Development of an Adaptive Workload Management System Using the Queueing Network-Model Human Processor (QN-MHP)

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***Abstract*—The risk of vehicle collisions significantly increases when drivers are overloaded with information from in-vehicle systems. One of the solutions to this problem is developing adaptive workload management systems (AWMSs) to dynamically control the rate of messages from these in-vehicle systems. However, existing AWMSs do not use a model of the driver cognitive system to estimate workload and only suppress or redirect in-vehicle system messages, without changing their rate based on driver workload. In this paper, we propose a prototype of a new queueing network-model human processor AWMS (QN-MHP AWMS), which includes a queueing network model of driver workload that estimates the driver workload in several driving situations and a message controller that determines the optimal delay times between messages and dynamically controls the rate of messages presented to drivers. Given the task information of a secondary task, the QN-MHP AWMS adapted the rate of messages to the driving conditions (i.e., speeds and curvatures) and driver characteristics (i.e., age). A corresponding experimental study was conducted to validate the potential effectiveness of this system in reducing driver workload and improving driver performance. Further development of the QN-MHP AWMS, including its use in in-vehicle system design and possible implementation in vehicles, is discussed.**

***Index Terms*—Adaptive system, driver workload, queueing network, workload management.**

I. Introduction

WITH THE development of in-vehicle system technology, increasingly more in-vehicle information and entertainment systems (e.g., navigation aides, mobile phones, e-mail, web browsers, vehicle-to-vehicle communication systems, and traffic information displays) are being used in vehicles. Multitasking between driving and using these systems may impose high information load on drivers, increasing their mental workload [1]–[3], which, in turn, increases the risk of vehicle collisions, compared with a single-task driving condition [1], [4]. Multitasking has also become particularly common for drivers with special duties. For example, police officers need to drive, communicate with other police officers, and monitor the speed of other cars via radar systems at the same time; ambulance drivers need to steer vehicles, navigate their vehicle to patients' locations, and communicate with dispatchers and hospitals at the same time; and fire-fighting vehicle drivers also need to steer and navigate vehicles to target locations and communicate with their headquarters at the same time to receive updates on the situation of target locations.

After Michon [5] proposed the basic concepts in designing an adaptive system for drivers, recently, several adaptive workload management systems (AWMSs) have been developed as one of the possible solutions in reducing driver mental workload [6] (see Table I). Some available systems include BMW's phone adaptive system [6] and Toyota's voice adaptive system [7] (see reviews in [8] and [9]). There are two important components in these systems: First, to estimate driver workload, these adaptive systems collect current driving information, such as steering wheel angle and lane position, and then use computational algorithms to directly estimate the current workload of the driver. In addition to these estimations of the workload, researchers can also use subjective workload questionnaires or psychophysiological measurement (e.g., event-related potential) to estimate the workload; however, these subjective and psychophysiological measurements either require subjects to perform additional tasks or attach certain electrodes onto the human body, making them very difficult to use in practical situations. Second, based on these estimations of driver workload, the systems propose corresponding actions to reduce driver workload, e.g., suppressing messages from in-vehicle systems [7] or redirecting messages into a voice mailbox when the driver's estimated mental workload is high [6].

There are two important aspects in the human factors of these AWMSs that need further improvement: First, at the human end, a cognitive model of the driver might be useful in estimating a driver's workload in a multitasking situation. Such a model may particularly be useful for the quantification of the effects of driving situations (e.g., speed and road curve), characteristics of drivers (e.g., age), and secondary tasks on the driver workload (e.g., the processing time of the secondary task

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TABLE I
SUMMARY OF FOUR AWMSs

Existing AWMS	Workload Estimation (Human): Human Model Used	Workload Estimation (Human): Dual Task (2nd Task's Property)	Message Management (System)
1. Phone Adaptive System (BMW, Germany) (Piechulla et al., 2003) [6]	No	Single (Not considered)	Redirect to a phone mailbox only
2. Voice Adaptive System (Toyota, Japan) (Uchiyama et al., 2004) [7]	No	Single (Not considered)	Suppress only
3. SAVE-IT Adaptive System (Delphi, 2004-2007)	Under development		Under development
4. In-Vehicle Message System (Leeds, UK) [10])	No	Single (Not considered)	Wait for driver's response only

in different components, i.e., perceptual, cognitive, and motor components, of the cognitive system). Second, at the system end, an all-or-nothing solution (suppressing or redirecting messages from the in-vehicle systems) might be too simplistic. A more general solution might be to treat the temporal delay between messages as a continuous variable (ranging from 0 to infinite), whose value is set, depending on various driving situations. In addition, if the in-vehicle messages are controlled by a driver's response, there are two potential problems: The drivers need additional actions to turn on (or off) the device, and drivers may not be able to manage or prioritize messages from the in-vehicle and the primary task (see a review by Haigney and Westerman [11] discussing the effects of concurrent mobile phone use on driving).

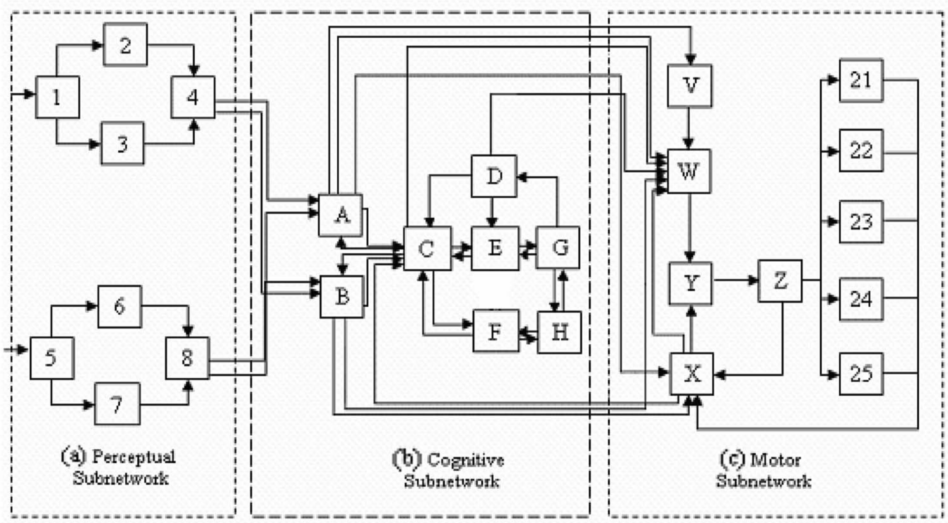
In this paper, we propose a new queueing network-model human processor AWMS (QN-MHP AWMS) that includes two components: 1) a model of the driver workload for estimating it based on research on cognitive modeling and 2) a message controller (MC) that determines the optimal delay times between messages and dynamically controls the rate of messages in various driving situations. In Section II, we describe the driver workload model (QN-MHP) in general, including its advantages in simulating driver workload. In Section III, we propose a prototype of this new AWMS (QN-MHP AWMS). Sections IV and V illustrate the first component in the QN-MHP AWMS, i.e., how the QN-MHP can be used to simulate driver workload and performance in an example of multitasking in driving. Section VI describes the second component in the QN-MHP AWMS, i.e., the detailed algorithms in the MC for determining the optimal delay times between messages. We also conducted a corresponding experimental study to validate the potential effectiveness of this system in reducing driver workload (See Section VII).

