Queuing Network Modeling of Driver Workload and Performance

Changxu Wu and Yili Liu

Abstract— **Drivers overloaded with information significantly increase the chance of vehicle collisions. Driver workload, a multi-dimensional variable, is measured by both performance-based and subjective measurements and affected by driver age differences. Few existing computational models are able to cover these major properties of driver workload or simulate subjective mental workload and human performance at the same time. We describe a new computational approach for modeling driver performance and workload—a queuing network approach based on the queuing network theory of human performance and neuroscience discoveries. This modeling approach not only successfully models the mental workload measured by the six NASA-TLX workload scales in terms of subnetwork utilization, but also simulates driving performance, reflecting mental workload from both subjective and performance-based measurements. In addition, it models age differences in workload and performance and allows us to visualize driver mental workload in real-time. Further usage and implementation of the model in designing intelligent and adaptive in-vehicle systems are discussed.**

Index Terms—**Mental workload, computational modeling, queuing network, driver performance**

I. Introduction

The expanding usage of in-vehicle systems increases the chance that drivers perform dual tasks in driving, e.g., driving and using a mobile phone concurrently. These dual tasks may impose high information load on drivers, increasing driver mental workload [1-3] which in turn may increase the chance of vehicle collisions by about 4 times compared to a single task condition [1],[4],[5]. Moreover, it is reported that older drivers' crash rates were higher than young drivers [6] and using in-vehicle systems is one of the main causes of this increase in crash rates since older drivers' information processing efficiency decreases with an increase in age [7]. In practice, modeling and predicting driver workload and performance is very useful in designing in-vehicle systems to prevent drivers (especially older drivers) from being overloaded with information [8]. Significant costs of implementation and modification can be saved if driver mental workload can be predicted at an early stage of vehicle design.

Several decades of research on mental workload has shown that mental workload has three important properties. First, it is a multidimensional variable (perceptual, cognitive, and motor dimensions) and operators are often capable of reporting the demands on separate workload dimensions [9-16]. Second, age differences are one of the most important factors in affecting driver workload [17]. Aging causes the slowing of older drivers' information processing in perceptual, cognitive and psychomotor aspects [7],[18-20]. For the same amount of information being processed in the same time period, older drivers usually perceive higher levels of mental workload than young drivers [21],[22]. Third, performance-based measurements alone may not fully reflect mental workload because of the potential dissociation of performance and mental workload [23]. Thus, subjective or physiological measurements of mental workload should be applied in addition to performance-based measurements [24]. In this regard, subjective measurements are relatively easy to implement, nonintrusive and inexpensive, and have a high face validity [3],[24]. For example, NASA-TLX (National Aeronautic and Space Administration Task Load Index, [25]) is one of the most frequently used subjective mental workload scales which reflect the multidimensional property of mental workload [15]. It measures mental workload with six rating scales: mental demand, physical demand, temporal demand, performance, effort, and frustration levels. NASA-TLX has been successfully applied in a number of multi-task system environments [26].

In accordance with the three properties of mental workload discussed above, a computational model of mental workload is expected to capture the multidimensional property of mental workload and to account for its age differences; it should also model mental workload from both performance-based and subjective measurements. Several computational models have been developed to model mental workload in driving (see Table 1). Using control theory, Horiuchi and Yuhara (2000) modeled drivers' mental and physical workload based on lead time constraints and steering wheel angle [27]. Lin et al. (2005) modeled driver performance using artificial neural network methods including counter propagation network, the radial basis function network and the back propagation network [28].

Manuscript received March 12, 2006; revised October 1, 2006. This article is based upon work supported by the National Science Foundation under Grant No. NSF 0308000.

C. Wu was with the University of Michigan Transportation Research Institute (UMTRI) and Department of Industrial & Operations Engineering, University of Michigan, Ann Arbor, MI 48109 USA. He is now with Department of Industrial & System Engineering, State University of New York, Buffalo, NY 14260-2050, USA (email: changxu@buffalo.edu).

Y. Liu is with Department of Industrial & Operations Engineering, University of Michigan, Ann Arbor, MI 48109 USA (email: yililiu@umich.edu).

A statistical model was applied to model visual workload/demand in the driving context by Easa and Ganguly (2005) [29]: regression analysis was used to determine the best regression model of visual demand with independent variables (e.g., lane width). Assuming the driver as a semiotic system, Goodrich and Boer (1998) modeled mental workload by interactions of several mental model agents [30]. Piechulla et al. (2003) estimated driver mental workload by multiplying a weight factor with a basic estimated workload (*w*) based on the road information (e.g., intersection ahead) [8]. Based on the production-rule architecture—ACT-R [31], Salvucci et al. (2001) developed a model of driving behavior to simulate driver performance in a dual task situation [32]. However, as shown in Table 1, few models are able to simulate human performance and mental workload in dual tasks while reflecting the multidimensional property of mental workload. None of these models takes into account the effect of age differences on driver workload or visualizes mental workload, an important feature for enhanced usability and applicability [33],[34].

In this paper, to model the major properties of driver mental workload summarized in Table 1, we describe how to model driver mental workload and performance using a new computational modeling approach—the queuing network modeling approach [35],[36]. First, we describe the queuing network mental architecture representing information processing in the mental system and how the model was used to account for subjective mental workload including its age differences. Then, we describe how the model was validated with an experimental study on driver performance and workload.

