criteria. This may be done to maintain a goal speed or to achieve a desired following distance behind a lead vehicle.

Models of car-following were developed as far back as the 1950s to evaluate traffic capacity and congestion (Pipes, 1953). Early models regulated either zero range error or zero range-rate (Pipes, 1953; Chandler et al., 1958; Gazis et al., 1961; Newell, 1961), though real drivers likely do both. This hypothesis was first discussed by Helly (1959).

Gipps (1981) proposed using a safe distance strategy rather than precisely following the speed changes of a lead vehicle. The model calculated a safe following distance based on the kinematic relationship between the lead vehicle and the following vehicle and on the braking conditions. The model used this as the desired distance in congested traffic, then switched to a second mode for free flow traffic conditions.

Many models measure dynamic variables and model driver decision as a continuous process, but psychophysical studies have provided some alternatives for modeling longitudinal control. Michael (1963) modeled driver behavior as a sequential control in which the driver responds to the lead vehicle's size change when it exceeds some threshold. Lee's model (1976) used time-to-collision, estimated using τ (angular separation over separation rate), as the perceptual threshold that triggered brake action, with the brake force based on the time rate of change of τ. Yilmaz and Warren (1995) verified this hypothesis. Reiter (1993) used a similar approach with range as the perceptual threshold.

To date, most models have attempted to simulate longitudinal control under ideal circumstances. Recently, Yang and colleagues (2008) developed an errorable car-following driver model. This model is based on a model for longitudinal control that normally achieves car-following tasks. In the model, driver errors are viewed as recurring events that could result in an accident when combined with events from surrounding vehicles. The human behavior and the surrounding events are both described by stochastic processes. With the proper probability functions, the model is capable of producing accident and incident behavior that is statistically similar to field testing results.

Multitasking and Driver Distraction

Most of the driving models discussed above simulate driving under ideal conditions. In actuality, drivers frequently divert attention from the road to perform other tasks. These situations, in which drivers are operating a motor vehicle while distracted, place the drivers and surrounding vehicles at an increased risk of being involved in an accident. Several models of driver distraction have been proposed.

Some models of driver distraction focus more on simulating aggregate or average outcomes, rather than the results of driving with a specific distraction. One example of this type of model is the model by Yang and colleagues (2008), described above. This type of model is useful for activities such as evaluating and designing active safety technology, but it is not helpful in predicting the effects of drivers' interactions with interfaces for in-vehicle tasks.

Other models focus on identifying driver distraction, but not predicting it. For example, a recent model by Ersal and colleagues (submitted) provides new insight into the effects of secondary tasks on driving performance. The model characterizes normal driving behavior for a particular driver and uses this to predict the driving performance in a given situation had there been no secondary task. The difference between the actual driving performance, with a secondary task, and the predicted performance allows one to quantify the impact of performing the secondary task. The model cannot, however, predict driver performance given a novel in-vehicle environment.

Other driving models do simulate a driver's interaction with a particular in-vehicle system and attempt to predict the resulting effects on driving performance and the in-vehicle task. Levison (1993) developed the integrated driver model to simulate driving performance while dialing and talking on a cell phone. The model was composed of two separate software modeling modules: a control theory based driver and vehicle module (Levison, 1989; Levison et al., 2001) and a procedural model of in-vehicle tasks. The model simulated continuous steering performance at a fixed speed, and visual attention was diverted from the road to one or more monitoring locations as the in-vehicle task was performed.

Salvucci and colleagues (2001) presented a driver performance model that integrates a cognitive modeling tool, ACT-R (Anderson & Libiere, 1998), with a task analysis of vehicle control. The model was further discussed in a later paper (Salvucci, 2006). The model primarily performed driving as a single task, but it did make decisions about where to direct the gaze to accomplish monitoring of the surroundings and when to attempt lane changes.

Salvucci and Macuga (2002) followed this with a model of cell phone dialing while driving. The model was able to predict a degradation in steering performance when the driver looked away from the road. The main drawback to this approach was a dependence on a serial line of cognitive processing. In the model, parallel processes are interleaved to one serial process, with a reliance on an explicit and often task-specific transfer of control between the concurrent tasks.

The QN-MHP has also been used to model driving while performing secondary in-vehicle tasks. Liu and colleagues (2006) simulated driving while completing an in-vehicle map reading task. Steering performance, glance behavior, and task time were found to be similar to empirical findings. Wu and Liu (2007) found that the QN-MHP could be used to successfully simulate changes in driver performance and mental workload when steering a driving simulator and performing a button-pressing task with varying difficulty level.

Though these previous studies have confirmed the validity and usefulness of the QN-MHP in simulating driving while performing secondary tasks, there have been some limitations. The driving task, as performed by the subjects and the model, was primarily a steering task, with longitudinal control limited to driving at approximately a fixed speed. This is consistent with driving scenarios people might encounter in lightly trafficked areas, but does not represent the frequent reality of congested roadways. In addition, the secondary tasks simulated had limited physical components. There was no physical interaction with the in-vehicle display for the map-reading task, and the button-pressing task required only an easy reach to a console directly adjacent to the steering wheel. An expansion of the QN-MHP driving model would allow for modeling of a greater variety of driving conditions and in-vehicle tasks.

Chapter 3

Driving Simulator Experiment: Driving with an In-Vehicle Task

Introduction

Increasing numbers of in-vehicle systems for tasks secondary to driving are used in motor vehicles. Examples include music players, GPS systems, communication systems, and email readers. The visual, cognitive, and physical requirements of using these systems can result in driver distraction. Driver attention problems are causal factors in many traffic accidents (Shinar, 1978). Many of these in-vehicle systems include substantial visual components, and allocation of the driver's visual resources to in-vehicle tasks and displays was found to be a factor in many crashes (Wierwille & Tijerina, 1996).

Previous studies have examined the effects of display and button position on driving performance. However, most have not combined visual, cognitive, and physical aspects of operating in-vehicle equipment and driving. In particular, no study has adequately addressed the difference between visual difficulty, represented by visual distance from the road scene ahead to the display, and physical difficulty, represented by reach distance from the driver's resting position to the task interface, in terms of the interference between driving and a secondary task.

Lamble et al. (1999) displayed a task using ten different monitor positions and found that time to collision decreased significantly with increasing eccentricity of monitor position. The task had no physical reach component, however. In addition, subjects were required to continuously look at the LED monitor while driving. This differs from natural driving conditions, in which the driver is generally watching the road and makes short glances at the monitor.

Wittmann et al. (2006) considered seven different monitor positions. The monitor positions were all conventional, with eccentricity between line of sight to the outside road and line of sight to the monitor between 4.4° and 50.6°. The physical control used in the task was located in a constant position, so variation in physical reach component was not considered.

A study conducted by Dukic et al. (2005) included a variable physical reach component. The subject was prompted to reach to and push one of five buttons located at different horizontal and vertical distances from the road ahead. This experiment included a minimal visual component, however, because the button to be pressed was identified with an auditory command.

Objective

In the current experiment, a driving simulator study designed to investigate performance on a secondary in-vehicle task while driving was completed. Based on previous studies, it was expected that performing the in-vehicle task would cause driver distraction, with resulting decreased driving performance.

The in-vehicle task was performed using a touch screen monitor that was placed in four locations with varying physical reach difficulty and visual difficulty, changing the visual and physical resources required for the in-vehicle task. It was hypothesized that performing the task with the monitor at a greater reach distance from the resting position of the hand on the steering wheel or at a greater visual angle from the road ahead would result in a decline in both task performance and driving performance.

In addition, it was hypothesized that shorter subjects would be more affected by the reach complexity. Therefore, subjects were selected to obtain a range of subject heights.

In the experiment, the vehicle dynamics of the simulator were varied to simulate two vehicle weights: a normal-weight vehicle and a heavy vehicle. The heavy vehicle had greater inertia, so it responded more slowly to changes in the accelerator and brake pedal positions, which resulted in a more difficult driving task. Driving performance and in-vehicle task performance were hypothesized to decrease with the more difficult driving condition.

This experiment examined how subjects chose to assign visual, cognitive, and physical resources to complete the in-vehicle task while maintaining performance on the primary driving task. Variations in strategy and performance were considered for different monitor positions. The goal was to understand driving behavior and resource-sharing while driving and performing a secondary in-vehicle task.

Methods

Subjects

Sixteen licensed drivers (eight male, eight female) between the ages of 19 and 30 (mean=24.1, SD=4) were recruited. The age range was chosen to be similar to that of military drivers exposed to convoy driving situations. Five of the male subjects were members of the Reserve Officers' Training Corps (ROTC), and one female subject had been discharged from the Army recently. Written informed consent was obtained, and the study was approved by the University of Michigan IRB (HUM00012234). Subjects received financial compensation for their time.

Subjects were recruited from the University of Michigan and Ann Arbor communities via newspaper advertisements and flyers. Subjects were required to have a far visual acuity of 20/40 or better and no history of motion sickness. Subjects were selected so that four subjects were included in each of the following height-gender groups: short female, 59-61 inches (150-155 cm); midsize female, 63-64 inches (160-162.5 cm); midsize male, 68-70 inches (172.7-177.8 cm); and tall male, 72-74 inches (182.9-188 cm). These heights were chosen to give a range of heights representative of approximately 5% female, 50% female, 50% male, and 95% male.

All subjects appeared healthy and displayed no symptoms of musculoskeletal or cognitive disorders. A summary of anthropometric and other data for the subjects is given below (Table 3.1). Subjects 1-4 were in the short female group, subjects 5-8 were in the midsize female group, subjects 9-12 were in the midsize male group, and subjects 13-16 were in the tall male group.

Table 3.1. Subject data for driving simulator study

Subject	*Age*	*Gender*	*Height (cm)*	*Seated Height (cm)*	*Arm Span (cm)*	*Weight (kg)*
1	30	Female	156.2	87.6	149.9	43.1
2	28	Female	153.0	83.2	158.8	77.1
3	20	Female	156.2	83.8	153.7	54.4
4	30	Female	152.4	83.8	149.9	47.6
5	21	Female	162.6	86.4	166.4	63.5
6	30	Female	162.6	83.8	170.2	62.6
7	24	Female	160.7	84.5	161.3	45.4
8	23	Female	164.5	86.4	167.6	68.0
9	24	Male	174.6	93.3	170.2	77.8
10	19	Male	175.6	90.2	175.3	80.6
11	21	Male	177.8	94.0	176.5	77.1
12	21	Male	177.8	94.0	176.5	93.0
13	21	Male	182.9	91.4	174.0	79.4
14	27	Male	187.3	91.8	177.8	108.9
15	20	Male	185.4	91.4	191.8	75.7
16	27	Male	189.9	99.1	198.1	68.0

Apparatus

Driving Simulator

The study was conducted in the University of Michigan Transportation Research Institute (UMTRI) driver interface research simulator. This fixed-based driving simulator consisted of a full-size vehicle cab with a projected instrument panel, a torque motor connected to the steering wheel, six video projectors and projection screens (200° forward field of view, 40° rear field of view), and a sound system, including a sub-bass sound system for vertical vibration. The forward screen was 16 to 17 feet (4.9-5.2 meters) from the driver’s eyes, depending on seat adjustment, requiring drivers to accommodate from the in-vehicle display (at 1-2 diopters) to approximately infinity (<0.25 diopters) whenever they looked at the screen straight ahead. The main simulation functions were controlled by hardware and software provided by DriveSafety (Vection and HyperDrive Authoring Suite, version 1.6.2).

Two vehicle dynamics settings were used. The first setting (normal-weight condition) simulated a standard-weight car. The second setting (heavy-weight condition) simulated a vehicle that was 35% heavier and consequently accelerated more slowly, increasing the difficulty of the primary driving task.

The driving simulator recorded information about the behavior of the vehicle and other simulated vehicles on the road, including velocity, distance travelled, and lateral lane position. This information was later used to quantify driving performance.

Video Collection

Video of the subjects was recorded in the frontal (forward and rear views) and sagittal planes using low-light cameras. A quad splitter was used to combine the three camera views with the video from the front screen into a single video file. This combined video was used to perform an analysis of the subjects' glance behavior, described in a later section.

In-Vehicle Task Equipment

The experiment used a tablet personal computer with a touch screen monitor (Lenovo, ThinkPad X60). The monitor was mounted in four different positions within the vehicle (Figure 3.1). The four display positions were chosen so that they differed in difficulty of physical reach and visual angle (Figure 3.2). The near high position was in the center console and had a short reach distance and a small visual angle from the road ahead. The near low position also had a short reach distance, but the visual angle was greater. The far high position had a large reach distance and a moderate visual angle. The far low position had a large reach distance and a large visual angle.

Figure 3.1. A subject is shown performing the in-vehicle task with the touch screen monitor in each of the four locations. Counterclockwise from top-left, the positions are near high, near low, far low, and far high.

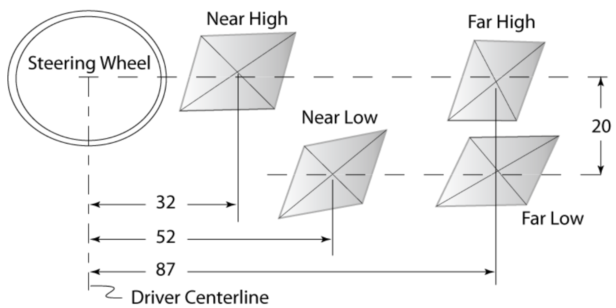


Figure 3.2. Measurements to define the locations in relation to the steering wheel are given (cm). All positions placed the center of the monitor approximately in the fore-aft plane of the steering wheel.

The program for the in-vehicle task was written using Visual Basic for Applications (Microsoft, 2007). For the in-vehicle task, the user interacted with a menu-based interface with fixed-location buttons on the touch screen monitor (Figure 3.3). The task required the subject to conduct a visual search to locate and match three pairs of “scouts” and “targets”. At the beginning of each trial, the user interface appeared on the touch screen monitor, with the six icons (three pairs) in random locations on the screen. The subject then pressed the “New Assignments” button to proceed to the second screen, in which the subject could select and match the icons. After the subject selected the two icons in the first pair and pressed the “Assign” button on the left side of the screen to complete the match, those icons disappeared from the screen. The subject repeated this procedure for the remaining two pairs of icons. To complete the task, the subject pressed the "Submit Assignments" button to return to the first screen, then pressed the "Execute Plan" button, which caused the interface to disappear from the screen and signaled the end of the trial. After 15 seconds, the interface reappeared with the icons in new positions, and the subject repeated the task. This continued throughout the drive.

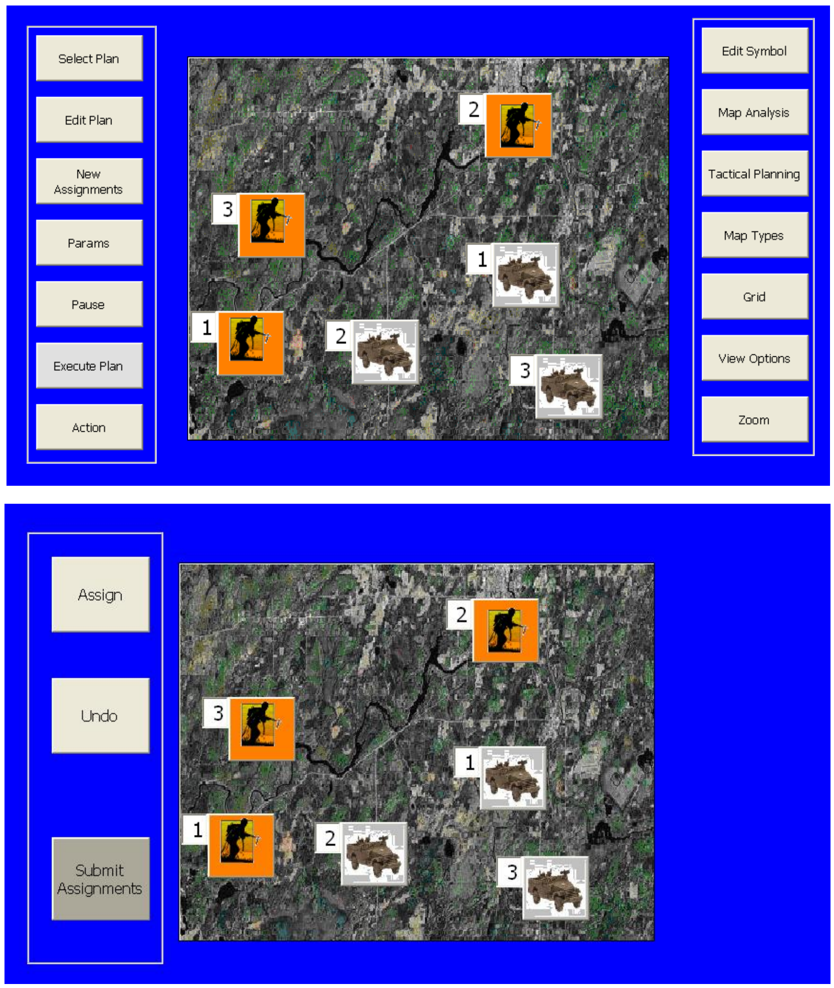


Figure 3.3. The front screen (top) and the second screen (bottom) of the in-vehicle task are shown. The subjects were required to match the correctly numbered "scout" (gray vehicle) and "target" (orange person) icons. For example, the subject first selected Scout 1 and Target 1, then pressed a button to complete the assignment. This sequence was repeated for the remaining icon pairs.

Procedure

The subject drove as the fourth vehicle in a simulated convoy and was instructed to remain in the lane and maintain a constant headway to the vehicle directly in front of him or her, hereafter referred to as the lead vehicle. The lead vehicle changed speed following a sinusoidal pattern with random frequency and amplitude. The subject drove on a four-lane divided highway with no other traffic.

At the beginning of each experimental session, the subject was informed that driving was the primary task. The subject was told to focus on following the lead vehicle's speed changes and remaining in the lane, and to perform the secondary task when he or she felt comfortable doing so.

The subject was taught to perform the in-vehicle task and then practiced the task with the monitor in the near high position and then with the monitor in the near low position. Next, the subject practiced driving in the simulator without performing the in-vehicle task. When the subject was comfortable with the driving task, the subject was instructed to add the concurrent in-vehicle task while continuing to maintain a constant distance to the lead vehicle. When the subject felt comfortable with the dual task, the regular trials began. After the first block of trials, when the vehicle weight was changed, the subject again practiced the driving task alone and then with the in-vehicle task for the new vehicle weight.

This study used a modified version of the coherence technique (Brookhuis et al., 1994; Ward et al., 2003). The lead vehicle changed between a low speed and a high speed at a frequency that ranged between 0.02 and 0.04 Hz. The minimum speed of the lead vehicle ranged between 55 and 60 mph (24.6 and 26.8 m/s), while the maximum speed ranged between 70 and 75 mph (31.3 and 33.5 m/s). This variation in frequency and amplitude was introduced to make it difficult for the subjects to predict the lead vehicle speed. The speed change trajectory was smoothed by basing the signal profile on a sinusoidal function.

Subjects were instructed to maintain a constant distance to the lead vehicle during each drive. They were told that distance-keeping was their primary task and that they should complete the in-vehicle task at a comfortable rate. To encourage subjects to maintain a reasonable distance from the lead vehicle, if the subject was more than 200 meters behind the lead vehicle, the experimental task was paused until the driver caught up and the headway distance fell below that threshold.

Experimental Design

After the practice drives, each subject completed ten drives for the experiment. The two within-subject factors that were varied were monitor position for in-vehicle task (four levels: near-high, near-low, far-high, and far-low) and vehicle weight (two levels: normal and heavy) (Table 3.2). Each subject also completed two drives with no in-vehicle task (the baseline condition). Stature was a between-subjects variable.

Monitor position order was blocked by vehicle weight so that subjects would have fewer adjustments to make to vehicle performance, but was counterbalanced across subjects. Half of the subjects (two from each stature group) were assigned to perform all the light vehicle trials first, and the other half were assigned to perform all the heavy vehicle trials first. The monitor position order was determined using a Latin square design. For each subject, the same order was used for both vehicle weights. The baseline condition was the third trial for each weight block. This was done to ensure that all subjects had equal amounts of experience with driving and the in-vehicle task when the baseline data were collected.

Table 3.2. Independent measures that were varied during the driving simulator experiment

Metric Collected	*Related to*	*Type*
Vehicle weight	Driving	Within-subjects
Monitor position	In-vehicle task	Within-subjects
Stature	Both	Between-subjects

Data Analyses

The dependent measures collected included metrics of driving performance, in-vehicle task performance, and glance behavior (Table 3.3). Outliers were identified by computing the inter-quartile range (IQR). Values that were farther than 1.5 times the IQR from the nearest quartile were removed.

Table 3.3. Dependent measures collected during the driving simulator experiment for use in analysis and modeling.

Metric Collected	*Related to*
RMS error of speed signals	Driving
Delay in speed change	Driving
Total task time	In-vehicle task
Button press timing	In-vehicle task
Total glance time	Glance behavior
Glance duration	Glance behavior
Time between glances	Glance behavior
Number of glances	Glance behavior

For the driving performance and in-vehicle task performance, statistical analysis was performed using SPSS Version 15.0 (SPSS Inc., Chicago, IL) and SAS 9.1.3 (SAS Institute Inc., Cary, NC, USA). Descriptive metrics calculated included mean and standard deviation. A repeated-measures analysis of variance (ANOVA) was also performed for some of the metrics.

Analyses of the glance data were performed using linear mixed-effects models. Linear mixed models (LMM) is a maximum-likelihood analysis method that can be used to estimate any number of random and fixed effects (McLean et al., 1991). For unbalanced within-subject designs, such as this one, LMM allows for proper estimation of random effects for within-subject F-tests without case-wise deletion of data, as is necessary for general linear models.

Analysis was performed in SAS 9.1.3 (SAS Institute Inc., Cary, NC, USA) using the Satterthwaite method for estimating denominator degrees of freedom. Backwards selection was used to identify effects in the final model. All main effects and interactions were initially included. Random effects included the main effect of subject as well as interactions between subject and each of the included fixed effects.

To examine the effects of reach distance and visual distance from the road ahead, the four-level monitor position variable was reformatted in SAS. The near-high and near-low monitor positions, which both had short reach distances, were grouped and compared to the far-high and far-low positions. Also, the near-high and far-high monitor positions, which were located at a short visual distance from the road ahead, were grouped and compared to the near-low and far-low monitor positions.

Driving Performance

Subjects were instructed to maintain a constant distance to the lead vehicle and to stay in their lane, so there were two ways to measure driving performance. The first looked at longitudinal control, or the fluctuation in the headway. The second considered lateral control, measured by the position of the car in the lane.

The lead vehicle speed and the subject vehicle speed were treated as two signals, and the mean RMS error between the signals was computed for each trial. In addition, the mean delay from the time when the lead vehicle changed speed to the time when the subject vehicle changed speed, identified by a change in the sign of the acceleration, was computed. These two results were used as metrics of performance of longitudinal control.

The simulator recorded measures of steering performance such as the orientation of the subject's car relative to the road heading and the distance of the car from the center of the lane. For lateral control, the mean and standard deviation of the lateral position of the car in its lane were considered.

In-Vehicle Task Performance

The mean in-vehicle task completion time for each trial was used to determine performance on the in-vehicle task. The total task time was the time required to complete the in-vehicle task, from the first touch on the screen to the final touch on the screen. The median total task time for each drive was used for the analysis.

Glance Behavior

Glance data were collected from face video of subjects during the experiment. Glance data were taken from the first two repetitions of the in-vehicle task for each condition. The glance metrics considered were the total glance time, the median glance duration, and the median time between glances.

The start of a glance was defined as the moment a subject's eyes started to move away from the road toward the touch screen monitor, or when the eyelids closed during a preparatory blink. The end of the glance was defined as the moment a subject's eyes started to move away from the monitor and back to the road. The glance duration was defined as the time between the start of a glance and the end of a glance. The median glance duration was the median of the glance durations for each repetition of the task. The total glance time was the sum of all glance durations during one repetition.

The time between glances (TBG) was defined as the time from the end of one glance to the start of the next glance. The median TBG was the median of the times between glances for each repetition.

The structure of the glance data is that of a within-subjects design; for most subjects, there were two observations of the same condition. This type of data is commonly analyzed using a repeated-measures method, such as ANOVA. However, not all drivers completed two full repetitions of the in-vehicle task for each condition, so the data are unbalanced. With more traditional forms of general linear models, entire cases are excluded from the dataset if it is missing an observation on one variable. Therefore, analysis was performed using a linear mixed-effects model, a broader form of the general linear model, which prevents the exclusion of this data. In addition, linear mixed-effects models make it possible to model the variance and covariance structure of the data, which can result in more accurate parameter estimates and test statistics.

The median time between glances for each subject and each monitor position was plotted against the median glance duration in order to illustrate and examine how glance strategies varied based on the location of the monitor for the in-vehicle task. This is similar to a technique used by Donmez and colleagues (2009) to examine risk-taking behavior in young drivers.

The following glance behavior hypotheses were tested:

1. The total task time will be greater when the display is farther from the subject because of increased reach distance and increased time looking away from the task. The total task time and the increase in total task time will be greater for shorter subjects, because the total glance time and the time between glances will be greater.
2. The total glance time will be greater when the display is farther from the subject because of increased reach distance and increased visual distance. The

total glance time will be greater for shorter subjects because the reach required to perform the task will be more challenging for them. The increase in total glance time between near and far monitor positions will be greater for shorter subjects because the subjects will need to use more complex movements that may involve more body parts in order to reach the far monitor positions.

3. The durations of individual glances will increase when the display is farther from the subject because of the increase in movement time needed to reach the monitor.
4. The durations of individual glances will decrease when the subject is driving the heavy vehicle, because this is a more difficult driving task.
5. The time between glances will increase when the display is farther from the subject. The increase in the time between glances between near and far monitor positions will be greater for shorter subjects because the more complicated movements that they must make will require additional motor planning.
6. The number of glances will increase when the display is farther from the subject. There will be a greater cost associated with performing a reach to the monitor in when it is in the far positions, so subjects are likely to perform the reach only when they have plenty of time. However, subjects will want to maintain awareness of the current state of the in-vehicle task, so they will make additional glances, not accompanied by reaches, to the monitor.

Results

In-Vehicle Task

In-vehicle task time, which was used as a measure of task performance, increased from a mean value of 23.5 s for the near-high monitor location to 45.4 s for the far low location with the normal-weight vehicle (Figure 3.4). The difference in mean task time was significant for each monitor location, $F(3,39) = 10.6$, $p < 0.001$. Vehicle weight had no significant effect on task completion time, $F(1,13) = 1.2$.

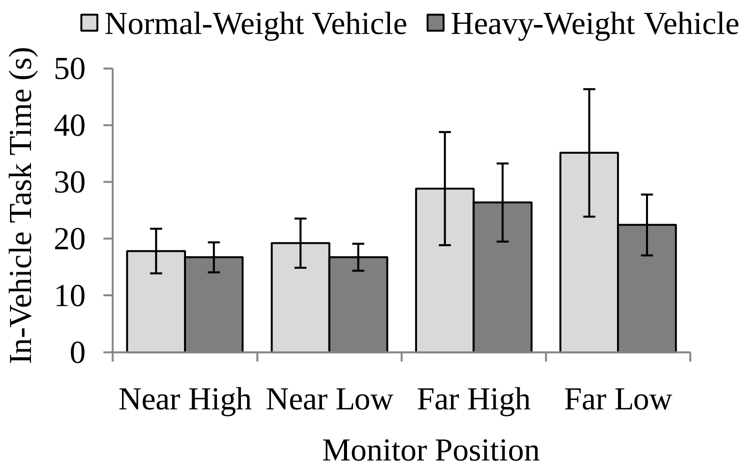


Figure 3.4. Mean time required to complete the in-vehicle task for all monitor positions and vehicle weight conditions. Error bars represent 95% confidence intervals on means across subjects.

The increase in task time for far monitor positions was most pronounced for the subjects in the shorter stature groups (Figure 3.5). Interaction between stature and monitor position was found to be significant, $F(9,24) = 6.1$, $p < 0.001$, confirming the hypothesis that shorter subjects were more affected by the greater reach distance than taller subjects were.

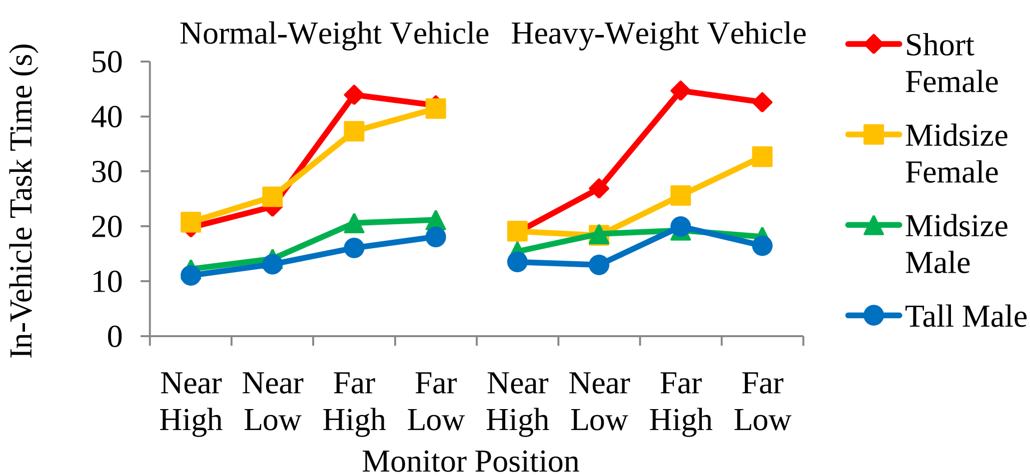


Figure 3.5. The in-vehicle task times for the four monitor locations and two vehicle weights are shown for each stature group.

Driving Performance

Longitudinal Control

Performing the in-vehicle task had a significant adverse effect on longitudinal driving performance, as measured by RMS error of speed, $F(1,15) = 126.2$, $p < 0.001$ and delay $F(1,14) = 77.5$, $p < 0.001$ for both vehicle weights (Figure 3.6). In addition, driving performance was worse for the heavy-weight vehicle compared to the normal-weight vehicle for all monitor positions, measured by RMS error of speed, $F(1,15) = 33.1$, $p < 0.001$, and delay, $F(1,14) = 74.8$, $p < 0.001$. There was no significant difference in longitudinal driving performance metrics among the four monitor positions, $F(3,45) = 0.5$. Statistical results were the same for the delay in following a speed change made by the lead vehicle (Figure 3.7).

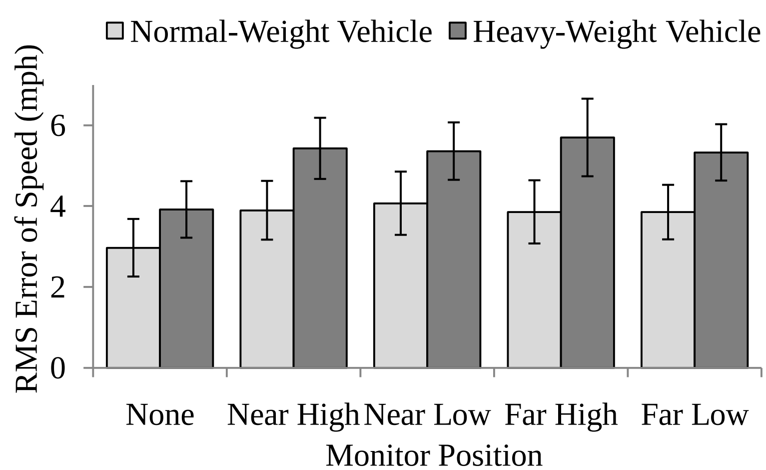


Figure 3.6. The RMS error in vehicle speed for the trials with no in-vehicle task and the trials for the four monitor locations and two vehicle weights. The error bars show the 95% confidence intervals.

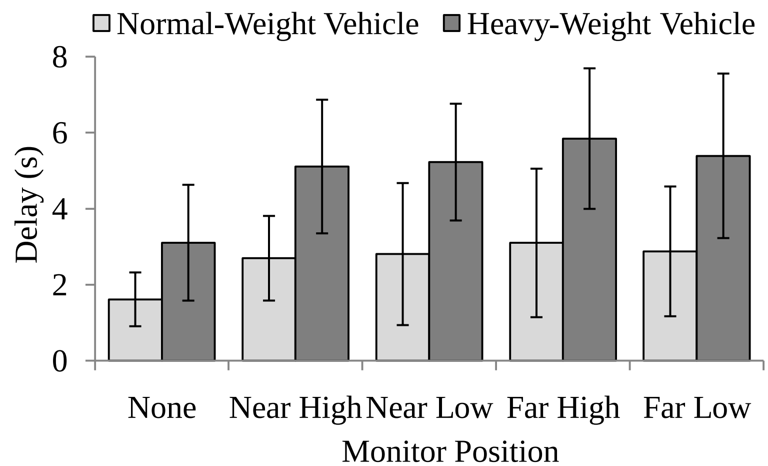


Figure 3.7. The delay in matching a speed change by the lead vehicle for the no in-vehicle task conditions and the four monitor locations and two vehicle weights. The error bars show the standard deviation.

Lateral Control

Two metrics of lateral control were considered: mean lane position and standard deviation of lane position. The mean lane position increased significantly for the far and low monitor positions $F(4,148) = 6.00$, $p < 0.001$, but vehicle weight had no effect, $F(1,148) = 0.55$. There was no interaction between monitor and vehicle weight, $F(4,140) = 0.20$. The mean lane position was 0.050 meters to the right of the center of the lane for the near high monitor position, 0.119 meters for the near low position, 0.216 meters for the far high position, and 0.233 meters for the far low position (Figure 3.8). For the baseline condition, with no secondary task, the mean lane position was 0.096 meters to the right of center.