II. QUEUEING NETWORK MODELING OF HUMAN PERFORMANCE AND MENTAL WORKLOAD

Along the line of research on developing unified theories of cognition advocated by Newell [12], we have been making steady progress in developing a queueing network architecture for human performance modeling [13]–[19]. Mathematical models based on queueing networks have successfully integrated a large number of mathematical models in response time [13] and in multitask performance [14] as special cases of queueing networks. As a computational model, we have established a bridge between the mathematical models of queueing networks and the symbolic models of cognition with our queueing network architecture called the QN-MHP [16]–[20] (see Figs. 1 and 2). QN-MHP is a simulation model of a queueing network mental architecture that represents information processing in the cognitive system as a queueing network based on neuroscience and psychological findings. Ample research evidence has shown that major brain areas with certain information processing functions are localized and connected with each other via neural pathways [21]–[23], which is highly similar to a queueing network of servers that can process entities traveling through the routes serially or/and in parallel, depending on specific network arrangements. Therefore, brain regions with similar functions can be regarded as servers, and the neural pathways connecting them are treated as routes in the queueing network (see Figs. 1 and 2). The information being processed in the network is represented by entities traveling in the network.

The QN-MHP represents its overall architecture as a queueing network, which is a major branch of mathematics and operations research, thus allowing comprehensive mathematical modeling. Furthermore, each of the QN-MHP servers is capable of performing procedure logic functions, allowing it to generate detailed task actions and simulate real-time behavior. For multitask performance modeling, a unique characteristic of the QN-MHP is its ability to model concurrent activities without the need either to interleave the production rules of concurrent tasks into a serial program or for executive process(es) to interactively control (lock/unlock) the task processes. The model has successfully been applied to quantify human performance in a variety of tasks, including simple and choice RT (RT) [24], transcription typing [17], [25], visual manual tracking [19], [26], psychological refractory period (PRP) [27], visual search [28], mental workload [16], [19], and a driving task of steering and map reading [20]. For a detailed description of the rationale, assumptions, structure, and implementation of the QN-MHP and how to use it in multitask modeling, see [20]. Simulation of human performance in a task requires three steps: 1) Model the environment (e.g., road curvatures); 2) analyze the task using an NGOMSL-Style method; and 3) perform simulation and analyze the simulation results.

In addition to modeling human performance in these tasks, the QN-MHP is also used to predict and account for mental



Perceptual Subnetwork	Cognitive Subnetwork	Motor Subnetwork
1. Common visual processing	A. Visuospatial sketchpad	V. Sensorimotor integration
2. Visual recognition	B. Phonological loop	W. Motor program retrieval
3. Visual location	C. Central executive	X. Feedback information collection
4. Visual recognition and location integration	D. Long-term procedural memory	Y. Motor program assembling and error detecting
5. Common auditory processing	E. Performance monitor	Z. Sending information to body parts
6. Auditory recognition	F. Complex cognitive function	21-25: Body parts: eye, mouth, left hand, right hand, foot
7. Auditory location	G. Goal initiation	
8. Auditory recognition and location integration	H. Long-term declarative & spatial memory	

Fig. 1. General structure of the queueing network model [16]–[20].

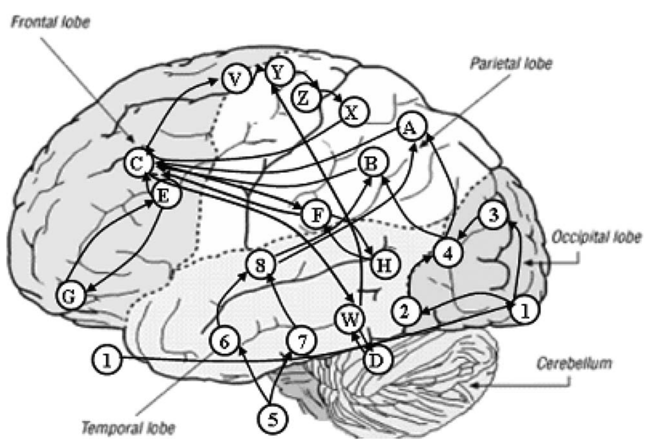


Fig. 2. Approximate mapping of the servers in the queueing network model onto the human brain [16]–[19].

workload. Among various models in quantifying mental workload, the QN-MHP is able to cover many important features of it, including its multidimensional properties [16], workload in both single and dual tasks [17], [19], age difference [29], prediction of subjective workload measured by NASA-TLX [16], [30], prediction of physiological workload reflected by the amplitude and latency of the P300 component (which are measured by event-related brain potential techniques [19]), [26], and workload visualization [18] (see Table II for a summary of the properties of workload modeled by the QN-MHP in comparison with other modeling approaches).

In the work of Wu and Liu [16], the subjective ratings of the workload in the six subscales in NASA-TLX were modeled using the following three equations:

$$\mathrm{PD} = Aa\left(\int_0^T \frac{\lambda m}{\sum_{j=1}^{Cm} \mu 0, j}\,dt\right)/T + b \tag{1}$$

$$\mathrm{TD} = \mathrm{EF} = \mathrm{PE} = \mathrm{FR} = Aa\left(\int_0^T \frac{\lambda_{\text{all } i}}{\sum_{j=1}^{C_{\text{all } i}} \mu 0, j}\,dt\right)/4T + b \tag{2}$$

$$\mathrm{MD} = Aa\left(\int_0^T \frac{\lambda_i = vp, ap, c}{\sum_{j=1}^{Ci=vp,ap,c} \mu 0, j}\,dt\right)/3T + b \tag{3}$$

where PD (physical demand), TD (temporal demand), EF (effort), PE (performance), FR (frustration), and MD (mental demand) represent the subjective rating of the workload of the six dimensions/subscales in NASA-TLX. A is the aging factor ($A = 1$ for young subjects); T is the total task time of each trial; λ is the arrival rate of the subnetwork, and C_i is the total number of servers in the subnetwork; $\mu_{0,j}$ is the original processing speed of server j for young adults in the QN-MHP; and a and b are constants in representing the direct proportional relation between the averaged utilizations and subjective responses ($a > 0$). The values of these parameters are obtained via the simulation model. In other words, when the QN-MHP simulates a certain type of task, the equations implemented in the simulation model can generate the prediction of mental

