Integrating Physical and Cognitive Human Models to Represent Driving Behavior

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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 in terms of modeling a task scenario with both cognitive and physical components: driving while performing a secondary in-vehicle task. The result is the Virtual Driver model.

INTRODUCTION

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.

A few groups have addressed the need for a combined cognitive-physical model in various levels of detail (Zhang, 2003; Badler et al., 2005; Raschke et al., 2005). In addition, several task analysis systems, such as MIDAS, the Crew Station Design Tool, and IMPRINT, include physical aspects the tasks (Gore et al., 2008; Walters et al., 2003; Allender, 2000). These physical models tend to be relatively simple, however, generally involving look-up tables or basic functions that represent the time required to perform a physical subtask rather than simulating the actual physical interaction with the task environment. Recent developments and improvements in both cognitive and physical modeling architectures 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 in order 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.

Previous models of driving and driver distraction, though valuable, have focused primarily on the cognitive demands (e.g. Levison, 1993; Salvucci et al., 2001). This research addresses the divide between cognitive and physical models by integrating a cognitive human model with a physical human model. The resulting model, the Virtual Driver, is used to examine driving while performing an in-vehicle task.

This work is a further development of a conceptual model presented previously (Tsimhoni & Reed, 2007). The structure of the model components and the integrated model will be presented. The application of the model to driving with a secondary in-vehicle task will then be discussed.

METHOD

Modeling

The Virtual Driver model consists of a cognitive human model, the Queuing Network – Model Human Processor (QN-MHP) and a physical human model, the HUMOSIM Ergonomics 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, using a client/server model.

The QN-MHP is a computational model that bridges mathematical models of queuing networks, which integrate models of response time and multitask performance, and symbolic models of cognition (Liu, 1996; 1997). It is a task-independent cognitive architecture that represents information processing as a queuing network, based on research findings in neuroscience and psychology that show that neural pathways connect major brain areas with certain information processing functions (Smith & Jonides, 1998; Faw, 2003). In the QN-MHP, brain regions are represented as servers in a queuing network, neural pathways in the brain are treated as routes in the network, and units of encoded information are represented as entities.

Entities in the QN-MHP travel along routes between servers and may move through the network and undergo processing serially or in parallel, immediately upon arriving at a server or after waiting in a queue until the server finishes processing a previous entity. Multitasking in the QN-MHP is represented by creating a different category of entity for each task. The servers in the QN-MHP are divided into three subnetworks: perceptual, cognitive, and motor (Figure 1). The QN-MHP is implemented in ProModel (ProModel Solutions, Version 2001), a simulation-based software widely used for manufacturing and operational applications.

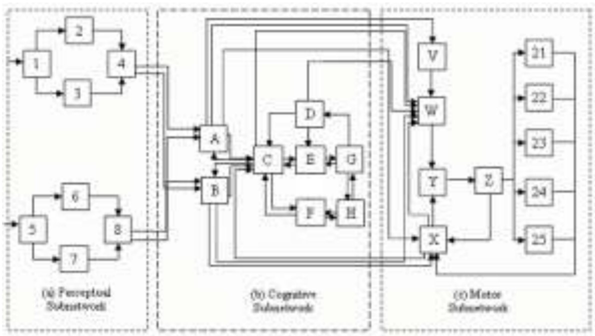

Figure 1. QN-MHP (adapted from Wu et al., 2008). (a) Perceptual: 1=common visual processing; 2=visual recognition; 3=visual location; 4=location and recognition integrator; 5=sound localization; 6=linguistic processing; 7=processing of other sounds; 8=linguistic and other sounds integrator. (b) Cognitive: A=visuospatial sketchpad; B=phonological loop; C=central executor; D=goal procedures; E=performance monitoring; F=high-level cognitive operations; G=goal selection; H=long-term declarative and spatial memory. (c) Motor: V=sensorimotor integration; W=motor element storage; X=movement tuning; Y=motor programming; Z=actuators; 21-25=body parts.