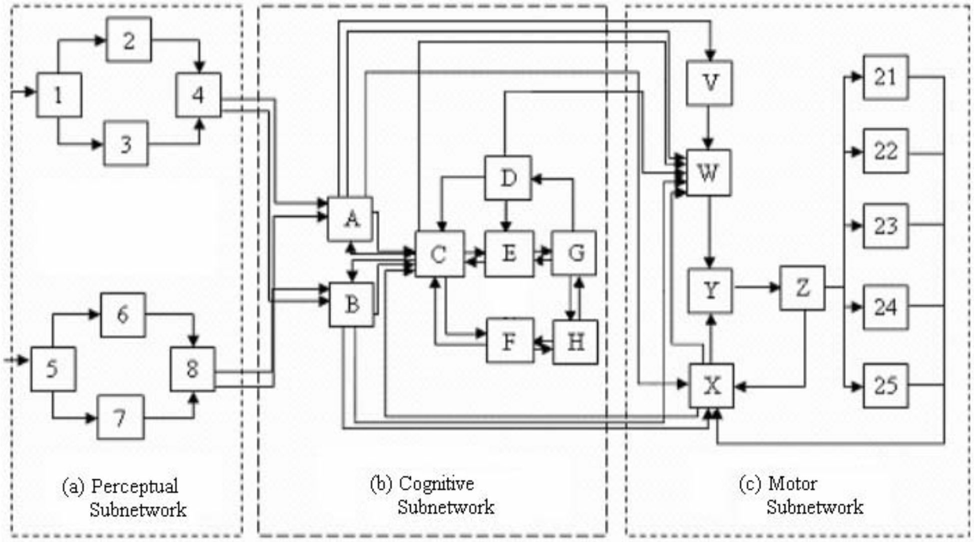
TABLE 1.
COVERAGE OF DRIVER MENTAL WORKLOAD IN COMPUTATIONAL MODELS

Computational Models	Multi-dimensional	Task	Subjective Measurement	Performance-based Measurement	Age Difference	Visualization
Queueing Network Model (Wu and Liu, this paper)	Yes	Dual	Yes	Yes	Yes	Yes
Control Theory (Horiuchi et al., 2000)	Mental and physical	Single	Yes	Yes	-	-
Neural Network (Lin, et al., 2005)	Mental only	Single	-	Yes	-	-
Semiotics model (Goodrich et al., 1998)	Mental only	Single	Yes	-	-	-
Statistic Model (Easa et al, 2005)	Visual only	Single	Yes	-	-	-
Engineering Model (Piechulla, et al., 2003)	Mental only	Single	Yes	-	-	-
Rule-based Model (Salvucci, et al., 2001)	Visual/Cog-nitive/Motor	Dual	-	Yes	-	-

-: not covered

II. QUEUING NETWORK MODELING OF HUMAN PERFORMANCE

In modeling human performance, computational models based on queuing networks have successfully integrated a large number of mathematical models in response time [35] and in multitask performance [36] as special cases of queuing networks. A simulation model of a queuing network mental architecture, called the Queuing Network-Model Human Processor (QN-MHP), has been developed to represent information processing in the mental system as a queuing network on the basis of neuroscience and psychological findings [37]. Ample research evidence has shown that major brain areas with certain information processing functions are connected with each other via neural pathways [38-41], which is highly similar to a queuing network of servers that can process entities traveling through the routes in the network serially and/or in parallel depending on specific network arrangements. Therefore, brain regions with similar functions can be regarded as servers and neural pathways connecting them are treated as routes in the queuing network (see Figures 1 and 2). Further, it has been discovered that information processed in the brain are coded in spike trains [42]; depending on different tasks and learning stages, the to-be-processed information represented by these spike trains sometimes are processed by the brain regions (servers) immediately; sometimes they have to be maintained in certain regions to wait for the previous spike trains finishing their processing [39],[43]. Hence, these spike trains can be regarded as entities in the queuing network.



Perceptual Subnetwork

1. Common visual processing (eyes, lateral geniculate nucleus, superior colliculus, primary and secondary visual cortex)
2. Visual recognition (dorsal system)
3. Visual location (ventral 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

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

V. Sensorimotor integration (premotor cortex)
W. Motor program retrieval (basal ganglia)
X. Feedback information collection (somosensoy cortex)
Y. Motor program assembling and error detecting (supplementary motor area (SMA) and the pre-SMA)
Z. Sending information to body parts (primary motor cortex)
21-25: Body parts: eye, mouth, left hand, right hand, foot

Fig. 1. The general structure of the Queuing Network -Model Human Processor (QN-MHP) Further developed from Liu, Feyen, and Tsimhoni (2006) [11]

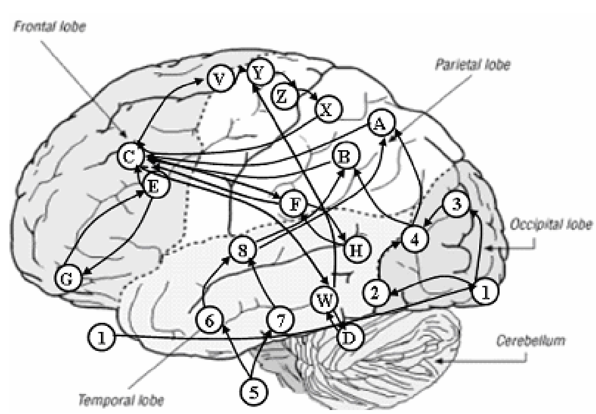


Fig. 2. Mapping servers of the queuing network model on corresponding brain areas

The QN-MHP consists of three subnetworks: perceptual, cognitive, and motor subnetworks as described in the following sections.

A. *Perceptual Subnetwork.*

The perceptual subnetwork includes a visual and an auditory perceptual subnetwork, each of which is composed of four servers. In the visual perceptual subnetwork, light waves (represented by numerical codes) are transmitted to neuron signal (represented by information entities) at the eye, the lateral geniculate nucleus, the superior colliculus, the primary visual cortex (V1), and the secondary visual cortex (V2, represented by Server 1) [38]. Then, these entities are transmitted in parallel visual pathways—the parvocellular stream (represented by Server 2) and the magnocellular stream (Server 3) where the object content features (e.g., color, shape, labeling etc.) and location features (e.g., spatial coordinates, speed etc.) are processed [38],[39],[44],[45]. The distributed parallel area (represented by Server 4)—including the neuron connections between V3 (part of the dorsal stream) and V4 (a cortical area in the ventral stream) as well as V4 and V5 (an area in the extrastriate visual cortex), the superior frontal sulcus, and the inferior frontal gyrus—integrates the information of these features from the two visual pathways and generates integrated perception of the objects [38],[44].

The auditory perceptual subnetwork also contains four servers: the middle and the inner ear (represented by Server 5) transmits sound to parallel auditory pathways, including the neuron pathway from the ventral cochlear nucleus to the superior olivary complex (represented by Server 7) and the neuron pathway from the dorsal and ventral cochlear nuclei to the inferior colliculus (Server 6) where location, pattern and other aspects of the sound are processed [38]. The auditory information in the auditory pathways is integrated at the primary auditory cortex and the planum temporale (represented by Server 8) [46].

B. *Cognitive Subnetwork.*

The cognitive subnetwork includes a working memory system, a goal execution system, a long-term memory system and a complex cognitive processing system.

Following Baddeley's working memory model, there are four components in the working memory system: a visuospatial sketchpad (Server A), representing the right-hemisphere posterior parietal cortex; a phonological loop (Server B), standing for the left-hemisphere posterior parietal cortex; a central executor (Server C), representing the dorsolateral prefrontal cortex (DLPFC), the anterior-dorsal prefrontal cortex (ADPFC), and the middle frontal gyrus (GFm); and a performance monitor (Server E), standing for the anterior cingulate cortex (ACC). The visuospatial sketchpad and the phonological loop store and maintain visuospatial and phonological information in working memory [39].

The goal execution system (Server G) represents the orbitofrontal region, brain stem including the locus coeruleus-norepinephrine (LC-NE) system, and the amygdala complex which are typically involved in goal initiation and motivation [47].

The long-term memory system represents two types of long-term memory in the human brain: 1) declarative (facts and events) and spatial memory (Server H), standing for the medial temporal lobe including the hippocampus and the diencephalons which store various kinds of production rules in choice reaction, long-term spatial information, perceptual judgment, decision making, and problem solving; 2) nondeclarative memory (procedural memory and motor program) (Server D), representing the striatal and the cerebellar systems which store all of the steps in task procedure and the motor programs related to motor execution [38].