TABLE II
COVERAGE OF THE EXISTING MODELS IN ACCOUNTING FOR THE MAJOR FEATURES OF MENTAL WORKLOAD

Models	Multi-dimensional	Dual Task	Task Covered	Age Differences	Subjective Workload Prediction	Performance Prediction	Physiological Prediction	Dynamic	Workload Visualization
QN-MHP (Wu & Liu, In Press, 2007) (Liu, Feyen, & Tsimhoni, 2006) (Wu & Liu, 2006a,2006b,2006c) [16, 18, 19, 26, 29, 30]	Visual/Auditory /Cognitive/Motor	Yes	Steering & operating in-vehicle system	Yes	Yes	Yes	Yes	Yes	Yes
Control Theory (Horiuchi et al., 2000) [31]	Mental and physical	-	Steering	-	Yes	Yes	-	Yes	-
Neural Network (Lin et al., 2005) [32]	-	-	Steering	-	Yes	Yes	-	-	-
Statistic Model (Easa & Ganguly, 2005) [33]	Visual	-	Steering	-	Yes	-	-	Yes	-
Probability Model (Vadeby, 2004) [34]	-	-	Steering	Yes	-	Yes	-	-	-
Piechulla 's Engineering Model (Piechulla et al., 2003) [6]	-	-	Steering	-	Yes	-	-	Yes	-
Rule-based Model (Salvucci, 2001)[35]	Visual /Cognitive/Motor	Yes	Steering & phone dialing	-	-	Yes	-	-	-

-: not covered or under development

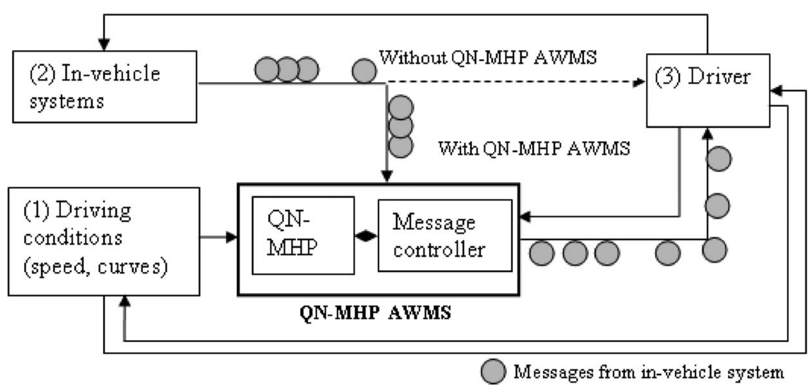


Fig. 3. Prototype of the QN-MHP AWMS.

workload (see a movie of this simulation process at http://www.acsu.buffalo.edu/~changxu/). The predictions of mental workload using these computational models have been validated with an empirical study [16]. Equation (2) is also used to predict the overall workload in various tasks. The equations and the simulation model of driver workload developed in the previous work provide a quantitative estimation of mental workload compared to qualitative models of workload and cognitive resources (e.g., Wicken's multiple resources theory).

As a continuation of our previous work, the current study focuses on the application of the simulation model (QN-MHP) and mathematical equations of mental workload into AWMS design and validates the potential effectiveness of the system in reducing the workload with an experimental study.

III. Designing a Prototype of the QN-MHP AWMS

The purpose of the QN-MHP AWMS is to regulate the rate of messages from the in-vehicle systems, based on the driving condition and properties of the secondary task, to effectively reduce driver workload. Fig. 3 shows the prototype of the adaptive system, which is composed of two parts: the QN-MHP and the MC. The QN-MHP AWMS receives three types of information: 1) driving conditions (e.g., current driving speed and curvatures); 2) the properties of a secondary task related to in-vehicle systems (e.g., the processing time at the perceptual, cognitive, and motor stages); and 3) the properties of the driver (e.g., age and level of driving experience).

Given the task information of a certain type of in-vehicle task (box 2 in Fig. 3), the QN-MHP simulates the driver workload and performance, depending on various driving conditions (box 1), and then, the MC determines the optimal delay times between messages and regulates the rate of messages in real time and outputs the messages to the driver (box 3) based on the simulation results (see the message flow from in-vehicle systems to the QN-MHP AWMS and then to the driver in Fig. 3).

In the following sections, the two components of the QN-MHP AWMS are described in detail, including how the QN-MHP can be used to simulate driver workload and performance in an example of multitasking (Sections IV and V) and the detailed algorithms in the MC for determining optimal delay times (Section VI).

IV. Example of Multitasking in Driving With Practical Importance

According to a report from NHTSA's National Center for Statistics and Analysis, speeding is one of the most prevalent factors contributing to automobile crashes. The economic cost to society of speeding-related crashes is estimated by the NHTSA to be \$40.4 billion per year; in 2004, speeding was a contributing factor in 30% of all fatal crashes, and 13 192 lives were lost in speeding-related crashes [36], [37]. Traffic law enforcement (police officers detecting speeding and issuing speeding tickets) is one of the most critical measures for preventing speeding. However, aside from detecting speeding, police officers also have to perform other tasks at the same time, e.g., communicating with dispatchers and navigating the vehicle to a target location. Based on an informal interview with four police officers at the Public Safety Service Center at the University of Michigan, it was found that one of their representative multitasking scenarios is performing the two tasks given here while steering the vehicle.

1) Speeding detection or judgment task (subtask 1): Officers need to read two numbers on a display of an in-vehicle radar system mounted on the dashboards of police vehicles. The first number is the speed of a target vehicle measured by the radar system; the second is the distance from the police vehicle to the target vehicle. Whether the target vehicle is speeding is determined by both the speed and the distance. For example, on a road with a speed limit of 55 mi/h, if the speed is between 56 and 64 mi/h and the distance is less than 100 yd, it is speeding; if the distance is more than 100 yd, it is judged as not speeding. On the other hand, independent of the distance, if the speed is above 65 mi/h, it is speeding; if the speed is below 55 mi/h, it is not speeding.
2) Radio message response task (Subtask 2): Messages received by the officers usually come from multiple sources (headquarters, other police officers, and maintenance), and the officers need to respond to higher priority messages (e.g., from headquarters) by pressing a button on the radio.