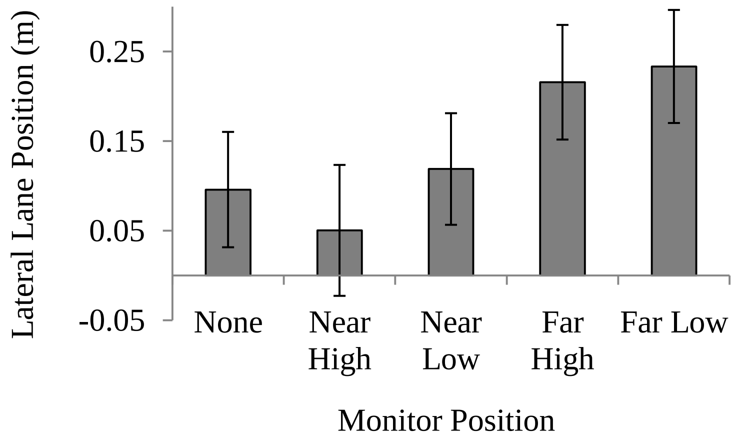


Figure 3.8. Mean lane position (meters from center) for each monitor position. Positive values indicate the vehicle is to the right of the centerline. The error bars show the 95% confidence intervals.

Driver stature had no significant effect on the mean lane position, $F(3,147) = 0.82$. In addition, there was no significant interaction between monitor position and driver stature, $F(12,120) = 0.55$.

For the standard deviation of lane position, there was a significant effect of both monitor position, $F(4,142) = 9.60$, $p < 0.0001$, and vehicle weight, $F(1,142) = 21.26$, $p < 0.0001$. Again, there was no interaction between monitor and vehicle weight, $F(4,140) = 0.28$. The standard deviation was 0.370 meters for the near high monitor position, 0.389 meters for the near low position, 0.456 meters for the far high position, and 0.460 meters for the far low position (Figure 3.9). For the baseline condition, with no secondary task, the standard deviation of lane position was 0.335 meters. The standard deviation of lane position was 0.373 meters for the normal-weight vehicle and 0.432 meters for the heavy vehicle.

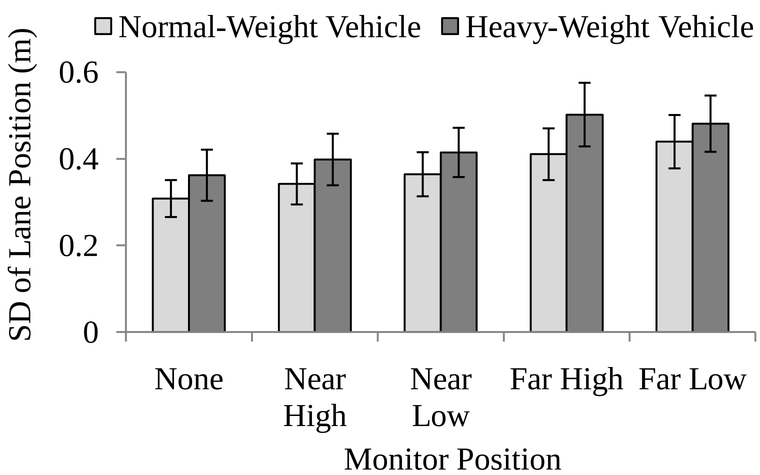


Figure 3.9. Standard deviation of lane position (meters) for each monitor position. The error bars show the 95% confidence intervals.

Driver stature had a significant effect on the standard deviation of vehicle position, $F(3,142) = 18.14$, $p < 0.0001$. The standard deviation of lane position was 0.471 for short females, 0.374 for midsize females, 0.377 for midsize males, and 0.386 for tall males. However, there was no significant interaction between stature and monitor position, $F(12,118) = 1.24$.

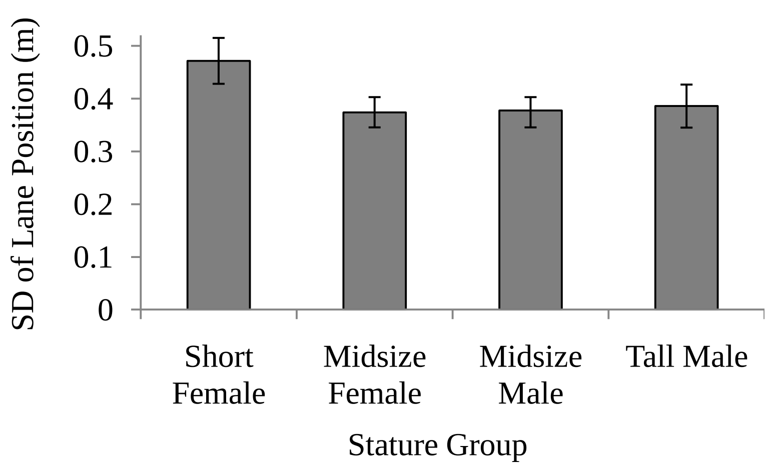


Figure 3.10. Standard deviation of lane position (meters) for each stature group. The error bars show the 95% confidence intervals.

Glance Behavior

Total Glance Time

The total glance time for a trial increased significantly with far and low monitor positions, $F(3,15.7) = 10.1$, $p < 0.001$ (Figure 3.11). The total glance time was 11.0 seconds for the near-high monitor position, 12.9 seconds for the near-low position, 14.4 seconds for the far-high position, and 15.7 seconds for the far-low position.

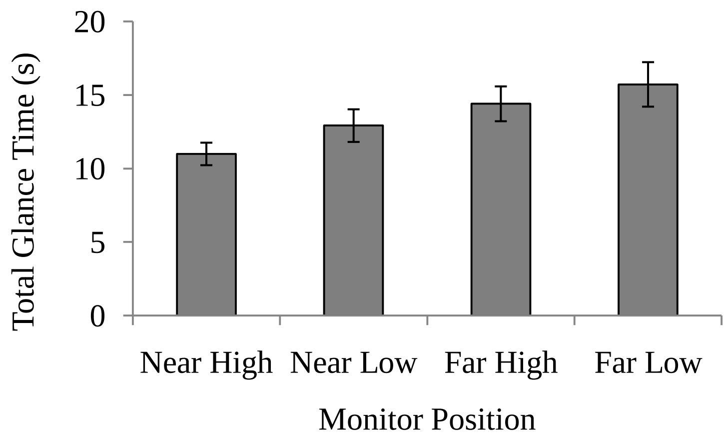


Figure 3.11. Mean total glance time (seconds) for each monitor position. The error bars show the 95% confidence intervals.

Total glance time decreased significantly with increasing subject stature, $F(3,3.81) = 6.14$, $p < 0.1$ (Figure 3.12). The mean total glance time was 16.6 seconds for short females, 13.2 seconds for midsize females, 12.2 seconds for midsize males, and 11.6 seconds for tall males. No interactions were significant.

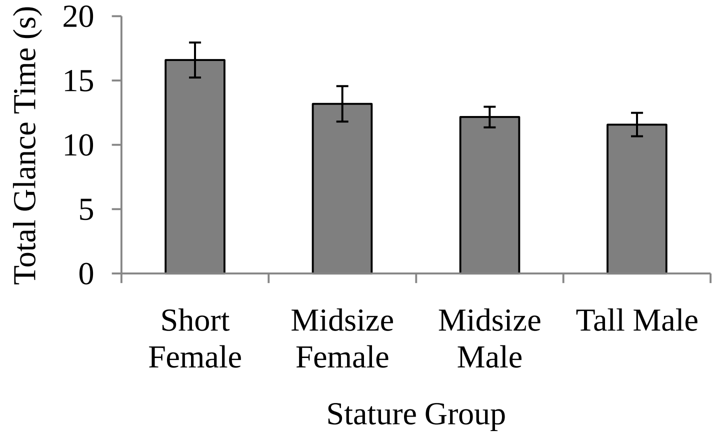


Figure 3.12. Mean total glance time (seconds) for each stature group. The error bars show the 95% confidence intervals.

Dividing monitor position into reach distance and visual distance provided additional information about the effects of monitor location. Total glance time to the far monitor position was 26.0% longer than to the near position, $F(1,214) = 34.7$, $p < 0.0001$. Placing the monitors in the low positions resulted in a 12.8% increase in total glance time compared to the high positions, $F(1,214) = 7.91$, $p < 0.01$.

Median Glance Duration

The median glance duration was affected by the combination of subject gender and stature, with the female subjects generally making shorter glances to the monitor (Figure 3.13). Although the effect was very small, it was significant, $F(3,118) = 7.74$, $p < 0.0001$. The median glance duration was 1.50 seconds for short females, 1.33 seconds for midsize females, 1.64 seconds for midsize males, and 1.47 seconds for tall males. The median glance duration was not affected by monitor position, $F(3,211) = 1.64$, or vehicle weight, $F(1,211) = 0.02$.

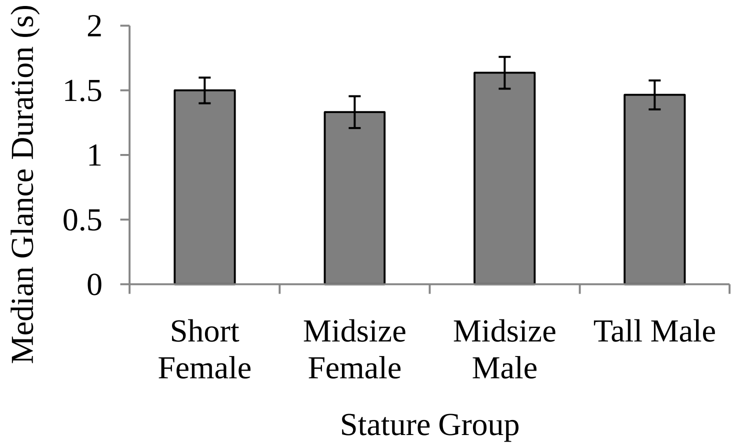


Figure 3.13. Median glance duration (seconds) for each stature group. The error bars show the 95% confidence intervals.

The effect of reach distance to the monitor on the median glance duration was not significant, F(1,215) = 1.41, nor was the effect of visual distance, $F(1,215) = 2.54$.

Time Between Glances

The effect of monitor position on the time between glances was significant, $F(3,2.31) = 7.49$, $p < 0.1$ (Figure 3.14). The median time between glances increased from 0.526 seconds for the near-high monitor position to 0.670 seconds for the near-low position to 1.16 seconds for the far-high position. It decreased slightly to 0.885 seconds for the far-low position.

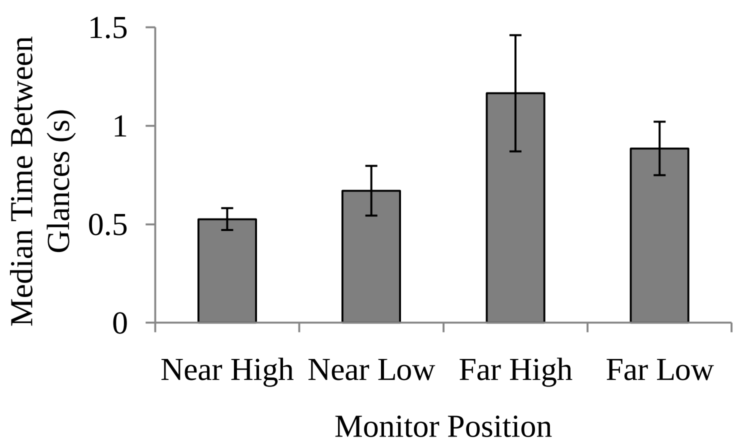


Figure 3.14. Median time between glances (seconds) for each monitor position. The error bars show the 95% confidence intervals.

Subject stature also had a significant effect on time between glances, $F(3,5.79) = 4.83$, $p < 0.1$ (Figure 3.15). Midsize females had the greatest median time between glances (1.12 seconds), followed by short females (0.802 seconds), midsize males (0.699 seconds), and tall males (0.652 seconds).

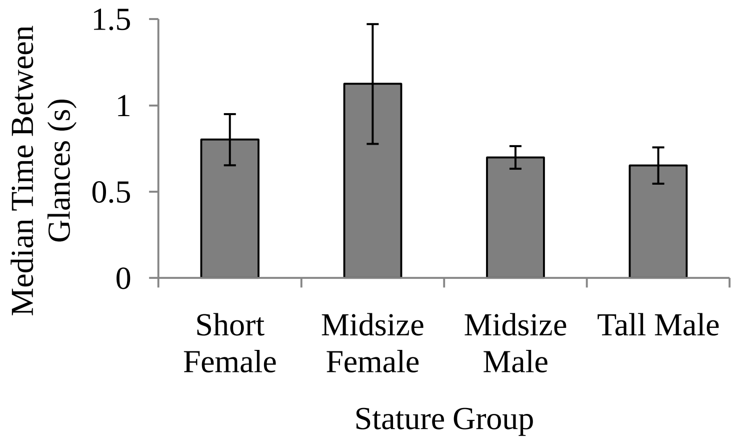


Figure 3.15. Median time between glances (seconds) for each stature group. The error bars show the 95% confidence intervals.

The effect of vehicle weight was not quite significant effect, $F(1,4.46) = 3.61$, $p = 0.12$. The median time between glances was 15.6% longer for drives in normal-weight vehicles compared to heavy vehicles. No interactions were significant.

The results were slightly different when monitor position was analyzed by reach distance and visual distance. Subjects looked at the road for 71.4% longer during the in-vehicle task when the monitor was in one of the far positions than when it was in one of the near positions, $F(1,16.2) = 17.41$, $p < 0.001$. However, visual distance did not have a significant effect on time between glances, $F(1,216) = 0.54$.

Time Between Glances vs. Glance Duration

The median time between glances was plotted against the median glance duration for each subject and each monitor position (Figure 3.16). Each point represents one subject's median time between glances and median glance duration across all trials for the given monitor position and vehicle weight. The spread of the glance durations was approximately the same for each position. The time between glances, however, was more variable for the far monitor positions.

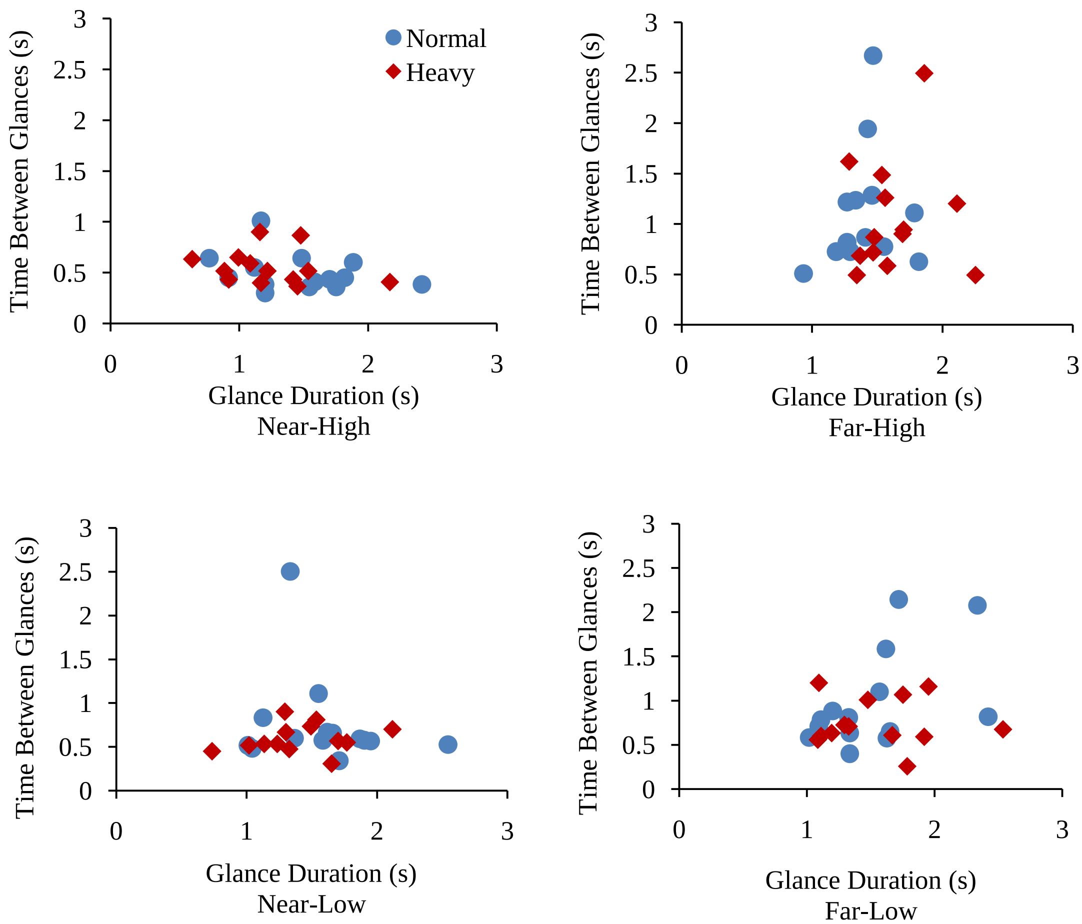


Figure 3.16. The median time between glances to the monitor for each subject is plotted against the median glance duration for each monitor position, with a distinction made between trials involving normal-weight and heavy vehicles.

Number of Glances

Shorter subjects made significantly more glances to the monitor for the in-vehicle task than did tall subjects, $F(3,175) = 10.00$, $p < 0.0001$ (Figure 3.17). The mean number of glances was 11.8 for short females, 9.98 for midsize females, 8.19 for midsize males, and 7.81 for tall males.

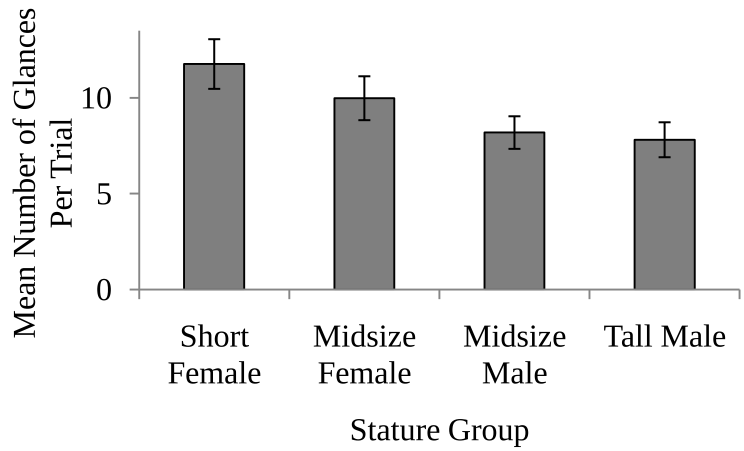


Figure 3.17. Mean number of glances per trial for each stature group. The error bars show the 95% confidence intervals.

The number of glances also increased as the monitor was moved farther from the subject and the road, $F(3,214) = 5.00$, $p < 0.005$ (Figure 3.18). No interactions were significant.

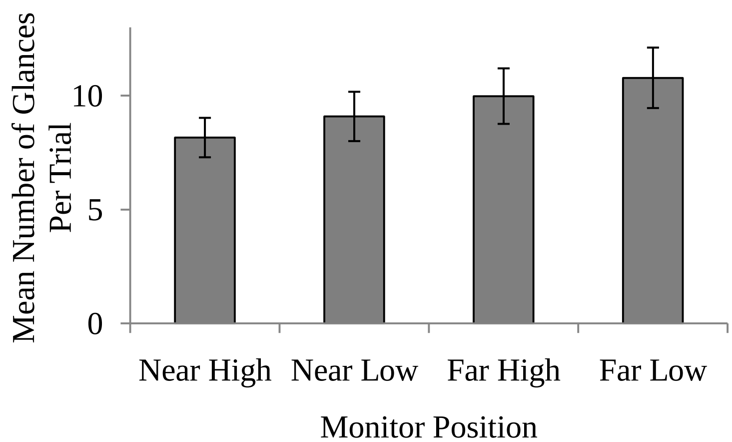


Figure 3.18. Mean number of glances per in-vehicle task iteration for each monitor position. The error bars show the 95% confidence intervals.

When the effect of the reach distance to the monitor was considered separately from the visual distance, reach distance had a significant effect on the number of glances, $F(1,215) = 12.28$, $p < 0.001$, with subjects making an average of 1.76 additional glances per trial to the far monitor positions, but visual distance did not, $F(1,216) = 2.75$. In addition, the interaction between reach distance and vehicle weight was significant,

$F(1,215) = 3.04$, $p < 0.1$, with a greater increase in number of glances to far monitor positions for the normal-weight vehicle, compared to the heavy vehicle.

Discussion

Performing the in-vehicle task was found to adversely affect driving performance for both vehicle weight conditions, as was expected. This is consistent with other studies that have demonstrated that adding a visually demanding in-vehicle task significantly degraded driving performance (Tsimhoni & Green, 2001).

The glance data used for analysis is not as accurate or precise as that which would be obtained using an eye tracking system. However, it is thought that this level of accuracy is acceptable for the current analysis. At present, there is limited information available related to how people attend visually to two concurrent tasks. Thus, the glance modeling performed represents a starting point toward greater understanding; detailed modeling of glance behavior was beyond the scope of this project.

Monitor Position

The time required for the subjects to complete the in-vehicle task while driving varied with the monitor position. The in-vehicle task performance was worse when the subject used the monitors that were physically farther from the driver, compared with those that were closer. This suggests that in some situations reach distance is an important factor for in-vehicle task performance.

There was no significant difference in performance on the longitudinal control driving task between different in-vehicle task monitor positions, though the RMS error and delay were greater when drivers were performing the in-vehicle task compared to the trials with no secondary task. It was expected that driving performance would suffer when the in-vehicle task was performed with the monitor in positions with greater visual angle from the road ahead and greater reach distance. However, the RMS error and delay were approximately the same for all monitor positions.

In contrast, performance on the lateral control driving task deteriorated when the monitor was in the far and low positions, as evidenced by the standard deviation of lane position. In addition, the mean lane position changed following a similar pattern.

When subjects are presented with a secondary task in a simulator, they frequently concentrate on this task to the exclusion of the primary task, a phenomenon called cognitive tunneling (Jarmasz et al., 2005). This may be caused by the decreased consequences of inattentive driving in a simulator compared to on a road. To minimize this phenomenon, the subjects were told that performance on the driving task was more important than performance on the in-vehicle task, as is the case in real driving. It appears that subjects followed these instructions and concentrated on maintaining performance on the driving task, while devoting attention to the in-vehicle task only when they felt comfortable doing so. This would explain the finding that longitudinal control was unaffected by the more difficult secondary task conditions caused by the far monitor positions, though it did decline when the secondary task was introduced compared to the trials with no secondary task. Sacrificing speed on the in-vehicle task to maintain safe driving performance is similar to the expected behavior of most drivers on the road.

The in-vehicle task was fairly complex, but it is possible that it was not difficult enough for the subjects, who were all relatively young. This could explain the lack of significant effect of monitor position on longitudinal control. The in-vehicle task could be "chunked" into smaller subtasks, i.e. matching the first pair, matching the second pair, and matching the third pair. Conversations with subjects suggested that this is how subjects partitioned the in-vehicle task. Time-sharing between driving and performing a task is easier when the task is relatively unaffected by interruptions at regular intervals than when the task must be performed continuously (Noy et al., 2004). When performing tasks that can be interrupted such as typing or dialing (Salvucci & Macuga, 2002), drivers have greater control over task sharing decisions.

Finally, it is possible that the metrics used to quantify performance of longitudinal control were not sensitive enough. That is, differences in driving performance with changing monitor position were not observable in the RMS and delay values recorded. This is supported by the finding of varying lateral control performance with different monitor positions. However, it is also possible that the findings were due to some combination of the above factors.

It was hypothesized from the literature that total task time would be greater when the display was farther away from the driver because of increased reach distance and increased time looking away from the task to the road. The results show that task time increased for far monitor locations compared to near, though there was no significant difference between low and high monitor positions.

It would be tempting to conclude that reach distance from the steering wheel is a more important factor in the design of in-vehicle systems than the visual angle from the road. However, this finding may not extend to monitor positions that are very different from those that were tested here. It is more conservative to state that a horizontal increase in reach distance of 35 to 55 cm (the distances between the near and far monitors for the low and high positions, respectively) has a greater effect on glance behavior than a vertical increase in visual distance of 20 cm.

The total glance time and number of glances also increased for far monitor positions compared to near, as was predicted. In addition, total glance time and number of glances increased for low monitor positions compared to high positions. There are at least two possible explanations for these findings. First, the glance time includes the time to move the eyes from the road to the monitor. Sometimes, it also included the time to reach from the steering wheel to the monitor, because the reach usually was made while the subject was looking at the monitor. Therefore, the increase in total glance time may reflect, in part, the greater time required for the eye and hand movements needed to complete the in-vehicle task. Second, it may have been more difficult for the subjects to perform the in-vehicle task when the monitor was in the far and low positions because of greater difficulty in seeing the icons on the screen and greater difficulty in achieving the manual precision required to press the icons correctly. This greater difficulty could have resulted in the subjects spending more time on the in-vehicle task.

It was hypothesized that glance duration might increase for far monitor positions because of increased movement time, but in fact, monitor position had no effect on the duration of individual glances. The increase in the total glance time was a result of more glances of the same duration rather than longer glances. In some cases, the driver started to move his or her hand towards the monitor prior to starting a glance. In the video from the experiment, the driver sometimes left his or her hand near the monitor between glances rather than moving the hand back to the steering wheel. In addition, drivers could have broken the in-vehicle task into more subtasks in order to avoid an increase in glance duration. Therefore, even though including the time to complete eye and hand movements in the glance time would have resulted in longer glances, drivers instead may have decided to complete a smaller portion of the task during each glance so that the duration of each glance away from the road remained approximately the same.

The far monitor locations also resulted in an increase in time between glances, as was predicted. Performing the in-vehicle task with the monitor in the far locations was more difficult than with the monitor in the near locations, so more attention was likely diverted from the concurrent driving task. The greater time between glances for the far monitor positions could reflect the need for more recovery time when working on the in-vehicle task (perhaps to regain the desired headway or to center the vehicle in the lane) and more preparation time before each glance away from the road (perhaps to stabilize the vehicle before moving the hand, head, and in some cases torso).

The number of glances subjects needed to complete the in-vehicle task increased for far monitor positions, as was expected. This, together with the increase in total glance time and no change in glance duration suggests that most subjects were making similar glances regardless of monitor position, but they required more glances and more time to complete the in-vehicle task when the monitor was in the far positions.

Two of the monitor positions used were outside the typical range of in-vehicle display positions. This could simulate aftermarket add-on displays, which frequently must be positioned non-optimally. These may also be realistic monitor positions in military vehicles or commercial large trucks, which are typically much larger than civilian vehicles and may require a greater number of in-vehicle systems. Because military convoys often drive at high speeds with closely spaced vehicles, longitudinal control is very important. It is expected that results from this experiment could be used in developing interfaces and planning tasks for military and commercial vehicles in order to minimize the likelihood of crashes.

Stature

Although there was no clear pattern in the effects of stature on longitudinal control, it appeared that the subjects in the shortest stature group had the greatest trouble with lateral control. However, there was no significant interaction between stature and monitor position, so the short subjects did not have significantly more trouble with lateral control when the monitor was in the more difficult positions. This could suggest at least two different things. First, the drivers in the shorter stature group may have used a different strategy for sharing resources between the driving and the secondary task. Specifically, they may have chosen to divert fewer resources to the secondary task, a theory supported by their decrement in task performance when the monitor was in the far positions. Second, it is possible that this group of subjects simply happened to be worse at operating the driving simulator than the other subjects were.

The total task time, the total glance time, and the time between glances were longest for the short females and midsize females, and shortest for the midsize males and tall males. This could indicate that the shorter subjects performed the reach using more complicated movements. The videos show some subjects in the shorter stature groups leaning with their torsos to reach some of the monitor positions, while the subjects in the taller stature groups could generally perform the reach using arm movements alone. The motor control literature suggests that more complicated motor actions require additional time for planning (Schmidt & Lee, 1999). Thus, the greater time between glances for short subjects could be attributable to the need for a longer planning stage during which the subjects began to prepare for the movement while still looking at the road. The greater total glance time for short subjects could include additional preparation time for the movement, when the subjects are looking at the monitor prior to making a reaching movement, as well as the greater time required to perform the more complicated movement.

Short and midsize female subjects also made shorter glances to the monitor and more of them. This suggests that these subjects did not feel comfortable taking their eyes off the road for very long. It is possible that these subjects were grouping the button presses into smaller chunks when performing the task, which required them to look at and reach to the monitor more times. Alternatively, they may have completed the same number of reaches to the monitor, but with longer periods of time between reaches to prepare or recover. To keep track of where they were in the task, they may have made additional glances to the monitor, unaccompanied by reaches.

All the subjects in the two shorter stature groups were female and all the subjects in the two taller stature groups were male. Therefore, it was impossible to distinguish between gender effect and stature effect. This confounding represents the reality of stature differences between the genders, so the observations from this study are likely representative of what would be found in a larger population. In addition, studies have shown that stature generally has a much larger effect than gender on reaching behavior for subject-selected motions when reaching to targets in a typical automobile interior (Chaffin et al., 2000).

Vehicle Weight

Driving performance, both in terms of longitudinal control and lateral control, was better in the normal-weight vehicle condition than with the heavy-weight vehicle. This result was expected, because the heavy-weight vehicle had lower maximum acceleration and deceleration values, so it was more difficult for subjects to reach a desired speed after responding to the lead vehicle's speed change. The greater momentum of the heavy vehicle also could have made it more difficult to steer than the normal-weight vehicle. In addition, subjects were likely more accustomed to driving cars, which are similar to the normal-weight vehicle, than trucks, which are more like the heavy-weight vehicle.

However, in-vehicle task performance for the heavy-weight vehicle condition was not significantly different than that in the normal-weight condition for most monitor positions, and performance improved for the far low position. It is possible that subjects decided they could not perform well on the driving task and therefore concentrated more on the in-vehicle task.

Vehicle weight had little if any effect on glance behavior. It was thought that glance duration would decrease for the heavy vehicle, because driving the heavy vehicle should be more difficult than driving the normal-weight vehicle, similar to driving on sharp curves (Tsimhoni & Green, 2003). Thus, subjects should feel constrained to take their eyes off the road for shorter amounts of time. However, there was no change in glance duration. The cost of short glances while trying to maintain lane position on a sharp curve is critical and immediate. In contrast, the cost of short glances while trying to maintain headway to a lead vehicle in a heavy vehicle is cumulative. Furthermore, the heavy vehicle was perhaps more predictable, thus requiring shorter glances to the road.

The time between glances was actually shorter for the heavy vehicle compared to the normal-weight vehicle, and subjects made slightly fewer glances to the monitor. This could indicate that subjects were rushing through the in-vehicle task in order to return to the driving task and perhaps caring less about their driving performance when the driving task was more difficult.

Interactions

The increase in total task time from near to far monitor locations was greater for shorter subjects, as was predicted. This is likely because the shorter subjects had more trouble than the taller subjects in reaching to the far monitor locations. It was hypothesized that shorter subjects would show a greater increase in total glance time and time between glances with the far monitor positions, but there were no significant interactions. It is possible that the short subjects were using different glance strategies to compensate for the greater difficulty they had in performing the task with the monitor in the far positions.

Strategies

The dual task scenario created in this experiment required subjects to decide how to share resources such as vision and information processing between two tasks: driving and the in-vehicle matching task. This research makes it possible to investigate whether glance strategies used by drivers vary as a function of the monitor position. This information could aid in the design of future in-vehicle systems, especially with regard to the need for adjustability. In general, the between-subject variability in driving and task performance was very large. This suggests that subjects used different strategies, with varying levels of success, to allocate resources in order to perform the in-vehicle task while driving.

The plots of time between glances against glance duration show some possible differences in glance strategy based on the monitor location. The plots for the two near monitor locations are very similar, with a wide range of glance duration and a narrow range of time between glances across subjects. Based on these plots, subjects can be divided into two behavioral categories: short time between glances with short glance duration and short time between glances with long glance duration. The second strategy is the more risky of these two, because long glances away from the road may increase the likelihood of collision. Long glance durations could indicate that the subject was engaged in cognitive tunneling, in which a subject presented with a secondary task in a simulator concentrates on this task to the exclusion of the primary driving task.

The two far monitor locations have glance duration spreads that are similar to those of the near monitors, but the range of values for time between glances is much larger. Thus, the far monitor locations show four categories of glance behavior: the two identified for the near monitor locations, long time between glances with moderate glance duration, and long time between glances with long glance duration. The third strategy indicates more time is being spent on the driving task than on the secondary task. The last strategy shows that equal time is spent on the two tasks, but the subject switched between the tasks infrequently. This strategy could be displayed by a subject who forgets to shift attention between the tasks or whose attention is captured by one of the tasks. Cognitive capture can cause a driver to focus on a secondary task to the exclusion of the more important driving task (Weintraub, 1987).

In the exit interviews, subjects were asked about how they chose to perform the dual tasks assigned in the experiment. Many subjects indicated that they avoided performing the in-vehicle task when driving around a curve, especially for the far monitor positions. This is consistent with the findings from Tsimhoni and Green (2003) that showed subjects made shorter glances to the display and longer glances to the road with increased road curvature.

All the subjects agreed that the far monitor positions were more difficult, but subjects varied in how they chose to manage the tasks. Some stated that they tried to complete the in-vehicle task as quickly as possible, while others felt that they took more breaks from the in-vehicle task while performing the task with the far monitor positions than when the monitor was at a shorter reach distance. Future work could examine how subject characteristics such as age, risk-taking behavior, and motivation contribute to changes in glance strategy.