The complex cognitive processing system (Server F) stands for brain areas performing complex cognitive functions—multiple-choice decision, phonological judgment, spatial working memory operations, visuomotor choices, and mental calculation. These brain areas include the 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 [39],[48],[49].

C. *Motor Subnetwork.*

The motor subnetwork includes 5 servers corresponding to the major brain areas in retrieval, assembling, and execution of motor commands as well as sensory information feedback. First, Server V represents the premotor cortex in Brodmann Area 6 which plays an important role in sensorimotor and sensory cue detection [40],[50],[51]. Second, the basal ganglia (Server W) retrieves motor programs and long term procedural information from long term procedural memory (Server D) [38],[52],[53]. Third, the supplementary motor area and the pre-SMA (Server Y) have the major function of assembling motor programs and ensuring movement accuracy [54]. Fourth, the function of the primary motor cortex (Server Z) is to address the spinal and bulbar motor neurons and transmit the neural signals to different body parts as motor actuators (mouth, left and right hand, left and right foot server etc., [40]). Fifth, the S1 (the somosensory cortex, Server X) collects motor information of efference copies from the primary motor cortex (Server Z) and sensory information from body parts and then relay them to the prefrontal cortex (Server C) as well as the SMA (Server Y) [40].

QN-MHP has been successfully used to generate human behavior in real time, including simple and choice reaction time [44], transcription typing [55], psychological refractory period [56], visual search [57], and driver performance [58].

A study most relevant to the current one is the computational modeling of human performance in dual task under the driving context [58]. Liu et al. (2006) have successfully modeled dual task performance (steering and reading a map concurrently) in driving with QN-MHP. Multitask performance emerges as the behavior of multiple streams of information flowing through a network without the need to interleave production rules or interactively control task processes. The study reported in this current paper focuses on how to extend the model of driver performance significantly to cover mental workload in driving, as well as to account for age differences in performance and workload.

III. Modeling Mental Workload in Driving

Since subjective mental workload reflects the perception of information processing throughout each trial in a task, the average utilization of a subnetwork ($\bar{\rho}_i$)—the average utilization of subnetwork *i* in total task time of each trial (*T*)—is regarded as a natural index of subjective mental workload in QN-MHP (see Equation 1). In computational modeling of mental workload, Rouse (1980) modeled mental workload in a single task situation using server utilization as an index of the workload [59]; Just et al. (2003) also regard the capacity utilization as a typical representation of mental workload [60]. In terms of the physiological mechanism of mental workload, it is also reasonable to use utilization as the index of mental workload: increasing utilization of certain brain regions causes the consumption of more neurotransmitters (e.g., amino acids, norepinephrine/NE, 5-hydroxytryptamine/5-HT) in synaptic transmissions, which in turn increase the perception of mental fatigue [61-65].

$$\bar{\rho}_i = \left(\int_0^T \rho_i dt\right) / T \qquad (0 \le \bar{\rho}_i \le 1) \tag{1}$$

where $\bar{\rho}_i$ can represent the average utilization of visual perceptual subnetwork ($\bar{\rho}_{vp}$), auditory perceptual subnetwork

($\bar{\rho}_{ap}$), cognitive subnetwork ($\bar{\rho}_c$), and motor subnetwork ($\bar{\rho}_m$), respectively. Moreover, based on the definition of each scale in NASA-TLX [25], the score of physical demand (*PD*) reflects workload at the motor component, and therefore it is in direct proportion to the average utilization of motor subnetwork ($\bar{\rho}_m$) (see Equation 2); the scores of temporal demand (*TD*), frustration (*FR*), performance (*PE*) and effort (*EF*) represent the overall workload in the system, which is reflected by the average utilization of all the subnetworks (see Equations 3-6); the score of mental demand (*MD*) is judged based on the perceptual and cognitive demands (how much perceptual and mental activities were required, [25]), and therefore it is in direct proportion to the average utilization of perceptual and cognitive subnetworks (see Equation 7).

$$PD = a\bar{\rho}_m + b \qquad (0 \le PD \le 100) \tag{2}$$

$$TD = a(\sum_{All\ i} \bar{\rho}_i)/4 + b \qquad (0 \le TD \le 100) \tag{3}$$

$$EF = a(\sum_{All\ i} \bar{\rho}_i)/4 + b \qquad (0 \le EF \le 100) \tag{4}$$

$$PE = a(\sum_{All\ i} \bar{\rho}_i)/4 + b \qquad (0 \le PE \le 100) \tag{5}$$

$$FR = a(\sum_{All\ i} \bar{\rho}_i)/4 + b \qquad (0 \le FR \le 100) \tag{6}$$

$$MD = a(\sum_{i=ap,vp,c} \bar{\rho}_i)/3 + b \qquad (0 \le MD \le 100) \tag{7}$$

where parameters a and b are constants in representing the direct proportional relation between the averaged utilizations and subjective responses ($a>0$). Equations 2-7 are implemented in the simulation model to generate subjective workload responses (See [58] for descriptions of how QN-MHP is able to simulate driver performance).

In addition, research evidence suggests that the major difference in information processing between the older and young adults is a generalized slowing in information processing speed for older adults [7],[26],[66]; therefore, considering age differences, the information processing speed at server j (μ_j) in the network is:

$$\mu_j = (\frac{1}{A})\mu_{0,\,j} \tag{8}$$

where A is a factor of aging ($A \ge 1$): the value of A is directly proportional to the driver's age; $\mu_{0,j}$ is the original processing speed of server j for young adults in QN-MHP [58]. Moreover, according to the traffic intensity function in queuing network theory [67], utilization of a certain subnetwork i (ρ_i) (the fraction of time the subnetwork i is processing entities in a defined time period) is in inverse proportion to the average processing speed of all the servers in the subnetwork ($\bar{\mu}_i$) (see Equation 9).

$$\rho_i \equiv \frac{\lambda_i}{C_i\bar{\mu}_i} = \frac{\lambda_i}{C_i[(\sum_{j=1}^{C_i}\mu_j)/C_i]} = \frac{\lambda_i}{\sum_{j=1}^{C_i}\mu_j} \qquad (0 \le \rho_i \le 1) \tag{9}$$

where λ_i is the arrival rate of the subnetwork i and C_i is the total number of servers in the subnetwork i.