The QN-MHP has been used to generate human behavior in a variety of situations. These include simple and choice reaction time (Feyen, 2002), transcription typing (Wu & Liu, 2004), visual search (Lim & Liu, 2004), driver workload (Wu & Liu, 2007), and driver performance (Liu et al., 2006). The QN-MHP has also been used to model driving while performing a secondary task (Liu et al., 2006). The model accurately predicted metrics of driving and task performance, performed both individually and simultaneously. Limitations of the previous study were the use of cruise-controlled speed rather than requiring the driver to perform longitudinal control and a relatively simple physical component for the in-vehicle task.

The HUMOSIM Ergonomics Framework 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. It is implemented in the Python programming language, accessing the JackScript Application Programming Interface in the Tecnomatix Jack software from Siemens. The Framework provides the physical representation of the human for the Virtual Driver (Figure 2).

Figure 2. Virtual Driver with 5% female and 95% male drivers.

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.

Driving Scenario

The integrated model is well-founded based on theory and previous literature (Liu et al., 2006; Tsimhoni & Reed, 2007), but additional data was necessary to fine-tune the physical task. A driving simulator study was conducted to obtain data, with a subset of the study data used to tune the model and the remainder of the data reserved for validation. Preliminary findings from this study were published previously (Fuller et al., 2008).

Subjects followed a lead vehicle in a fixed-base driving simulator while performing a secondary in-vehicle task using a touch screen monitor (Figure 3a). To complete the in-vehicle task, the subject was required to match three pairs of numbered icons (Figure 3b). One match consisted of pressing the correctly numbered gray (“Scout”) icon, then the orange (“Target”) icon, and finally the “Assign” button on the left side of the screen.

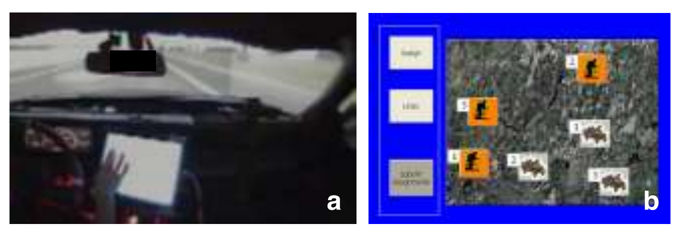

Figure 3. (a) A subject performs the in-vehicle task while driving. (b) The user interface for the in-vehicle task, which requires the driver to match three numbered pairs of icons.

Subjects were instructed to remain in the right lane of a four-lane divided highway and to maintain a consistent headway to a lead vehicle that changed speed randomly. The results were measured in terms of delay in following speed changes of the lead vehicle, variability of lateral lane position, secondary task time, and metrics of glance behavior, including average glance duration and time between glances.

To vary the physical difficulty of the in-vehicle task, each driver performed the task with the monitor placed in four different fixed locations in the vehicle. In addition, subjects were chosen to represent a range of statures, from 5% female to 95% male.

The 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. The goal was to understand driving behavior and resource-sharing while driving and performing a secondary in-vehicle task.

Driving Behaviors

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, a subset of which are presented and discussed here. 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.

When performing the in-vehicle task, 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.

In choosing how to allocate resources between driving and the in-vehicle task, subjects appeared to consider both the current and the anticipated driving difficulty. For example, a subject would generally halt work on the in-vehicle task when on a curve. If the in-vehicle task began when the subject was approaching a curve, the subject would often neglect to start the task until completing the curve.

Reach capability affected the difficulty of the in-vehicle task when the monitor was positioned far from the steering wheel. Shorter subjects 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.

RESULTS

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 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. Lateral control entities, which represent information related to performing lateral control such as current lane position and road curvature, are given a higher priority than longitudinal control entities, because subjects in the driving simulator experiment described above tended to prioritize keeping the car in its lane over maintaining a constant headway to the lead vehicle, especially when they traversed curves.

The model can make steering corrections to keep the vehicle in its lane while navigating curves of different radii, determining the necessary 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.

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 model is an expanded version of a model that performs accurate car-following, adding three types of error-inducing behaviors to the basic car-following model: perceptual limitation, distraction, and time delay.

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 represents the procedural part of the long-term memory, which stores information about how to accomplish a task.