Conclusions

The results of this study demonstrate both strengths and limitations of drivers' abilities to cope with secondary tasks while driving. The instructions that subjects were given emphasized that they should assign the most priority to the simulated driving task and perform the secondary task as well as possible within that context. In terms of overall performance of both tasks, they were partly successful in following those instructions. On the positive side, the effect of far (difficult) monitor positions was limited to performance on the secondary task and on the lateral driving task, while performance on the longitudinal driving task was virtually unchanged. However, driving performance for all monitor positions was somewhat reduced relative to the control condition in which the secondary task was not performed. It is not immediately obvious how to explain the fact that, although driving performance was not entirely independent of the secondary task, it was relatively unaffected by substantial changes in the difficulty of the secondary task, as influenced by monitor position. One possibility is that the mere presence of the secondary task interfered with some general, executive-level process. Alternatively, the results could be explained in terms of the internal performance criteria that were adopted by the subjects. It may be that the reduced level of driving performance that was observed for all monitor positions corresponded to what the subjects considered a minimum (but nevertheless acceptable) level. The higher driving performance that they achieved when they were not performing the secondary task may thus have been considered, in their explicit or implicit strategic calculations, higher than actually required.

At a more detailed level, it appears that the coping strategies used by these subjects involved performing the secondary task in discrete subtasks. Thus, the increased difficulty caused by more distant monitor positions resulted in more glances to the monitor rather than longer glances. Secondary tasks presumably vary in how easily they can be divided into manageable subtasks. The secondary task used here may have been particularly easy to divide, since it consisted of a series of similar components involving locating and identifying icons and matching them by pressing the corresponding locations on the touch screen.

In order to make practical recommendations for equipment and procedures to be used in a range of secondary tasks, it is necessary to consider various aspects of the demands of the secondary tasks. Among these are the extent to which various secondary tasks can be divided into subtasks, as well as the fundamental perceptual, cognitive, and motor requirements of the tasks. Ideally, a comprehensive model should be developed to integrate information about the demands of secondary tasks from this study and from various possible extensions. Important ways in which the current results could be extended include: (1) Use of other measures of driving performance. For example, even within the context of a vehicle-following task, the frequency and abruptness of changes in lead-vehicle speed could be continuously varied so that the task could range from being a relatively predictable tracking task to one in which subjects had to detect unpredictable, heavy braking events. (2) The effects of monitor location on perceptual and motor demands could be separated by varying the monitor's visual characteristics (e.g., size or level of detail in the icons) and motor characteristics (e.g., size of touch-sensitive areas, level of force, or duration of continuous contact required for a response). (3) Instructions to the subject about the strategic importance of the secondary task relative to driving could be varied.

Chapter 4
Virtual Driver Model

Introduction

The Virtual Driver model uses the Queuing Network – Model Human Processor (QN-MHP) to simulate a human's cognitive processing. The HUMOSIM Framework is used to represent the physical characteristics of the human and the environment. The interface between the models allows the HUMOSIM Framework to pass information about the physical task environment to the QN-MHP, which responds with motor commands. The Framework executes these commands and reports the results to the QN-MHP, which uses the information for subsequent decisions.

This chapter begins with a list of human behaviors that a good model of driving should be able to produce. Next, the conceptual structure of the QN-MHP, the HUMOSIM Framework, and the Virtual Driver are described, including a discussion of the inclusion of the driving behavior features. A description of the software implementation of the model follows in the next chapter.

Important Features of Driving Behavior

Subjects were observed to engage in a number of distinctive strategies and behaviors during the driving simulator experiment. Some of these behaviors are commonly acknowledged, while others are less well-known or have not been discussed explicitly in the existing literature. Based on an evaluation of the results from the experiment and a survey of the literature, a suite of critical features of driving behavior was identified, with a particular focus on driving while performing an in-vehicle task.

To accurately represent multitasking while driving, a model should be able to reproduce these behaviors, which should emerge naturally from the model structure, rather than being scripted. These behaviors can be grouped into the categories of workload management, between subjects differences, and in-vehicle task-specific.

Several of the behaviors deal with how the driver divides his or her attention between the driving task and the in-vehicle task. More complete driver models could aid in predicting how drivers will interact with in-vehicle systems and understanding the causes and effects of driver distraction. Therefore, it is essential that such models correctly capture the workload management strategies that actual drivers use.

Some driving behaviors varied from subject to subject. These behavioral differences could be due to physical diversity among subjects, such as stature, or psychological differences, such as propensity for risk taking. Such behaviors could be represented in a model by parameters that are varied to obtain the desired combination of physical size and personality.

Certain behaviors that drivers displayed deal specifically with the in-vehicle task studied in the driving simulator experiment, but may extend to similar tasks. The in-vehicle task in the experiment required subjects to look at the monitor and press buttons to navigate between screens to complete the task. Button presses are common in in-vehicle tasks, so the task for the driving simulator experiment was similar to tasks actual drivers perform on the road.

The behaviors are listed in order of importance and described below. Any model of driving while performing a secondary in-vehicle task should be judged based on its ability to represent the following characteristics. Ideally, such a model would be able to represent all of these behaviors. However, to provide useful information about the tendencies and abilities of drivers, a model should, at the minimum, include the first six behaviors.

1. Secondary task scheduling

The decision to perform secondary in-vehicle tasks is based on the difficulty of the primary driving task. Most drivers decline to begin or temporarily discontinue working on in-vehicle tasks when the primary driving task becomes more difficult. For example, most subjects in the simulator study would pause in the in-vehicle task in order to return full attention to driving when going around a curve or when the headway to the lead vehicle became very short. This was especially true when the in-vehicle task required more resources, such as with the far monitor locations.

Many studies of driver distraction have forced performance of the in-vehicle task to occur at certain times (e.g. Wikman et al., 1998; Salvucci & Beltowski, 2008). Others have ostensibly allowed the subjects greater freedom, but still encouraged subjects to participate in the in-vehicle task at the expense of driving performance. For example, Donmez and colleagues (2009) had subjects perform a self-paced in-vehicle secondary task, giving the subjects the freedom to interact with the task whenever they felt comfortable. However, they also offered financial incentive for greater speed and accuracy on the secondary task, which may have motivated the subjects to neglect the driving task.

The tendency of many studies to strongly encourage performance of the in-vehicle task may explain why many studies do a poor job of representing experienced driver behavior. The use of in-vehicle devices has greatly increased in recent years (NHTSA, 2009a) , but the incidence of accidents has remained fairly steady (NHTSA, 2009b). This suggests that, in general, drivers are fairly good at determining when it is safe to divert attention from the road in order to perform an in-vehicle task.

Some studies of driver distraction have attempted to recreate the type of driving atmosphere that is common under normal circumstances. Tsimhoni (2003, p. 14) conducted a driving simulator experiment in which subjects performed an in-vehicle secondary task while negotiating curves of variable radii; subjects were instructed to "perform the task only if you think you can remain in the lane," and told "remember your first priority is to stay on the road." The results demonstrated that sharper curves resulted in a greater total task time, a shorter single glance duration, and more glances to the road, although there was no significant effect of road curvature on the total time spent looking at the monitor. The conclusion was that subjects demonstrated flexibility in how they partitioned the task when driving demands changed, presumably as they would if driving on the road.

Most models of distracted driving focus on how the secondary task impacts driving performance, but pay little attention to how driving conditions affect secondary task performance. Recently, some modelers have begun to address this issue indirectly. Brumby and colleagues (2009) developed a model that was able to simulate changes in secondary task performance when drivers were told to focus on either driving or dialing a cellular phone. Both the experimental data and the model showed that subjects took longer to complete the dialing task when steering was prioritized. These results could be extended by reasoning that drivers internally prioritize driving over a secondary task to a greater extend when the driving task becomes more difficult. However, the modeling work does not explicitly demonstrate if drivers are sensitive to the changing demands of typical real-world driving environments.

2. Effect of reach capability on in-vehicle task difficulty

Reach capability affected the difficulty of the in-vehicle task when the monitor was positioned far from the steering wheel. Shorter subjects, who also had a shorter reach capability, had to lean farther than taller subjects to reach the monitor. The greater relative reach distance increased the difficulty of the in-vehicle task, but it also may have affected driving. Subjects who leaned to reach the monitor may have found it more difficult to perform the physical task of steering. In addition, the changed viewpoint relative to the road could greatly increase the cognitive load associated with maintaining control of the vehicle. Finally, some of the shorter subjects chose to shift laterally towards the monitor in their seats prior to beginning a reach to a far monitor position. This resulted in the addition of an extra step to the in-vehicle task that was not required for taller subjects.

The driving simulator study conducted is significant because secondary tasks used in previous studies of driving did not have meaningful physical difficulty. Dukic and colleagues (2005) examined a button pressing task with varying button locations, but none of the locations involved a significant physical reach. In addition, the study did not consider subject stature or reach capability.

Current models of driver distraction also pay little attention to the physical requirements of the secondary task. In general, they consider secondary tasks with little or no physical component such as dialing and speaking on a cellular phone (Levison, 1993; Salvucci & Macuga, 2002). As such, there is no significant difference between subjects or test conditions in the physical difficulty of the task.

3. Effect of prioritization of dual tasks on performance

Individual decisions about prioritization of driving versus the in-vehicle task, which are impacted by the amount of risk a driver will accept, will affect performance on both. Drivers displayed apparently different prioritization of driving and the in-vehicle task, even though all drivers in the simulator study were instructed to treat the driving task as primary and to perform the in-vehicle task only when they could do so safely and comfortably. Some subjects tolerated large decrements in driving performance to complete the in-vehicle task rapidly, while others sacrificed performance on the in-vehicle task to maintain good driving performance.

Differences in prioritization during simulator studies are often related to subject instructions. Brumby and colleagues (2007) investigated how people adapt their strategy for interleaving multiple concurrent tasks when their objectives change by observing how drivers performed on a cellular phone dialing task. For each trial, the experimental instructions and feedback on performance encouraged the subjects to focus either on the driving task or the dialing task.

Horrey and colleagues (2006) also examined the effect of experimental instructions and feedback on prioritization of driving over a task in which subjects read telephone numbers from a head-down display. When subjects were encouraged to maintain a stable lane position, they took more time to complete the secondary task and made additional glances back to the road, thereby improving their lane-keeping performance. Conversely, when subjects were encouraged to complete the secondary task quickly, they made fewer glances to the road, which resulted in a less-stable lane-keeping performance.

The differences in prioritization were also related to the amount of risk a subject was willing to take. Drivers varied in their willingness to neglect the primary task, accepting more or less risk that they would leave the roadway or collide with the lead vehicle. The glance analysis showed that some subjects generally made long glances to the monitor and short glances back to the road. This is a riskier strategy than that of the subjects who made short glances to the monitor with long glances to the road. In addition, some subjects continued to perform the secondary task even when the driving was more difficult, such as on curves, while others suspended the in-vehicle task during periods when driving required more resources.

A driver's willingness to engage in non-driving tasks can contribute to driver distraction. Such a willingness is often tied to a lack of experience, and several studies have shown that inexperienced drivers are less able to safely multitask while driving. Inexperienced drivers make longer fixations and scan smaller areas of the visual scene (Mourant & Rockwell, 1972). When performing secondary tasks, young and inexperienced drivers tend to look away from the road with longer and more variable glances. Wikman and colleagues (1998) found that 29% of young drivers had glances of greater than three seconds away from the road, while none of the more experienced drivers made glances that long.

In addition, evidence suggests that attitudes and behavioral differences influence crash involvement (Parker et al., 1992). Deery and Fildes (1999) surveyed 16 to 19 year old drivers and identified several distinct types of driving behavior that varied based on the propensity for risk-taking. In a simulator study, the drivers who had been classified as risky demonstrated impaired attention-management performance in high-workload situations.

Drivers can be categorized based on their behavior when engaged with in-vehicle tasks and their driving performance. Donmez and colleagues (2009) conducted a simulator study in which subjects performed a secondary in-vehicle task while following a lead vehicle. Based on their eye-glance behavior, subjects were divided into three groups using cluster analysis. Subjects in the high-risk group had the longest mean glance duration, as well as the worst driving performance, as measured by the minimum time to collision.

4. Grouping of in-vehicle task elements

Subjects grouped the secondary in-vehicle task elements into blocks of several button presses. The number of elements in these blocks and the block duration was determined by balancing the need to not look away from the road for too long with the desire to take advantage of the benefits gained from task continuity. For example, subjects almost always pressed a certain series of three buttons during a single glance and without returning the hand to the steering wheel between button presses.

A review of the literatures suggests that the ability of a driver to break a particular in-vehicle task into smaller blocks is important for multitasking. Noy and colleagues (2004) found that time-sharing between driving and performing a task is easier when the task is relatively unaffected by interruptions at regular intervals than when the task must be performed continuously. This may be due to the fact that drivers have greater control over task sharing decisions when they are performing tasks that can be interrupted (Salvucci & Macuga, 2002).

Various studies have identified chunking behavior during in-vehicle tasks. For example, Brumby and colleagues (2007) observed that subjects dialing a ten-digit telephone number tended to chunk the number into sets of three digits, three digits, and four digits, with the time between two digits in the same chunk much shorter than the time between chunks. The model developed to explain the chunking behavior assumes an additional time cost to retrieve relevant state information from memory if the strategy chosen disrupts the chunk structure of the dialing task (Brumby et al., 2009).

Chunking may be explained by the observation that people use subtask boundaries as a cue to switch between tasks (Miyata & Norman, 1986; Payne et al., 2007). This is related to the finding that workload decreases at subtask boundaries (Bailey & Iqbal, 2008).

5. Effect of anticipated driving difficulty changes on in-vehicle task performance

Drivers adjust their performance of the secondary task, including decisions about when to initiate the task, based on anticipated as well as current driving difficulty. For example, if the in-vehicle task began as the driver was approaching a curve, the driver would usually delay beginning the task. Similarly, a driver who had nearly completed the in-vehicle task as a curve approached would rush to complete it before the curve started.

This indicates that drivers have a mental model of the resource requirements for the primary and secondary task and are aware of when the combination of the two will pose an unacceptable workload, resulting in an unacceptable primary task performance decrement. This is different from making decisions about how to share resources during multitasking by simply reacting to being overloaded by the secondary task or finding that driving performance is suffering during multitasking.

This aspect of skilled drivers' behavior may be one of the reasons multitasking while driving is not more dangerous than it is. Good drivers know in advance when driving is going to require full attention and adjust their performance of secondary tasks accordingly.

Little research has been done in this area. There is the potential for substantial gains in knowledge about strategies drivers use to safely multitask, and future studies should consider investigating this behavior.

6. Driving performance variability between subjects

There were clear differences in driving performance between subjects during the baseline condition, in which there was no in-vehicle task. This variability is important because how well a driver controls the vehicle will affect how he or she can attend to the secondary task. For example, drivers in the simulator study who had more trouble navigating the curves in the road would often drive off the road if they tried to work on the in-vehicle task while on a curve. As a consequence, these drivers were forced to suspend work on the in-vehicle task while on curves in order to maintain control of the vehicle.

There are several possible contributing factors to the variability in driving performance. First, some subjects may simply have better driving skills than others. These subjects may have had more practice with driving vehicles or may have better senses of spatial awareness and faster reaction times, so that they could more accurately navigate the vehicle around curves and follow speed changes by the lead vehicle.

Studies have shown that drivers vary in how they use the accelerator and brake pedals, how they turn the steering wheel, and the amount of headway they deem safe and comfortable when following a lead vehicle (Fancher et al., 1998; Ohta, 1993). Such these differences in driving behavior have been captured in models as well. For example, Miyajima and colleagues (2007) showed that a driver model based on spectral features of pedal operation signals can be used to accurately model individual differences between drivers. Some models have also focused on the effects of driving practice and experience on performance. For example, Liu and colleagues (2009) developed a training protocol for enhancing driver performance based on a cognitive driver model implemented in ACT-R. With practice, drivers were able to improve their behavior in emergency situations.

The second factor is that subjects may have had differing internal definitions of what constitutes acceptable driving performance. Some subjects worked very hard to maintain a constant lane position and headway, while others appeared satisfied with simply remaining in the lane and not running into the lead vehicle. This factor is likely more related to a driver's desire to perform the driving task well, possibly to gain approval from the experiment supervisor, than to the driver's actual driving ability.

Finally, some subjects may have adjusted to driving in a driving simulator better than others. The fixed-base driving simulator used in the experiment differs from on-road driving in that there is no vestibular feedback, which is especially important when navigating curves.

The last possibility suggests that outcomes may have been different had the study been conducted on the road rather than in a simulator. Numerous studies have shown that the dynamic performance of operators is similar in simulators to on the road (Lincke et al., 1973; Leonard & Wierwille, 1975; McRuer & Klein, 1975; Bertollini et al., 1994). However, the performance of driving tasks such as speed control and lane keeping in fixed-base simulators is less precise than on the road because of a lack of motion cues (McLane & Wierwille, 1975; Blaauw, 1980; Alicandri et al., 1986; Reed & Green, 1999).

Studies have indicated that fixed-base driving simulators are likely to produce poor absolute validity but good relative validity for many measures of driving performance (McLane & Wierwille, 1975; McRuer & Klein, 1975). Reed and Green (1999) found that speed performance was comparable in a fixed-base simulator, but lane-keeping, as measured by the standard deviation of the lane position, was less precise. In addition, they observed that the decrement in performance when subjects performed a secondary in-vehicle task (dialing a cellular phone) was greater in the simulator than on the road, and the difference was magnified for older subjects. They speculated that the absence of danger associated with lane-keeping errors may contribute to larger errors in the simulator than on the road.

The sensitivity of driving simulators to within-subject factors suggests that they could be useful for investigating responses to in-vehicle tasks. However, the sensitivity to between-subjects factors, along with the finding by Blaauw that lane-keeping performance measures are more sensitive to subjects' driving experience differences in simulators than on the road (1980; 1982), indicates that it is important to compare a subject's driving performance during a task to that subject's baseline performance.

7. Strategies for switching between driving and the in-vehicle task

Drivers use different strategies to decide when to switch between driving and the in-vehicle task. There were notable between-subjects differences in the frequency of shifting between tasks. A glance strategy in which subjects employ long glances to the monitor and long glances to the road is nearly as risky as one where subjects make long glances to the monitor and short glances to the road. However, the first strategy indicates that the subject is switching between tasks less frequently. This could be caused by cognitive capture, indicating that the subject's attention has been captured by each task, with the result that the subject forgets to switch back to one task when working on the other. Some people may be more susceptible than others to cognitive capture.

8. Strategies for maintaining driving performance

Drivers employ different strategies to attempt to maintain driving performance. Adding an in-vehicle task with a significant visual component can overload drivers, who may respond by abandoning the task, reducing the task priority, modifying the task, reducing the task quality, or postponing execution of the task in order to perform acceptable on the driving task (Wierwille, 1995). In the simulator experiment, there were noticeable differences in the strategies drivers used in an attempt to maintain driving performance.

Based on interviews following the simulator study, some subjects who chose to perform the in-vehicle task quickly felt there would be less of a decrement in driving performance if they rushed to complete the in-vehicle task in order to return all attention to the driving task sooner. Others performed the in-vehicle task slowly and with many breaks, feeling that this would allow them to better maintain driving performance.

This difference in resource sharing strategy is significant because drivers who are willing to tolerate very poor driving performance for a short time are probably at greater risk of being in a collision. Such drivers would be much less able to respond to changes in the driving environment such as the sudden braking of a lead vehicle. Horrey and Wickens (2007) pointed out that the unsafe conditions leading to crashes reside not at the mean of a distribution but at in the tails, indicating that long glances to a display more problematic than many shorter glances. Drivers who increase the duration of the task, which results in more frequent but less serious decrements in driving performance, are able to perform certain compensatory behaviors such as chunking and anticipatory inhibition of the secondary task.

9. Visual search during in-vehicle task

Strategies for an in-vehicle task vary based on whether controls are in predictable locations or a visual search is required. Based on exit interviews with subjects, an important distinction was made between pressing the fixed-location buttons and those that varied from trial to trial. For the static buttons, subjects often started to reach to the button without looking at the screen or with only a quick look to get the approximate location of the screen. Once close to the monitor, subjects would perform a glance to confirm the remembered position and guide the finger to the exact button location. In contrast, for the variable-location buttons, subjects would generally locate the button on the screen prior to beginning a reach. If they had looked back to the road during the reach, they would then look back to the monitor to confirm the location before pressing the button. This behavior suggests that drivers adapt their task element chunking based on task demands, such as the level of detail needed in a visual search.

10. Glance behavior based on monitor location

The glance behavior changes based on the location of the monitor for the in-vehicle task. Glance strategies that drivers used to perform the in-vehicle task changed when the monitor was farther away. Though the approximate duration of each glance remained about the same, the number of glances increased, along with the total glance time.

Dukic and colleagues (2005) also found changes in glance behavior when a target button was placed in different locations. In particular, the time off road increased as the angle between the normal line of sight and the button location increased. It is difficult to compare their results precisely to the present simulator study, as their in-vehicle task, a simple button press, required only one glance.

11. Feed-forward and feed-back control for reaches to the monitor

Drivers utilize both feed-forward and feed-back control when performing in-vehicle tasks that require reaches. The difference in strategy for pressing a fixed-location button versus a variable-location button demonstrates that a model of driving with a physical secondary task should include both feedforward and feedback control. The initial reach, especially to a fixed-location button, was often performed in an open-loop fashion with respect to visual feedback, with the driver looking at the road rather than the hand or display. However, the final portion of the reach always used closed-loop control.

12. Physical interaction with in-vehicle interface

Drivers may physically interact with the interface for an in-vehicle task in different ways. For any task that requires multiple button presses, it is important to understand how the subject presses the buttons in order to accurately model the task. In this case, most subjects used only one finger to perform the button presses. However, some subjects used multiple fingers, which could allow them to perform the in-vehicle task more rapidly. In addition, some subjects kept their right hands near the monitor for multiple button presses rather than returning them to the steering wheel, even when they looked back to the road between button presses.

Queuing Network – Model Human Processor (QN-MHP)

Introduction

The QN-MHP is a model of human cognition. The QN-MHP was developed in an effort to model concurrent activities in a truly concurrent fashion. It uses one underlying context-free mental architecture rather than having separate task-specific modeling modules. The QN-MHP provides a modeling and simulation architecture for generating real-time mathematical modeling of parallel and complex activities.

The QN-MHP unites separate modeling theories and processes, building off of them to create a new computational architecture that combines the mathematical theories and simulation methods of queuing networks (QNs) with the symbolic and procedural methods of GOMS and the Model Human Processor (MHP), described previously in the background section. Previous research has shown that QNs are well-suited for modeling parallel activities and complex mental architectures because of their network architecture (Liu, 1996; Liu, 1997). In addition, symbolic models such as GOMS and the MHP are useful for generating a person’s actions in specific task situations. Combining the models makes it possible to model the complex cognitive interactions between a person and the task environment.

Basic Model Structure

The architecture of the QN-MHP is essentially that of a queuing network. A detailed description of the original QN-MHP model is provided by Feyen (2002). In the current version, there are 26 servers that represent different functional modules of the human perceptual, cognitive, and motor information processing system. These servers are divided into three subnetworks: perceptual, cognitive, and motor (Figure 5.2). Entities, which represent stimuli or chunks of information, enter the perceptual subnetwork carrying perceptual information. They are processed by the cognitive subnetwork and converted into actions. The motor programs for these actions are assembled in the motor subnetwork, which sends the motor command to the HUMOSIM Framework. The Framework then completes the action and reports back to the QN-MHP on the outcome.

Driving

The act of driving is a hierarchical combination of navigation, guidance, and vehicle control (McRuer et al., 1977). The driver must decide where to direct the vehicle while also maintaining lateral and longitudinal control of the vehicle to avoid leaving the lane and crashing into a car in front. In addition, it is necessary to scan the roadway for obstacles, make glances to the rearview mirror to look for hazards from behind and emergency vehicles, and check the blind spot when making a lane change.

In its most basic form, two main aspects of driving are fundamental. Lateral control, commonly called steering, is performed using the steering wheel, and longitudinal control consists of operating the accelerator and brake pedals in order to achieve a desired speed or following distance from some lead vehicle.

The QN-MHP treats these aspects of driving as separate goals that can conflict with each other. Hence, driving, often considered as a single task, is considered to be a form of multitasking when modeled in the QN-MHP. Lateral control entities are given a higher priority than longitudinal control entities, because subjects in the driving simulator experiment tended to prioritize keeping the car in its lane over maintaining a constant headway to the lead vehicle, especially when they traversed curves.

Lateral Control

The model has the ability to make steering corrections to keep the vehicle in its lane while navigating curves of different radii. It can make decisions about the magnitude of a lateral control correction and the timing of when to implement the correction. The steering model, which is described more thoroughly in previous work (Tsimhoni, 2004), combines several concepts, including a hierarchical task structure, the flow of visual input, the roles of focal and ambient visual systems, a near-far dichotomy, and concurrent cognitive processing.

Steering itself is actually a hierarchical combination of subgoals for the perception of visual information about the vehicle, the choice of steering strategy, and the coordination of the steering correction. These subgoals are accomplished in separate servers in the QN-MHP, so they may be processed concurrently rather than serially. The magnitude of the necessary steering angle is calculated not at the task level, but at a lower level of processing in the model.

The relevant visual inputs for the steering task are splay angle of a lane edge, which is the angle in the optical projection between a straight line and the line perpendicular to the horizon and is independent of forward speed, and optical flow, the movement of an environmental point in the visual field (Loomis & Beal, 1998; Chatziastros et al., 1999; Wann & Land, 2000). In the QN-MHP, the servers account for the estimated time for visual processing, so that the inputs are available to be used in calculations without actual processing of the road scene. The information provided by the perceptual subnetwork includes the vehicle lateral position, the yaw angle, the curvature of and distance to upcoming curves, and the distance remaining in a current curve.

Steering uses both focal and peripheral vision. The research on visual guidance while driving has distinguished between the roles of the focal and the ambient visual systems (Mourant & Rockwell, 1970; Leibowitz & Owens, 1977; Summala, 1998; Owens & Tyrrell, 1999). Most visual input for immediate steering is perceived by the peripheral visions, with typical areas of visual input being in the lower periphery, around lane markers and directly in front of the vehicle.

Steering can be separated into two phases: a guidance level, in which anticipatory open-loop corrections are made, and a stabilization level, which involves closed-loop connections (Donges, 1978). As drivers enter a curve, they make anticipatory glances of one to two seconds (Land & Lee, 1994). During negotiation of the curve, they make glances at the tangent of the curve. The QN-MHP uses similar notions of near and far, with peripheral perception of visual inputs from lane markers and straight ahead at up to one second in front of the vehicle and foveal perception of visual inputs from greater distances, about two to four seconds down the road. In curves, the gaze is directed around the center of the lane at the point of tangency, and the information is used for determining the road curvature and heading changes.

To perform lateral control, the cognitive subnetwork of the QN-MHP triggers eye movements towards the desired stimuli in the road scene, directs information for analysis in the cognitive subnetwork, and generates actions based on the results. To model the fact that all of these activities can occur concurrently, the consecutive processes in the QN-MHP need not wait for their predecessors to finish before they can start.

Longitudinal Control

Longitudinal control is a new addition to the QN-MHP. The longitudinal control model used is based on the errorable car-following driver model developed by Yang and colleagues (2008). The errorable model was designed to make mistakes similar to some that human drivers make, to generate accidents and near-accidents for research purposes.

The errorable car-following model was developed using data from the Road-Departure Crash-Warning System Field Operational Test (LeBlanc, 2006). The data suggested that as long as the desired vehicle state, in this case speed, was roughly achieved, the driver would accept some deviations due to things such as the imperfection in control, perceptual limitations, and exogenous disturbances.

The model is an expanded version of a model that performs accurate car-following. The modeling approach considers driving as a stochastic process, rather than modeling stochastic behavior as noise. The car-following model uses the sliding mode control technique to represent how drivers typically regulate range or time headway in addition to non-zero range-rate. It mimics a human driver's behavior by constraining the vehicle states on a sliding surface that is defined as zero range error.

The errorable driver model adds three types of error-inducing behaviors to the basic car-following model: perceptual limitation, distraction, and time delay (Figure 4.1). Perceptual limitation is modeled by imposing a visual limitation on the perceivable changes in range and range-rate. To include the effects of driver distraction, actual longitudinal driving data was analyzed to identify properties of distracted driving, including the duration and frequency of distracted periods. A random distraction generator with output that could match the empirical data was then added to the model. Time delay, due to neuromuscular and cognitive processing, was simulated by creating a time delay sequence using a probability distribution of time delay from the experimental data.

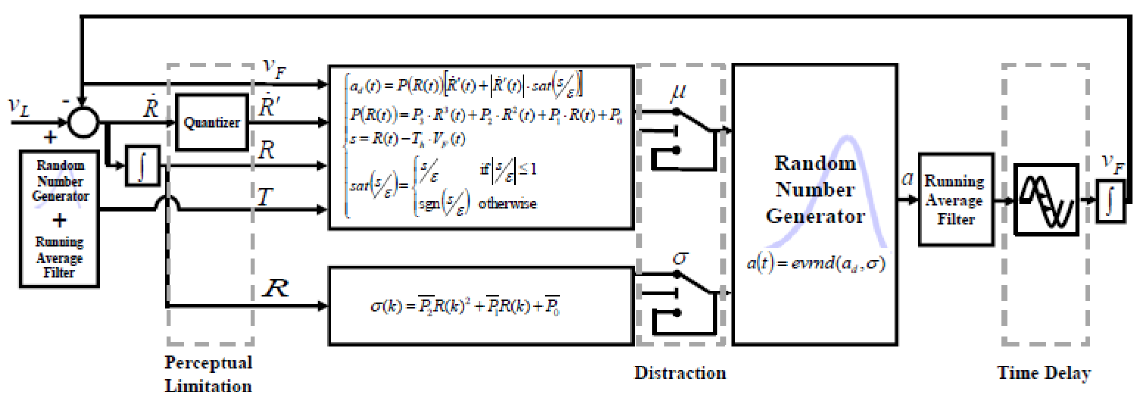


Figure 4.1. Diagram of the errorable stochastic driver model of longitudinal control (Yang et al., 2008).

When implementing longitudinal control in the Virtual Driver, the basic car-following model was used, with the addition of the perceptual limitation model (Figure 4.2). Driver distraction is represented in the Virtual Driver by the resource sharing required to complete the in-vehicle task while driving. Time delay is also already built in to the QN-MHP. Therefore, the Virtual Driver's longitudinal control model uses equations from the car-following model, but substitutes $\dot{R}'$ for $\dot{R}$, where $\dot{R}'$ is the perceived value of the range-rate.

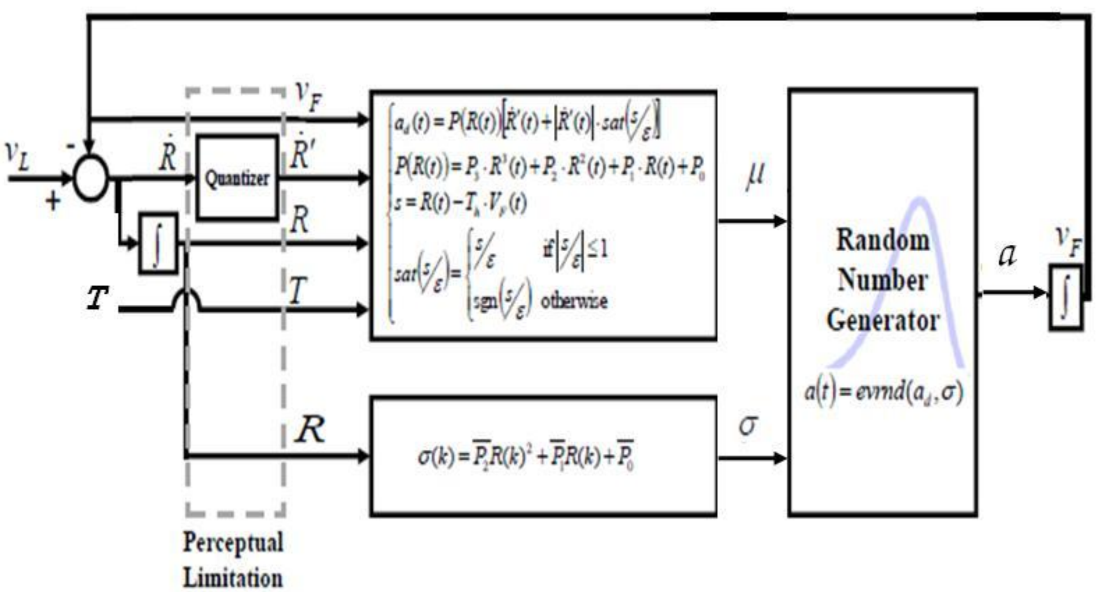


Figure 4.2. Diagram of the errorable stochastic driver model of longitudinal control (adapted from Yang et al., 2008).

Limitations to Driving Model

There are several limitations to the current driving model. These include perceptual inputs, as well as how the model would handle driving in a real-life situation. Additions to future versions of the model would allow for more robust driving behavior.

Vestibular inputs, which contribute to balance and the sense of spatial orientation, can have considerable effects on speed adjustments, especially on curves (Reymond et al., 2001). However, for the sake of simplicity, these were not considered in the current model. In future versions of the model, the use of vestibular inputs could be simulated by decreasing the error between actual and perceived changes in range-rate.

In addition, the model is not equipped to deal with other traffic on the road, apart from a single lead vehicle. For example, the model cannot check for other traffic to change lanes to pass nor monitor following vehicles.

In-Vehicle Task

The in-vehicle task is modeled in the QN-MHP as a third task, in addition to lane-keeping and longitudinal control. It has a lower priority than either of the driving tasks, so that if there is conflict between the entities, the model delays performing the in-vehicle task in favor of maintaining driving performance. The model was designed this way to match the results of the simulator experiment and the likely behavior of actual drivers on the road, who are expected to sacrifice speed on an in-vehicle task in order to maintain safe driving performance.

An important part of modeling the in-vehicle task is generating an accurate NGOMSL-style task analysis. This analysis represent the procedural part of the long-term memory, which stores information about how to accomplish a task.

Due to the structure and requirements of the in-vehicle task, the model must be able to perform certain actions. These actions, along with a description of how they are implemented in the QN-MHP, are outlined below.