Mathematically, we can derive that the expected subjective mental workload of older drivers is equal to or greater than young drivers from the equations above. Combining Equations 1-9 above, we have:

$$PD = a(\int_0^T \rho_m dt)/T + b = a(\int_0^T \frac{\lambda_m}{\sum_{j=1}^{Cm}\mu_j}dt)/T + b \tag{10}$$

$$= a(\int_0^T \frac{\lambda_m}{\sum_{j=1}^{Cm}(\mu_{0,\,j}/A)}dt)/T + b = a(\int_0^T \frac{\lambda_m}{(\frac{1}{A})\sum_{j=1}^{Cm}\mu_{0,\,j}}dt)/T +$$

$$= Aa(\int_0^T \frac{\lambda_m}{\sum_{j=1}^{Cm}\mu_{0,\,j}}dt)/T + b$$

Similarly, we can derive:

$$TD = EF = PE = FR = Aa(\int_0^T \frac{\lambda_{all\ i}}{\sum_{j=1}^{C_{all\ i}}\mu_{0,\,j}}dt)/4T + b \tag{11}$$

$$MD = Aa(\int_0^T \frac{\lambda_{i\ =\ vp,\,ap,\,c}}{\sum_{j=1}^{C_{i=vp,ap,c}}\mu_{0,\,j}}dt)/3T + b \tag{12}$$

If the arrival rate (λ_m, $\lambda_{all\ i}$, $\lambda_{i\ =\ vp,\,ap,\,c}$) and the total task time of each trial (T) remain the same in different age groups,

$$\because\ A \ge 1$$
$$\therefore\ PD_{old} \ge PD_{young},\ TD_{old} \ge TD_{young},\ EF_{old} \ge EF_{young},$$
$$PE_{old} \ge PE_{young},\ FR_{old} \ge FR_{young},\ \text{and } MD_{old} \ge MD_{young} \tag{13}$$

Similarly, age differences in driving performance can also be quantified. In queuing network theory, the performance of a network (HP) is in direct proportion to its servers' processing speeds (see Equation 14, [67]).

$$HP = (1/A)\,\underset{all\ j}{\Omega}(\mu_j) \tag{14}$$

where Ω is a function describing a negative relationship between human performance and all of the servers' processing times as variables. Since $A \ge 1$, the expected performance of older drivers is equal to or lower than young drivers.

IV. An Experiment on Driver Workload and Performance

Feyen and Liu (1998) conducted an experimental study in which drivers of two age groups performed a dual task of vehicle steering and button-pressing in a simulator (see Figure 3) [22]. In the primary vehicle steering task, subjects were asked to keep the vehicle in control by maintaining the lane position and the same driving speed (45 miles/hour). In the secondary button-pressing task, subjects were instructed to press one of the buttons on a panel mounted on the right side of the steering wheel when they saw a command presented on the display.

Fig. 3. Subject responded to a command prompt during driving [22]

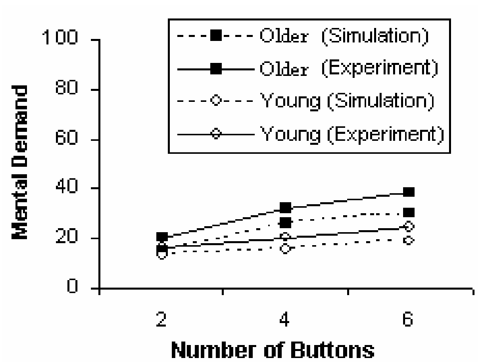
The independent variables were: 1) the age group of the subjects (four young drivers, 17-30 years old; four older drivers, 61-75 years old); 2) the number of buttons on the panel with 3 difficulty levels (2, 4, or 6 buttons). The dependent variables included: 1) the lane position deviation difference from the baseline (LPDDB) and it was calculated by subtracting a baseline lane position standard deviation from the lane position standard deviation during the task time segment (a negative value indicated a more stable lane positioning while a positive value indicated a less stable lane positioning); 2) reaction time of the button-pressing task as a performance-based mental workload measurement: the time interval between the command presentation and pressing of a button; 3) subjective ratings on the 6 scales of NASA-TLX after each trial. Since overall mental workload calculated by weighting the scales does not appear to add to the sensitivity of the NASA-TLX [24],[68], the overall mental workload was not collected in this experimental study [22].

V. SIMULATION RESULTS AND VALIDATION

By implementing Equations 2-7 described in the previous section in the queuing network simulation model, the simulation results are obtained and then compared with the experimental results (see Appendix for the method of setting parameters in these equations).

A. *Driver Workload*

Figure 4 shows the comparison between the simulation results and experimental results for each of the scales of NASA-TLX. Table 2 summarizes the R square and RMS of the model for each scale.



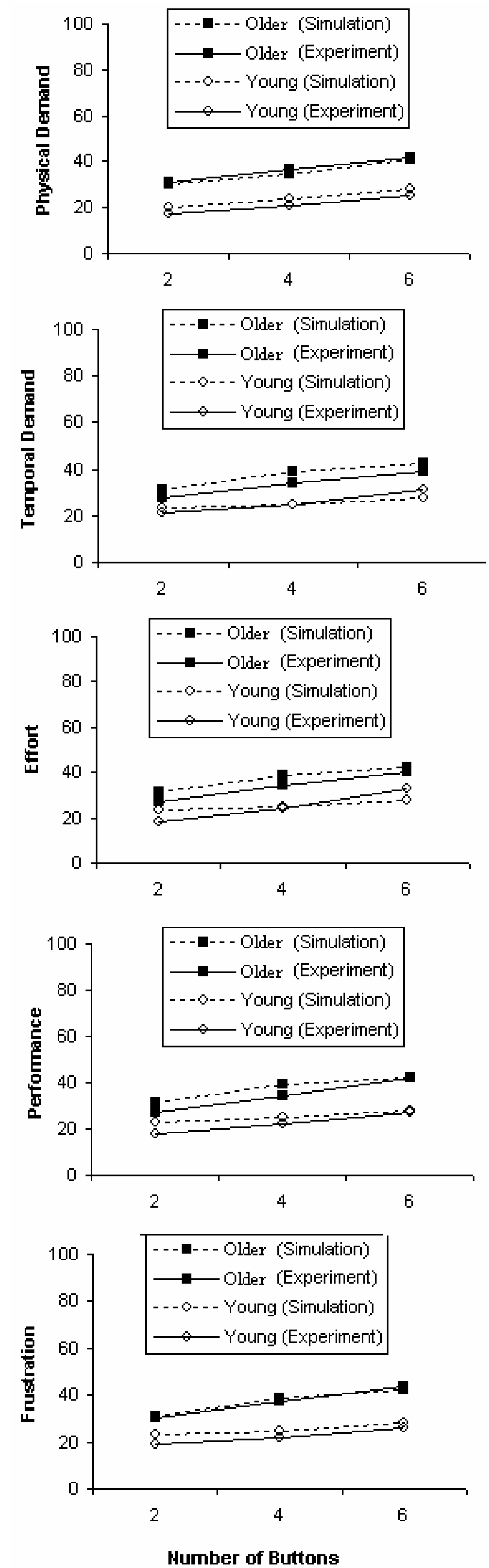


Fig. 4. Subjective mental workload in the experimental study of Feyen & Liu (1998) (solid lines) in comparison with the simulation results (dashed lines).