The most frequent order of these two tasks, based on the interview, is the radar speeding detection task, followed by the message response task (the duration between the presentation of the numbers in the speed detection and the presentation of the voice message of the message response task is called "message delay time" or "$Delay$" in this paper).[1,2] This sample multitasking scenario of police officers was also inspired by the ALERT project of the Texas Transportation Institute, which focused on the development of an integrated interface of various devices (radar detection system, radio, video recording systems, etc.) for police officers to improve their performance and safety [41].

[1] Since the sample task is composed of a pair of two subtasks, i.e., the speeding detection task (RTs), followed by the message response task (RTm), the reaction time of the secondary task (ST) as a representative performance index of the whole secondary task is defined as $ST = (RTs + RTm)/2$.

[2] This message delay time in the majority of multitasking cases, based on the interview, is longer than 3 s.

This sample multiple-task simulation can also be generalized into other multitasking situations in driving since it captures several important characteristics of multitasking in driving: 1) It considers one of the most important variables in multitasking, i.e., the delay time between the presentations of information for different tasks; the delay time is similar to stimuli onset asynchrony (SOA) in PRP, which is the most basic form of multitasking (SOA is the temporal delay between the presentations of the stimuli of two choice reaction tasks). 2) Multitasking information in driving is typically presented in a multimodal format: either through the visual (e.g., looking at a map or a display of a navigation system) or the auditory modality (e.g., listening to messages from cellular phones or warning systems). 3) It covers perceptual, cognitive, and motor processing in multitasking. For example, the speed-detection task might be similar to a secondary task in using a navigation system while driving: Drivers read directions for and the distance to the next turn from the display (perceptual processing), perform mental calculations to decide whether and when to switch to a different lane (cognitive processing), and possibly engage the turning signal and turn the steering wheel (motor processing).

V. Simulation of Multiple Tasks in Driving With the QN-MHP

A. Simulation Using the QN-MHP

Following the steps described in simulating human performance and workload using the QN-MHP [16], [20], the multiple tasks in driving were simulated as follows:

To model the driver workload and performance, the input to the model was modified to represent the following: 1) a road with two levels of curvature (straight and curves of 250-m radius) and 2) the driving speed (45 and 65 mi/h). The task analysis of a driving task was described in the work of Liu *et al.* [20] in detail. The standard deviation (SD) of the lateral position in the model originates from the competition of the entities (the entities of the driving task and the entities of the secondary task) in getting the service of the servers in the network.

To model the secondary task, a new input to the model was added to represent the stimuli of the secondary task based on its arrival interval (i.e., the message delay time). An NGOMSL-style task analysis was performed so that the model could route and process the entities (information) among different servers in the network (see Table III; each step in the NGOMSL-Style corresponds to an operator in the model, and the operators determine the processing of the entities in the model [16]–[20]). The perceptual processing time of the entities of the secondary task is determined by the perceptual cycle time in the QN-MHP [16]–[20], and the cognitive processing time is determined by the number of processing cycles of the entities based on the NGOMSL-style task analysis. In addition, the physical distances from the steering wheel to the target buttons on an in-vehicle user interface, as well as the sizes of the buttons (see the description of the experimental task), were also input to the model, so that the implemented Fitts' law in the model was able to simulate the motor execution time of in-vehicle messages. The aging effect is modeled by setting the parameter A in (1)–(3) according to Proctor *et al.* [38].

TABLE III
NGOMSL-STYLE TASK DESCRIPTION OF THE SECONDARY TASK

GOAL: Do visual speeding judgment task
Method for GOAL: Do visual speeding judgment task
Step 1. Watch for <the first number> on <the display>
Step 2. Retain < the first number>
Step 3. Retrieve from LTM <lower and upper boundary>
Step 4. Decide: If <the first number> is <less than> <the lower boundary> than go to step 6; else go to step 5
Step 5. Decide: If <the first number> is <less than> <the upper boundary> than go to step 7; else go to step 11
Step 6. Current task completes, go to step 1
Step 7. Watch for <the second number> on <the display>
Step 8. Retain <the second number>
Step 9. Retrieve from LTM <detection limit>
Step 10. Decide: If the second number is <less than> <detection limit> then go to step 11; else go to step 6
Step 11. Press <SPEEDING button>
GOAL: Do auditory response task
Method for GOAL: Do auditory response task
Step 1. Listen to <the voice > from <the speaker>
Step 2. Retain <the voice>
Step 3. Retrieve from LTM <target voice>
Step 4. Compare <the voice> with <the target voice> in memory
Step 5. Decide: If match, then go to step 6; else go to step 7
Step 6. Press <H button>
Step 7. Current task completes, go to step 1

Fig. 4 shows a snapshot of the simulation model developed in the Promodel simulation environment when it was simulating the multitask situation in driving. The total length of road driven by the model was 5 km in each run (the model performed six replications with different sets of random numbers).

B. Simulation Result

1) Younger Driver Group: Figs. 5 and 6 show the simulation results of the overall workload and the delta overall workload (ΔWorkload$=$Workload$_{\text{delay}\,i}-$Workload$_{\text{delay}\,i-1}$, delay$_1=3$; delay$_2=5$, delay$_3=10$, delay$_4=15$, delay$_5=20$, and delay$_6=30$),[3] which represent the change of subjective workload when the delay time increases.

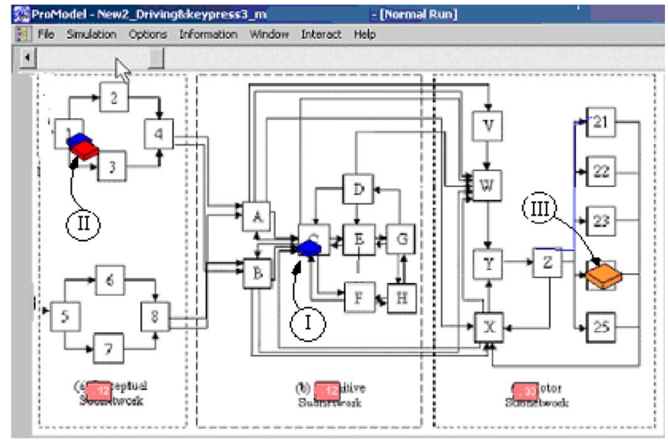
The SD of the simulated lane positions and its delta values are shown in Figs. 7 and 8. In addition, the simulated average RT of the secondary task is presented in Fig. 9.