Make simple decisions about what action to do next

Most decisions about actions are made in the Central Executive server. The model references the task analysis to determine the next action that is necessary in order to accomplish the task goal. The appropriate processing logic and information routing are selected based on the current step in the task.

Recall from long-term memory the steps needed to perform the task

The decision to recall information from long-term memory is made in the Central Executive server, based on the task analysis for the in-vehicle task. Processing is halted for the length of time needed to retrieve the information from the task array representing the long-term memory.

Conduct a visual search for a button

Visual search is not currently modeled in the QN-MHP, though it was included in some previous versions of the QN-MHP (Tsimhoni, 2004; Lim, 2007). A visual search routine could be reintroduced at a later time. Instead, the model halts processing for the length of time that would be needed in order to conduct a visual search. To simulate the difference between searching for a fixed-location button and a variable-location button (Driving Behavior 9), the processing pause is longer when the location of the target varies from trial to trial.

Reach to and press a button

At the beginning of the simulation, the HUMOSIM Framework provides a list of available reach targets to the QN-MHP. The available targets must map to those defined in the task list. The model uses input from the task analysis to make the decision at the Central Executive server that a reach is required and to select the target. The model may initiate the reach before the eyes are on the monitor, but only if it expects that there will be time to glance to the monitor soon after the reach is begun so that the hand does not hover in the air for more than a few seconds. To represent the difference between pressing a fixed-location button and a variable-location button (Driving Behavior 9), the amount of time the model requires for the glance is longer if the target is a variable-location button.

Store information to and retrieve information from the short-term memory

To track progression on the task, the model needs to store information about its progress after completing one step, then retrieve the information to determine what the next step should be. This requirement is included as a step in the task analysis. Entities are routed to the short term memory servers to represent storage and retrieval of information.

Dual Task Performance

Originally, the QN-MHP was designed to process one task at a time, but Tsimhoni (2004) added dual goal processing. The QN-MHP accomplishes dual goal processing by using two separate goal lists, consisting of the subtasks needed to accomplish each goal. These two lists can be processed simultaneously and independently of each other, simulating a person's ability to multitask.

The queuing network structure of the model makes it possible to represent multitasking in this fashion. Competition between goals occurs at the server level, because the entities flowing through the network are associated with a particular goal. Priority decisions that result in processing one entity ahead of another are made in real time. These decisions are also made locally, at the server level, rather than centrally, at the executive level.

HUMOSIM Framework

Introduction

The HUMOSIM Framework consists of an interconnected, hierarchical set of posture and motion modules that control aspects of human behavior such as gaze and upper extremity motion (Reed et al., 2006). The Framework is innovative in that it provides a comprehensive system for motion simulation and ergonomic analysis that is independent of any particular human modeling system. It incorporates modules that are lightweight algorithms based on closed-form equations and simple numerical methods that can be implemented in any computer language.

Important aspects of the module algorithms are "behavior-based", using results from laboratory studies. The empirical models developed from these studies are used to resolve the large amount of redundancy that is inherent in the human kinematic linkage.

Physical Representation of Environment

A major advantage of the Virtual Driver over previous models using the QN-MHP is the detailed representation of the physical environment that is made possible by the connection to the HUMOSIM Framework. If the appropriate measurements are taken, it is possible to duplicate an existing workstation for the manikin to interact with. Similarly, a new workstation could be created digitally.

Rather than using estimated times from a look-up table, movement times can be determined by asking the manikin to perform certain motions in the workspace. With the appropriate constraints on movements speed, it is then possible to determine the time required to reach to a certain location.

Physical Capabilities of Driver

The physical characteristics of the driver can be modeled using the HUMOSIM Framework. For the purposes of modeling the simulator experiment, the most important dimensions are stature and reach capability. Driver strength could also be relevant for the far monitor locations. However, this is only likely to affect results if the strength of the subject is well below the capabilities of the average driver, which was not the case in this study.

The Framework is also capable of accounting for the physical difficulty of a task. Reed and colleagues (2003) studied the subjectively reported difficulty of reaches to push-button targets located throughout the driver's right-hand workspace. A reach difficulty model based on this research is implemented in the HUMOSIM Framework. Given a reach target location and driver stature, the model returns the predicted reach difficulty on a scale from 1 to 10, with 1 as the easiest reach and 10 as the boundary of achievable reaches, or a maximally difficult reach.

Motor Control and Coordination

The HUMOSIM Framework can simulate the coordination of body segments and subsystems of segments during complex whole-body motions (Reed et al., 2006). There are three levels of coordination that the Framework is capable of representing. Individual modules produce coordinated patterns of behavior within a subsystem of segments, modules communicate to produce inter-region coordination, and multiple subsystems cooperate to control common body segments during complex tasks.

For the purposes of modeling driving with the in-vehicle task in the Virtual Driver, only a subset of the available modules is needed. Looking at the monitor requires coordination between the eye, neck, and trunk, especially when that glance is combined with a reach. In addition, reaching to the monitor requires coordination between the segments of the arm. Coordination with the torso is also required for reaches to the far monitor positions. In practice, a person's entire body is involved in long seated reaches, so the movement simulations in the current study used the whole body.

The Virtual Driver: Integration of Cognitive Model and Physical Model

Introduction and Motivation

The main focus of this modeling work was the integration of a model of human cognition with a physical human model. This type of model, which can make decisions based on the physical environment and carry them out by issuing motor commands to the physical representation, does not currently exist in any complete form.

The lack of any real integrated physical and cognitive human model is somewhat surprising for a couple of reasons. First, many tasks that humans complete as acts of daily living contain significant physical components. Though the decision-making processes could be simulated using existing models, there is no way to model the full task performance. Second, research has shown that cognitive tasks may affect concurrent physical tasks (e.g. Pellecchia, 2003; Alexander et al., 2005) and vice versa (e.g. Kerr et al., 1985; Faulkner et al., 2006). Therefore, it is not possible to accurately capture human behavior during such a combined task using a solely cognitive model. In addition, it is difficult or impossible to predict human performance in novel task environments if there is a significant physical component to the task.

The development of the integrated model makes it possible to study and understand human behavior during task performance more thoroughly than ever before. In the future, it could be used to design new workstations that improve human performance and safety.

Model Structure

Conceptual Structure

In the broadest terms, the QN-MHP is responsible for modeling the cognitive workings of the human driver, while the HUMOSIM Framework models the physical workings. The QN-MHP represents the mind and the HUMOSIM Framework is the body.

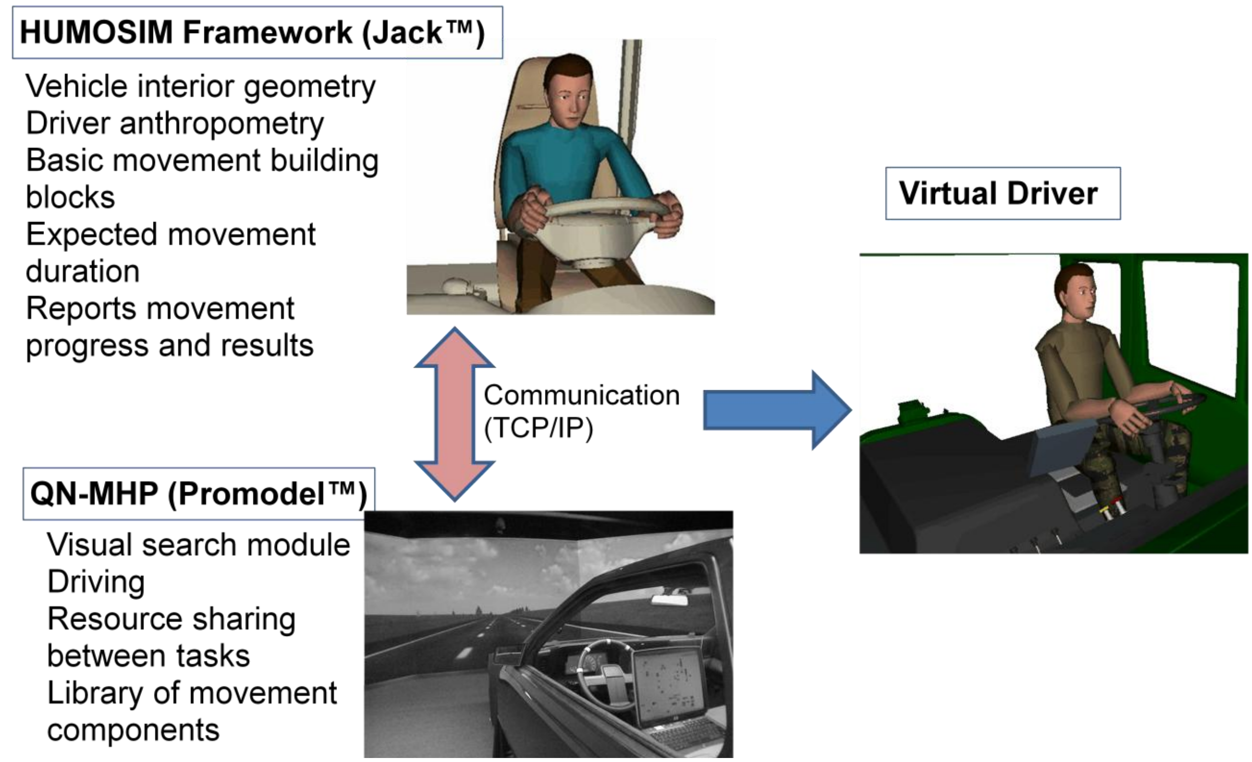


Figure 4.3. The Virtual Driver is composed of the QN-MHP and the HUMOSIM Framework.

Model Connection

The two models are connected in such a way that they can send information between them throughout the performance of the dual tasks. This simulates the perceptual information input, motor command output, and feedback input that occur in humans.

The interaction between the models begins when the QN-MHP sends an initialization request to the HUMOSIM Framework at the beginning of the task. This is comparable to a person's decision to begin collecting information about the environment prior to beginning to work on a task.

The HUMOSIM Framework then provides the QN-MHP with perceptual information about the physical environment and task constraints. This includes information about the simulated human's dimensions, such as height and reach range. It details the available gaze and reach targets. The Framework also provides time and difficulty estimates for reaches to each target.

The QN-MHP uses the information about the task environment and the human's physical abilities to make decisions about how to perform the task. These include choices of where to direct the gaze, how to perform a reach, and when to shift attention from the primary to the secondary task. These decisions are converted to outputs that are sent to the HUMOSIM Framework, simulating how motor commands are sent to the body.

The HUMOSIM Framework accepts the motor commands and carries out the intended actions. It constrains the model's actions to match human capabilities, limiting the model to realistic movements. The Framework then sends information about the outcome of the actions, including progress and time of successful completion, back to the QN-MHP.

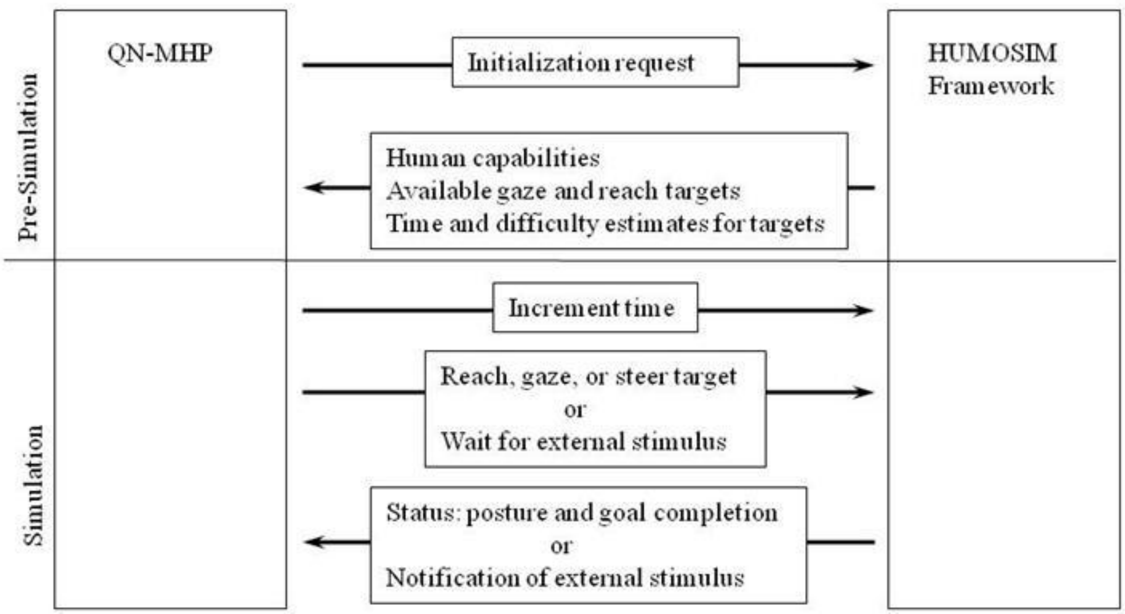


Figure 4.4. The connection between the QN-MHP and the HUMOSIM Framework, including information flow between the two models.

Modeling Driving with an In-Vehicle Task

The act of driving while completing an in-vehicle task is modeled as three separate tasks, with a distinct type of entity representing information for each task, in the Virtual Driver. There is separate processing and routing logic at each server for the different types of entities.

For the steering task, the model collects data on the heading of the road and the heading of the vehicle when the gaze is directed at the road. It then performs a calculation to determine if a heading correction is necessary to keep the car within the “dead zone”, the lateral space on the road in which the driver would like to have the car remain.

By looking ahead at the road, the model can determine if the road heading will change soon, enabling it to react to anticipated changes in the driving task (Driving Behavior 5). If a large steering correction will be likely in the near future, the model will keep its gaze on the road rather than directing the gaze to the monitor to work on the in-vehicle task.

At the same time, entities related to the longitudinal control task are undergoing processing to determine if it is necessary to for driver to depress the accelerator or brake pedals. Information regarding the location and speed of the lead vehicle is collected when the gaze is on the road. If the range and range rate to the lead vehicle are outside an acceptable range of values, the driver performs a longitudinal correction.

For both the lateral control and longitudinal control, the QN-MHP sends a motor command to the HUMOSIM Framework if a correction is necessary. The Framework then performs the requested movement of the arm or leg and reports back to the QN-MHP.

Entities for the in-vehicle task are being processed in the servers at the same time, though they have lower priority than the entities for the driving tasks. As such, they may be required to wait in queues prior to being processed if the QN-MHP is busy, indicating a high workload.

The QN-MHP can perform some processing of in-vehicle task entities when the gaze remains on the road. These include actions such as storing to and recalling from memory. When the eyes are required for the task, such as when the next step in the task is to locate and press a button, the in-vehicle task entities request the eyes. The model then checks whether the driving performance is within acceptable bounds and whether the driving difficulty will change soon. If it determines that it can afford a glance to the monitor, the QN-MHP sends a motor command to the Framework to perform the glance.

The virtual driver must reach to the monitor to press buttons for the in-vehicle task. Such reaches are performed in two steps, representing the division between feedforward and feedback movements (Driving Behavior 11). When a reach is desired and the driver is currently looking at the monitor or expects to be able to look at it within a few seconds, the QN-MHP sends a motor command for a reach to the Framework, which simulates a reach to the hover position, a few inches away from the monitor. The initial reach is performed using feedforward control. When the gaze shifts to the monitor and the desired button is located, the QN-MHP sends a second reach command to the Framework, which simulates reaching to the button on the screen using feedback control from the visual input.

Representing Features of Driving Behavior in the Virtual Driver Model

Given the structure of the Virtual Driver model described above, there are various ways to represent the features of driving behavior identified earlier. Some possibilities are described below. Not all features of driving behavior are currently represented in the model, but it would be possible to incorporate all of these in subsequent versions of the model.

1. Secondary task scheduling: The decision to perform secondary in-vehicle tasks is based on the difficulty of the primary driving task.

In the case of the Virtual Driver and other models with elements of queuing networks, this behavior should emerge naturally from the model. As the primary driving task, which is assigned higher priority at the beginning of the modeling session, increases in difficulty, the number of entities in the network associated with that task will also increase, due to an increase in processing time required. Because of the higher priority of these entities, servers will select these entities for processing over the entities associated with the in-vehicle task, so the model will concentrate on performing the driving task and neglect the in-vehicle task.

2. Effect of reach capability on in-vehicle task difficulty: Reach capability affects the difficulty of the in-vehicle task, especially for extreme monitor locations.

The easiest way to model this characteristic of the secondary task would be to assign a reach difficulty factor to each target location. This factor would vary based on both target location and driver stature (Reed et al., 2003). The model could account for this factor when making decisions related to the timing of reaches.

3. Effect of prioritization of dual tasks on performance: Individual decisions about prioritization of driving versus the in-vehicle task, which are impacted by the amount of risk a driver will accept, will affect performance on both.

This difference between subjects in assigning resources when multitasking could be modeled in two different ways or using a combination of both. First, the probability function that is used to determine when a subject looks back to the road from the monitor could be adjusted to create longer glance times. In addition, the priority assigned to each of the subtasks could be changed so that there is less of a difference in priority between the driving subtasks and the one for the in-vehicle task. This would result in more of the processing resources being devoted to the performance of the in-vehicle task.

4. Grouping of in-vehicle task elements: Drivers group in-vehicle task elements into blocks.

The grouping behavior displayed by subjects in the simulator experiment could be modeled by decreasing the probability of looking away from the monitor between button presses within blocks and increasing the probability between blocks. A downside to modeling the chunking behavior in this way is that it requires the modeler to determine the locations of natural boundaries in a task. Due to the strong influence of cultural norms on chunking behavior, it may be impossible to avoid this requirement.

5. Effect of anticipated driving difficulty changes on in-vehicle task performance: Drivers anticipate changes in the driving task difficulty and adjust the performance of the in-vehicle task accordingly.

This feature can be modeled by including a "look ahead" component to the driving behavior. The driver develops a curve workload estimate based on the curvature of the upcoming road and does not initiate the secondary task, or interrupts the task if it has already begun, when the anticipated workload within a certain timeframe is projected to exceed a level that is deemed maximally acceptable.

6. Driving performance variability between subjects: Drivers differ in driving performance, even when there is no in-vehicle task.

Differences in driving ability could be modeled by adding a stochastic term to the response of a driver to discrepancies between the desired state of the vehicle and the actual state. This term could have a multiplier that would increase for drivers who are less experienced or less capable. Differences in opinions about acceptable driving performance could be modeled by inserting a "dead zone", or a range of discrepancies in which no correction occurs. A large dead zone would represent a driver who accepts poor performance on the driving task, while a small dead zone would represent a driver who feels that it is necessary to correct even minor differences between desired and actual vehicle state.

7. Strategies for switching between driving and the in-vehicle task: Drivers use different strategies to decide when to switch between driving and the in-vehicle task.

Strategies for switching between tasks could be represented in a model by adjusting the probability of glancing between the road and monitor. Subjects who switch between tasks more frequently would be modeled as having a greater probability of shifting attention back to the road after each button press. In contrast, subjects who are prone to cognitive capture would be modeled with a decreased probability of shifting between tasks, even as the time spent on the task increases.

8. Strategies for maintaining driving performance: Drivers employ different strategies to attempt to maintain driving performance.

The model could represent this variation in behavior by a combination of altering the driver's willingness to engage in risky behavior and adjusting the priorities of completing the in-vehicle task and maintaining good driving behavior. Drivers who rush through the secondary task in order to return to the driving task more quickly would have a greater willingness to engage in risky behavior and would assign greater priority to completing the in-vehicle task. If a driver with these characteristics also displays poor driving performance, the probability of collision will increase greatly.

9. Visual search during in-vehicle task: Strategies for an in-vehicle task vary based on whether controls are in predictable locations or a visual search is required.

There are two steps that are necessary in order to model this. First, the visual search time should be considerably shorter for the fixed-location buttons. Drivers will know approximately where to look to find these and will only need the glance in order to refine the location. Second, the reach behavior of the model should be different for the two types of buttons. In both cases, the model should be allowed to begin a reach prior to looking at the monitor, because the driver will have an internal model that includes the location of the monitor. However, the reach should only begin when the driver expects to have enough time to glance to the monitor in order to complete the reach within a few seconds of the start of the reach. For reaches to the fixed-location buttons, the driver knows that the glance will take less time than for reaches to variable-location buttons. Therefore, the model should be more likely to begin a reach when the time available to glance is limited if the reach is to a fixed-location button rather than a variable-location button.

10. Visual search during in-vehicle task: The glance behavior changes based on the location of the monitor for the in-vehicle task.

This behavior should emerge naturally from the Virtual Driver model. The presence of the task will encourage the driver to look at the monitor. At the same time, the greater difficulty associated with reaches to the far monitor will decrease the probability of the driver reaching to the monitor during any given glance. In addition, the reach will take longer, so the driver will be able to complete a smaller proportion of the task before feeling it is necessary to look back to the road.

11. Feed-forward and feed-back control for reaches to the monitor: Drivers utilize both feed-forward and feed-back control when performing in-vehicle tasks that require reaches.

Modeling the difference in strategy for reaching to fixed-location buttons as opposed to variable-location buttons will likely represent the results of this driver behavior as well. However, to accurately capture the behavior, it is also important to address the communication between the cognitive model and the physical model. Feed-forward reaches can be performed with a single command from the cognitive model, but feed-back reaches should require additional input from the cognitive model as it processes visual inputs related to the reach.

12. Physical interaction with in-vehicle interface: Drivers may physically interact with the interface for an in-vehicle task in different ways.

The difference in where subjects position their hands could be modeled by adjusting the value of some multiplier that contributes to the probability of returning the hand to the steering wheel between button presses. At this point, the model is not sufficiently developed to demonstrate the actual difference in using one finger as opposed to multiple fingers, but it could be represented by making the movement time to press a button shorter when the subject uses more than one finger.

Mapping of Model Elements to Motor Control Concepts

The Virtual Driver model contains representations of several important motor control concepts that were discussed previously. The implementation of these concepts in the Virtual Driver is discussed below.

Internal Model

An internal model of the driver's physical capabilities and surroundings is contained in the HUMOSIM Framework. This includes information about the driver's reach capacity and strength, as well as locations of relevant objects in the task environment. The Framework sends information about these dimensions, such as time and difficulty estimates, to the QN-MHP so that they may be used in making decisions about how to complete the task.

The QN-MHP also contains an internal model of the driver's cognitive capabilities. This is used to predict if the driver will be overwhelmed by an impending cognitive load. If this is likely, the model will make decisions that will adjust the workload so that this does not occur.

Perceptual Input

The QN-MHP requires certain information about the driver's environment in order to complete the driving and in-vehicle tasks it is programmed to perform. Some of this information is assumed to have been learned prior to the start of the task so that it now exists in an internal model. However, much of the information the QN-MHP needs is obtained in the form of perceptual input, relayed by the HUMOSIM Framework.

Currently, all of this information is visual. The Framework tracks the gaze trajectory and sends information that would be available to a driver based on the current gaze target to the QN-MHP.

Motor Actions

There are several steps that the Virtual Driver takes in order to perform an motor action. First, the action is selected, based on the steps in the task analysis and knowledge of the task environment. Next, a motor command is sent to the HUMOSIM Framework from Server Z, which represents the primary motor cortex. At the same time, a copy of the motor command is sent to Server X, which represents the somosensory cortex and is involved in the collection of feedback information.

After the Framework has received the motor command and started an action, it begins to send feedback from the motor action to the QN-MHP. These messages include information about the current state of the physical system and the progress made toward completing the action. Currently, the feedback takes the form of the current location of the hand or eyes and the percent of progress toward the goal. In the future, more detailed feedback, including joint angles and level of discomfort, could be included. The QN-MHP can use this information when making subsequent decisions and may even decide to abort the current motor action by sending a new action to the Framework.

Open- and Closed-Loop Movements

The Virtual Driver is capable of both open-loop and closed-loop movements. Open-loop movements are performed with no feedback. Experience with task environment and a correct internal model allows the model to make a reach towards a general area without visual feedback.

In contrast, closed-loop movements require feedback but enable greater precision. In order to complete a reach to a specific location, such as a button on the display, the model requires that the gaze be directed at that location.

Motor Programs

The HUMOSIM Framework contains a large number of motor programs that the QN-MHP can use as building blocks to assemble a movement. Examples include programs for reaching with a hand, gaze transition, and shifting the torso. The QN-MHP determines the action necessary to produce the desired outcome and issues a command to the Framework for that action. The Framework then coordinates joint angles and timing to produce a realistic movement.

Modeling Differences Between Drivers

A very important part of the Virtual Driver model is the ability to model differences between drivers. The unsafe driving behaviors that lead to crashes lie at the tails of a distribution rather than at the mean (Horrey & Wickens, 2007). Therefore, it is much more important to consider the performance of individual drivers rather than to look at aggregate measures of driving performance over the entire range of the driver population.

Subject Physical Characteristics

The physical characteristics of the driver are modeled in the HUMOSIM Framework, including stature and reach capability. By combining reach capability and target location, the Framework assigns a reach difficulty to each monitor location. This makes it possible for the Virtual Driver to model how reach capability affects the difficulty of the in-vehicle task (Driving Behavior 2). The QN-MHP accounts for this difficulty when deciding how to time reaches to the monitor during performance of the in-vehicle task.

Task Prioritization and Risk Taking Behavior

Even when given the same instructions about how to prioritize the driving and secondary tasks, some drivers assign greater priority to the driving task than others (Driving Behavior 3). This is included in the model by adjusting the relative priorities of the driving tasks and the in-vehicle task, which results in changes in how rapidly the servers begin to process the entities associated with each task. A driver who places greater priority on the in-vehicle task is also likely to engage in more risky driving behavior, so the factors determining how the gaze moves between the road and monitor will also be adjusted.

Differences between drivers in the tendency to engage in risky behavior influence the willingness of drivers to neglect the driving task (Driving Behavior 3). Drivers who are willing to take greater risks will make longer glances to the in-vehicle display and shorter glances to the road. This is modeled by changing the conditions under which the driver is willing to look at the monitor and the probability of looking back to the road. Riskier driving behavior is represented in the model by a decrease in the minimum headway and the minimum time to line crossing that the driver will accept when starting to glance away from the road. Once the risky driver is looking at the monitor, the probability of looking back to the road after a certain amount of time is lower.

In addition, a risky driver is more likely to tolerate operating at the edge of safe driving performance. To represent this in the model, the dead zones in which the driver judges that no steering correction and longitudinal correct are necessary are larger for risky drivers.

Driving Performance

Drivers differ significantly in their driving behavior even when they are not performing in-vehicle tasks (Driving Behavior 6). These differences are represented in the model by adding a stochastic term to the desired steering and longitudinal control responses for all drivers to determine the actual responses. This stochastic term is larger, on average, in the model of a driver who displays poor driving performance. Driving performance is also affected by risk-taking tendencies, so the changes in the dead zones for steering and longitudinal corrections also apply to driving performance.

Task Strategies

Several different behaviors could be considered types of task strategies. These include grouping task elements into blocks (Driving Behavior 4), differences in switching between tasks (Driving Behavior 7), and approaches to maintaining driving performance (Driving Behavior 8).

A block of task elements is defined by a short amount of time between button presses within the block compared to the amount of time between blocks. In addition, a block is completed in a single glance and with one reach to the monitor. This behavior is captured in the model by adjusting the probability of looking back to the road after each button press so that the probability is lower within a block than between blocks.

Differences in the frequency of switching between tasks may reflect the susceptibility of the driver to cognitive capture. A driver who is more prone to cognitive capture is modeled by decreasing the probability of moving the gaze between the monitor and road.

The different approaches that drivers use to maintain driving performance result in more or less risky driving behavior. In the simulator experiment, drivers who attempted to achieve a higher average driving performance often preferred to rush through a task when the driving workload was about to increase. This strategy for maintaining driving performance is modeled by changing the parameters to permit more risky driving behavior for a short period of time if the in-vehicle task is nearly complete. In contrast, drivers who focus on maintaining a consistent driving performance are modeled by keeping the settings for less risky driving performance in place at all times.

Physical Interaction with In-Vehicle Task

The only physical interaction with the monitor for the in-vehicle task that is currently modeled is the hand location throughout the task (Driving Behavior 12). Some drivers in the simulator experiment preferred to keep the right hand near the monitor in a "hover" position throughout all or most of the task. Others returned the hand to the steering wheel between button presses.

The hand behavior is modeled in two ways. First, certain events will cause the driver to return the hand to the steering wheel. These include extreme steering corrections and emergency braking actions. In addition, the completion of the task will trigger the decision to withdraw the hand to the steering wheel. Second, a probability function determines whether the hand is returned to the wheel under normal circumstances. This function is determined partially by the location in the task. Drivers were more likely to return their hands to the wheel when there was a natural break in the task. The function is adjusted using a multiplier that reflects the differences between drivers. A driver who reached back to the wheel more frequently is modeled by increasing the probability of returning the hand to the wheel after each button press.

Emergent Driving Behaviors

Certain driver behaviors emerge naturally in the Virtual Driver model. This emergence is largely due to the queuing network structure of the QN-MHP.

Workload Effects

When tasks require greater processing time, either because the task itself is more difficult or the environment in which the task must be performed is more complex than usual, entities remain at the servers and in the network longer than they otherwise would. For example, calculating a new steering angle when navigating a curve takes more time than deciding the keep the steering wheel position the same when on a straight road. This causes greater congestion in the network, which represents increased workload.

Entities associated with driving are given a higher priority than those associated with the in-vehicle task, reflecting the fact that people will choose to respond to a driving input over a in-vehicle task input, assuming they detect both inputs. Thus, servers in the QN-MHP will process the driving entities ahead of the in-vehicle task entities. This results in longer task completion times for the in-vehicle task when the driving task is more difficult (Driving Behavior 1).

Glance Behavior

Drivers in the simulator study displayed different glance behavior when the monitor was moved (Driving Behavior 10). In particular, the number of glances and the total glance time both increased when the monitor was farther away. The approximate duration of each glance remained the same, however.

Entities associated with the in-vehicle task will enter the QN-MHP when the task is visible on the monitor, which will encourage the driver to glance to the monitor. However, the greater difficulty associated with reaches to the far monitor, communicated to the QN-MHP by the HUMOSIM Framework, will decrease the probability of the driver reaching to the monitor during each glance. The reach will take longer, due to the greater distance, so the driver will be able to complete a smaller proportion of the task before feeling it is necessary to look back to the road. This will result in the driver requiring more glances to complete all steps of the in-vehicle task.

Chapter 5

Modeling the Convoy Experiment with the Virtual Driver Model

Introduction

As drivers use in-vehicle devices with increasing frequency while driving, there is a growing need for driver models in order to improve the understanding of the effects of such multitasking. While driving itself does not have a major physical component, many secondary tasks that drivers perform do require significant movements, especially when they are done at the same time as driving. Therefore, it is important for a driver model to represent both physical and cognitive human processes.

There have been a number of different driving models developed. Some focus on one particular part of driving, such as steering or longitudinal control, while others are more comprehensive. More recently, researchers have worked to model the effects of driver distraction on performance. An overview of these driving models will be presented here. For a more in-depth discussion, please refer to Chapter 2.

Lateral control, or steering has been modeled by several groups. One example is the UMTRI driver model, a lateral control model for linear or quasi-linear closed-loop steering applications (Macadam, 1981; Smith & Jonides, 1998). This was later expanded into a model capable of handling nonlinear, near-limit operating conditions, the GM/UMTRI driver model (Macadam, 2001).

Longitudinal control has also been modeled in various ways. Early models regulated either zero range error or zero range-rate (Pipes, 1953; Chandler et al., 1958; Gazis et al., 1961; Newell, 1961), though real drivers likely do both. A later model used a safe distance strategy rather than strictly following the speed changes of a lead vehicle (Gipps, 1981). Most models have attempted to simulate perfect longitudinal control, but Yang and colleagues (2008) recently developed an errorable car-following driver model that can produce realistic accident and incident behavior.

Most driving models simulate driving under ideal conditions, but drivers frequently divert attention from the road in order to multitask, a behavior captured in newer models of driver distraction. Some models of driver distraction focus more on simulating aggregate or average outcomes, rather than the results of driving with a specific distraction (e.g. Yang et al., 2008). Other models focus on identifying driver distraction by monitoring driving performance (e.g. Ersal et al., submitted).

Models that simulate a driver's interaction with a particular in-vehicle system and attempt to predict the resulting effects on driving performance and the in-vehicle task include those by Levison (1993), Salvucci et al. (2001), and Salvucci and Macuga (2002). The QN-MHP has also been used to model driving while performing secondary in-vehicle tasks. Liu et al. (2006) simulated driving while completing an in-vehicle map reading task. Steering performance, glance behavior, and task time were found to be similar to empirical findings from a driving simulator experiment. Wu and Liu (2007) found that the QN-MHP could be used to successfully simulate changes in driver performance and mental workload when steering a driving simulator and performing a button-pressing task with a varying level of difficulty.

Though these previous studies have confirmed the validity and usefulness of the QN-MHP in simulating driving while performing secondary tasks, there have been some limitations. Longitudinal control was not simulated. In addition, the secondary tasks simulated had only minor physical components. There was no physical interaction with the in-vehicle display for the map-reading task, and the button-pressing task involved an easy reach to a console directly adjacent to the steering wheel. The expansion of the QN-MHP driving model described here allows for modeling of a greater variety of driving conditions and in-vehicle tasks.

This chapter describes the application of the Virtual Driver model to simulate the driving simulator experiment described in Chapter 3. The integration of the QN-MHP in ProModel and the HUMOSIM Framework in Jack is described, along with the modeler-entered parameters used (Figure 5.1). The parameter values were determined based on values in the literature and empirical findings from a subset of subjects in the driving simulator experiment. Results of the simulations were compared to the laboratory findings.