TABLE 2.
R SQUARE AND RMS OF THE MODEL FOR EACH SCALE

Scales	Young Drivers		Older Drivers	
	R^2	RMS	R^2	RMS
Physical Demand	.99	1.83	.95	1.74
Temporal Demand	.99	1.26	.97	3.92
Effort	.99	2.43	.97	4.01
Performance	.97	2.37	.93	3.79
Frustration	.99	1.78	.95	1.69
Mental Demand	.99	1.52	.99	6.56
Average	.99	2.11	.96	3.62

B. Driver Performance

Figures 5 and 6 show the simulation results of driver performance in comparison with the experimental results (LPDDB: R square=.98, RMS=.03; RT to the secondary task: R square=.94, RMS=50.4).

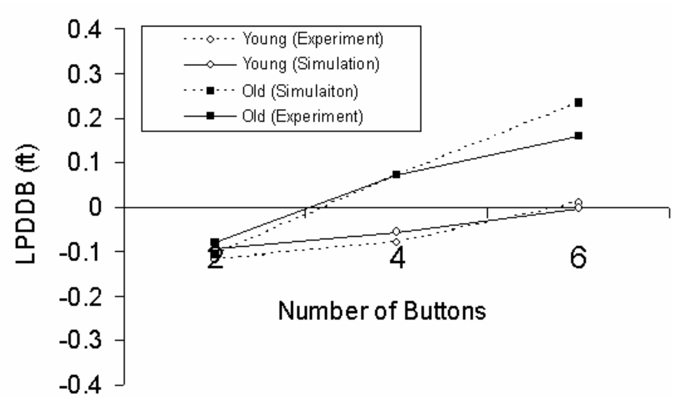


Fig. 5. LPDDB in the experimental study (solid lines) in comparison with simulation results (dashed lines)

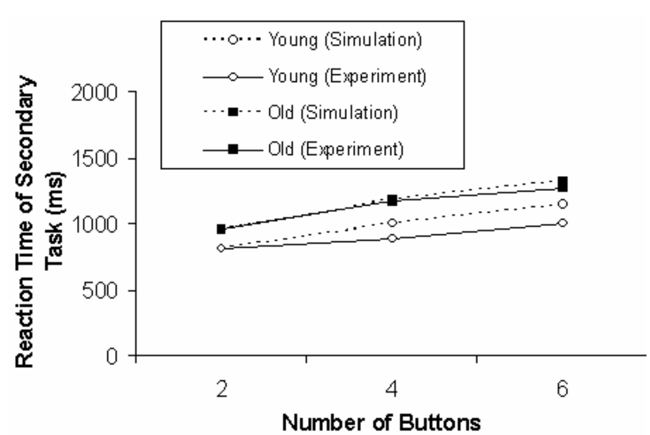
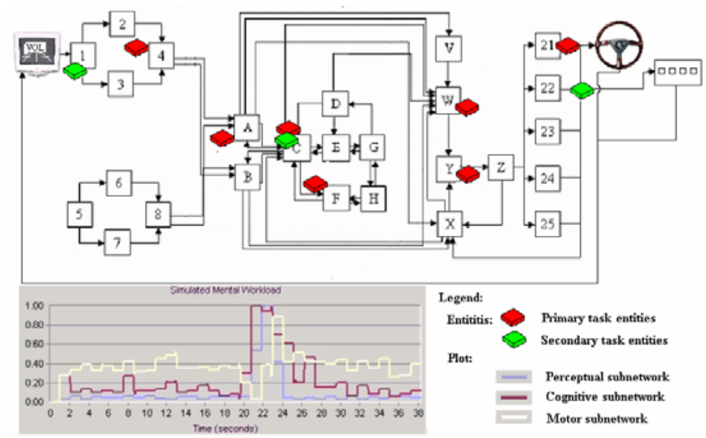


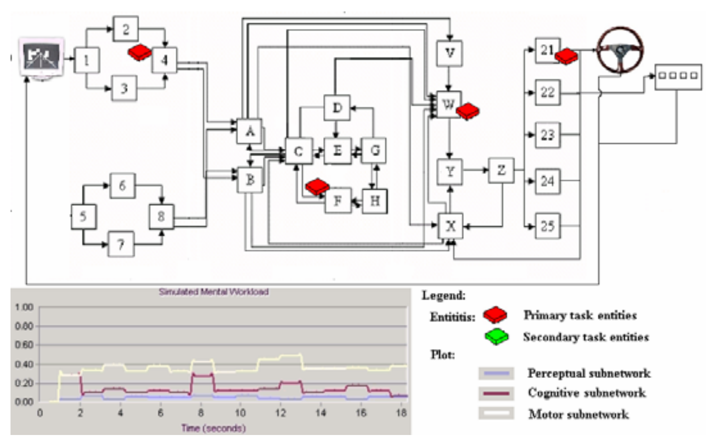
Fig. 6. Reaction time to the secondary task in the experimental study (solid lines) in comparison with simulation results (dashed lines)

C. Workload Visualization

As shown in Figure 7, the model allows a modeler to visualize the overall and the subnetwork mental workload by observing the entity activities and the network flow patterns during the simulation. Dynamic values of subnetwork utilizations are also shown in the simulation so that the user of the model can observe the dynamic changes of mental workload in real-time.



(a) High mental workload condition



(b) Low mental workload condition

Fig. 7. Visualizing mental workload in QN-MHP during the simulation
A short movie clip can be seen on the website:
http://www.acsu.buffalo.edu/~changxu/

VI. CONCLUSIONS

We described a queuing network modeling approach to model subjective mental workload and multitask performance including their age differences in a driving context, reflecting the multidimensional nature of mental workload from both subjective and performance-based measurements. Few existing computational models are able to simulate all of these major properties of driver workload at the same time in dual task situations. This modeling work offers a natural quantification of subjective mental workload with subnetwork utilization and initiates a step in connecting the output of an engineering model with the measurement of the subjective mental workload.

In practice, this modeling approach has several significant values for user interface design of in-vehicle systems. First, the queuing network simulation model is able to predict and visualize where workload is concentrated in the perceptual (auditory or visual), cognitive or motor subnetworks. For example, if the visual perceptual workload predicted by the model is heavy in certain circumstances, interface designers can design the user interface to present auditory information and use the model to test whether driver's visual perceptual workload can be reduced and whether the design creates other workload and performance problems.

Second, an accurate estimation of mental workload is vital for the design of intelligent or adaptive driver support and warning systems. Typically, these systems rely on computational models to estimate driver workload and propose actions to prevent traffic accidents (e.g., redirecting messages into a voice mailbox, [8], [70], [71]). By implementing this computational model into these systems, driver mental workload in different information processing components can be estimated more accurately.

Third, the capability of mental workload visualization is unique feature of the current modeling approach. Information visualization is an important step to increase the usability and face validity of a model [34] and allows users of the model to view the input, processing activities, and output of the model intuitively. Moreover, the dynamic change of mental workload in perceptual (auditory or visual), cognitive and motor subnetworks can be viewed and estimated directly in real time. This may help users of the model predict when the mental workload reaches "red-line" (reflected by a certain level of the average subnetwork utilization) as well as by how much and for how long it exceeds that red-line (see Figure 7).