The grouping behavior displayed by subjects in the simulator experiment is 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.

Multitasking

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 each entity moving through the network is 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.

The effect on multitasking of the current and the anticipated driving difficulty is modeled by implementing a workload variable. Workload increases when the current driving difficulty exceeds some threshold, or when the driving difficulty is expected to increase beyond this threshold within a certain period of time. When the total workload, including the secondary task workload, is too great, resources are diverted to the task that is considered more important.

Reach capability is included in the calculation of workload. Shorter statures and farther monitor locations result in greater workload.

Integrated Model

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. The two models are connected in such a way that they can send information between them throughout the performance of the dual tasks, simulating the perceptual information input, motor command output, and feedback input that occur in humans (Figure 4).

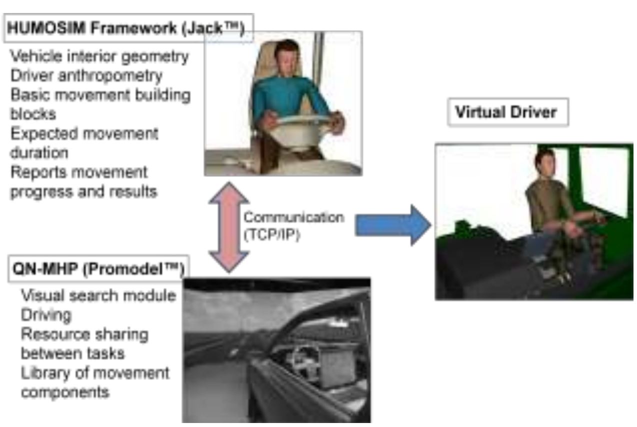

Figure 4. The integration of the HUMOSIM Framework and the QN-MHP to produce the Virtual Driver.

The HUMOSIM Framework provides the QN-MHP with perceptual information about the physical environment and task constraints. This includes the available gaze and reach targets, as well as the 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, including 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, constraining the model's actions to match human capabilities. The Framework then sends information about the outcome of the actions, including progress and time of successful completion, back to the QN-MHP.

DISCUSSION

The initial implementation presented here of the Virtual Driver, a combined cognitive and physical model, can simulate lateral and longitudinal control comparable to subjects' performance in the simulator. It can also simulate performance of the in-vehicle task. In addition, the Virtual Driver duplicates certain driving and multitasking behaviors that subjects in the simulator study displayed.

The ability of a driver to break a particular in-vehicle task into smaller blocks is important for multitasking (Noy et al., 2004), possibly because drivers have greater control over task sharing decisions when they are performing tasks that can be interrupted (Salvucci & Macuga, 2002). 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).

Subjects and the model adjust performance on the secondary task based on anticipated as well as current driving difficulty, indicating 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. This differs from deciding how to share resources during multitasking by simply reacting to being overloaded by the secondary task. This aspect of skilled drivers' behavior may be one of the reasons multitasking while driving is not more dangerous than it is, as drivers can adjust their performance of secondary tasks when they expect driving to be more difficult.

Driver perception of workload is affected by factors such as road geometry, road type, lane driven, and traffic volume (Tsimhoni & Green, 2004; Schweitzer & Green, 2006). It is important to be able to model driver workload perception and prediction because the perceived workload will influence a driver's willingness to engage in secondary tasks. (Schweitzer & Green, 2006). The QN-MHP has been used successfully to model driver workload (Wu & Liu, 2007), and the Virtual Driver is also able to account for the physical demands of an in-vehicle task.

As is the case with any driving simulator study, there is the concern that the observed behaviors were artifacts of the simulator. To reduce the effects of cognitive tunneling, often seen in driving simulators, the importance of the driving task was emphasized in the subject instructions.

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 produced an accurate and detailed representation of the physical human that will make it possible to learn about how people perform tasks and why they select one strategy over another, as well as to examine the interactions between physical and cognitive requirements of tasks. The integrated physical component of the Virtual Driver allows the direct representation of aspects of a task that would be difficult to represent using the look-up tables or time functions used in most task analysis tools.

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.

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