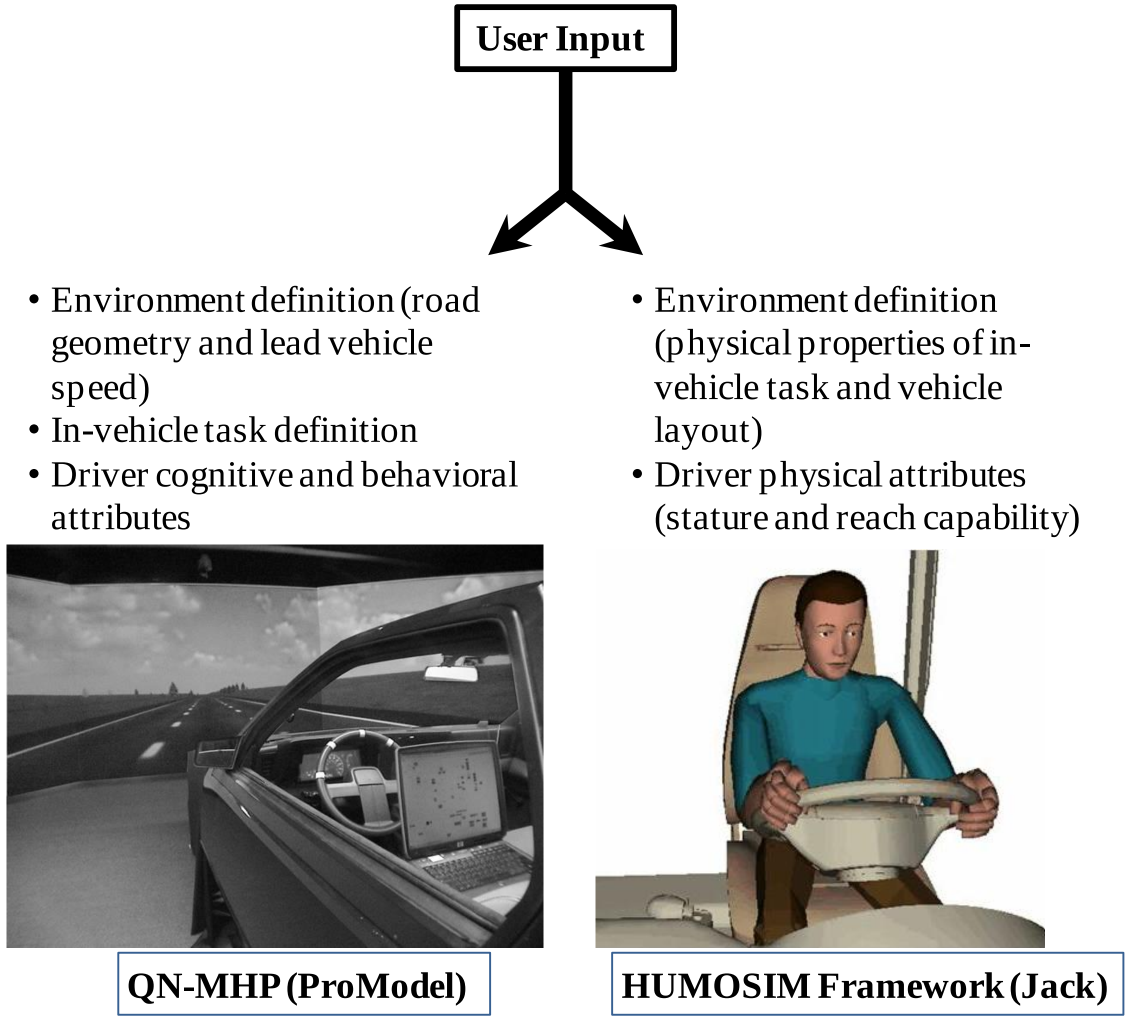


Figure 5.1. The modeler-entered information that is used for making decisions about how to perform the assigned task.

Methods

QN-MHP Implementation in ProModel

The QN-MHP is implemented in ProModel (ProModel Solutions, Version 2001), a simulation-based software widely used for manufacturing and operational applications. This software is designed for simulating manufacturing processes that are readily conceptualized as queuing networks. The software contains build-in analysis tools and strong visualization capabilities. ProModel has been used for all previous applications of the QN-MHP (Feyen, 2002; Tsimhoni, 2004; Lim, 2007; Wu, 2007). The current work adapted the most recent QN-MHP version (Wu, 2007).

The ProModel implementation of the QN-MHP includes 26 servers, although not all of those are used for modeling the multitasking scenario considered here. In particular, the servers corresponding to auditory perception and short-term storage of auditory information are not utilized. The servers are divided into three subnetworks: perceptual, cognitive, and motor.

Entities, which represent pieces of information, move through the network along paths between the servers. Each server has a set capacity. If a server is full when an entity arrives, it must wait in a queue until the previous entities leave the server. When the entities enter the servers, they undergo assigned processing, which includes routing logic to determine the path the entity follows next.

Important Modeling Terminology

There are several terms that are important for understanding the Virtual Driver. Some of these are specific to ProModel, while others were created for use in the Virtual Driver. The important ProModel components are summarized below (Table 5.1).

Table 5.1. Important ProModel components used in the QN-MHP.

Component	*Definition*
Location	Place in the model where entities are routed for processing or storage
Path	Route between locations
Entity	Object that moves between locations along paths, representing information movement
Processing Logic	Code that describes what happens when an entity enters a location; may change the value of a global variable, store information to an array, determine the routing destination of the entity, etc.

There are certain commands that are used frequently in the processing logic at many of the servers (Table 5.2). These are important for simulating the processing of information that occurs in the brain.

Table 5.2. Important ProModel commands used in the QN-MHP.

Command	*Definition*
WAIT	Simulates the time needed to process an entity by halting processing of the entity for the time specified; the rest of the model continues to run
ORDER TO	Sends an entity to the specified location; the entity that generated the ORDER command is not affected and remains in the location for additional processing
ROUTE	Sends the entity that generated the ROUTE command to the specified location; entities may be routed to the EXIT, in which case they leave the network and undergo no further processing

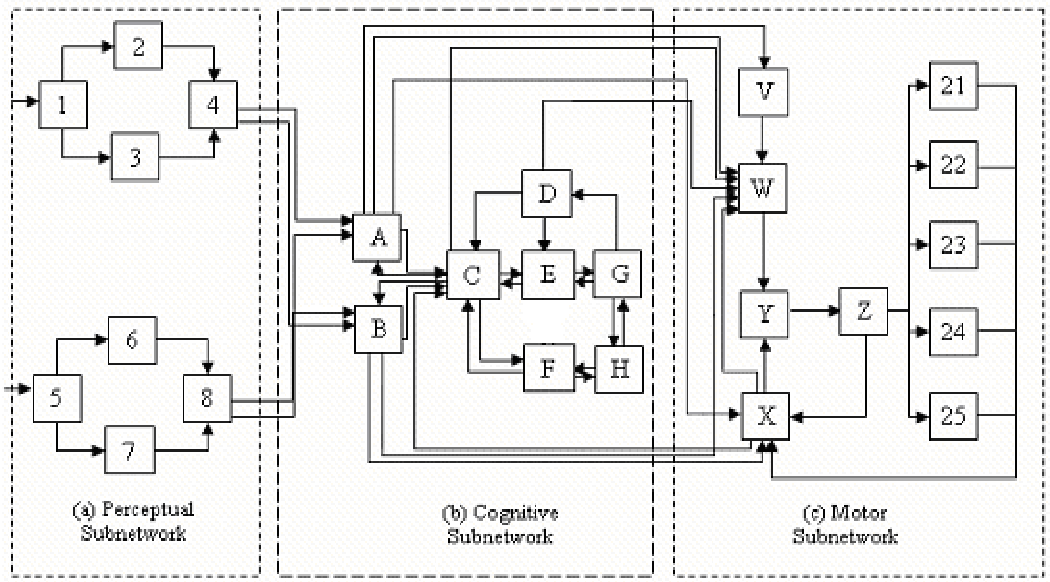
Finally, there are several user-defined inputs to the QN-MHP (Table 5.3). These inputs will be described in greater detail in the section on model parameters.

Table 5.3. Inputs to the QN-MHP.

Input	*Definition*
Task analysis array	Array of numerical codes that represents the steps necessary to complete the in-vehicle task, e.g. “search for”, “reach to”
Gaze list	List of all the possible gaze targets in the task environment
Reach list	List of all the possible reach targets in the task environment

Overall Structure of QN-MHP

The QN-MHP may be divided into three subnetworks: the perceptual subnetwork, the cognitive subnetwork, and the motor subnetwork (Figure 5.2). Each subnetwork consists of a group of servers, and entities move along paths within and between the subnetworks.



Perceptual Subnetwork (a)

1. Common visual processing (eyes, lateral geniculate nucleus, superior colliculus, primary and secondary visual cortex)
2. Visual recognition (ventral system)
3. Visual location (dorsal system)
4. Visual recognition and location integration (distributed parallel area including the connections among V3 , V4 and V5, superior frontal sulcus, and inferior frontal gyrus)
5. Common auditory processing (middle and inner ear)
6. Auditory recognition (area from dorsal and ventral cochlear nuclei to the inferior colliculus)
7. Auditory location (area from ventral cochlear nucleus to the superior olivary complex)
8. Auditory recognition and location integration (primary auditory cortex and planum temporale)

Cognitive Subnetwork (b)

A. Visuospatial sketchpad (right-hemisphere posterior parietal cortex)
B. Phonological loop (left-hemisphere posterior parietal cortex)
C. Central executive (dorsolateral prefrontal cortex (DLPFC), anterior-dorsal prefrontal cortex (ADPFC) and middle frontal gyrus (GFm))
D. Long-term procedural memory (striatal and cerebellar systems)
E. Performance monitor (anterior cingulate cortex)
F. Complex cognitive function: decision, calculation, anticipation of stimulus in simple reaction etc. (intraparietal sulcus (IPS), the superior frontal gyrus (SFS), the inferior frontal gyrus (GFi), the inferior parietal cortex and the ventrolateral frontal cortex, the intraparietal sulcus and the superior parietal gyrus)
G. Goal initiation (orbitofrontal region and amygdala complex)
H. Long-term declarative & spatial memory (hippocampus and diencephalons)

Motor Subnetwork (c)

V. Sensorimotor integration (premotor cortex)
W. Motor program retrieval (basal ganglia)
X. Feedback information collection (somatosensoy cortex)
Y. Motor program assembly and error detection (supplementary motor area (SMA) and pre-SMA))
Z. Transmission of information to body parts (primary motor cortex)
21-25: Body parts: eyes, torso, left hand, right hand, foot

Figure 5.2. Diagram showing the locations and paths in the QN-MHP (adapted from Wu et al., 2008).

Perceptual Subnetwork

The perceptual subnetwork has visual and auditory components, with each subsection composed of four servers. In the visual perceptual subnetwork, Server 1, which represents the eyes, lateral geniculate nucleus, superior colliculus, primary visual cortex, and secondary visual cortex, is responsible for common visual processing. In Server 1, light waves, represented by numerical codes, are transformed into neural signals, represented by information entities (Bear et al., 2001).

The entities are next transmitted via parallel visual pathways to Server 2, the parvocellular stream, and Server 3, the magnocellular stream (Bear et al., 2001; Simon et al., 2002; Feyen, 2002). Server 2 performs visual recognition of object features, including color and shape. Server 3 performs visual location, which includes identifying spatial coordinates and speed. The information from these two visual pathways is integrated in Server 4, which includes the neuron connections between V3 (part of the dorsal stream) and V4 (a cortical area in the ventral stream), the connections between V4 and V5 (an area in the extrastriate visual cortex), the superior frontal sulcus, and the inferior frontal gyrus. The entities that enter the cognitive subnetwork from Server 4 represent an integrated perception of the object viewed.

Auditory information enters the auditory perceptual subnetwork via Server 5, which represents the middle and inner ears. From there, sound is transmitted along parallel auditory pathways to Server 6 and Server 7. Server 6 represents the neuron pathway from the dorsal and ventral cochlear nuclei to the inferior colliculus and is responsible for auditory recognition, such as identifying sound pattern (Bear et al., 2001). Server 7, representing the neuron pathway from the ventral cochlear nucleus to the superior olivary complex, is responsible for auditory location. The auditory information is integrated in Server 8, which represents the primary auditory cortex and the planum temporale (Mustovic et al., 2003).

Cognitive Subnetwork

After undergoing initial processing by the perceptual subnetwork, entities enter the cognitive subnetwork. The cognitive subnetwork contains a working memory system, a goal execution system, a long-term memory system, and a complex cognitive processing system.

The working memory system in the cognitive subnetwork is organized following Baddeley's working memory model, with four components: a visuospatial sketchpad (Server A), a phonological loop (Server B), a central executor (server C), and a performance monitor (Server E). The visuospatial sketchpad, which represents the right-hemisphere posterior parietal cortex in the brain, stores and maintains visuospatial information in the working memory (Rieke, 1997). The phonological loop, which represents the left-hemisphere posterior parietal cortex, stores and maintains phonological information in the working memory. The central executor represents the dorsolateral prefrontal cortex, the anterior-dorsal prefrontal cortex, and the middle frontal gyrus. The performance monitor represents the anterior cingulate cortex.

The goal execution system (Server G) represents structures in the brain that are often involved in goal initiation and motivation. These are the orbitofrontal region, the amygdala complex, and the brain stem, including the locus coeruleus-norepinephrine system (Rolls, 2000).

There are two types of long-term memory represented by the long-term memory system. Declarative memory, which includes facts and events, and spatial memory are represented by Server H. The brain area associated with this server is the medial temporal lobe, including the hippocampus and the diencephalons (Bear et al., 2001). This part of the brain stores production rules used in choice reaction tasks and long-term spatial information; it is involved in perceptual judgment, decision making, and problem solving. Nondeclarative memory, represented by Server D, is used to store information about how to perform actions and includes procedural memory and motor programs. The brain regions associated with Server D are the striatal and cerebellar systems, which store the steps in task procedure and the motor programs related to motor task execution.

The complex cognitive system is represented by Server F. The associated brain areas are the intraparietal sulcus, the superior frontal gyrus, the inferior frontal gyrus, the inferior parietal cortex, the ventrolateral frontal cortex, and the superior parietal gyrus (Rieke, 1997; Fletcher & Henson, 2001; Manoach et al., 1997). These brain areas are involved in performing complex cognitive functions such as multiple-choice decision making, phonological judgment, spatial working memory operations, visuomotor choices, and mental calculations.

Motor Subnetwork

There are five servers in the motor subnetwork that correspond to the major brain areas involved in retrieval, assembly, and execution of motor commands and sensory information feedback. Five other servers represent body parts that are relevant to the performance of the dual task in the driving simulator experiment. Additional servers could be added to represent necessary body parts when new tasks are modeled in the future.

The premotor cortex in Brodmann Area 6 is involved in sensorimotor and sensory cue detection and is represented by Server V (Mitz et al., 1991; Roland, 1993; Kansaku et al., 2004). The basal ganglia, which retrieves motor programs and long term procedural information from the long term procedural memory, is represented by Server W (Bear et al., 2001; Gilbert, 2001). The supplementary motor area (SMA) and the pre-SMA, represented by Server Y, are responsible for assembling motor programs and ensuring movement accuracy. The primary motor cortex, represented by Server Z, addresses the spinal and bulbar motor neurons to transmit the neural signals to different body parts (Roland, 1993).

The body parts act as motor actuators and currently include the eyes (Server 21), torso (Server 22), left hand (Server 23), right hand (Server 24), and right foot (Server 25). The somosensory cortex (S1) is represented by Server X. S1 collects motor information in the form of efference copies of motor signals from the primary motor cortex and sensory information from body parts and relays them to the prefrontal cortex and the SMA (Roland, 1993).

Modeling Tasks in the Virtual Driver

The Virtual Driver is able to simulate a human's performance on a variety of tasks. These include lateral and longitudinal control during driving. In addition, the Virtual Driver can perform the in-vehicle task from the driving simulator study and decide how to adjust its actions to accomplish multitasking.

Lateral Control

The Virtual Driver uses a steering model that combines several concepts. These include a hierarchical task structure, visual input flow, roles of focal and ambient systems, a near-far dichotomy, concurrent cognitive processing, and steering movements. (For more detail, see Tsimhoni & Liu, 2003.)

The inputs to the steering model enter the QN-MHP at Server 1 (common visual processing). These inputs include the vehicle heading relative to the road when fixating on a far point down the road (approximately 2 seconds in front of the vehicle), the lateral position of the vehicle relative to the center of the lane, and the road curvature during curves and approaches to curves (Tsimhoni, 2004).

Maintaining a consistent position in the lane is the main goal of the steering model. The cognitive processing for this goal is separated into subgoals for detecting the orientation parameters of the vehicle, selecting a steering strategy, and steering the vehicle.

A "watch for" cognitive command at Server D (long-term procedural memory), currently represented by a task analysis array, directs the model's visual attention so that the necessary information can be accessed at Server 1 (eyes, lateral geniculate nucleus, superior colliculus, primary visual cortex, and secondary visual cortex). This includes heading and curvature, which are accessed when the eyes are at a far point, and lateral position, determined when the eyes are at a near point.

The steering action is selected in Server F (complex cognitive function) based on the expected orientation of the vehicle within a look-ahead time, currently set to one second. If the vehicle's orientation will be close to the center of the lane, within a predetermined dead zone that varies between drivers, no steering correction is made. If the orientation is outside of the dead zone but still within the lane, a normal steering action is initiated. If the vehicle will be outside the lane boundaries, an imminent steering action is initiated.

The desired steering angle is calculated at Server F, then the motor command is assembled by Servers W (motor program retrieval), and Y (motor program assembly and error detection). The command is communicated to Server Z (transmission of information to body parts), which then sends the desired action to Server 23 (the left hand). The hand movement results in a change in steering wheel angle.

Longitudinal Control

The longitudinal control model is adapted from work presented by Yang and colleagues (2008). The approach considers driving as a stochastic process in which the driver intends to achieve a desired vehicle state but accepts some deviations. The equations used in the Virtual Driver are based on the sliding mode control law by Yang et al. (2008).

Processing for longitudinal control in the QN-MHP is similar to that for lateral control. The inputs at Server 1 are the range, or headway, to the lead vehicle and the range rate. These are calculated based on the current velocity and position of the lead vehicle, taken from a representative trial of the driving simulator study, and the velocity and position of the model's vehicle.

The perceptual limitation is introduced at Server 4 (visual recognition and location integration). This is simulated as a quantized range rate input. The literature suggests that the just noticeable difference of velocity discrimination is from 0.05 to 0.2 (ΔV/V) (Harris & Watamaniuk, 1995; Watamaniuk & Heinen, 2003). A value of 0.1 is chosen to represent the average driver, but this parameter can be varied to simulate perceptual differences between drivers. The perceived range-rate is calculated as follows.

$$\boldsymbol{\dot{R}'(k)} = \begin{cases} \boldsymbol{\dot{R}(k)}, \ \boldsymbol{abs}\left(\frac{\boldsymbol{\dot{R}(k)-\dot{R}'(k-1)}}{\boldsymbol{\dot{R}'(k-1)}}\right) \geq \mathbf{0.1} \\ \boldsymbol{\dot{R}'(k-1)}, \ \boldsymbol{otherwise} \end{cases} \tag{5.1}$$

The longitudinal control entity is then routed to Server C (central executive), where the desired acceleration is calculated based on a desired time headway. The following equations are used.

$$a_d(t) = P(R(t)) \cdot (\dot{R}(t) + |\dot{R}(t)| \cdot sat(^{s}/_{\varepsilon})) \quad \textbf{(5.2)}$$

$$P(R(t)) = (P_3 \cdot R^3(t) + P_2 \cdot R^2(t) + P_1 \cdot R(t) + P_0) \quad \textbf{(5.3)}$$

$$s = R(t) - T_h \cdot V_F(t) \quad \textbf{(5.4)}$$

$$\sigma(R(t)) = \bar{P}_2 \cdot R^2(t) + \bar{P}_1 \cdot R(t) + \bar{P}_0 \quad \textbf{(5.5)}$$

R gives the range between the two vehicles, P_i is a set of polynomial coefficients that vary based on the behavior of the driver to be modeled, *sat*() is a saturation function, s is a sliding surface, T_h is the desired time headway, and a is the acceleration of the vehicle.

The entity is routed through Servers W (motor program retrieval), Y (motor program assembly and error detection), and Z (transmission of neural signals to body parts) to simulate the assembly of the motor program. It is then sent as a motor command to Server 25 (right foot), where the actual acceleration is calculated based on the desired acceleration. The following equation, in which f is a random number generator that represents motor noise is used.

$$a(t) = f(a_d, \sigma) \quad \textbf{(5.6)}$$

In-Vehicle Task

With the QN-MHP, driver distraction emerges as a result of the performance of the in-vehicle task, which in the current case requires glances to the display and reaches of varying difficulty. The processing time at each server accounts for the cognitive time delay, while neuromuscular time delay in the Virtual Driver is represented by the movement time between servers and the WAIT statements in the processing logic.

In general, all physical movements involve the same routing and processing, after the decision to perform the movement has been made. Entities that have been involved in movement decisions are routed to Server W (motor program retrieval), then through Servers Y (motor program assembly and error detection) and Z (transmission of neural signals to body parts). Server Z routes the entity, which now represents a motor command, to the appropriate body part server (Server 21 for the eyes, 22 for the torso, 23 for the left hand, 24 for the right hand, and 25 for the right foot).

To simulate the in-vehicle task used in the simulator experiment, the model had to decide which button should be pressed next, locate the button on the monitor, reach to and press the button, and keep track of which parts of the task had been completed.

Entities associated with the in-vehicle task enter the modeled environment at the monitor location, corresponding to information available on the monitor in the actual task. When the model is looking at the monitor, the entities enter into the visual part of the perceptual subnetwork if the current step in the task is visual (e.g. locate button). If the model is not looking at the monitor and the current task element does not have a visual component (e.g. recall number of current icon pair), the visual entities are routed to Server C (central executive). Otherwise, they exit and are effectively ignored.

An entity routed from the perceptual subnetwork into the cognitive subnetwork passes through Server A (visuospatial sketchpad) and enters Server C, where a decision about the next routing is made. The entity's route is chosen based on the task analysis array, which represents the long-term procedural memory, taking the place of Server D.

The first decision the model makes after choosing to begin work on the in-vehicle task is whether or not to shift the torso towards the monitor. If the reach difficulty is greater than 8, then the model initiates the rightward torso shift observed among small female subjects performing tasks at the far monitor locations. The torso shift command is performed by routing the entity through Servers W, Y, and Z. The entity is then sent to Server 22 (torso) to simulate the movement.

At certain points in the task, the model must retrieve from the long-term memory information about how to perform the task. When the entity enters Server C, it triggers a subroutine that retrieves the necessary information from the task analysis array. A WAIT statement is included to simulate the time necessary to retrieve the information.

Information is also stored in and retrieved from the short-term memory. When the model is storing information to the short-term memory, the entity waits in Server C for the cognitive processing time. When the information is needed, the entity is directed to wait again in Server C for the cognitive processing time, and the model runs a subroutine that retrieves the desired information.

To perform the button presses required in the in-vehicle task, the model must reach to the touch screen monitor. The parts of this subtask vary based on the current eye location. If the model is already looking at the monitor when it decides to perform the reach, the entity will be routed through Servers W, Y, Z, and 24 (right hand) to perform the reach. If the model is not currently looking at the monitor, a glance is requested, and the reach continues as described previously as soon as the eyes are on the monitor. In addition, the model can reach to the hover location without looking at the monitor; it then completes the reach to the monitor once the model looks at the monitor.

Visual Search

For the in-vehicle task, the subject was required to locate and press a series of buttons on the touch screen monitor. Some of these buttons were in fixed locations on the screen, while the positions of others varied from trial to trial. At the beginning of the task, there were three pairs of variable-location buttons, for a total of six buttons. After a match was performed, that pair would disappear, so there were four buttons to choose between for the second match and two for the third match.

Because the visual search process was not a focal point of this research, a WAIT time was added to the model to represent the time required for the search. The times were estimated based on information from the literature, along with experimental results from a subset of four subjects in the driving simulator experiment.

In a visual search, the time required to locate the fixed buttons, which are in the same locations for each trial, should be shorter than the time to find the variable buttons, because the driver will remember the approximate locations of the fixed buttons. In addition, the time to locate the variable buttons should decrease as the number of buttons in the field decreases, as there will be fewer possible button choices.

The above requirements for visual search time were implemented in two ways. For the fixed-location buttons, the time was determined experimentally, based on the button press timing for four subjects performing the in-vehicle task while in a stationary vehicle during the simulator study. For the variable-location buttons, the following equation for the mean time to find a target using the serial search model (Neisser et al., 1964) was used.

$$\boldsymbol{T = {}^{N \times I}/_{2}} \qquad \textbf{(5.7)}$$

The total number of items in the search field is *N*, and the mean inspection time for each item is *I*. The value used for *I* was determined based on the subset of four subjects. To represent the variability due to subject differences and the randomness of the button locations between trials, a uniform distribution, with a mean of 1 second and a half-range of 0.5 seconds, was used for *I*. The serial search model is a reasonable representation of searching for the variable-position buttons because none of the buttons is more conspicuous than the others, and drivers have no expectations about the button location.

When the model reaches the task step that requires the visual search, it checks the task array, which specifies the name of the current target button. The visual search duration is then set based on whether the button to be found is a fixed- or variable-location button and on the number of buttons currently on the screen. If the eye is already on the monitor when the search is initiated, the model waits for the length of time required to locate the desired button. Otherwise, the model sends a request to Server C to look at the monitor. When the model decides to perform the glance, the entity is routed through Servers W, Y, and Z, then to Server 21 (eyes).

Multitasking

The QN-MHP simulations multitasking by simultaneously processing two or more goal lists. Indeed, one of the strengths of the QN approach is that multitasking performance emerges naturally from the competition and congestion that results in the network as the entities associated with each task are processed. Each goal list is associated with one of the tasks. The driving simulator experiment was modeled using goal lists for lateral control, longitudinal control, and the in-vehicle task.

The simulated driver can detect the start of the secondary task when looking outside of the vehicle. This represents the reality that subjects were able to detect the appearance of the task on the monitor using their peripheral vision, so there was no need for them to periodically check the monitor to see if the task had begun.

The structure of the QN-MHP makes it possible for the model to multitask without explicit knowledge of the task structure, due to the prioritization of entities being routed through servers. However, some metacognition is required to schedule certain activities such as glances and reaches.

When the in-vehicle task requires the model to look at the monitor, a request for the use of the eyes is sent to Server C (central executive). If the current driving workload is sufficiently low and not expected to increase above a target level in the near future, the entity is routed to Server 21 (eyes) to simulate the glance. Otherwise, the entity is routed to the exit, and the model waits for a set period of time before checking again to see if driving workload will permit a glance to the monitor.

In order to reach to the touch screen monitor, the model must be looking at the monitor. If the model is not currently looking at the monitor, it will need to decide if the driving workload is currently low enough to permit a glance to the monitor and if there is time to complete the glance before the workload increases. If there is not time, the model can still reach to the hover location without looking, then complete the reach when the driving workload decreases enough to allow the model to look at the monitor.

Once the model is looking at the monitor, it must decide if there is time to reach to the monitor, based on the anticipated driving workload. If there is time, the reach is performed using the routing described above. If there is not currently sufficient time relative to the anticipated workload, due to, for example, the curvature of the road ahead, the entity will exit and the model will check again periodically until there is enough low-workload time available for the reach.

HUMOSIM Framework Implementation in Jack

The HUMOSIM Framework Reference Implementation (HFRI) is the development version of the Framework. Because the HFRI is the only complete implementation of the Framework to date, the term Framework is here to refer to the HFRI. The Framework is implemented in the Python programming language, accessing the JackScript Application Programming Interface in the Tecnomatix Jack software from Siemens. The research described here was performed using Jack version 6.0.2 running in a Windows environment.

The Framework provides a high-level interface to control basic motions, such as gaze transitions and reaches. Movement goals are described as “tasks” that are passed to an hmsHuman, a software abstraction that wraps the HUMOSIM Framework functionality around the Jack human figure. A typical task includes the body component to be used, the desired start time (including immediately), and the target of the task. For example, the hmsHuman can be told to reach immediately with the right hand to a particular object in the environment. The Framework then computes and executes the appropriate joint movements to perform the necessary motion in a realistic manner.

For the current research, a TCP/IP interface was developed so that tasks could be passed to the hmsHuman via a network connection. On the Framework side, a TCP/IP server is initiated that sends and receives short text messages. This is described in detail below. During a simulation, the Framework runs continuously, updating the goals of each body component as instructed by the QN-MHP running in ProModel.

Integration of QN-MHP and HUMOSIM Framework

The previous task-specification interface for the QN-MHP model was a Microsoft Excel file containing data about actuators, actions in use, parameters available in the long term memory, and goal lists based on a GOMS-style task analysis (Liu et al., 2006). The file also included information about the environment, including stimuli and descriptions of task objects. Output data files recorded the actions, such as hand reaches and eye movements. In the new implementation, input files are still used for specifying the in-vehicle task and details about the driving task, such as the road curvature and the lead vehicle speed, but the burden of tracking the in-vehicle task physical input and output information has shifted onto the HUMOSIM Framework.

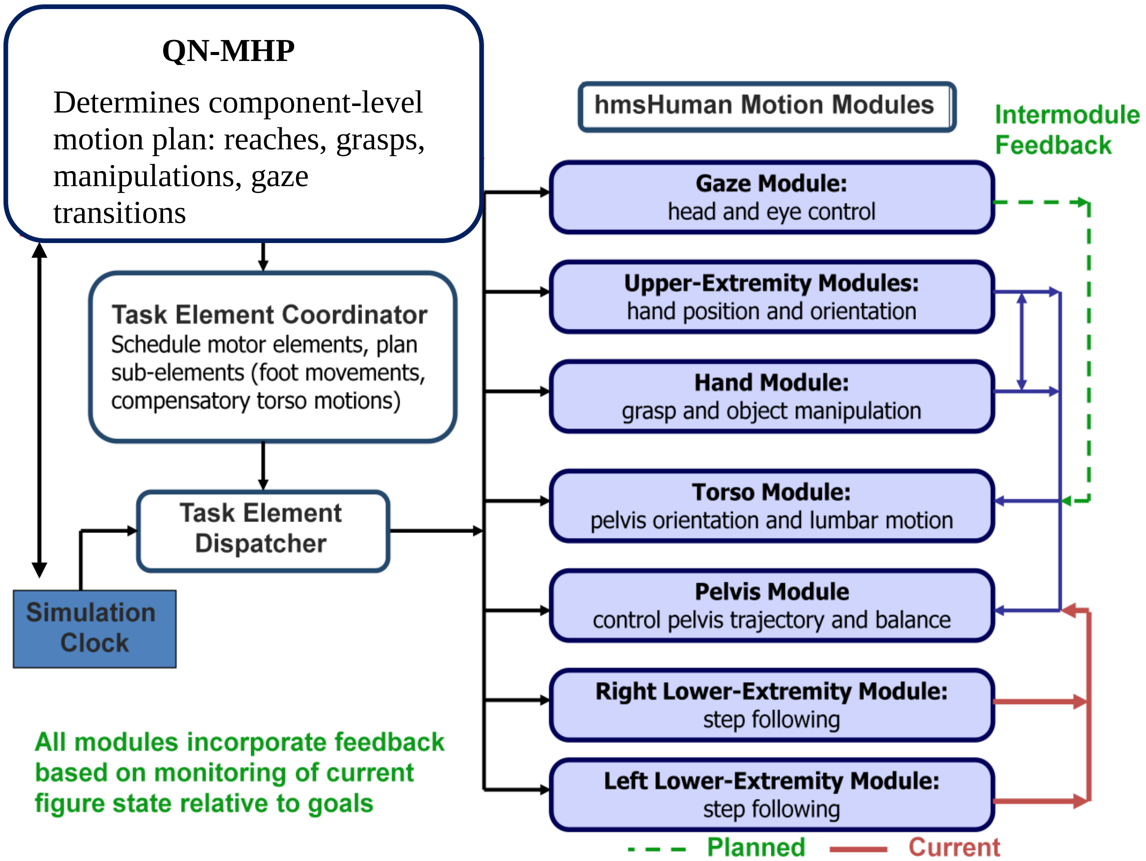


Figure 5.3. HUMOSIM Ergonomics Framework (Reed et al., 2006) integrated with the QN-MHP to form the combined model.

Connection Between QN-MHP and HUMOSIM Framework

Communication between the QN-MHP and the HUMOSIM Framework is performed using a TCP/IP socket connection that permits the two models to exchange information asynchronously. Sockets allow programs on different computers to communicate using a client/server model. The server, also called the host, creates a socket and binds it to an internet protocol (IP) address and port, then listens for the client. To connect to the server, the client creates a socket that references the designated IP address and port. In the current implementation, the HUMOSIM Framework running in Jack is the host and the QN-MHP running in ProModel is the client. Once the connection is made, the server and client are peers with respect to sending and receiving information. The QN-MHP controls the progression of the simulation, as described below.

A dynamic link library (DLL) file was created to facilitate the connection between the QN-MHP and the Framework. The DLL provides common functions not available in ProModel, including network communication. The DLL was created by compiling a C++ program, made using the New Project Wizard in Microsoft Visual Studio (2005), in a format recognized by ProModel.

To use the DLL, ProModel calls internal subroutines using the XSUB command, which then references functions in the DLL. Once connected, the DLL sends, receives, or stores information based on the command issued by ProModel (Figure 5.4).