In addition, the current modeling work accounts for age differences by simply considering an aging factor in servers' processing times, and it is consistent with findings in empirical studies on age differences. For example, Salthouse (1982, 1985) suggested that age differences are simply a function of a generalized slowing of information processing in older adults [18],[19]. Moreover, the current modeling work simplifies the estimation of 4 scales of NASA-TLX (TD, EF, PE and FR) by using the same index in the network (averaged utilization of all the subnetworks). This simplification is supported by empirical studies developing and using NASA-TLX in dual tasks. Hart and Staveland (1988) found that there is a high correlation among TD, EF, PE and FR (correlation efficient >.65) when NASA-TLX is used to measure the subjective mental workload in a dual task [25].

Even though the current modeling approach demonstrates its effectiveness and simplicity in accounting for the six mental workload scales in NASA-TLX in the driving context, several important topics need to be investigated in future research. The model in the future may need to differentiate the workload scores in the four scales (*PE, EF, FR, TD*) since they may stem from different psychological mechanisms. For example, frustration (*FR*) may be not only related to the utilization of resources or capacities in the system, but also affected by a person's subjective sensitivity to temporal pressure. Compared with mental workload measured by the other scales related to the utilization of resources or capacities, the mental workload measured by the performance (*PE*) scale may result from a complex subjective self-evaluation of one's performance including his or her prior experience in performing the same or relevant tasks, self-confidence, and self-evaluation strategies. This is also relevant to the modeling of individual differences, which is a very important topic to be covered in our future research and development of the queuing network model. In addition, even though the overall mental workload calculated by weighting the scales does not appear to add to the sensitivity of the NASA-TLX [24],[68], its value is another important topic to be investigated in the future because evaluation of some systems only need one index to represent mental workload.

We are extending the current modeling approach to other related mental workload research including modeling physiological measurements of mental workload. Overall, our current work demonstrates the value of the queuing network modeling approach in modeling and quantifying driver subjective mental workload and performance.

APPENDIX

In simulating subjective mental workload, the values of parameters a and b in Equations 2-7 are estimated based on the parameter setting method in a classic cognitive modeling work [69]—a and b are estimated only for the physical demand scale (change the value of these two parameters to generate the maximum fitness between the modeling results and experimental results), and then the same value is used to estimate subjective responses on the other 5 scales. Therefore, no free parameter is used in estimating the subjective responses in all the other 5 scales for young and older drivers (free parameter refers to parameters whose value is adjusted by researchers so that the modeling results fit the experimental results). Moreover, based on the method in calculating R square, the high R square values indicate that without using parameter a and b in Equations 2-7, the average subnetwork utilizations in Equations 2-7 are able to predict the variance of subjective mental workload accurately. In addition, no free parameter is used in predicting human performance.

The aging factor, A, is set according to a review of Proctor et al. (2005): Proctor et al. reviewed seven experimental studies and found that the mean reaction time for younger adults (24 years old on average) in spatial-visual choice RT task is 417 ms (compatible condition: 369 ms; incompatible condition: 465 ms); mean RT for older adults (70 years old on average) is 527 ms (compatible condition: 457 ms; incompatible condition: 597 ms) (see Table 1 in [70]). Therefore, A=1.26 (527/417=1.26) is selected for older drivers; and A=1 for young drivers [70].

REFERENCES

[1] H. Alm and L. Nilsson, "The Effects of a Mobile Telephone Task on Driver Behavior in a Car Following Situation," *Accident Analysis and Prevention,* vol. 27, pp. 707-715, Oct 1995.

[2] D. Wagner, M. Vercruyssen, and P. Hancock, "A computer-based methodology for evaluating the content of variable message signage," *ITS Journal,* vol. 3, pp. 353-373, 1997.

[3] C. Wickens, A. Kramer, L. Vanasse, and E. Donchin, "Performance of Concurrent Tasks - a Psychophysiological Analysis of the Reciprocity of Information-Processing Resources," *Science,* vol. 221, pp. 1080-1082, 1983.

[4] D. A. Redeleier and R. J. Tibshirani, "Associatation between Cellular-Telephone Calls and Motor Vehicle Collisions," *New England Journal of Medicine,* vol. 336, pp. 453-458, 1997.