2) Older Group: Simulation results of the workload (Figs. 10 and 11), the SD of the lane positions (Figs. 12 and 13), and the average RT of the secondary task of the older driver group (Fig. 14) were obtained and plotted.

VI. ALGORITHMS IN DETERMINING OPTIMAL DELAY TIMES IN THE MC

After the simulated workload and driver performance are obtained using the QN-MHP, the function of the MC in the QN-MHP AWMS is to determine the optimal delay times between the messages from the in-vehicle systems using certain algorithms. Once optimal delay times are known, the MC regulates the rate of these messages according to different driving situations.

[3]The setting of the delay time is based on the following logic: If the interval between different delay times is too large, it may not sensitively reflect the change of workload across different delay times. However, if the delay time is too small (e.g., 1 or 2 s), the change in the driver workload will become too small, which will create a problem in experimental validation: Given a limited number of levels in independent variables in one experiment (if we have 20 levels of the delay time, the experiment will have to test all 80 ($20 \times 2 \times 2 = 80$) conditions, which makes the experiment very time-consuming (e.g., 80*5 min = 6.7 h).



Entity I: Entity (representing information) of the driving task
Entity II: Entity of the speeding judgment task (subtask 1 of the 2nd task)
Entity III: Entity of the auditory message response task (subtask 2 of the 2nd task)

Fig. 4. Multiple-task driving simulation.

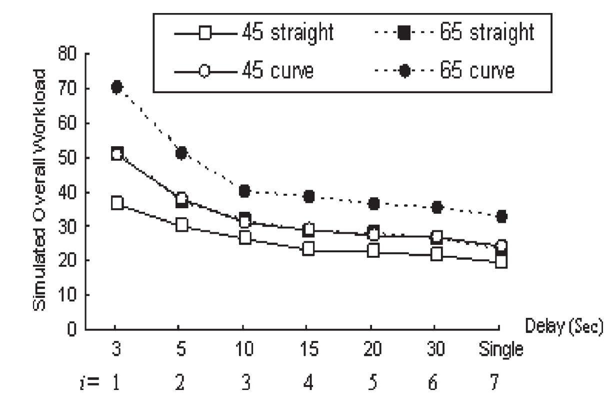


Fig. 5. Simulated overall workload using the QN-MHP (younger driver group).

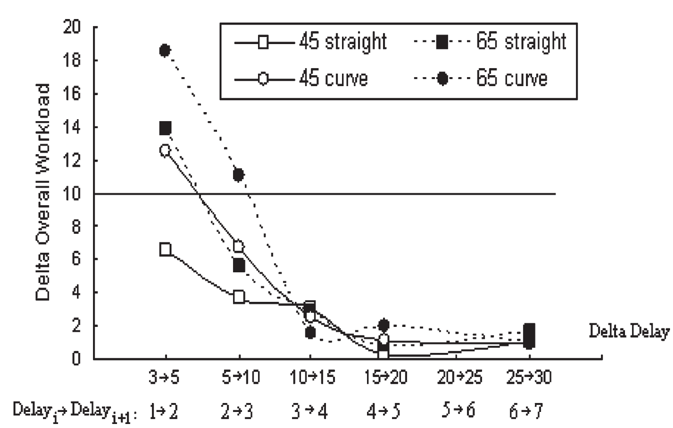


Fig. 6. Simulated delta overall workload (Workload$_{\text{delay}\,i}$ $-$ Workload$_{\text{delay}\,i-1}$) (younger driver group).

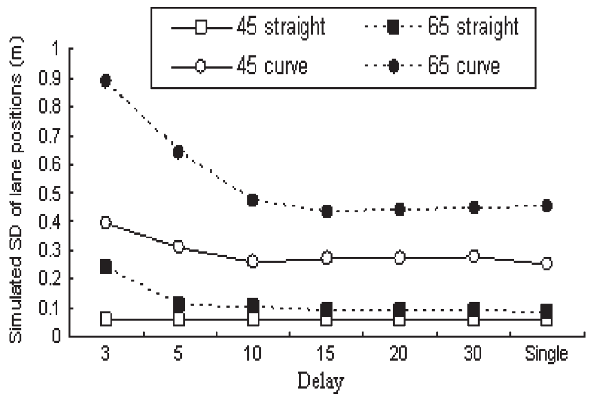


Fig. 7. Simulated SD of the lane positions using the QN-MHP (younger driver group).

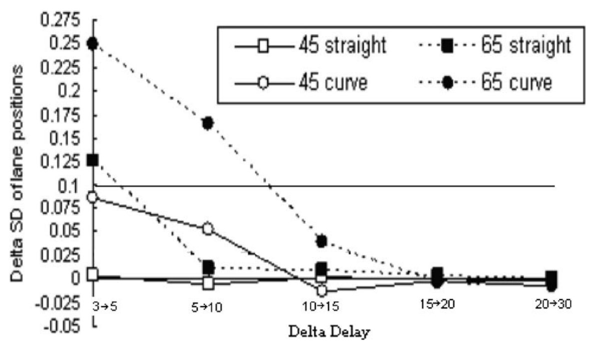


Fig. 8. Simulated delta SD of the lane positions $(\mathrm{SD}_{\mathrm{delay}\ i} - \mathrm{SD}_{\mathrm{delay}\ i-1})$ (younger driver group).

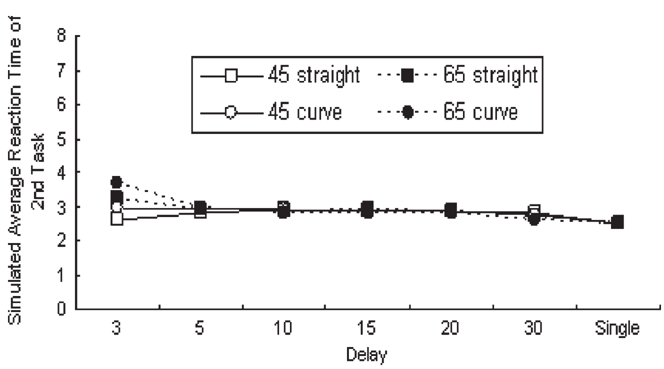


Fig. 9. Simulated average RT of the secondary task (younger driver group).