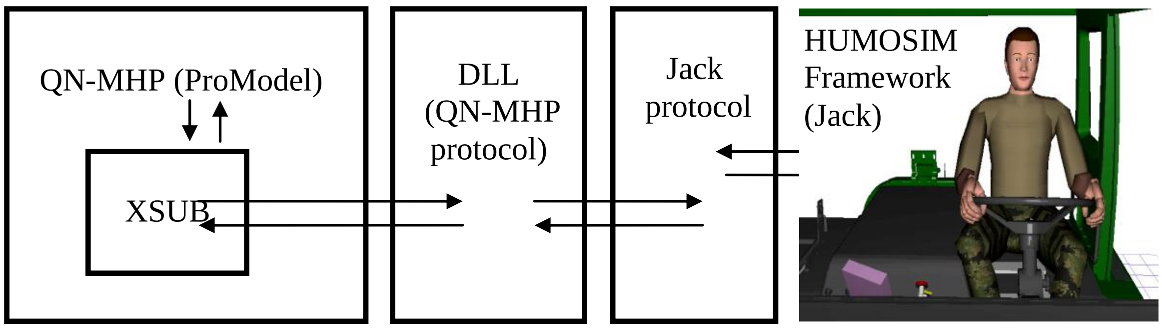


Figure 5.4. Set-up of communication between the QN-MHP and the Framework.

After the connection has been made, the QN-MHP sends an initialization string with the simulation starting time (seconds) and the simulation time step (seconds). When the Framework receives the initialization command, it sends a list of available gaze targets and a list of available reach targets, along with estimated difficulty values (0-10) for looking at and reaching to each target. These times can then be used by the QN-MHP to make decisions about when to make glances and reaches. An example of the initialization communication follows.

QN sends:	INITIALIZE T0 TS
Framework sends:	GAZETARGETLIST target1 difficultytarget1 target2 difficultytarget2
	REACHTARGETLIST target1 difficultytarget1 target2 difficultytarget2

To synchronize the simulation times of the QN-MHP and the Framework, the QN-MHP sends tick commands in which the tick parameter, “tn”, is the time up to which the Framework should execute. After executing the tasks that occur prior to this time, the Framework responds with a status command containing a tick parameter that is the value of the Framework's current simulation time. When the Framework parameter matches the tick parameter sent by the QN-MHP, the QN-MHP starts processing again. The QN-MHP sends tick commands at a constant interval rather than sending a command after each movement command. The following is an example of the tick and status commands.

QN sends: TICK 0.05
Framework sends (while performing the motor tasks) and QN sits waiting:
STATUS 0.0 component1 target1state1 component2 target2 state2
STATUS 0.033333 component1 target1state1 component2 target2 state2
QN starts processing again and Framework waits for another TICK command

The status command sent by the Framework contains the tick parameter value, each motor component, the current target for each component, and the temporal (not spatial) fraction of attainment of the goal (between 0 and 1). When the attainment value is 1, the component is holding at the specified target. The value following the steer parameter name is the current steering wheel angle (radians), with a negative value indicating the wheel is rotated at a clockwise angle. An example of the status command is as follows.

STATUS 12.3 RightHand HandprintDisplay 0.7 LeftHand HandprintLeftWheel 1 Gaze VisionTargetRoad 1 Steer 0.0

To send a movement command to the Framework, the QN-MHP sends a command string with parameters for the intended movement. Tasks can be specified at any time prior to their intended start time. The motor task commands used in the current simulation are steer, reach and gaze. The tasks and their parameters are shown below (Table 5.4).

Table 5.4. Motor commands from the QN-MHP to the Framework.

Task	*Parameters*	*Definition of Parameter*
STEER	TargetWheelAngle	Radians counterclockwise from straight-ahead (Note: The current functionality does not allow a parameter value of more than ±45 degrees ≈ 0.7854 radians)
REACH	Hand	Which hand to use: “Right” or “Left”
	Target	Named reach target from reach target list
	TimeAtTarget	If included, the Framework will automatically schedule a return to the previous hand position after the specified amount of time at the target.
GAZE	Target	Named gaze target from gaze target list (Note: All reach targets can be used as gaze targets)
	TimeAtTarget	If included, the Framework will automatically schedule a return to the previous gaze target after a specified time at the target

It is possible but not required to specify a time at target in the movement commands. The following is an example of the movement commands used in the simulation. The time-at-target parameter allows the Framework to automatically queue a “return” motion following the button press.

```
STEER 0.3
REACH Hand Right Target Right_S1
GAZE Target VisionTargetDisplay
```

Details about the subroutines used to communicate between the QN-MHP and the Framework are shown below. The subroutines and corresponding commands in ProModel are included.

Table 5.5. ProModel subroutines and corresponding XSUB commands

ProModel Subroutine	*Input Parameters*	*XSUB Command*	*Function*
Init_Client	None	(DLL, 1)	Connects to host
Send_Initialize	T0, Ts	(DLL, 2, T0, Ts)	Sends initialization string
			Receives gaze target list and reach target list
			Writes gaze targets to an array for later use
			Writes reach targets and their expected times into an array for later use
Send_Tick	tickTn	(DLL, 3, tickTn)	Sends tick string
			Waits for status string with tick parameter sent to continue
Send_Steer	targetwheelangle	(DLL, 4, targetwheelangle)	Sends steer string
Send_ReachLeft	reachtarget, timeattarget	(DLL,5, reachtarget, reachlefttimeattarget)	Sends reach left string
Send_ReachRight	reachtarget, timeattarget	(DLL, 6, reachtarget, reachlefttimeattarget)	Sends reach right string
Send_Gaze	gazetarget, timeattarget	(DLL, 7, gazetarget, gazetimeattarget)	Sends gaze string

Subtask Definitions and Model Parameters

The parameters that specify the dual task scenario of driving while performing an in-vehicle task were defined in ProModel and the Framework. Variables related to the cognitive performance of the tasks were entered in ProModel, and variables related to the physical task performance were entered in the Framework.

Basic QN-MHP Model Parameters

There are several basic model parameters in the QN-MHP, summarized below (Table 5.6). The processing time for an entity at a server is exponentially distributed with a mean of 42 ms and a minimum of 25 ms for a server in the perceptual subnetwork (ppt), a mean of 18 ms and a minimum of 6 ms for a server in the cognitive subnetwork (cpt), and a mean of 24 ms and a minimum of 10 ms for a server in the motor subnetwork (mpt) (Feyen, 2002).

The eyemovementime is the time needed to move the eye to a known target location. Its value is based on the eye movement time of the Model Human Processor (Card et al., 1986). The footmove is the time to move the foot between the gas pedal and the brake (Wu, 2007).

Table 5.6. Basic QN-MHP parameters.

Parameter	*Definition*	*Value (seconds)*	*Source*
ppt	Perceptual processing time	E(0.042,0.025)	Feyen, 2002
cpt	Cognitive processing time	E(0.018,0.006)	Feyen, 2002
mpt	Motor processing time	E(0.024,0.010)	Feyen, 2002
eyemovementtime	Time to complete an eye movement	0.23	Card et al., 1986
footmove	Time to move the foot	0.08	Wu, 2007

Definition of In-Vehicle Task

The steps for the in-vehicle task (Table 5.7) were specified using an NGOMSL-style analysis (Kieras, 1997). The analysis was performed on the in-vehicle task alone, so steps related to driving or multitasking are not represented.

Table 5.7. NGOMSL analysis for in-vehicle task.

Level 1

Method for goal: Complete the in-vehicle task
Step 1: Accomplish goal: Press stationary button (“New Assignments”)
Step 2: Store in STM current pair number: 1
Step 3: Accomplish goal: Match all scout and target icons
Step 4: Forget current pair number
Step 5: Accomplish goal: Press stationary button (“Submit Assignments”)
Step 6: Accomplish goal: Press stationary button (“Execute Plan”)
Step 7: Return with goal accomplished

Level 2
Method for goal: Match all scout and target icons
Step 1: Recall current pair number from STM
Step 2: Accomplish goal: Match icons for current pair number
Step 3: Decide: If no icon pairs remaining, then return with goal accomplished
Step 4: Store in STM next current pair number = current number + 1
Step 5: Forget old pair number
Step 6: Goto 1

Level 3
Method for goal: Match icons for current pair number
Step 1: Store to STM icon type: target
Step 2: Accomplish goal: Select icon (target)
Step 3: Forget icon type: target
Step 4: Store to STM icon type: scout
Step 5: Accomplish goal: Select icon (scout)
Step 6: Forget icon type: scout
Step 7: Accomplish goal: Press stationary button ("Assign")
Step 8: Return with goal accomplished

Level 4
Method for goal: Press stationary button
Step 1: Recall location of button from LTM
Step 2: Look at button
Step 3: Reach to button
Step 4: Return with goal accomplished

Method for goal: Select icon
Step 1: Accomplish goal: Locate icon
Step 2: Reach to icon
Step 3: Return with goal accomplished

Level 5
Method for goal: Locate icon
Step 1: Recall from STM icon type
Step 2: Recall from STM current pair number
Step 3: Accomplish goal: Examine icon (of current type)
Step 4: If number on icon matches current pair number, go to 5, else return to 3
Step 5: Return with goal accomplished

Level 6
Method for goal: Examine icon
Step 1: Look at icon
Step 2: Read number on icon

This task analysis was used to create the task analysis array, which was entered in a Microsoft Excel (2007) file. The action to be performed for each step in the task is coded numerically in the array used in the model. The task analysis array also contains the name of the target button for visual searches and reaches. The value in the "Break" column gives the probability that the driver takes a break from the in-vehicle task to look back to the road after completing that step. A value of 0 indicates the driver will never look back to the road after that step, while a value of 1 indicates the driver will always look back to the road. The break values were determined based on observations of how subjects performed the task during the simulator experiment. The break values can be increased to represent drivers who make frequent glances to the road and decreased to simulate drivers who perform multiple actions before looking back to the road.

Table 5.8. The task analysis array that defines the in-vehicle task. The action, target button (if applicable), and probability of taking a break in the task to look back to the road are included.

Action	*Break*	*Button Name*
Watch for (task to begin)	0.5	
Perform torso shift	0.1	
Retrieve from LTM (recall how to begin task, i.e. press button)	0.5	
Watch for (find "New Assignments" button)	0.25	New Assignments
Reach to touch screen ("New Assignments" button)	0.25	New Assignments
Watch for (watch for screen to change)	0.9	
Retrieve from LTM (recall how to begin matching, i.e. with pair 1)	0.25	
Watch for (find "Target 1")	0.01	Scout 1
Reach to touch screen ("Target 1" button)	0.01	Scout 1
Watch for (find "Scout 1")	0.01	Target 1
Reach to touch screen ("Scout 1" button)	0.25	Target 1
Watch for (find "Assign" button)	0.1	Assign
Reach to touch screen ("Assign" button)	0.25	Assign
Store to STM (store pair number completed)	0.9	
Retrieve from STM (recall next pair number, i.e. pair 2)	0.25	
Watch for (find "Target 2")	0.01	Scout 2

Action	*Break*	*Button Name*
Reach to touch screen ("Target 2" button)	0.01	Scout 2
Watch for (find "Scout 2")	0.01	Target 2
Reach to touch screen ("Scout 2" button)	0.25	Target 2
Watch for (find "Assign" button)	0.1	Assign
Reach to touch screen ("Assign" button)	0.25	Assign
Store to STM (store pair number completed)	0.9	
Retrieve from STM (recall next pair number, i.e. pair 3)	0.25	
Watch for (find "Target 3")	0.01	Scout 3
Reach to touch screen ("Target 3" button)	0.01	Scout 3
Watch for (find "Scout 3")	0.01	Target 3
Reach to touch screen ("Scout 3" button)	0.25	Target 3
Watch for (find "Assign" button)	0.1	Assign
Reach to touch screen ("Assign" button)	0.25	Assign
Store to STM (store pair number completed)	0.9	
Watch for (find "Submit Assignments" button)	0.1	Submit Assignments
Reach to touch screen ("Submit Assignments" button)	0.25	Submit Assignments
Watch for (screen to return to front screen)	0.9	
Watch for (find "Execute Plan" button)	0.1	Execute Plan
Reach to touch screen (press "Execute Plan" button)	0.25	Execute Plan

Visual Search

There were two parameters used for the visual search part of the in-vehicle task. The main parameter was the time to locate a single target in the visual search field. To determine that time, the mean inspection time I for each parameter was needed. The “Scout” and “Target” buttons were located in random places on the screen that changed with each trial. To represent this, along with the variability between subjects, a uniform distribution, with a mean of 1 second and a half-range of 0.5 seconds, was used for I.

Table 5.9. Visual search parameters.

Parameter	*Definition*	*Value (seconds)*	*Source*
T	Time to locate a target in the visual search field	N*I/2 sec	Neisser et al., 1964
I	Mean inspection time for each item	U(1, 0.5) sec	Subset of four subjects from driving simulator study

Task Chunking

Task chunking refers to grouping elements or steps in a task into groups. Often, a group is defined by task timing: the amount of time between two elements in a group is shorter than the amount of time between the last element of one group and the first element of the next.

The tendency of subjects to perform chunking of task elements was simulated by varying the probability of looking back to the road and returning the right hand to the steering wheel between button presses. Increasing the probability of interrupting the task to return to driving at subtask boundaries is consistent with results reported in the literature suggesting that people use subtask boundaries as a cue to switch between tasks (Miyata & Norman, 1986; Payne et al., 2007).

Definition of Driving Tasks

Steering and longitudinal control were modeled as separate tasks. The important parameters for each were defined using separate worksheets in a Microsoft Excel file. At the beginning of the simulation, ProModel imported the values from the Excel file and stored them in arrays. During the simulation, these arrays were referenced to obtain the necessary information about the task environment, including the road geometry and the lead vehicle location.

For the steering task, the road was defined by specifying a road heading in degrees for every meter from the starting point. In addition, the distance to the start of the next curve and the curve distance remaining, if the car was currently on a curve, were given. These variables are important for the look-ahead workload model.

The road used for the model was defined to match the road in the driving simulator experiment. The model drove in the left lane of a four lane divided highway.

Each lane was 3.6 meters wide. The road was in the shape of a round-corner square, with sides 1750 meters long. The curves at the corners were each 492 meters long, giving a radius of 313 meters. All curves were to the left.

Table 5.10. Steering input parameters.

Parameter	*Definition*	*Source*
HeadingDiff_Future	Difference between current vehicle heading and road heading in 2 seconds	Tsimhoni, 2004
LateralPosition	Lateral position of vehicle relative to center of lane	Tsimhoni, 2004
RoadCurvature	Road curvature, considered on curves and on approaches to curves	Tsimhoni, 2004

For the longitudinal control task, the velocity and acceleration of the lead vehicle were specified every 0.1 seconds. The model performs the necessary calculations to determine headway. The lead vehicle velocity was taken from one trial of the driving simulator experiment. To make it possible to compare the performance of the model when the monitor location was varied, the same velocity profile was used for each run (Figure 5.5).

Table 5.11. Longitudinal control input parameters.

Parameter	*Definition*	*Source*
LeadVelocity	Velocity of lead vehicle	Yang et al., 2008
LeadAcceleration	Acceleration of lead vehicle	Yang et al., 2008
Th	Desired time headway to the lead vehicle	Yang et al., 2008

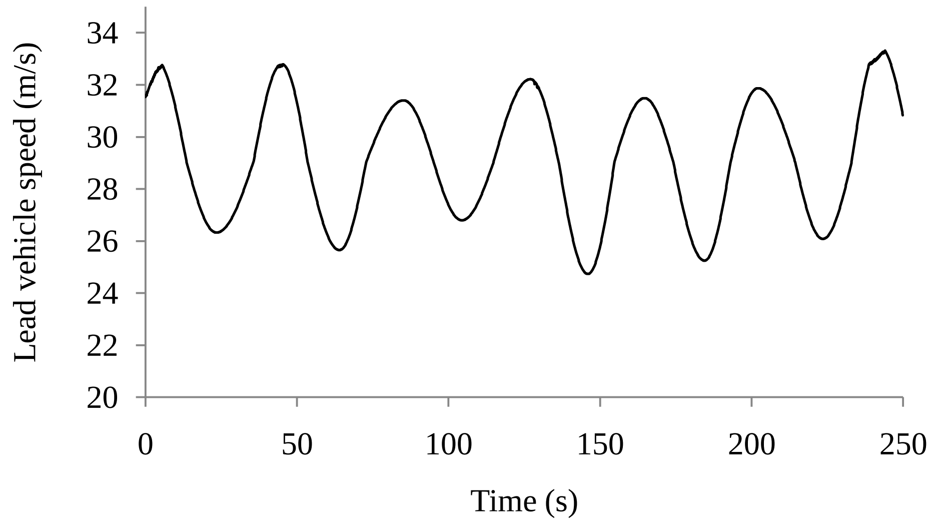


Figure 5.5. The velocity profile of the lead vehicle for the simulation.

To model different driving styles, certain variables were altered during some of the model runs. This made it possible to simulate the differing levels of driving ability, risk-taking propensity, and internal definition of adequate driving performance. The parameters are defined below (Table 5.11).

In particular, the values of NoCorr_pos and NoCorr_heading were increased to represent a greater tolerance for poor driving performance. In addition, the time headway (Th) was increased to simulate a more cautious driver and decreased to simulate a more aggressive driver.

Table 5.12. Driving parameters that were varied to simulate differences between subjects. Standard values are listed.

Parameter	*Driving Task*	*Use*	*Value*	*Source*
NoCorr_pos	lateral control	Maximum lateral deviation from center for which no steering correction is made	0.1 m	Tsimhoni, 2004
NormalCorr_pos	lateral control	Maximum lateral deviation from center for which a normal steering correction is made	1 m	Tsimhoni, 2004
NoCorr_heading	lateral control	Maximum difference between vehicle and road headings that generates no steering correction	2º	Wu, 2007
NormalCorr_heading	lateral control	Maximum difference between vehicle and road headings that generates a normal steering correction	3º	Wu, 2007
Th	longitudinal control	Desired time headway	1 (seconds)	Yang et al., 2008
Epsilon	longitudinal control	Threshold for sliding mode control	7 (unitless)	Yang et al., 2008
C	longitudinal control	Constant gain for range regulation	0.15 (unitless)	Yang et al., 2008

Definition of Physical Task Environment

There are several components in the physical task environment that were defined in Jack. These include the monitor position, driver stature, and cab geometry.

The monitor position was defined relative to the vehicle geometry. As such, it was consistent for all subjects, and the shorter subjects were required to perform a more difficult reach to access the monitor.

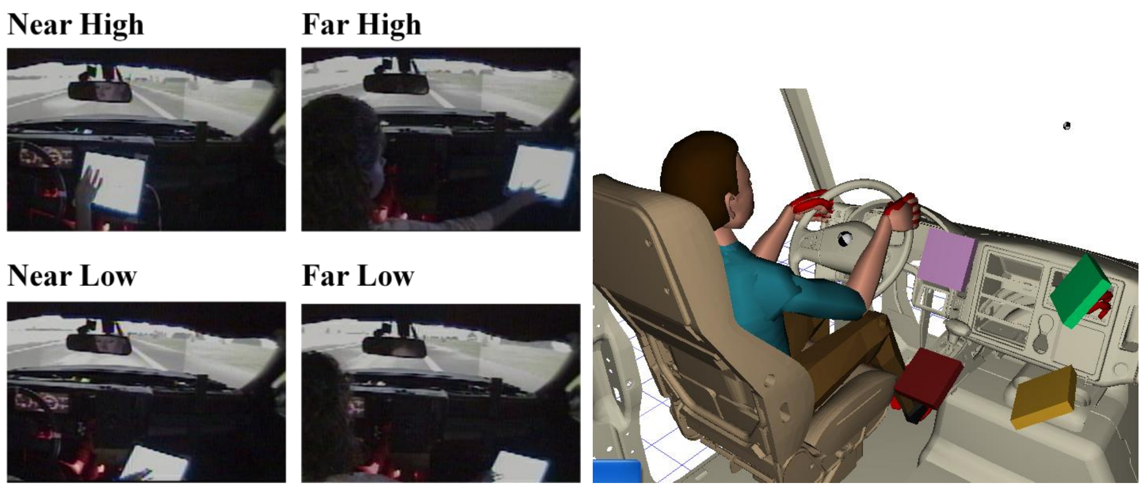


Figure 5.6. The four monitor positions are shown in photographs from the driving simulator study (left) and simulated in Jack (right).

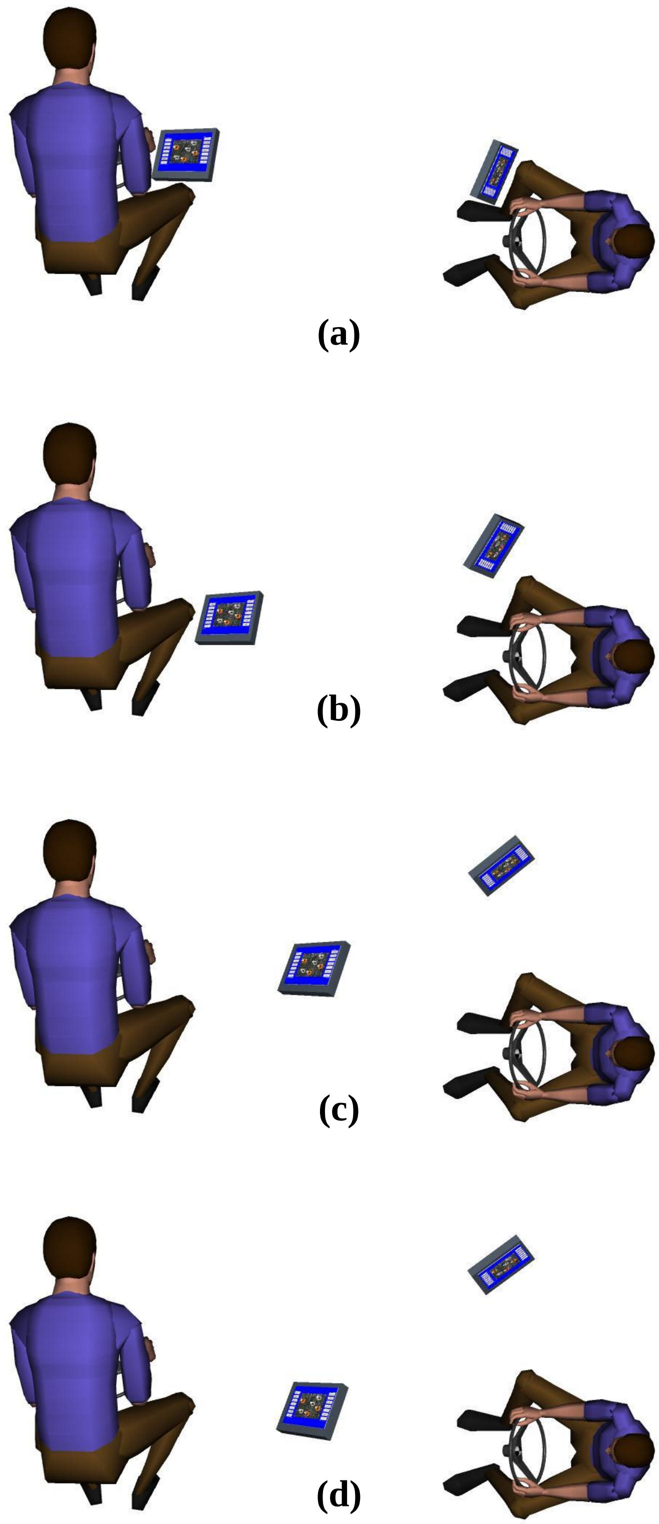


Figure 5.7. The midsize male figure shows the four monitor positions: near high (a), near low (b), far high (c), and far low (d).

The relevant anthropometric measurements defined in Jack were the subject's height and arm span. The subjects from the simulator experiment were grouped into four stature categories. One model was created to represent the midpoint of each stature group. The models are shown reaching to the far low monitor position (Figure 5.8).

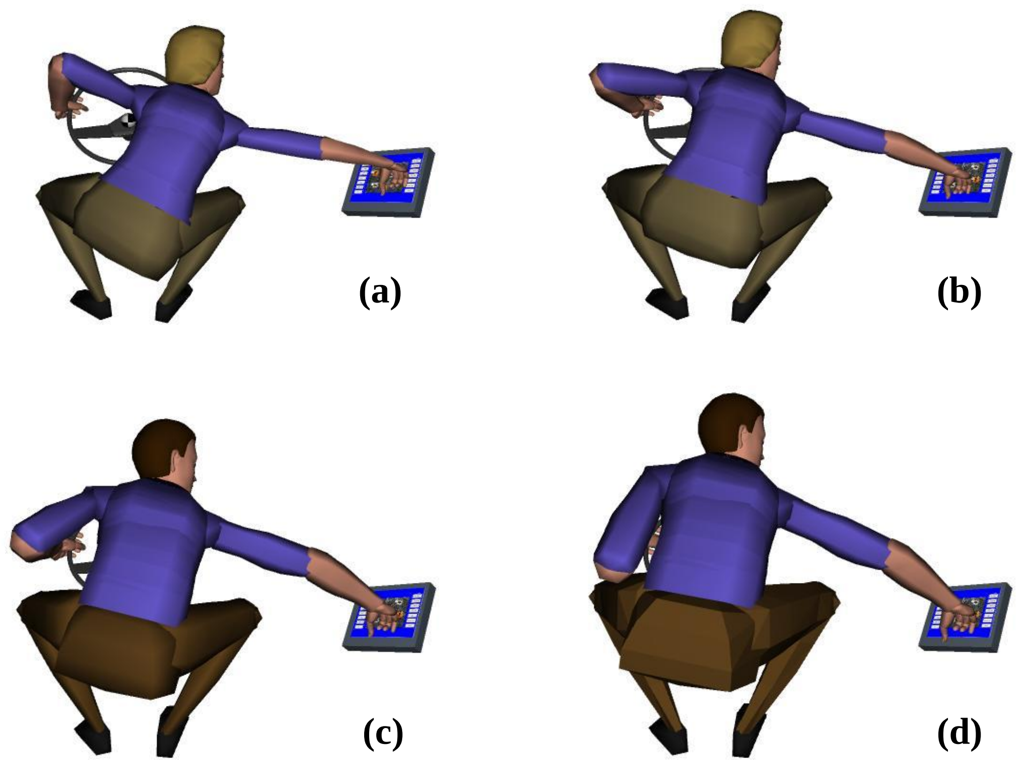


Figure 5.8. A figure representing the midpoint statures of the short female (a), midsize female (b), midsize male (c), and tall male (d) groups reaching to the monitor in the far low position.

The geometry of the vehicle cab was also defined in Jack. The primary factor was the position of the seat relative to the steering wheel. The fore-aft seat position was adjusted by subjects at the beginning of each session of the driving simulator experiment and the values were recorded. Once the stature was defined for the model, the appropriate seat position was chosen from the results.

The physical aspects of the in-vehicle task were condensed into two metrics for use by the QN-MHP. At the beginning of the simulation, the Framework communicated the visual difficulty and the physical difficulty of the monitor position to the QN-MHP.

In addition, the Framework sent the approximate time needed to look to the monitor and to reach to the monitor.

The visual difficulty of the monitor was affected by three factors. First, the location of the driver's head was set, based on the driver's stature and the seat position. The other two factors were determined by the placement of the monitor within the vehicle cab. This was measured in terms of the vertical angle (elevation) and the horizontal angle (aximuth) of the monitor. The angle between the sight vector and straight ahead (3D angle) was also calculated.

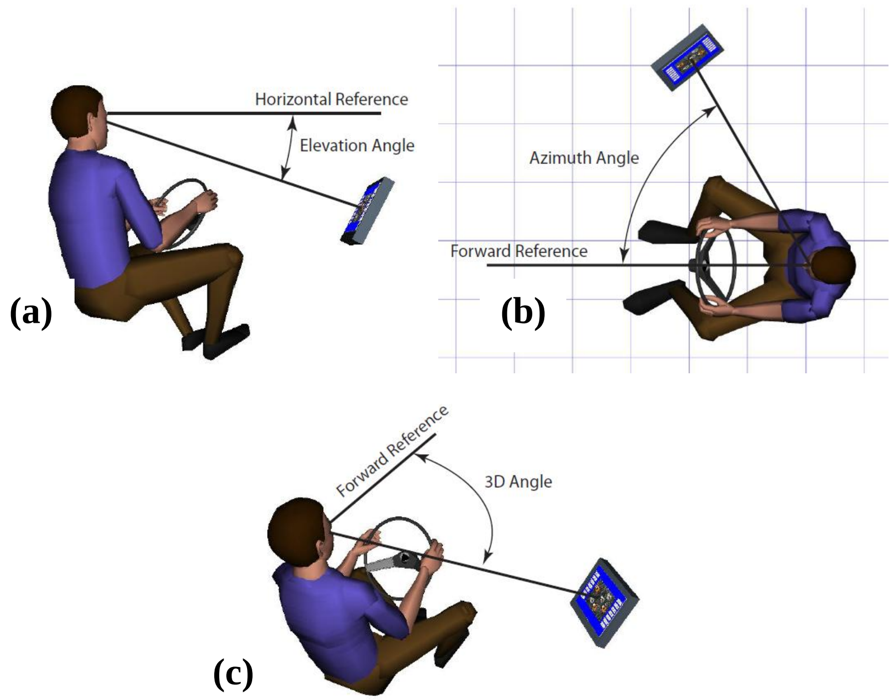


Figure 5.9. Definitions of the elevation (a), azimuth (b), and 3D (c) angles.

Table 5.13. Visual angles (vertical, horizontal, 3D) by subject stature and monitor location.

	Near High			*Near Low*			*Far High*			*Far Low*		
	Vert.	*Horiz.*	*3D*	*Vert.*	*Horiz.*	*3D*	*Vert.*	*Hori.z*	*3D*	*Vert.*	*Horiz.*	*3D*
Short Female	24	35	41	34	48	56	15	63	64	25	63	64
Midsize Female	27	33	42	36	46	56	17	62	63	26	62	65
Midsize Male	31	31	43	38	45	56	20	60	62	29	60	64
Tall Male	33	29	43	39	42	55	23	58	60	31	58	63

These angles were linearly transformed into values of visual difficulty (Table 5.14). The difficulty affected the duration of a visual search for an item on the monitor. Due to the minimal effect of stature on the visual angles, the visual difficulty is similar for all stature groups.

Table 5.14. Visual difficulty by subject stature group and monitor location.

	Near High	*Near Low*	*Far High*	*Far Low*
Short Female	1.28	5.48	7.72	7.72
Midsize Female	1.56	5.48	7.44	8
Midsize Male	1.84	5.48	7.16	7.72
Tall Male	1.84	5.2	6.6	7.44

In the Framework, nominal reach durations are predicted based on regression analyses of movements measured in laboratory studies. For the current simulations, reach durations were predicted using models from Faraway (2000) based on data from a seated reach study (Zhang & Chaffin, 2000). The models take into account reach distance and subject stature and are specific to the driving posture. Because reach distances to the various button locations varied only slightly, nominal reach durations from the steering wheel to all buttons were predicted based on the distance to the center of the display.

The physical difficulty of each monitor location was determined by the stature of the driver and the location of the monitor. The possible difficulty values ranged from 0 (a very simple reach) to 10 (a maximally difficult reach). The difficulty value was determined using the modeling method presented by Reed and colleagues (2003).

Table 5.15. Reach difficulty (and estimated reach duration) by subject stature group and monitor location.

	Near High	*Near Low*	*Far High*	*Far Low*
Short Female	2.8 (1.05 sec)	3.3 (1.17 sec)	9.4 (1.31 sec)	8.4 (1.33 sec)
Midsize Female	2.0 (0.97 sec)	2.6 (1.08 sec)	8.6 (1.21 sec)	7.6 (1.23 sec)
Midsize Male	1.4 (0.88 sec)	2.1 (0.98 sec)	7.9 (1.1 sec)	7.0 (1.1 sec)
Tall Male	1.0 (0.81 sec)	1.8 (0.90 sec)	7.4 (1.01 sec)	6.5 (1.03 sec)

Dual Task Performance

The model generated requests to look at the monitor when the in-vehicle task was available. To evaluate whether or not it should do so, the model used a function that was a linear combination of factors that are important to driving workload and factors related to the secondary task workload. These are summarized, along with their weights, which were hand-fit based on a subset of four subjects from the simulator study (Table 5.16).

Table 5.16. Components of task workload

Parameter	*Weight*	*Workload*
Heading difference	1	Driving (Lateral Control)
Road curvature (0 if no curve, 2 if curve)	1	Driving (Lateral Control)
Lateral lane position	1	Driving (Lateral Control)
Headway difference	0.5	Driving (Longitudinal Control)
Perceived range rate	1	Driving (Longitudinal Control)
Reach Difficulty	0.2	In-Vehicle Task
Gaze Difficulty	0.2	In-Vehicle Task

Running the Simulations

A different random number string and seed was used for each simulation. Ten repetitions each were run for the driving task alone and for the in-vehicle task alone. For the dual task condition, sample combinations of stature and monitor position were run.

Results

Driving Performance

Lateral Control

The Virtual Driver is capable of steering the vehicle so that it remains in the lane during stretches of straight road and on curves. The lane position in meters is shown for one run of the model with no in-vehicle task (Figure 5.10). A lane position of zero indicates that the midpoint of the vehicle is aligned with the center of the lane. Negative values indicate that the car is to the left of the center, while positive values indicate it is to the right. The boxes on the plot show the locations of the curves. For comparison, the lateral lane position of Subject 12 driving the same stretch of road in the normal-weight vehicle with no in-vehicle task is shown.