[5] J. M. Violanti and J. R. Marshall, "Cellular phones and traffic accidents: an epidemiological approach," *Accident Analysis & Prevention,* vol. 28, pp. 265-270, 1996.
[6] F. X. McKelvey and N. Stamatiadis, "Highway accident patterns in Michigan related to older drivers," *Transportation Research Record,* vol. 1210, pp. 53- 57, 1989.
[7] J. Y. C. Hing, N. Stamatiadis, and L. Aultman-Hall, "Evaluating the impact of passengers on the safety of older drivers," *Journal of Safety Research,* vol. 34, pp. 343-351, Win 2003 2003.
[8] W. Piechulla, C. Mayser, H. Gehrke, and W. Konig, "Reducing drivers' mental workload by means of an adaptive man-machine interface," *Transportation Research, Part F,* vol. 6, pp. 233-248, 2003.
[9] J. Annett, "Subjective rating scales: science or art?," *Ergonomics,* vol. 45, pp. 966-987, Nov 15 2002.
[10] S. Card, T. P. Moran, and A. Newell, *The psychology of human-computer interaction*. Hinsdale, NJ: Lawrence Erlbaum, 1983.
[11] K. C. Hendy, K. M. Hamilton, and L. N. Landry, "Measuring Subjective Workload - When Is One Scale Better Than Many," *Human Factors,* vol. 35, pp. 579-601, Dec 1993.
[12] Y. H. Lee and B. S. Liu, "Inflight workload assessment: Comparison of subjective and physiological measurements," *Aviation Space and Environmental Medicine,* vol. 74, pp. 1078-1084, Oct 2003.
[13] M. Ohsuga, F. Shimono, and H. Genno, "Assessment of phasic work stress using autonomic indices," *International Journal of Psychophysiology,* vol. 40, pp. 211-220, Apr 2001.
[14] S. Rubio, E. Diaz, J. Martin, and J. M. Puente, "Evaluation of subjective mental workload: A comparison of SWAT, NASA-TLX, and workload profile methods," *Applied Psychology-an International Review-Psychologie Appliquee-Revue Internationale,* vol. 53, pp. 61-86, Jan 2004.
[15] P. S. Tsang and V. L. Velaquez, "Diagnosticity and multidimensional subjective workload ratings," *Ergonomics,* vol. 39, pp. 358-381, Mar 1996.
[16] B. Xie and G. Salvendy, "Review and reappraisal of modeling and predicting mental workload in single-and multi-task environments," *Work & Stress,* vol. 14, pp. 74-99, 2000.
[17] W. B. Verwey, "On-line driver workload estimation. Effects of road situation and age on secondary task measures," *Ergonomics,* vol. 43, pp. 187-209, Feb 2000.
[18] T. A. Salthouse, *Adult Cognition. An Experimental Psychology of Human Aging*. New York: Springer-Verlag, 1982.
[19] T. A. Salthouse, *Speed of behavior and its implications for cognition*. New York: Van Nostrand Reinhold, 1985.
[20] N. H. Kirby and T. Nettelbeck, "Speed of information processing and age," *Personality & Individual Differences,* pp. 183-188., 1991.
[21] P. D. Tomporowski, "Performance and perceptions of workload among young and older adults: effects of practice during cognitively demanding tasks," *Educational Gerontology,* vol. 29, pp. 447-466, 2003.
[22] R. Feyen and Y. Liu, "Driver Performance Model for Instrument Panel Control Use, Technical Report: 99-03," Department of Industrial and Operations Engineering, University of Michigan 1998.
[23] M. A. Vidulich and C. Wickens, "Causes of dissociation between subjective workload measures and performance: Caveats in the use of subjective assessments," *Applied Ergonomics,* vol. 17, pp. 291-296, 1986.
[24] A. Johnson and R. W. Proctor, *Attention*. London: SAGE Publications, 2004.
[25] S. G. Hart and L. E. Staveland, "Development of a multi-dimensional workload rating scale: Results of empirical and theoretical research.," in *Human mental workload,*, P. A. Hancock and N. Meshkati, Eds. Amsterdam: North-Holland, 1988.
[26] J. Mcdowd, M. Vercruyessen, and J. E. Birren, "Aging, divided attention, and dual-task performance," in *Multiple Task Performance*, D. L. Damos, Ed.: Taylor & Francis, 1991.
[27] S. Horiuchi and N. Yuhara, "An analytical approach to the prediction of handling qualities of vehicles with advanced steering control system using multi-input driver model," *Journal of Dynamic Systems Measurement and Control-Transactions of the Asme,* vol. 122, pp. 490-497, Sep 2000.
[28] Y. Lin, P. Tang, W. J. Zhang, and Q. Yu, "Artificial neural network modeling of driver handling behaviour in a driver-vehicle-environment system," *International Journal of Vehicle Design,* vol. 37, pp. 24-45, 2005.
[29] S. Easa and C. Ganguly, "Modeling driver visual demand on complex horizontal alignments," *Journal of Transportation Engineering-ASCE,* vol. 131, pp. 583-590, Aug 2005.
[30] M. A. Goodrich and E. R. Boer, "Semiotics and mental modes: modeling automobile driver behavior," in *IEEE ISIC/CIRA/ISAS Joint Conference*, Gaithersburg, MD, 1998.
[31] J. R. Anderson and C. Lebiere, *The Atomic Components of Thought*: Lawrence Erlbaum Associates, 1998.
[32] D. D. Salvucci, E. R. Boer, and A. Liu, "Toward an Integrated Model of Driver Behavior in a Cognitive Architecture," *Transportation Research Record,* In press.
[33] S. Koshman, "Comparing usability between a visualization and text-based system for information retrieval," *Journal of Documentation,* vol. 60, pp. 565-580, 2004.
[34] S. B. Trickett, J. G. Trafton, and C. D. Schunn, "Blobs, dipsy-doodles and other funky things: Framework anomalies in exploratory data analysis," in *Proceedings of the 22nd Annual Conference of the Cognitive Science Society*, Mahwah, NJ, 2000.
[35] Y. Liu, "Queuing network modeling of elementary mental processes," *Psychological Review,* vol. 103, pp. 116-136, Jan 1996.
[36] Y. Liu, "Queuing network modeling of human performance of concurrent spatial and verbal tasks," *IEEE Transactions on Systems Man and Cybernetics Part a-Systems and Humans,* vol. 27, pp. 195-207, Mar 1997.
[37] Y. Liu, R. Feyen, and O. Tsimhoni, "Queueing Network-Model Human Processor (QN-MHP): A Computational Architecture for Multitask Performance," *ACM Transaction on Human Computer Interaction,* vol. 13, pp. 37-70, 2006.
[38] M. F. Bear, B. W. Connors, and M. A. Paradiso, *Neuroscience: exploring the brain*, 8th ed. Baltimore, MD: Lippincott Williams & Wilkins,, 2001.
[39] E. E. Smith and J. Jonides, "Neuroimaging analyses of human working memory," *Proc. Natl. Acad. Sci. USA,* vol. 95, pp. 12061-12068, 1998.
[40] P. E. Roland, *Brain activation*. New York, NY: Wiley-Liss, 1993.
[41] B. Faw, "Pre-frontal executive committee for perception, working memory, attention, long-term memory, motor control, and thinking: A tutorial review," *Consciousness and Cognition,* vol. 12, pp. 83-139, Mar 2003.
[42] F. Rieke, D. Warland, R. R.S., and W. Bialek, *Spikes: Exploring the Neural Code (Computational Neuroscience)*: MIT Press, 1997.
[43] J. Taylor, B. Horwitzc, N. J. Shaha, W. A. Fellenzb, H.-W. Mueller-Gaertnera, and J. B. Krausee, "Decomposing memory: functional assignments and brain traffic in paired word associate learning," *Neural Networks,* vol. 13, pp. 923-940, 2000.
[44] R. Feyen, "Modeling Human Performance using the Queuing Network-Model Human Processor (QN-MHP)," in *Department of Industrial and Operations Engineering* Ann Arbor: University of Michigan, Doctor Thesis, 2002.
[45] S. R. Simon, M. Meunier, L. Piettre, A. M. Berardi, C. M. Segebarth, and D. Boussaoud, "Spatial attention and memory versus motor preparation: Premotor cortex involvement as revealed by fMRI," *Journal of Neurophysiology,* vol. 88, pp. 2047-2057, Oct 2002.
[46] H. Mustovic, K. Scheffler, F. Di Salle, F. Esposito, J. G. Neuhoff, J. Hennig, and E. Seifritz, "Temporal integration of sequential auditory events: silent period in sound pattern activates human planum temporale," *Neuroimage,* vol. 20, pp. 429-434, Sep 2003.
[47] E. T. Rolls, "Memory systems in the brain," *Annual Review of Psychology,* vol. 51, pp. 599-630, 2000.
[48] P. C. Fletcher and R. N. A. Henson, "Frontal lobes and human memory - Insights from functional neuroimaging," *Brain,* vol. 124, pp. 849-881, May 2001.
[49] D. S. Manoach, G. Schlaug, B. Siewert, D. G. Darby, B. M. Bly, A. Benfield, R. R. Edelman, and S. Warach, "Prefrontal cortex fMRI signal changes are correlated with working memory load," *Neuroreport,* vol. 8, pp. 545-549, Jan 20 1997.
[50] K. Kansaku, T. Hanakawa, T. Wu, and M. Hallett, "A shared neural network for simple reaction time," *Neuroimage,* vol. 22, pp. 904-911, Jun 2004.
[51] A. R. Mitz, M. Godschalk, and S. P. Wise, "Learning-Dependent Neuronal-Activity in the Premotor Cortex - Activity During the Acquisition of Conditional Motor Associations," *Journal of Neuroscience,* vol. 11, pp. 1855-1872, Jun 1991.