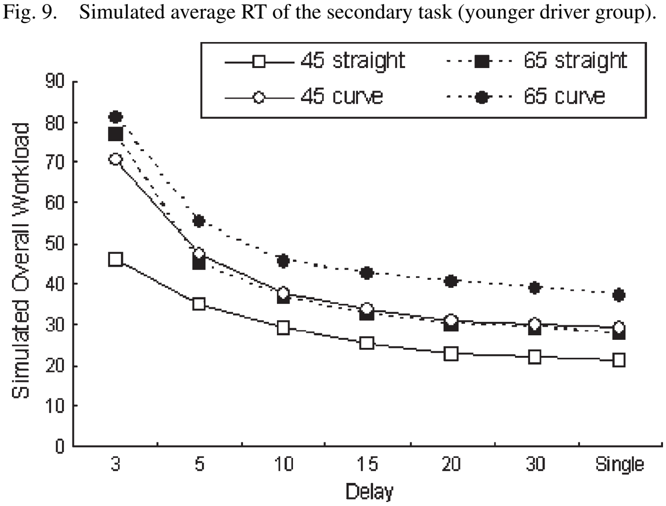


Fig. 10. Simulated overall workload using the QN-MHP (older driver group).

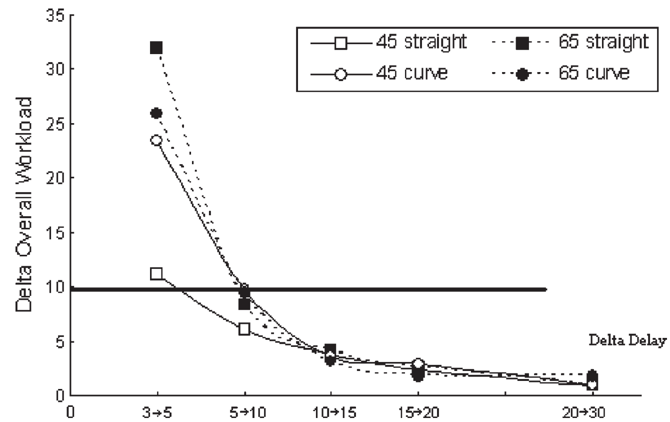


Fig. 11. Simulated delta overall workload $(\mathrm{Workload}_{\mathrm{delay}\ i} - \mathrm{Workload}_{\mathrm{delay\ i}-1})$ (older driver group).

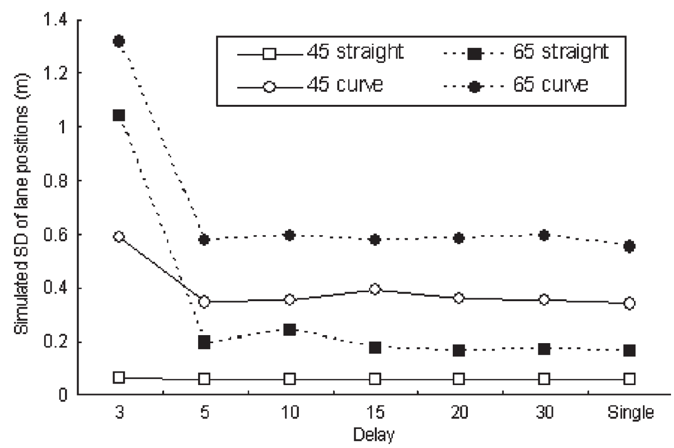


Fig. 12. Simulated SD of the lane positions using the QN-MHP (older driver group).

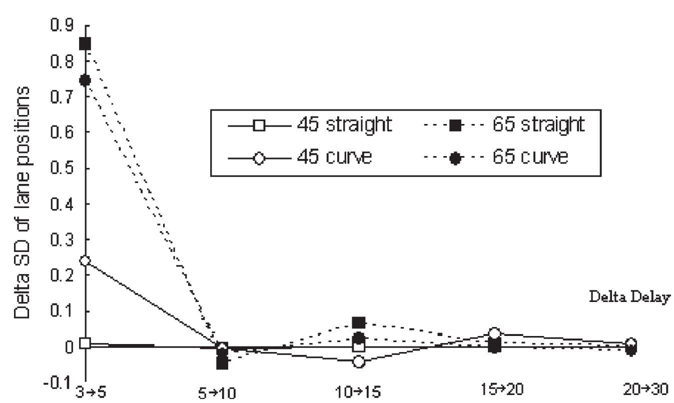


Fig. 13. Simulated delta SD of the lane positions $(\mathrm{SD}_{\mathrm{delay}\ i} - \mathrm{SD}_{\mathrm{delay}\ i-1})$ (older driver group).

The optimal delay time $ODelay$ at the workload dimension $(ODelay_{WL})$, the SD of the lane position SDLP dimension $(ODelay_{1\mathrm{SDLP}})$, and the RT of the secondary task $(ODelay_{ST})$ dimension can be obtained using the following algorithms (see Table IV), where $ODelay$ is quantified as the upper bound of a minimal increase $(i = 1, 2, 3, \ldots; j = 1, 2, 3, \ldots; k = 1, 2, 3, \ldots)$ of the message delay time that reduces the mental workload WL, SDLP, or the average RT of the secondary task by less than one major unit. In the default setting of the system, M_{WL} is equal to 10, which is a major unit in

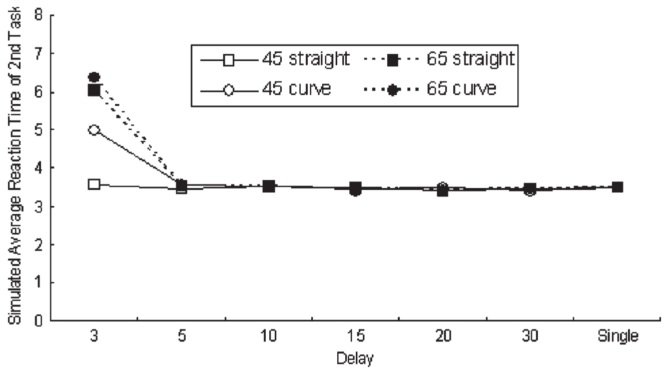


Fig. 14. Simulated average RT of the secondary task (older driver group).