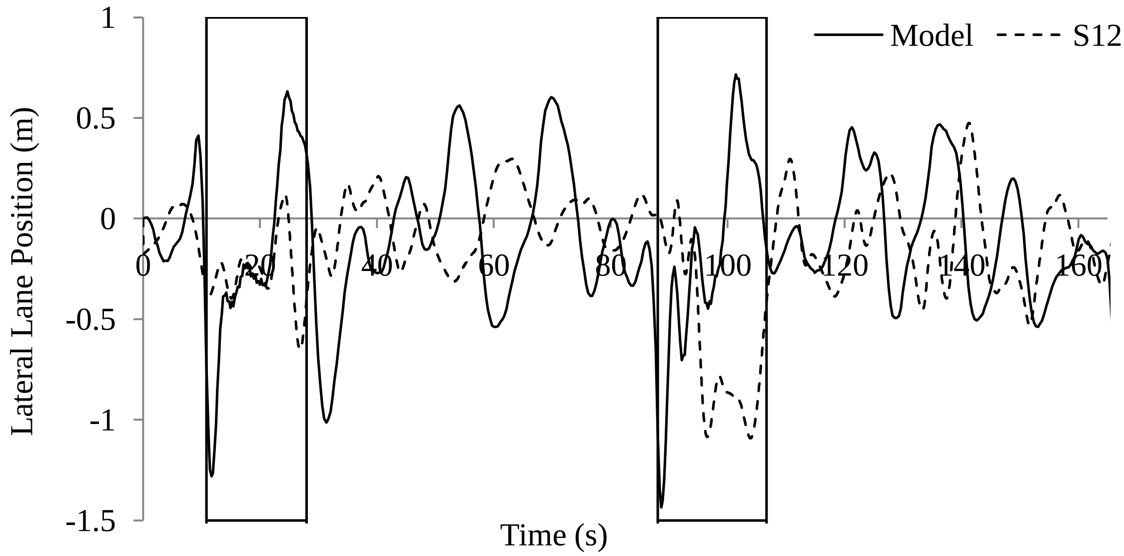


Figure 5.10. The lateral lane position in meters from the lane center for the model and a representative subject. The boxed areas represent the curves.

The standard deviation of the lateral lane position, a measure of the driver's lateral stability is shown for the model. The mean value for all subjects is also shown, along with the values for each subject during the normal-weight vehicle drive with no secondary task. The model's lateral lane position is slightly more variable than most subjects, but it is still within the range of all subjects.

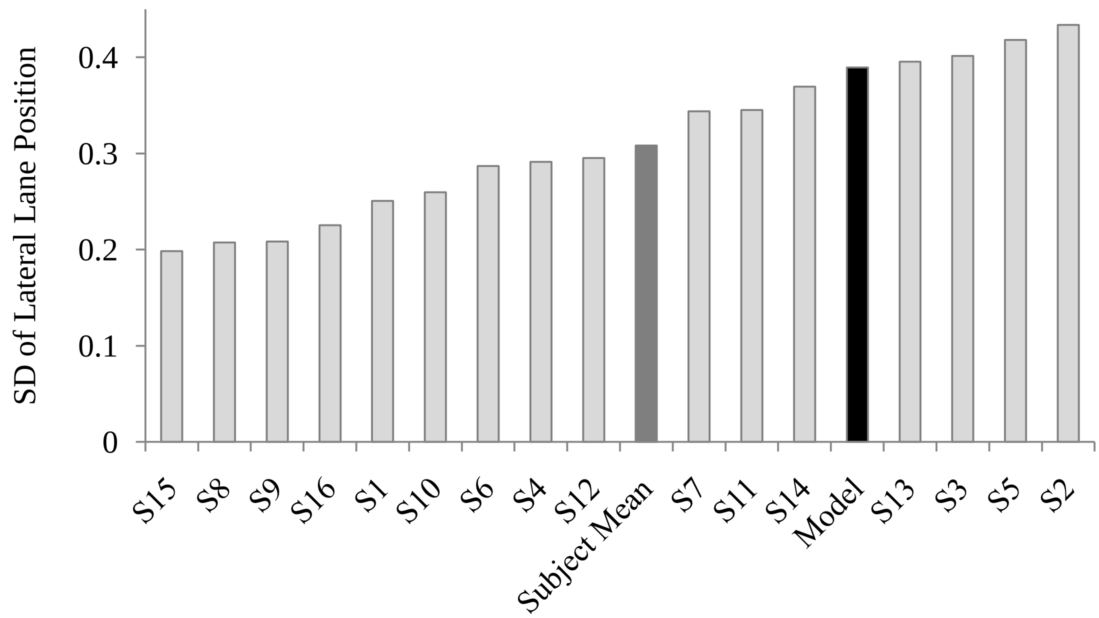


Figure 5.11. The rank-ordered standard deviation of the lateral lane position for the model (black), each subject (light gray), and the mean of all subjects (dark gray) for the normal-weight vehicle with no secondary task.

The variable NoCorr_pos gives the distance from the center of the lane (m) to the edge of the dead zone, in which no steering correction takes place. The width of the dead zone is twice the value of NoCorr_pos. Increasing the size of the dead zone for the model resulted in greater deviations from the center of the lane and a more variable lane position (Figure 5.12).

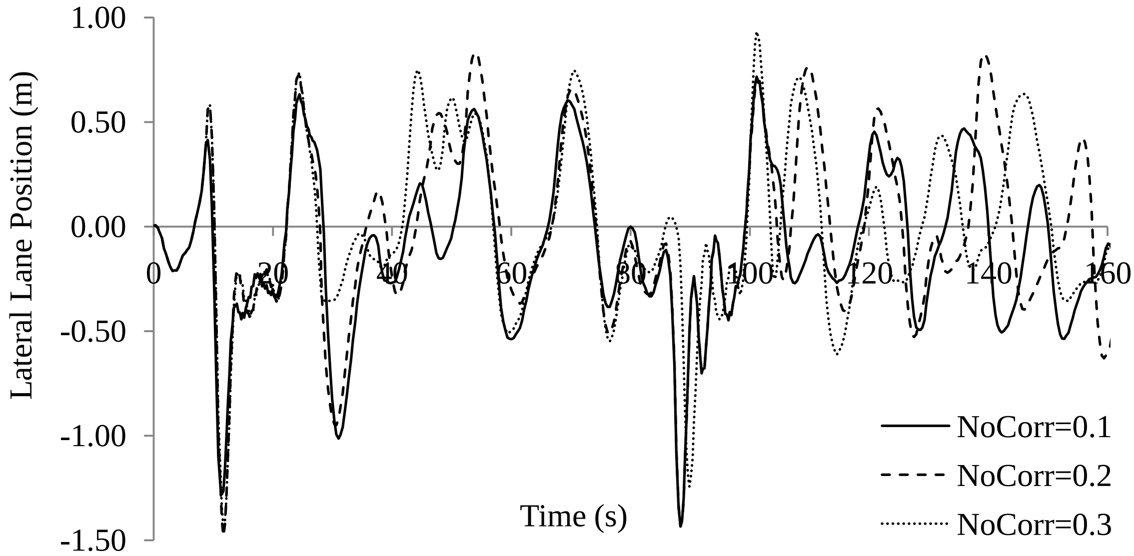


Figure 5.12. The lateral lane position for the model is shown for three dead zone values.

Longitudinal Control

The model was also capable of adjusting its velocity to follow the speed changes of the lead vehicle in order to maintain a constant headway (Figure 5.13). For comparison, the speed of Subject 12 following the same lead vehicle while driving the normal-weight vehicle with no in-vehicle task is shown.

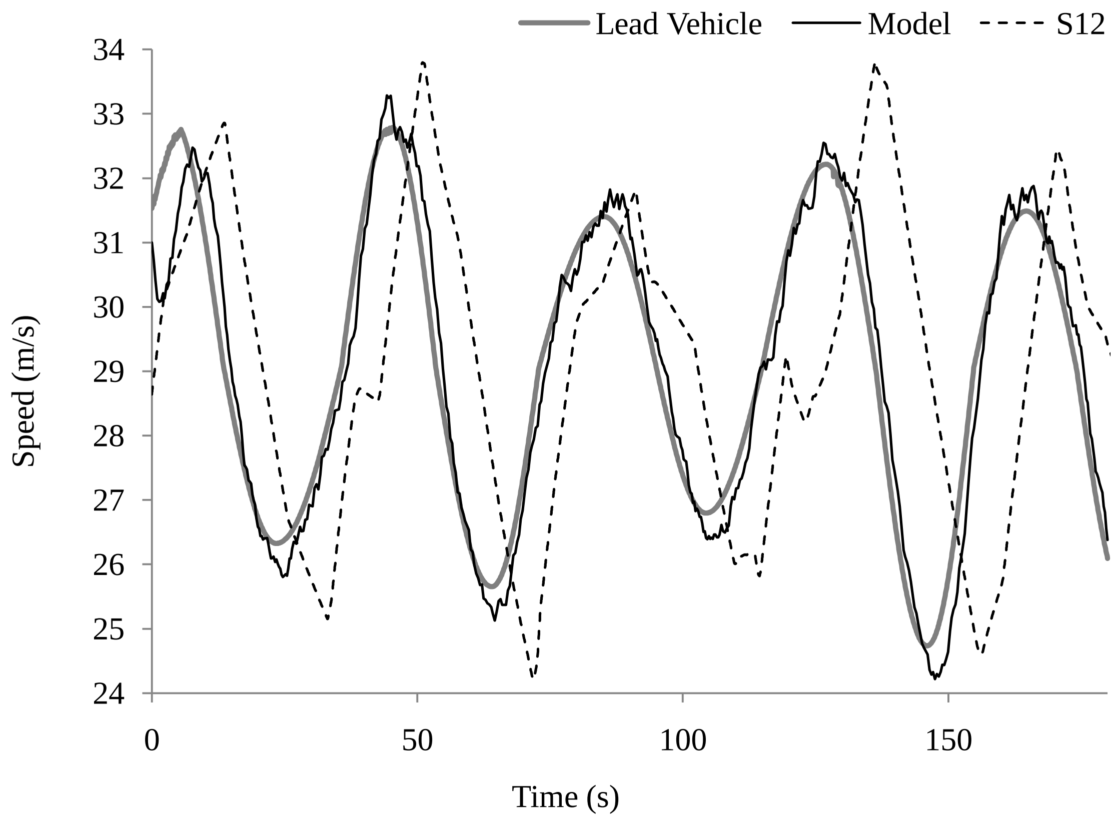


Figure 5.13. The speeds of the lead vehicle, the model (Th=1), and Subject 12.

The input variable Th specified the desired time headway in seconds. Changing Th resulted in differences in the actual headway, though the model continued to follow the speed changes of the lead vehicle in approximately the same way (Figure 5.14).

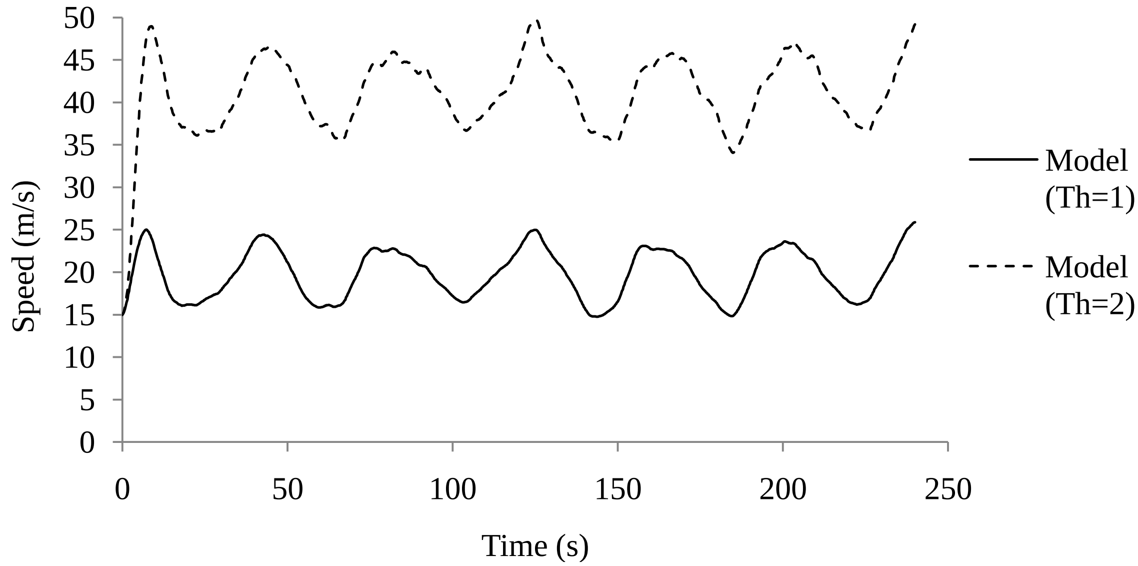


Figure 5.14. The model's headway (m) to the lead vehicle is shown for a desired time headway of 1 second and a desired time headway of 2 seconds.

In-Vehicle Task Performance

Visual Search

The time required for the model to search for and then reach to press the buttons on the touch screen monitor varied based on whether the button was in a fixed or moving location. The way in which the model chose to chunk the task was also important to the in-vehicle task time.

Matching Task Only

When the model simulated performing the in-vehicle task in a stationary vehicle, the mean time required to perform the task, from the first button press to the final button press, was 14.64 seconds, with a standard deviation of 0.08 seconds. Because there was no additional driving task, this time is also equal to the total glance time. The mean time for subjects to complete the in-vehicle task when there was no concurrent driving task was very similar, at 15.28 seconds, but the mean value of the standard deviation within subjects was considerably higher, at 2.62 seconds. The mean value for the model is approximately in the middle of the values for all subjects, but the model is much less variable than the subjects were (Figure 5.15).

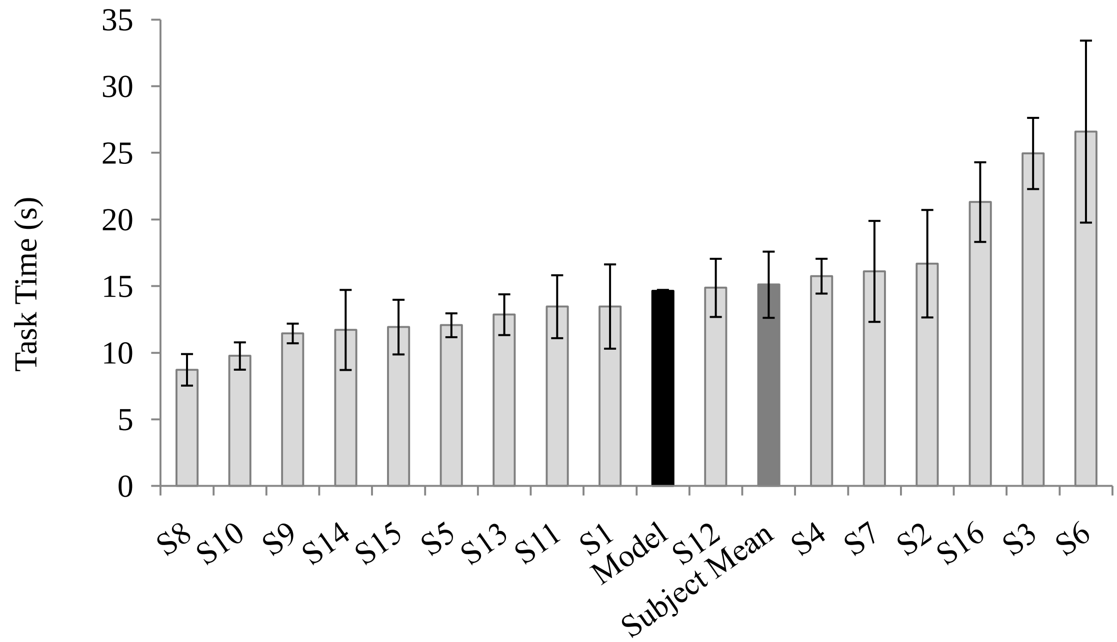


Figure 5.15. The rank-ordered time required to perform the in-vehicle task in a stationary vehicle for the model (black) and all subjects (light gray). The error bars show the standard deviation of the task time for each subject between trials. The mean task time for all subject is also plotted (dark gray), and the error bars for the mean task time show the mean of the subjects' standard deviations.

The model displayed a subtle pattern of chunking when performing the in-vehicle task alone. The model grouped the three button presses required to match a pair (Target-Scout-Assign) into a block, and there was additional time between blocks. A similar pattern was noticed in the data from the simulator experiment. For comparison, the timing of the button presses for the model are plotted along with the timing of the button presses when Subject 12, a midsize male, was performing the in-vehicle task without driving (Figure 5.16).

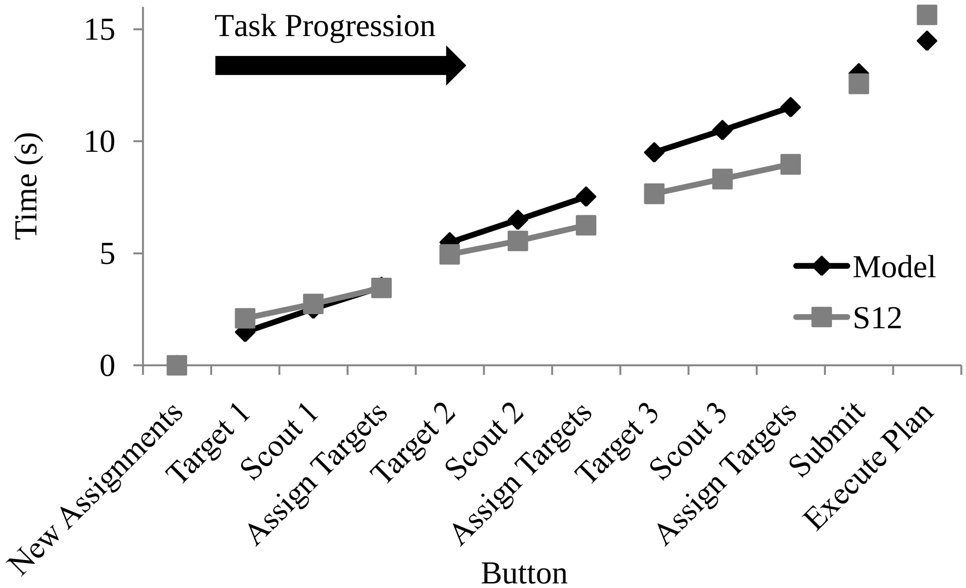


Figure 5.16. The lines indicate the chunks in the timing of the button presses when the model performs the in-vehicle task alone and when Subject 12 (midsize male) performs the in-vehicle task alone.

The pattern is more clear when the time between button presses is considered. The times between pressing "Scout" and "Target" and "Target" and "Assign" are much shorter than the times between other button presses (Figure 5.17).

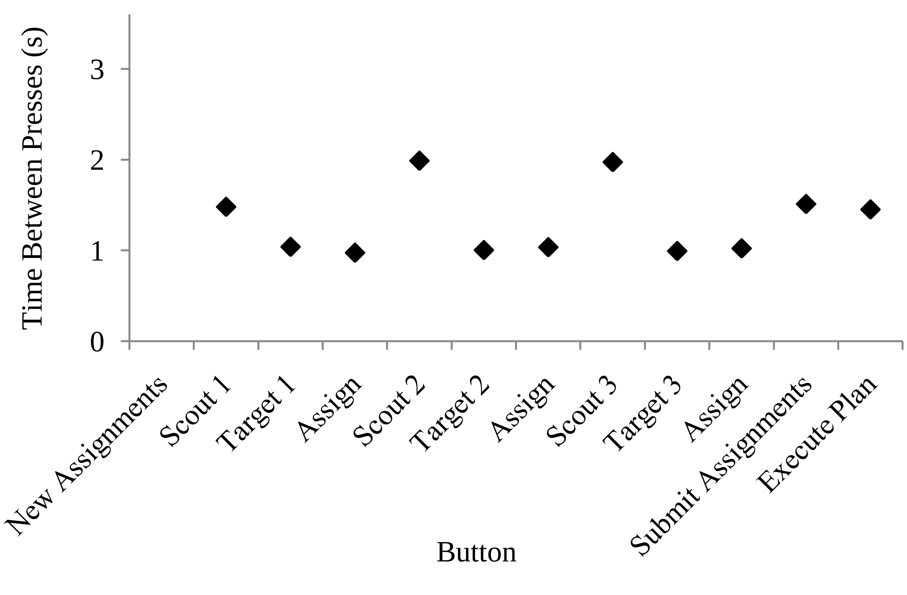


Figure 5.17. The time between button presses when the model performs the in-vehicle task alone.

This pattern was duplicated by many of the subjects when performing the in-vehicle task without driving. An example trial from Subject 12 is shown (Figure 5.18).

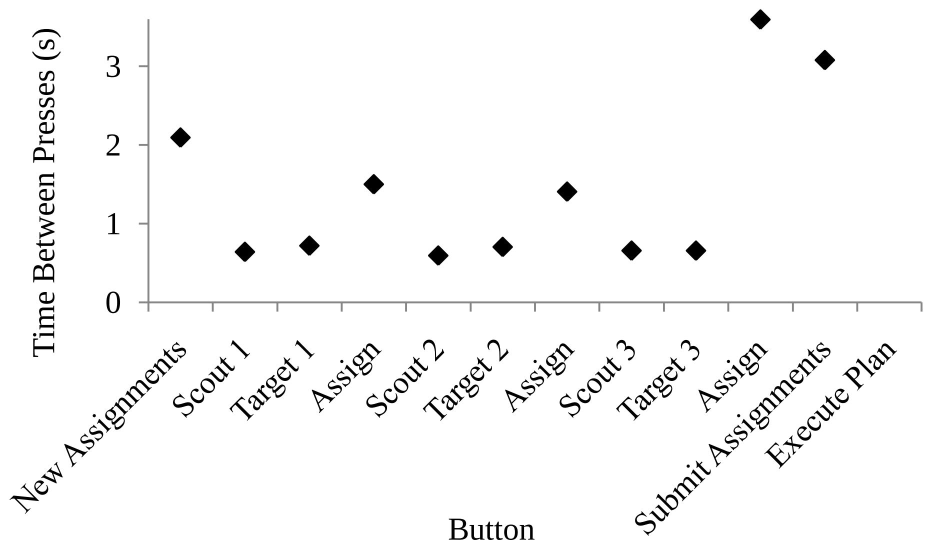


Figure 5.18. The time between button presses when Subject 12 (midsize male) performed the in-vehicle task alone.

Dual Task Performance

The Virtual Driver, simulating a short female, performs the in-vehicle task with the monitor in the near high position while continuing to drive, though lane-keeping performance does suffer slightly compared to when the model is driving on a straight road without working on the secondary task (Figure 5.19). The line at the top shows the button index, which increments each time a button is pressed on the monitor. The eye position, which is 1 when the model is looking at the road and 2 when the model is looking at the monitor, is also shown. The boxes represent times when the model is on a curve. Notice that the model avoids performing the secondary task on the curves; the model glances at the monitor before the curve begins and immediately after exiting the curve. The task appears on the monitor as the vehicle is approaching the curve, and the model does not begin to press buttons until the curve is complete.

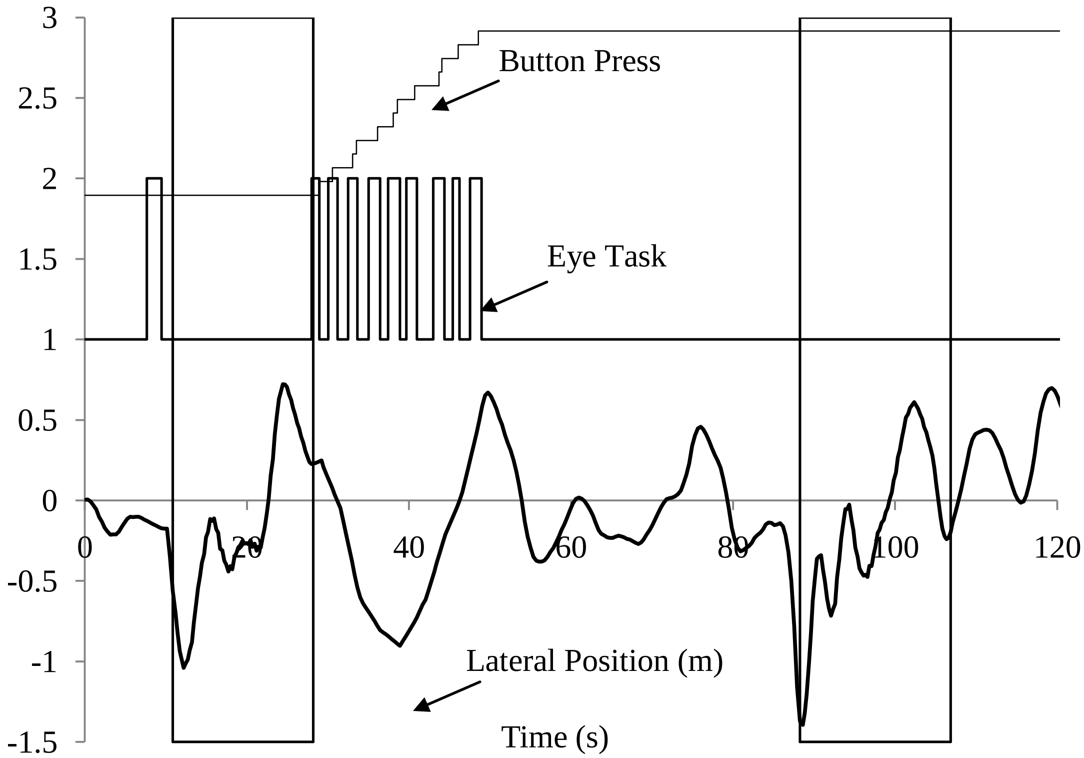


Figure 5.19. The Virtual Driver, simulating a short female, performs the in-vehicle task with the monitor in the near high position while driving.

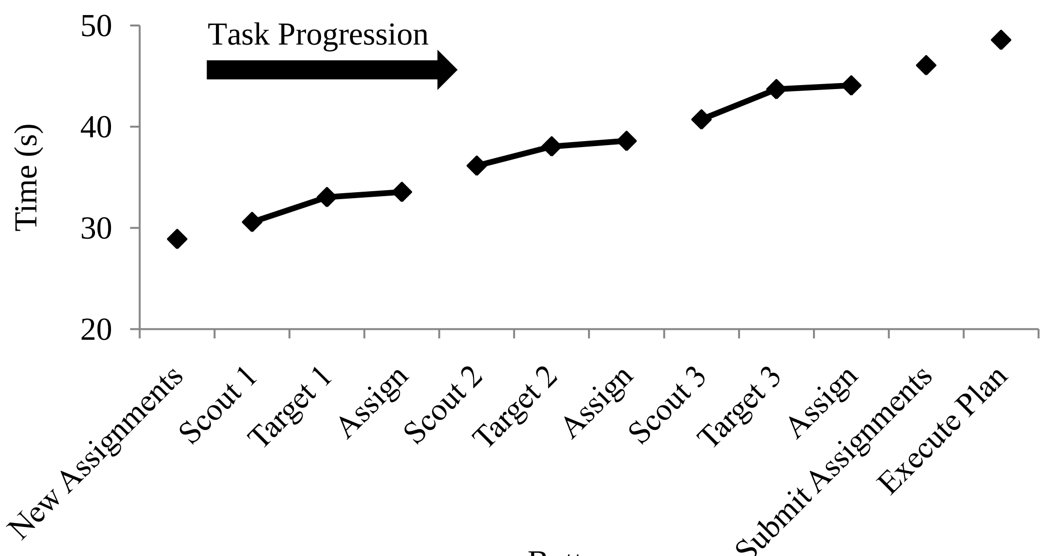


Figure 5.20. The time between button presses when a simulation of a short female drove while performing the in-vehicle task with the monitor in the near high position.

Discussion

Driving Performance

The Virtual Driver was able to simulate both lateral and longitudinal performance while following a lead vehicle on a road with curves. The model's lateral lane position was slightly more variable than those of most subjects, and its performance was more affected by the curves. However, the overall range and standard deviation of the lateral lane position matched the empirical results fairly closely.

The model was considerably better than subjects at performing longitudinal control. It responded to speed changes more quickly than the subjects and had a smaller overshoot. It is possible that the representation of perceptual limitation in the model was not equivalent to what subjects experienced. In addition, the model may have been more "motivated" than the subjects to maintain the desired headway.

In-Vehicle Task Performance

The Virtual Driver correctly simulated performing the in-vehicle task that was used in the driving simulator experiment. The total task time and the time between button presses, for both fixed-location and variable-location buttons, were comparable to those generated by the subjects. Most importantly, the model displays the same chunking behavior that subjects used, grouping the "Scout", "Target", and "Assign" buttons.

Dual Task Performance

The Virtual Driver is currently able to perform the driving tasks and secondary task simultaneously while maintaining reasonable performance on each most of the time. However, it does not yet display all of the resource-sharing behaviors that drivers in the simulator study displayed and that were expected to emerge from the model.

The concept of workload is very important to sharing resources between tasks, both to the model and to actual drivers. The probability of drivers performing the secondary task at a given time depends greatly on both the current workload and the expected workload that performing the task would impose.

The model appears to be very sensitive to the task parameters related to workload. If the parameters used in deciding to switch attention to the secondary task are set too high, the model never performs the secondary task. However, if these parameters are set too low, the driving performance deteriorates more than drivers would find acceptable in an actual driving situation.

The driving simulator experiment that was conducted did not provide a good way to estimate the parameters used for workload. Future studies should consider the best way to measure these variables. In addition, it is necessary to have different values for these parameters that correspond to different levels of risk taking, motivation, and experience.

The probability of returning attention from the monitor to the driving task at any given point is both a function of time and the structure of the task. If the proper combination of amount of time spent away from the road and natural break in the secondary task occurs, the driver will look back to the road. Due to the design of the driving simulator study and the secondary task, which was very amenable to chunking, it was impossible to truly separate these components. The parameters were estimated based on knowledge of the task format and the glance data, but it is likely that more accurate values are needed to simulate the actual behavior of the subjects.

Subjects during the driving simulator study appeared to have the ability to estimate how long a task chunk would take, in addition to how long a single reach would take. They maintained the chunking behavior seen during the performance of the in-vehicle task alone by only reaching to the monitor when they expected to have time to complete all the button presses for the current chunk, whether that was a single button or a group of three. In contrast, the model does not differentiate between small and large chunks prior to starting an action. It has no concept currently of how long a glance will take before it starts it, and its eyes can be drawn back to the road before the chunk is complete if it is alerted to unacceptable driving performance by the peripheral vision. Because of this, the chunking behavior that the model displayed when performing the in-vehicle task while driving was less pronounced than the behavior when the model was performing the in-vehicle task alone and than the behavior of the subjects in both situations.

Tuning Model Parameter Values

A number of parameters were used in the Virtual Driver model. Some of the values of these parameters were determined from the literature (e.g. Card et al., 1986), including previous versions of the QN-MHP (e.g. Feyen, 2002). Others were fit using a subset of the experimental data from the driving simulator study presented earlier.

In some cases, there was no clear value in the literature, and the values could not be extracted from the experimental data. In these cases, a sensitivity analysis was performed. If the value chosen for the parameter had little effect on the model outcome, the accuracy of the parameter value was considered to be relatively unimportant and a value in the middle of the range tested was used.

Conversely, if changing the value of the parameter significantly altered the model outcome, selecting the parameter value was more difficult. There are two main strategies to use in this case. The first is to choose a value that yields results similar to a majority of the subjects. For example, though the important variables for steering were identified in the literature (Tsimhoni, 2004), some of the parameter values were not specified. A linear combination of the variables was assumed, and multipliers were chosen so that the model remained in the lane and displayed steering characteristics qualitatively similar to sample subjects.

The second strategy is to show the results of multiple parameter values, which could represent differences between subjects. This was done for the driving variables representing the dead zone for lateral control and the desired following time for longitudinal control.

Future studies could refine the values of the model parameters. For example, it is currently unclear how the model should quantify workload. An experiment that varied the workload variables in a controlled manner could be used to determine the appropriate weight to assign each variable. It is likely that drivers perceive workload differently, so it may be necessary to have different sets of weighting values for different driver physical characteristics and personality types.

Modeling Important Features of Driving Behavior

The model displays some of the important features of driving behavior that were described earlier. The implementation of these and the modeling results that show them are discussed.

1. Secondary task scheduling: The decision to perform secondary in-vehicle tasks is based on the difficulty of the primary driving task.

Driving difficulty, which is based on the road curvature, the heading difference between the vehicle and the road, the range to the lead vehicle, and the range rate to the lead vehicle, is calculated in the model. This value is then used when the model makes decisions about whether to look away from the road or to reach to the monitor. The result is that the model concentrates on driving rather than performing the in-vehicle task when the driving task is difficult, such as when navigating a curve. This behavior was also observed in many of the subjects during the simulator experiment.

2. Effect of reach capability on in-vehicle task difficulty: Reach capability affects the difficulty of the in-vehicle task, especially for extreme monitor locations.

Each of the four monitor positions was assigned a reach difficulty value based on the monitor location and the subject stature. This value was used to alter the probability of looking away from the road and reaching to the monitor. It also affected the probability of returning attention to the road between steps of the in-vehicle task.

3. Effect of prioritization of dual tasks on performance: Individual decisions about prioritization of driving versus the in-vehicle task, which are impacted by the amount of risk a driver will accept, will affect performance on both.

By changing the probability of looking back to the road after a certain length of time and disabling the peripheral vision alerts, it was possible to cause the model to generate longer glances to the monitor. This in turn affected the performance on the driving task. A decreased probability of looking back to the road represented drivers who are willing to neglect the primary driving task in order to improve performance on the secondary in-vehicle task.

4. Grouping of in-vehicle task elements: Drivers group in-vehicle task elements into blocks.

The probability of looking back to the road after completing a button press was affected by both the time since the last glance to the road and the current step of the in-vehicle task. By increasing the probability of looking to the road after pressing a button that completed a pre-defined chunk, it was possible to approximate with the model the chunking behavior demonstrated by subjects. However, it is necessary to add to the model a representation of expected chunk duration so that the model knows the amount of time it will need to complete a chunk prior to starting it.

5. Effect of anticipated driving difficulty changes on in-vehicle task performance: Drivers anticipate changes in the driving task difficulty and adjust the performance of the in-vehicle task accordingly.

In addition to tracking the current driving difficulty, the model also predicted the impending driving difficulty, based on the curvature of the upcoming segment of road. This was used in conjunction with the predicted time to reach to the monitor to determine whether there was enough time to complete the reach before the driving difficulty would increase to an unacceptable level.

6. Driving performance variability between subjects: Drivers differ in driving performance, even when there is no in-vehicle task.