[52] A. S. Cook and M. H. Woollacott, *Motor Control: Theory and Practical Applications*: Williams& Wilkins, 1995.
[53] P. F. C. Gilbert, "An outline of brain function," *Cognitive Brain Research,* vol. 12, pp. 61-74, Aug 2001.
[54] A. M. Gordon and J. F. Soechting, "Use of tactile afferent information in sequential finger movements," *Experimental Brain Research,* vol. 107, pp. 281-292, 1995.
[55] C. Wu and Y. Liu, "Modeling human transcription typing with queuing network-model human processor.," in *Proceedings of the 48th Annual Meeting of Human Factors and Ergonomics Society*, New Orleans, Louisiana, USA, 2004, pp. 381-385.
[56] C. Wu and Y. Liu, "Modeling Psychological Refractory Period (PRP) and Practice Effect on PRP with Queuing Networks and Reinforcement Learning Algorithms," in *Proceedings of the 6th International Conference on Cognitive Modeling (ICCM-2004)*, Pittsburgh, PA, USA., 2004, pp. 320-325.
[57] J. Lim and Y. Liu, "A queueing network model of menu selection and visual search," in *Proceedings of the 48 Annual Conference of the Human Factors and Ergonomics Society*, New Orleans, Louisiana, USA, 2004, pp. 152-157.
[58] Y. Liu, R. Feyen, and O. Tsimhoni, "Queueing Network-Model Human Processor (QN-MHP): A Computational Architecture for Multitask Performance," *ACM Transaction on Human Computer Interaction,* in press.
[59] W. B. Rouse, *Systems Engineering Models of Human-Machine Interaction*. New York: North Holland, 1980.
[60] M. A. Just, P. A. Carpenter, and A. Miyake, "Neuroindices of cognitive workload: Neuroimaging, pupillometric and event-related potential studies of brain work," *Theoretical Issues in Ergonomics Science,* vol. 4, pp. 56-88, Jan-Jun 2003 2003.
[61] E. Blomstrand, "Amino acids and central fatigue," *Amino Acids,* vol. 20, pp. 25-34, 2001.
[62] E. Blomstrand, "A role for branched-chain amino acids in reducing central fatigue," *Journal of Nutrition,* vol. 136, pp. 544S-547S, Feb 2006.
[63] J. M. Davis, "Carbohydrates, Branched-Chain Amino-Acids, and Endurance - the Central Fatigue Hypothesis," *International Journal of Sport Nutrition,* vol. 5, pp. S29-S38, Jun 1995.
[64] E. A. Newsholme and E. Blomstrand, "The plasma level of some amino acids and physical and mental fatigue," *Experientia,* vol. 52, pp. 413-415, May 1996.
[65] E. A. Newsholme and E. Blomstrand, "Branched-chain amino acids and central fatigue," *Journal of Nutrition,* vol. 136, pp. 274S-276S, Jan 2006.
[66] D. Bunce and A. Macready, "Processing speed, executive function, and age differences in remembering and knowing," *Quarterly Journal of Experimental Psychology A: Human Experimental Psychology,* vol. 58, pp. 155-168, Jan 2005 2005.
[67] D. Gross, *Fundamentals of queueing theory*: John Wiley & Sons, Inc, 1998.
[68] F. T. Eggemeier and G. F. Wilson, "Performance-based and subjective assessment of workload in multi-task environment," in *Multiple Task Performance*, D. L. Damos, Ed.: Taylor & Francis, 1991.
[69] M. D. Byrne and J. R. Anderson, "Serial modules in parallel: The psychological refractory period and perfect time-sharing," *Psychological Review,* vol. 108, pp. 847-869, Oct 2001.
[70] R. W. Proctor, K. L. Vu, and D. F. Pick, "Aging and response selection in spatial choice task," *Human Factors,* vol. 47, pp. 250-270, 2005.

Changxu Wu received the M.S. and the Ph.D. degrees in industrial & operational engineering from the University of Michigan-Ann Arbor, in 2004 and 2007 respectively. He also received the M.S. degree in engineering psychology & human-computer interaction from Chinese Academy of Sciences in 2002 and the B.S. degree in psychology with the focus on engineering and mathematical psychology from Zhejiang University, P.R. China in 1999.

He is an Assistant Professor of Department of Industrial and System Engineering at the State University of New York (SUNY), Buffalo, starting from August 2007. Before he joined the faculty at SUNY-Buffalo, he was a Research Assistant in Human Factors Division at the University of Michigan Transportation Research Institute (UMTRI) and Department of Industrial & Operations Engineering at the University of Michigan. He has published papers in International Journal of Human-Computer Studies, Acta Psychologica Sinica, Ergonomics in Design as well as several other journals. The main theme of his current research is the development of computational models of human performance and mental workload, addressing both fundamental and neurological issues of perceptual-motor behavior and human cognition with their applications in designing intelligent transportation systems. He also received the Outstanding Student Instructor Award from the American Society of Engineering Education (ASEE) at the University of Michigan in 2006.

Dr. Wu is a member of Human Factors & Ergonomics Society (HFES), Society of Automobile Engineers (SAE), Cognitive Science Society, and American Society of Engineering Education (ASEE). He served IEEE and other academic organizations as a reviewer of IEEE Transactions on Intelligent Transportation Systems, Applied Ergonomics, and IEEE Intelligent Transportation Systems Conference. He was a co-chair in one of the Human Performance Modeling sessions in the Annual Meeting of Human Factors & Ergonomics Society in 2005.

Yili Liu (S'90-M'91) received the M.S. degree in computer science and the Ph.D. degree in engineering psychology from the University of Illinois, Urbana-Champaign, in 1990 and 1991.

He is Arthur F. Thurnau Professor and Associate Professor of Industrial and Operations Engineering at the University of Michigan. His research and teaching areas are cognitive ergonomics, human factors, computational cognitive modeling, and engineering aesthetics. He has published refereed journal articles in Psychological Review, IEEE Transactions on Systems, Man, and Cybernetics, Human Factors, and Ergonomics, as well as several other journals. He is the recipient of University of Michigan Arthur F. Thurnau Professorship Award (selected by the Provost and approved by the Regents of the University of Michigan), College of Engineering Education Excellence Award, College of Engineering Society of Women Engineers Professor of the Year Award (twice recipient), and Alpha Pi Mu Professor of the Year Award (five time recipient). He is a co-author of a human factors textbook titled An Introduction to Human Factors Engineering.

Dr. Liu is a member of IEEE, ACM, Human Factors and Ergonomics Society, American Psychological Association, and Sigma Xi.