TABLE IV
ALGORITHMS IN THE MC TO DETERMINE THE OPTIMAL DELAY TIME IN THE WORKLOAD, THE SDs OF THE LANE POSITION (SDLP) DIMENSION ($ODelay_{\mathrm{SDLP}}$), AND THE REACTION TIME OF THE SECONDARY TASK ($ODelay_{\mathrm{ST}}$) DIMENSION

```
i=1
While ΔWL_{Delay i →Delay i+1} ≥ M_WL Do
    {i=i+1}
Return ODelay_WL = Delay_{i+1}

j=1
While ΔSDLP_{Delay j→Delay j+1} ≥ M_SDLP Do
    {j=j+1}
Return ODelay_SDLP = Delay_{j+1}

k=1
While ΔST_{Delay k→Delay k+1} ≥ M_ST Do
    {k=k+1}
Return ODelay_ST = Delay_{k+1}
```

the workload scale (e.g., 10 in the 0–100 workload rating); the major unit in the SDs of the lane position M_{SD} is set at 0.1 [39]; and the major unit in the average RT of the secondary task M_{ST} is set at 1 s (the designer of the adaptive system can change the values of M_{WL}, M_{SD}, and M_{ST}, depending on different situations, e.g., different road widths and the RT requirement of the secondary task).

The final optimal delay $ODelay$ in a particular speed and curve condition, considering the three dimensions, can be obtained by

$$ODelay = \mathrm{Max}\{W_{WL}ODelay_{WL}, W_{\mathrm{SDLP}}ODelay_{\mathrm{SDLP}}\ W_{ST}ODelay_{ST}\} \quad (4)$$

which takes the maximum values of $ODelay_{WL}$, $ODelay_{\mathrm{SDLP}}$, and $ODelay_{ST}$ with their weights W_{WL}, W_{SDLP}, and W_{ST}, respectively (whose default values are equal to 1 but can be set to 0 or 1, according to the different emphases on workload, driving performance, or secondary task performance).

Accordingly, based on the preceding algorithm and the current simulation results of the workload (Figs. 5 and 6), the optimal delay times in the workload dimension are obtained for younger drivers (25–35 years old) under the following four driving conditions: 1) 65-mi/h curve: $Delay \geq 15$ s; 2) 65-mi/h straight: $Delay \geq 10$ s; 3) 45-mi/h curve: $Delay \geq 10$ s; and 4) 45-mi/h straight: $Delay \geq 5$ s For example, in the 65-mi/h-curve condition, when the $Delay$ increases from 10 to 15 s (the upper bound is 15 s), ΔWL is less than 10; therefore, the value of $ODelay_{WL}$ in that driving condition is 15 s. Similarly, the optimal delay times in the SDLP dimension are obtained for younger drivers (25–35 years old) under the following four driving conditions (see Figs. 7 and 8): 1) 65-mi/h curve: $Delay \geq 10$ s; 2) 65-mi/h straight: $Delay \geq 5$ s; 3) 45-mi/h curve: $Delay \geq 3$ s; and 4) 45-mi/h straight: $Delay \geq 3$ s. The optimal delay times in the average RT of the secondary task under the four driving conditions are given as follows: 1) 65-mi/h curve: $Delay \geq 5$ s; 2) 65-mi/h straight: $Delay \geq 5$ s; 3) 45-mi/h curve: $Delay \geq 3$ s; and 4) 45-mi/h straight: $Delay \geq 3$ s (see Fig. 9).

Based on (4), the following equations are derived:

$$\begin{aligned} ODelay(65, \text{Curve}) &= \mathrm{Max}\{1 \times 15, 1 \times 10, 1 \times 5\} \\ &= 15 \qquad (5) \\ ODelay(65, \text{Straight}) &= \mathrm{Max}\{1 \times 10, 1 \times 5, 1 \times 5\} \\ &= 10 \qquad (6) \\ ODelay(45, \text{Curve}) &= \mathrm{Max}\{1 \times 10, 1 \times 3, 1 \times 3\} \\ &= 10 \qquad (7) \\ ODelay(45, \text{Straight}) &= \mathrm{Max}\{1 \times 5, 1 \times 3, 1 \times 3\} \\ &= 5. \qquad (8) \end{aligned}$$

Thus, we can derive the following suggestions about the optimal delays for the four driving conditions when a younger driver is performing the secondary task: 1) 65-mi/h curve: $Delay \geq 15$ s; 2) 65-mi/h straight: $Delay \geq 10$ s; 3) 45-mi/h curve: $Delay \geq 10$ s; and 4) 45-mi/h straight: $Delay \geq 5$ s. In other words, in the AWMS, the rates of messages presented to a driver may follow the final suggestion list given to reduce drivers' overall workload and improve the driving performance and the performance of the secondary task. The same simulation model can be used to model the driver workload and performance when the properties of the secondary task or the driving conditions change. The algorithms in Table IV and (4) that determine the optimal delay times were implemented using a Microsoft Visual Basic for Applications program.

For older drivers (60–75 years old), based on Figs. 10 and 11 and the aforementioned algorithms, the following optimal delay times in the workload dimension are obtained under the following four driving conditions: 1) 65-mi/h curve: $Delay \geq 15$ s; 2) 65-mi/h straight: $Delay \geq 10$ s; 3) 45-mi/h curve: $Delay \geq 15$ s; and 4) 45-mi/h straight: $Delay \geq 10$ s. Similarly, the optimal delay times in the SDLP dimension are given as follows: 1) 65-mi/h curve: $Delay \geq 5$ s; 2) 65-mi/h straight: $Delay \geq 5$ s; 3) 45-mi/h curve: $Delay \geq 5$ s; and 4) 45-mi/h straight: $Delay \geq 3$ s (see Figs. 12 and 13). The optimal delay of messages in the secondary task for older drivers might be at least greater than 5 s for the 45-mi/h (curve condition) and 65-mi/h conditions, including the straight and curve conditions (3 s for the 45-mi/hr straight condition) (Fig. 14). Using (4), we can derive the following suggestions for the optimal delays for the four driving conditions when an older driver is performing the secondary task: 1) 65-mi/h curve: $Delay \geq 15$ s; 2) 65-mi/h straight: $Delay \geq 10$ s; 3) 45-mi/h curve: $Delay \geq 10$ s; and 4) 45-mi/h straight: $Delay \geq 5$ s.