Differences in driving ability were modeled by adding a stochastic term to the response of a driver to discrepancies between the desired state of the vehicle and the actual state. A multiplier in the term increases for drivers who are less experienced or less capable. Differences in opinions about acceptable driving performance were modeled by inserting a dead zone, or a range of discrepancies in which no correction occurs. A large dead zone represents a driver who accepts poor performance on the driving task, while a small dead zone represents a driver who feels that it is necessary to correct even minor differences between desired and actual vehicle state.

7. Strategies for switching between driving and the in-vehicle task: Drivers use different strategies to decide when to switch between driving and the in-vehicle task.

This behavior was added to the Virtual Driver model by adjusting the probability of glancing between the road and monitor. Subjects who switch between tasks more frequently are modeled as having a greater probability of shifting attention back to the road after each button press. In contrast, subjects who are prone to cognitive capture are modeled with a decreased probability of shifting between tasks, even as the time spent on the task increases.

8. Strategies for maintaining driving performance: Drivers employ different strategies to attempt to maintain driving performance.

This driving behavior is not currently included in this implementation of the Virtual Driver model. However, it could be added in the future by adjusting the parameters that influence risky behavior. This would make it possible to simulate the drivers who are willing to engage in risky driving behavior temporarily in order to complete the task before reaching a curve, as well as the drivers who refuse to change their level of risk-taking.

9. Visual search during in-vehicle task: Strategies for an in-vehicle task vary based on whether controls are in predictable locations or a visual search is required.

The difference between reaching to fixed-location buttons and variable-location buttons was simulated by altering the visual search time. This time was considerably shorter for the fixed-location buttons, to represent the fact that the driver already knew approximately where these buttons were located.

10. Visual search during in-vehicle task: The glance behavior changes based on the location of the monitor for the in-vehicle task.

Due to limitations of the driving difficulty parameters and the in-vehicle task probabilities, the current implementation of the model does not simulate this behavior. However, if the parameters are set correctly to allow the model to share resources between the driving and in-vehicle tasks as the subjects did, this behavior should emerge naturally. The presence of the task would encourage the driver to look at the monitor. At the same time, the greater difficulty associated with reaches to the far monitor would decrease the probability of the driver reaching to the monitor during any given glance, resulting in a greater number of glances for the far monitor locations. In addition, reaching to a far monitor takes longer, so the driver would complete a smaller proportion of the task before feeling it was necessary to look back to the road.

11. Feed-forward and feed-back control for reaches to the monitor: Drivers utilize both feed-forward and feed-back control when performing in-vehicle tasks that require reaches.

This driving behavior is not modeled in this implementation of the Virtual Driver. Future versions of the Virtual Driver should improve the communications between the QN-MHP and the HUMOSIM Framework so that feed-forward reaches can be performed with a single command from the cognitive model, but feed-back reaches require additional input from the cognitive model as it processes visual inputs related to the reach.

12. Physical interaction with in-vehicle interface: Drivers may physically interact with the interface for an in-vehicle task in different ways.

This driving behavior is also not currently included in the model. To accurately represent such differences, it would be necessary to add greater complexity to the internal model of the human body in the QN-MHP. Changing the movement time to press a button would be a temporary method to partially simulate the differences. Shorter movement times would represent subjects who use more than one finger to press the buttons, as their movement times for each button press could essentially overlap.

Suggested Model Additions

Several additions to the model should be considered in future versions. Some of these would address limitations in the QN-MHP, while others would be related to the connection between the QN-MHP and the HUMOSIM Framework.

Currently in the model, Server D, which represents the long-term procedural memory, is replaced with a task analysis array. This array is available globally in the model, so entities at any server can access the information. In order to truly simulate referencing the long-term memory, the information should be stored at the server, so that entities must be routed to the server to obtain the task information.

Although Server V (sensorimotor integration) is represented in the QN-MHP, it is not actually in use at this time. This does not have much effect on the task studied during the driving simulator experiment, but it could be important for examining future activities. For example, if there is a change in the environment between the time when an action was initiated in the cognitive subnetwork and when it is processed in the motor subnetwork, Server V would be able to adjust for small changes or reroute the entity for additional processing if there are large differences between the expected and actual scenarios.

In terms of the connection between the QN-MHP and the HUMOSIM Framework, several changes should be made. In general, these would all promote greater communication between the models.

Server W is responsible for motor program assembly in the QN-MHP. Currently, this is represented by a WAIT statement that halts processing in the model for a length of time that simulates the time needed to build a motor program for a movement.

In the future, motor program assembly should involve communication with the Framework to obtain the motor program. The time that this takes should vary so that it is longer if the motor program selected is more complex or less familiar.

Another server that is represented in the QN-MHP but not fully functional is Server X, which is responsible for feedback information collection. In theory, this server will gather the copy of the motor command that was sent to the muscles and compare it to feedback from various perceptual systems, including vision and proprioception. It can then report any discrepancies to the cognitive subnetwork so that the model can make adjustments.

In the current model, there are no significant perturbations in the environment that could cause the expected action to be different from the actual action, so there is no real need for Server X at this time. However, in future versions of the model, feedback from the HUMOSIM Framework should be collected at Server X. To simulate this, an entity could be routed back to Server X from Server Z, which sends motor commands to the body parts. This entity would represent the efference copy of the motor command, containing information about the predicted movement and its expected sensory feedback.

Chapter 6

Conclusion

Introduction

The research presented here describes the development of an integrated cognitive-physical human model. This model is an important accomplishment because it is the most complete simulation model to date addressing both the cognitive and physical aspects of performing a task. Most previous human models have been either cognitive, focusing on the information processing underlying the decisions made when performing a task and containing a highly simplified representation of the physical aspects of a task, or physical, representing postures and motions used to perform the task but requiring a person experienced with the task and the software to enter detailed information about how and when the movements should be made. Many tasks have both cognitive and physical components, which may interact in ways that could not be predicted using a cognitive or physical model alone. The new integrated model, however, can be used to model complex cognitive-physical tasks. In doing so, it provides a method for predicting human performance and testing the designs of different interfaces, as well as a means for better understanding why people interact with a task environment in certain ways.

Driving while performing a secondary in-vehicle task is an example of an activity with significant cognitive and physical components that many people perform successfully on a daily basis. When drivers fail to properly balance the demands of the dual tasks, however, the results can be tragic. Because of the prevalence and consequences of distracted driving, the integrated cognitive-physical human model was applied to study driving with an in-vehicle task, resulting in the Virtual Driver model. The model was tuned and calibrated using the results of a driving simulator experiment. Increasing the visual and physical difficulty of the in-vehicle task affected the resource-sharing strategies drivers used and resulted in deterioration in driving and in-vehicle task performance, especially for shorter drivers. The Virtual Driver replicates basic driving, in-vehicle task, and resource-sharing behaviors and provides a new way to study driver distraction.

The remainder of this concluding chapter contains a brief summary of the results of the driving simulator study and the driver modeling work, as well as a discussion of the implications of this research. As is the case with nearly all research, the knowledge gained by the end suggests changes to the experimental method that could have improved the final results, and these are discussed. The assumptions and limitations related to the model are also covered. Finally, some possible ideas for future work are presented.

Summary of Results

The driving simulator study showed that performing a secondary in-vehicle task had a significant impact on driving performance. That impact was greater when the monitor was located farther from the subject and when the subject was relatively short, making the reach to the monitor more difficult. More importantly, the study made it possible to identify strategies that drivers may employ, knowingly or otherwise, to reduce workload and improve performance in a dual-task environment.

The initial implementation of the Virtual Driver, a combined cognitive and physical model, was able to simulate lateral and longitudinal control comparable on several important measures to subjects' performance in the simulator. It also successfully simulated performance of the in-vehicle task. In addition, the Virtual Driver duplicated certain multitasking behaviors that subjects in the simulator study displayed, such as ceasing to work on the in-vehicle task when the workload of the primary driving task reached some threshold,~~.~~

Taken together, the driving simulator study and the modeling work addressed the specific aims identified at the beginning of the dissertation. They also added to the knowledge on driver distraction and generated new questions that could lead to future work in this field.

Specific Aims

Specific Aim 1: Conduct a driving simulator experiment and analyze the results to determine the behavioral strategies used to perform a secondary task while driving, given different task environments. The description and results from the driving simulator study were presented in Chapter 3. Performance on the driving and in-vehicle task varies with driving difficulty, measured by vehicle weight and road curvature, and secondary task difficulty, measured by monitor location and subject stature. In addition, several driver behaviors and strategies were identified and described in Chapter 4.

Specific Aim 2: Integrate the cognitive QN-MHP human model with the physical HUMOSIM Framework to produce a combined cognitive-physical human model. The QN-MHP and the HUMOSIM Framework were combined in the conceptual Virtual Driver model (Chapter 4). This model was then implemented using ProModel and Jack (Chapter 5). The integrated model was able to drive while performing a secondary in-vehicle task.

Specific Aim 3: Add representations of more complex motor behavior to the combined cognitive-physical model. Proprioceptive sensory input, feedforward control, and motor programs were added to the Virtual Driver. The proprioceptive sensory input is in the form of feedback from the HUMOSIM Framework describing the effective posture of the limb in terms of percentage attainment of a goal. This information can be used by the QN-MHP for future movement decisions. Feedforward control occurs when a motor command is generated by the QN-MHP and sent to the Framework, which executes the movement. The motor programs are contained in the Framework, which can use them to provide information to the QN-MHP about possible movements.

Specific Aim 4: Use the combined cognitive-physical model to simulate changes in dual task performance strategies during driving while performing a secondary in-vehicle task. The Virtual Driver uses knowledge of the physical demands of the in-vehicle task, as well as the workload associated with the primary driving task, to make decisions about when to switch attention between the tasks. When the monitor is located in one of the far positions, the model is less likely to look at or reach to the monitor when the driving workload is high, such as when traversing a curve. The likelihood of interacting with the in-vehicle task under such circumstances decreases even more when physical characteristics of the driver, such as stature, would result in a greater workload.

Contributions and Implications of Research

Driving Behaviors and Driver Distraction

Driving while performing in-vehicle tasks is a topic that has received much attention in the media recently, due to the potential dangers of this activity. The technology available to drivers is changing more rapidly than researchers can study its effects on safety. Additional regulations might reduce crash risk, but it is unclear what those regulations should be in order to have the optimal impact.

A better understanding of driving behavior could aid in making decisions about designing and regulating in-vehicle tasks. Both driving simulator studies and modeling work can contribute to the knowledge of how drivers allocate resources when performing an in-vehicle task and the effects on driving performance.

Based on the driving simulator study presented here and a review of the literature, twelve main attributes of driving behavior were identified. The current research advances the understanding of four in particular: secondary task scheduling, the effect of anticipated driving difficulty changes on in-vehicle task performance, the effect of reach capability on in-vehicle task difficulty, and the effect of prioritization of dual tasks on performance. These are all related to how drivers direct attention and other resources when performing multiple tasks.

Knowing how people choose to schedule secondary tasks while driving is very important because it can aid in understanding how people allocate resources between conflicting tasks to maintain performance on each. Ultimately, it may help to design tasks and interfaces in such a way that a driver can accomplish a secondary goal while maintaining safe driving performance.

In the driving simulator experiment described in this work, drivers were observed to account for both the primary driving task difficulty and the secondary in-vehicle task difficulty when deciding when to switch attention from the road to the in-vehicle task monitor. When driving difficulty was greater, such as when navigating a curve, drivers often concentrated on driving and delayed performing the secondary task until the driving difficulty decreased. Drivers were most likely to do this when the in-vehicle task was also difficult, such as when the monitor was in one of the far positions. This suggests that drivers had some internal model of combined task difficulty. When the overall task difficulty exceeded an acceptable level, the driver focused on the primary task to the exclusion of the secondary task.

Many previous driving studies have encouraged task performance to occur at certain times rather than allowing the driver to choose when to perform the task. This may be an accurate representation of certain tasks, such as answering a cellular phone. However, drivers often have greater discretion over when to perform a task, such as when they place a phone call, compose a text message, or enter an address into a navigation system. The driving simulator study presented here offers insight into when and for how long drivers choose to divert attention from the road.

Knowledge of how task difficulty is quantified and what level is considered acceptable is necessary to predict performance on a dual task. Future driving studies could vary the driving difficulty in smaller increments than those used in the present study. Different factors that affect driving difficulty could also be examined. Along with road curvature, these include factors such as traffic congestion, predictability of lead vehicle behavior, and visibility.

In addition to the current difficulty of the primary driving task, drivers also appeared to consider the anticipated driving difficulty in deciding when to work on the secondary task. For example, if the in-vehicle task appeared on the screen when a driver was approaching a curve, the driver would often postpone working on the in-vehicle task until exiting the curve, even though the current driving difficulty was not great. In addition, some subjects reported that they preferred to work on the in-vehicle task when the lead vehicle was accelerating rather than when it was decelerating, because they knew they would not have to monitor the headway as closely.

Anticipated driving difficulty is a topic that previous driving studies have apparently not considered. It is important, however, because an error in predicting driving difficulty during the time it will take to complete a step of an in-vehicle task could result in a crash. Though the present driving simulator study identified anticipated driving difficulty as an important factor in timing performance on an in-vehicle task, additional studies are needed to determine how driving difficulty is predicted and the frequency of prediction errors.

As discussed above, subjects appeared to consider the combined difficulty of the primary driving task and the secondary in-vehicle task when deciding how to divide resources between the two tasks. Previous driving studies considered in-vehicle task difficulty in terms of the cognitive complexity of the task, such as the production rate and complexity of speech in passenger and cell phone conversations (Drews et al., 2008), or the visual difficulty of looking at a target (Dukic et al., 2005), but none of these in-vehicle tasks had noteworthy reach difficulties. In contrast, the driving simulator study presented here varied the location of the touch screen monitor to create significant differences in reach difficulty.

Due to the physical component of the in-vehicle task, the reach capability of the driver affected the overall difficulty of the task in the driving simulator study. Shorter drivers, who experienced relatively more difficult reaches than the taller drivers, took longer to complete the in-vehicle task and were more likely to suspend work on the task while on a curve. The effect of reach capability, essentially driver stature, on the in-vehicle task difficulty is a topic that has not been considered in previous driving studies. There is the potential to extend the findings to investigate the effects on drivers of physical injury or disability, loss of range of motion as might occur with age, and presence of obstructing garments.

Drivers in the simulator study demonstrated different intrinsic levels of prioritization of the driving task over the in-vehicle task, though all drivers were given the same instructions. Some drivers tolerated large decrements in driving performance to perform the in-vehicle task quickly, while others were willing to sacrifice speed on the in-vehicle task to maintain good driving performance.

Previous studies have examined the effects of encouraging performance on driving or the in-vehicle task (Horrey et al., 2006; Brumby et al., 2007), but few studies have considered differences between drivers in task prioritization given neutral instructions. It may be possible to use some measure of personality, likely related to risk-taking tendencies, to predict how a driver will assign priority to an in-vehicle task. This prioritization will affect how the driver chooses to allocate resources between the driving task and the in-vehicle task.

Future driving simulator studies of driver prioritization could implicitly manipulate the prioritization process by altering the consequences of driving performance decrements. For example, the lane lanes could be replaced concrete barriers such as those used in construction zones, so that a lane departure would result in a (virtual) crash.

The Virtual Driver Model

The Virtual Driver represents a valuable extension of the existing body of human modeling work. The cognitive human models that have been developed in the past have contained very limited representations of the human body. Combining the QN-MHP with the HUMOSIM Framework made it possible to have an accurate and detailed representation of the physical human.

Human modeling can be an important tool for learning about how people perform tasks and why they select one strategy over another. With the integrated Virtual Driver model, it is possible to examine the interactions between physical and cognitive requirements of tasks.

The Virtual Driver can be used to investigate the important question of how drivers allocate resources to perform the growing number of possible in-vehicle tasks while maintaining driving performance. Additional road and simulator studies could be conducted to examine the effects of new in-vehicle technology on driving behavior, but such studies are very resource-intensive. With some additions, the new Virtual Driver model could be a valuable resource for -predicting performance in a dual task scenario in novel task environments. It could also be a useful tool for evaluating and improving driver interfaces.

Lessons Learned

The overall goal of this research was to develop a model that would combine cognitive decision-making with a non-trivial representation of human physiology and motor coordination. The driving simulator study was designed to generate data that could be used to tune and evaluate the Virtual Driver model. However, the empirical study itself generated interesting new knowledge. With hindsight, certain changes to the experimental protocol would have made data from the empirical study more useful for the modeling work. Oscar Wilde wrote, “Experience is the name every one gives to their mistakes,” but in this case, the ideas discovered were worth the inconvenience.

The road in the driving simulator was in the shape of a rounded-corner square, with sides 1750 meters long. This was chosen to provide variety in the driving difficulty. However, because subjects were allowed to choose when to begin and complete the in-vehicle task, there was no consistency among trials in the occurrence of curves during the task. Some trials had no curves, and those that were interrupted by a curve could have it occur at the beginning, middle, or end of the trial. This made it very difficult to compare trials within and between subjects.

However, the presence of the curves, while vexing from a statistical analysis standpoint, led to an interesting observation about the differences between subjects. Though a few subjects were relatively unaffected by the curves and continued to work on the in-vehicle task during them, most changed their behavior in some way. Some subjects completely suspended the in-vehicle task during the curve, or declined to begin the task while on the curve. Others would continue to glance to the monitor but not perform button presses until the curve ended.

The lesson gained from the presence of the curves is that drivers account for and even anticipate the primary task workload when deciding how and when to engage in performance of a secondary in-vehicle task. Differences between drivers in physical and cognitive capabilities and experience could account for some of the differences in response to the curves.

Unfortunately, because the effect of varying primary task workload was not considered in the design of the experiment, the experiment did not include a way to measure responses to multiple levels of workload. Important questions to answer in future research are: What level of current or anticipated primary task workload causes people to suspend secondary tasks and how well do drivers gage the true difficulty of the primary task? For example, the short following distances observed in many on-road studies suggest drivers often misjudge their ability to brake quickly, and the high prevalence of rear-end collisions confirms the importance of this misjudgment. Given the link demonstrated in this research between drivers’ perception of primary task difficulty and their willingness to perform distracting secondary tasks, more research is needed on the factors that lead to accurate assessment of primary task workload.

In addition to primary task workload, future studies could consider the difficulty of the secondary task, to investigate whether people are sensitive to a combined measure of primary and secondary task workload. The driver behavior in the current study demonstrated that subjects' internal models of the physical, temporal, and cognitive requirements of the secondary task affected their decisions about when the primary task was sufficiently under control that the secondary task could be performed. This required level of primary task control might be greater when the secondary task is more difficult.

The design of the simulator experiment had the unintended consequence of confounding the primary and secondary task workload, particularly for shorter subjects. The far monitor positions were chosen to make the visual and physical components of the secondary in-vehicle task more difficult, but they also substantially altered the primary task environment by causing subjects to alter their physical driving posture. This change is similar to the difference between steering from the driver's seat and reaching across to steer from the passenger's seat.

The short female subjects were particularly affected by the far monitor locations. To understand this finding, it helps to consider the physical differences in the task when the monitor is in the far low position for short females as opposed to tall males (Figure 6.1).

Figure 6.1. The short female and the tall male models, each looking at the road scene ahead while reaching to the monitor.

When drivers worked on the in-vehicle task, they would frequently glance back to the road to verify that conditions permitted them to continue with the task. During these short glances, they would generally leave their hands near the monitor. This was likely done to minimize the in-vehicle task time and effort, as returning the hand to the steering wheel would add to the time and motions spent on the task.

This strategy for optimizing in-vehicle task performance resulted in a substantially altered driving position for short subjects (Figure 6.2). In particular, the position and orientation of the head were very different from the position and orientation in a normal driving posture.

Figure 6.2. The short female model looks at the monitor while performing the in-vehicle task, then glances back to the road while continuing to reach to the monitor.

In contrast, tall males were relatively unaffected by the far monitor positions. This is likely due to the relatively small change in head and trunk posture when reaching to the monitor, compared to the normal driving posture (Figure 6.3).

Figure 6.3. The tall male model looks at the monitor while performing the in-vehicle task, then glances back to the road while continuing to reach to the monitor.

The greater lean that short drivers experience results in perceptual changes. The head and trunk are no longer vertical, and there is a difference in proprioceptive feedback. Visually, the driver is no longer looking straight at the road. This results in a greater cognitive load associated with steering and perhaps with longitudinal control as well. To truly separate the effects of the workload due to the in-vehicle task and the workload due to the altered driving posture, the experiment could have included one drive in which the subjects were required to keep a hand near the monitor but did not look at the monitor nor perform the in-vehicle task.

Though most passenger vehicles enable the driver to make many adjustments to accommodate different physical dimensions, not all vehicle components can be moved. Therefore, it is likely that this difference in driving workload based on the physical orientation required for a secondary task could be observed in actual driving situations. Additional analysis of the effects of posture on workload could yield valuable information for use in vehicle design.

The simulator experiment also confounded the physical and visual complexity of the in-vehicle task, though an attempt was made to separate these by locating the near low monitor within easy physical reach but difficult visual range. Both of the far monitor locations, which were chosen to require a relatively difficult reach, also were difficult for subjects to interact with visually because it was more difficult to read numbers and button names on them. Physical and visual difficulty could have been decoupled by making the physical difficulty of the task due to the required level of fine motor control rather than the gross posture. For example, the monitor could have remained in one place while the size of the buttons changed. Such a change also would have allowed the manipulation of physical difficulty to be independent of subject body size.

Finally, the experiment offered no way to determine certain differences between subjects, such as propensity for risk taking and driving ability, independently of driving performance. In some cases, it was difficult to determine if subjects did not perform the in-vehicle task because they did not feel comfortable doing so or because they were not motivated to work on it. Future experiments designed to collect information for use with the Virtual Driver model should consider additional ways to classify differences between subjects apart from body dimensions.

Modeling Assumptions and Limitations

Some of the limitations to the current Virtual Driver model are associated with the conceptual model, due to simplifying assumptions that were made in the interests of evaluating the concept of an integrated cognitive and physical human model. These limitations could be addressed in future versions of the Virtual Driver. Other limitations may be traced to inadequacies in ProModel's ability to represent the desired model structure. To address these, it will be necessary to transfer the QN-MHP to a new modeling platform.

Conceptual Virtual Driver Model

There were a number of assumptions made during the development of the conceptual Virtual Driver model, and some of these have inherent limitations. Most of the assumptions were made for simplification purposes to facilitate the development of the first integrated cognitive and physical driving model and could be corrected in a later version of the model.

A significant limitation is that the model assumes that motor control is handled entirely by the physical side. For example, a discrete reach is treated as a single unit. After the QN-MHP specifies when and where to reach, the HUMOSIM Framework decides how to execute the reach. From this point on, the QN-MHP has no control over the elements of the reach, and the performance of the reach incurs no cognitive penalty. During an actual reach, communication between the brain and the body would allow for cognitive control of many elements of the reach. This limitation is mitigated to a certain extent by the ability of the QN-MHP to send a second motor command that would override the first, effectively changing the reach trajectory.

Another limitation is the lack of modeling of feedback processes associated with making the reach. Though the calculation of the reach trajectory does account for this to a certain extent in the equations used, there is no real modeling of the process or dynamics of feedback. These feedback processes belong on the physical side of the model. For example, the effect of wearing an obstructing garment or of experiencing the disruption from a vibratory environment would be represented as additional physical inputs. Therefore, feedback modeling could be added as a new module in the HUMOSIM Framework in future versions of the model.

Currently, the Virtual Driver performs no comparison between the copy of the motor command that was sent and the actual feedback. This is not a significant problem given the current modeling scenario, because there is little in the modeled environment that would cause the expected result of a motor command to be substantially different from the actual result. However, it would not be unreasonable to expect the model to be able to represent an environment with substantial whole-body vibration, as often occurs in large vehicles driven over rough terrain. In addition, it could be important to model a human driver with a diminished response to motor commands, as could occur in situations of disease or fatigue. Given this, future versions of the model should contain processing logic in the QN-MHP that compares the expected result with the actual result of a motor command. This comparison should occur during a movement rather than only at its conclusion, so that additional motor commands could be sent to alter the trajectory or final destination.

At this time, there is no model of visual search or scan in the Virtual Driver. Instead, the model includes a WAIT statement that halts processing for a length of time assumed to be sufficient to find the target. A visual search model would reside primarily in the QN-MHP, which would interpret the contents of the visual field and compare them to the desired item, held in short term memory. The HUMOSIM Framework would be responsible for relaying the list of visible items, based on the task environment and the gaze direction, to the QN-MHP.

Finally, there is currently no representation of learning the internal model of the task environment. Instead, information that would be available in the internal model, such as expected reach time and the location of targets outside the current field of vision, is relayed to the QN-MHP by the HUMOSIM Framework. This assumes that the practice necessary to learn the internal model has already occurred prior to the start of the simulation. Learning an internal model is a fairly complex process to represent; as a research topic in its own right, it is beyond the scope of the current implementation of the model. In addition, behavior differs significantly in trained operators as opposed to untrained operators in many situations, and most driving is done by trained operators. Therefore, a model that assumes the operator already possesses an internal model of the cab environment still would be useful for studying many driving scenarios.

Implementation of Virtual Driver Model

Visual angles and difficulty were calculated based on the seated position of the subject. However, if the subject leans to reach the monitor, as the short females were required to do, the visual angle will change. This change was not accounted for in the model. Additional testing would be required to determine if the change is detrimental, because it results in inconsistent visual input for the subjects, or beneficial, because it brings the subjects closer to the monitor.

A fairly important limitation is in the communication between the QN-MHP and the HUMOSIM Framework. Reach requests are currently sent as a single command. However, in order to accurately simulate the differences between feed-forward and feed-back control, it will be necessary in the future to require additional input from the QN-MHP between the start and completion of a reach that uses feedback. The communication protocol developed in this research is capable of handling feedback interactions, but the additional implementation of these processes, including planning, monitoring, and corrections, is needed on both sides.

The physical representation of human motor functions in the QN-MHP is fairly limited at the moment. The only body parts currently represented are the eyes, torso, left hand, right hand, and right foot, and all are modeled as simple deterministic actuators. To simulate more complex movement, such as pressing buttons with multiple fingers, it will be important to expand this representation to include additional body parts.

Though the structure of the Virtual Driver shows great promise, it is substantially limited by its dependence on the functional capabilities of ProModel. None of the limitations were substantial enough to affect the overall pattern of results in the current modeled scenario. However, the simplifying assumptions necessary in order to implement the model in ProModel may hinder its future development.

ProModel is widely used for manufacturing and operational applications. Though it provides a natural programming environment for queuing network simulations, it was never intended for use in modeling the human mind. Attempting to extend ProModel in this way has caused certain difficulties, which may have had significant effects on the modeling work.

The most notable problem with ProModel is its structure as an event-based simulation program. Its speed of operation is a function of the number of events firing at any given moment.

In essence, the model functions as a push system, with information being fed into the model at a predefined rate. In contrast, a human functions more like a pull system, choosing to attend to information at certain times. This can be simulated in ProModel by routing the entities to the exit to represent inattentiveness. However, the entire functionality of the model is based upon processing entities. The model cannot run pieces of code unless they are initiated by the entry of an entity into the location housing the code.

Another limitation with ProModel is its lack of mathematical functionality. The software is capable of performing simple mathematical calculations such as addition, subtraction, multiplication, and division, and it can calculate squares and square roots of numbers. However, more complex mathematical functions such as logarithms are beyond the abilities of ProModel.

A particular failing is the lack of trigonometric functions such as sine and cosine, which are used in many calculations in the Virtual Driver model. There are three possible ways to simulate such functions in ProModel. The first, which was used previously in the QN-MHP, is to include a look-up table that contains a list of sine or cosine values for certain angles. ProModel can interpolate to give a value for an angle that is not included in the table. This is a cumbersome, slow, and inelegant solution. The second way, which is used currently, is to write a subroutine that uses a finite portion of the Maclaurin series representation of trigonometric functions to approximate the value. For example, $\cos x = \sum_{n=0}^{\infty} \frac{(-1)^n}{(2n)!} x^{2n}$. The last way, the route that ProModel appears to recommend, is to write an external subroutine that uses a DLL to communicate with a language more capable of performing math, such as C.

Finally, ProModel was simply never designed to represent processing in the brain. The human brain can receive new stimuli every 50 ms and is capable of processing enormous amounts of information very rapidly (Card et al., 1986). This information is represented by entities in the QN-MHP. However, ProModel is generally used to model manufacturing scenarios, in which entities represent processed goods or products. As such, ProModel was never intended to handle the volume of entities that are necessary to accurately represent information flow in the mind. Large volumes of entities can cause ProModel to crash or to run exceedingly slowly.

Future Work

The goal of this dissertation project was to integrate a cognitive human model with a physical human model and to evaluate the resulting combined model. The Virtual Driver model is currently implemented in a relatively straightforward way. Several additions to the model could be considered for future research.

More Accurate Representations of Task Parameters

A significant limitation in the model currently is the use of overly coarse and simplistic parameters to represent driver workload and the probability of switching between tasks while multitasking. More complex parameters are necessary to accurately capture driver behavior and to represent differences between individuals. Future studies should be designed in such a way that important variables can be separated in order to better understand what factors are important to drivers. A more detailed glance analysis could be used to determine ways to classify drivers into different behavioral groups.

Visual Search

A more accurate model of visual search would be a valuable addition to the Virtual Driver. Though it was possible to obtain modeling results that were consistent with the empirical study in the current work, it will be important to have a functional visual search in order to predict performance in novel task environments.

The QN-MHP has been used previously to model eye movement (Lim, 2007). In particular, it has been used to simulate visual search and menu selection (Lim & Liu, A queueing network model for eye movement, 2004), the effects of a concurrent task on visual search performance (Lim, 2007), and the influences of top-down and bottom-up processes in learning eye movements (Lim & Liu, 2009). The findings of these studies provide a good starting point for adding visual search to the Virtual Driver.

Fatigue

Including a representation of the mechanisms for and effects of fatigue in the model could add a useful dimension. Gunzelmann and colleagues (2009) represented fatigue in the ACT-R cognitive architecture using two central cognitive mechanisms that are associated with the production execution style in the ACT-R model. The first addition to the model was microlapses, mechanisms that create opportunities for brief breakdowns in the cognitive processing. They also added a secondary process to represent the influence of explicit effort, which decreases the likelihood of a microlapse occurring but increases the probability of using lower-cost, less effective strategies to achieve the desired goal.

A significant advantage the Virtual Driver would have over the ACT-R model in representing fatigue is the physical component of the model. It would be possible to examine physical as well as cognitive fatigue and the interactions between them. Such a model could permit predictions about degradations in driving performance and secondary task performance associated with sleep deprivation and circadian rhythms, which would be useful for studying workers who are on duty outside of normal work hours, such as truck drivers and military personnel.

Physical Additions

The Virtual Driver has the potential to provide a more detailed representation and analysis of task environments than previous models, but it will require certain additions to represent physical variables. Many of these could be added to the HUMOSIM Framework side of the model. With the proper additions and communication between the QN-MHP and the Framework, the Virtual Driver should be able to represent physical effects such as those due to age, disease, clothing, and handedness.

More General Representation of In-Vehicle Tasks

The representation of the in-vehicle task in the QN-MHP is currently very specific to the particular task that was investigated during the driving simulator experiment. However, people choose to perform a wide variety of distracting in-vehicle tasks while driving, so it would be useful to have a model with enough flexibility to represent a range of tasks. Ideally, the model should be able to do this with only minimal surface changes, so that a person without a modeling background could use the model.

Extension Beyond Driving

Additional future research in this area could focus on extending the combined cognitive-physical model to non-driving situations. The physical focus of the model currently is the upper body, so additional research would be necessary to determine how best to model lower body activities, such as walking. In addition, it would be valuable to obtain and model more precise movement data in the future, possibly using motion tracking technology.

There is a large amount of redundancy in the human musculoskeletal structure. As a result, people can perform movements in a variety of different ways. Consider, for example, lifting an object from the ground. A person might bend at the waist to retrieve the object or squat to be closer to the object, then lift with the legs. Which method a person chooses to use may depend on a variety of factors. The person may know the approximate weight of the object and choose to squat for heavier objects. Similarly, the person may realize he or she is fatigued, and so choose to squat for a lighter object that is nevertheless too heavy for the person to handle easily in the current state. Alternatively, the person may have a knee injury that makes squatting difficult, so the person may choose to stoop to lift the object.

A movement may also vary based on what preceded and what will come after the movement. People who have performed a task requiring obstacle avoidance tend to continue the movement along the same path for at least the first iteration after the obstacle is removed. A person picks up a glass differently based on whether he or she intends to put the glass away on a shelf or invert it to fill it with a beverage.

With the present modeling technology, it is difficult to predict how a person will perform an immediate action, let alone an action that will occur several steps in the future. The combined cognitive-physical model, with its decision-making capabilities, will be a valuate tool for making predictions about how a person will choose to perform a task. With additional development, the model could be very useful for performing ergonomic evaluations of worksites and jobs. It should be possible to rapidly vary the environmental conditions and personal capabilities of a subject to predict workload and injury risk to people in many different scenarios.

Closing Comments

The Virtual Driver model shows great promise in its initial implementation. With some refinement, it should be able to predict detailed driving behaviors and secondary task performance in novel environments. Given the recent focus on driver distraction, this is exciting and timely research. In the future, the model could be used to design in-vehicle interfaces and make predictions about staffing requirements and performance.

The additions suggested for the Virtual Driver could add greatly to its functionality. It is also important that it move away from the ProModel platform, to avoid the limitations inherent with using that program to have the resources necessary to model a complex cognitive environment.

Though the Virtual Driver is currently limited to driving with a secondary task, it has the potential to expand to many other arenas. Many tasks with significant cognitive and physical components cannot be modeled correctly at present due to the cognitive-physical divide in the modeling world. This combination of the QN-MHP cognitive model and the HUMOSIM Framework physical model could provide researchers with new insight into human performance and help designers to create safer and more efficient products and workspaces.

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