VII. Experimental Exploration of the Prototype of the QN-MHP AWMS

A. Experimental Design

A 2 × 2 two-factor mixed subject design was used in this experiment to test the effectiveness of the prototype of the adaptive system. The independent variables were given as follows: 1) the within-subject variable of the two conditions of the system (random versus adaptive) (in the adaptive condition, the delay time was adapted to the different driving conditions and drivers' ages based on the optimal delay times calculated from the algorithms in the MC and the simulation results of the QN-MHP) and 2) the between-subject variable of the age of drivers, i.e., younger (25–35 years old) versus older (60–75 years old). The dependent variables were the driver workload, which is measured by NASA-TLX; the driving performance, which is measured by the SD of the lane position; and the performance of the secondary task, which is measured by its task completion time (or RT) and error rate. Each participant experienced two conditions of the system (adaptive and random), combined with four levels of driving conditions (straight or curve, cross multiplied with a speed of 45 or 65 mi/h). Participants were randomly assigned to one of two groups: The members of each group performed the experimental task either, first in the adaptive condition and, then, in the random condition or *vice versa*. Within each of these groups, the order of the four levels of driving conditions was also randomized, and each of these driving conditions appeared once for each participant.

B. Participants

Sixteen licensed drivers were paid to participate in this experiment, including a group of eight younger subjects (aged 25–35 years, mean = 30, SD = 2.9) and a group of eight older subjects (aged 60–75 years, mean = 65, SD = 3.8). All participants were right handed and had corrected far visual acuity of 20/40 or better and midrange (80 cm) visual acuity of 20/70 or better. Prescreening of all participants ensured that they had good driving records and were physically healthy.

C. Equipment and Test Materials

1) Driving Simulator: The simulator consisted of a full-size cab, computers, video projectors, cameras, audio equipment, and other items (Fig. 15). The simulator has a forward field of view of 120° (three channels) and a rear field of view of 40° (one channel). The forward screen was approximately 16–17 ft (4.9–5.2 m) from the driver's eyes. The vehicle mockup consisted of the A-to-B pillar section of a 1985 Chrysler Laser with a custom-made hood and back end. Mounted in the mockup was a torque motor connected to the steering wheel (to provide steering feedback), a liquid-crystal display projector under the hood (to show the speedometer/tachometer cluster), a subbass sound system (to provide vertical vibration), and a five-speaker surround system (to provide simulated background road noise). The five-speaker sound system was obtained from a 2002 Nissan Altima and was installed in the A pillars, the lower door panel, and behind each of the two front seats. A stock amplifier (from the 2002 Nissan Altima) drove the speakers.

Fig. 15. UMTRI driving simulator.

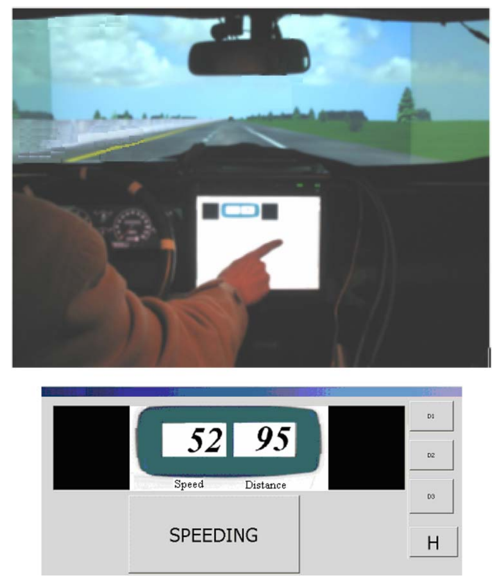


Fig. 16. Driver's view of the road and the touch screen.

The main simulator hardware and software was a DriveSafety Vection simulator running version 1.6.2 of the software [40].

2) Simulated Roads: The simulated roads had two levels of road curvature (straight sections and curves of 250-m radius), which were consistent with the input to the QN-MHP. Both lanes of the two-lane road were 3.66 m (12 ft) wide. Speed-limit signs (45 and 65 mi/h) were placed in each section (straight and curved). The length of each road section was 5 km (half of the road is straight, and the other half is curved), which is consistent with the input to the QN-MHP.

3) Touch Screen: An IBM laptop X60 with a 12-in touch screen was located at the center console of the vehicle, 23° ± 3° below the horizontal line of sight and 30° ± 3° to the right of center (the distance from the center of the right-hand rest area on the steering wheel to the center of the touch screen was 30 cm). The average width of the buttons on the screen was 4 cm, and the height of the digits on the display was 11 mm (see Fig. 16; the layout of the touch screen was set based on the existing radar and message response systems in police vehicles).

D. Experimental Task and Procedure

1) Driving task: Participants were instructed to drive in the right lane and maintain a speed consistent with the speed-limit signs on the simulated roads. For them to maintain driving speed, each participant heard a computer-generated voice saying "too fast" or "too slow" if he/she drove 5 mi/h above or below the speed shown on the speed-limit signs, respectively.[4]

2) Secondary Task: The secondary task was composed of two subtasks simulating a typical multitasking scenario when a police officer was patrolling a road, as described earlier in this paper in the example of multitasking in driving.

The first subtask was a radio-message response task: Participants were instructed to press the button marked "H" on the touch screen (see Fig. 16) as quickly as possible and then loudly say "en route" once they hear the word "headquarters" from the speakers. If they heard "maintenance," they did not need to respond.

The second subtask was a speeding judgment task. Participants were asked to judge whether other vehicles were speeding, based on the two numbers displayed by a radar system (the number on the left is the detected speed, and the number on the right is the distance from the participant's car to the other car) (see Fig. 16). In making the judgments, the participants had to follow three rules: 1) If the speed was above 65 mi/h (including 65 mi/h), it was speeding. 2) If the speed was at or below 55 mi/h, it was not speeding. 3) If the speed was between 56 and 64 mi/h (including 56 mi/h and 64 mi/h), it was speeding if the distance was less than 100 yd (91.4 m), and it was not speeding if the distance was more than 100 yd.

If participants judged that the other car was speeding based on the numbers on the screen, they were instructed to press the "SPEEDING" button on the touch screen as quickly as possible. Just before the numbers of the second subtask were shown on the screen, a short (50 ms) high-pitched tone was presented to the subjects as a cue for the visual stimuli. All of the buttons on the touch screen produced an auditory feedback (a 100-ms beep) when pressed.

During the experiment, the stimuli of the two subtasks in the secondary task were serially presented to a participant (e.g., a radio message, followed by the numbers of the radar system or another radio message). The duration between stimuli was called the delay time, which is manipulated in the adaptive and random conditions [in the adaptive condition, the intervals between messages are controlled by the adaptive system according to the calculated optimal delay time, as described in Section VI (the average interval is 14 s)]. In the random condition, the intervals are controlled by the $rand()$ function in a Visual Basic Application in Excel program (the average interval is the same as that in the adaptive condition). Each subtask in the secondary task appeared with equal probability throughout the experiment.

After filling in the pretest forms and taking vision tests, the participants first practiced the single-task situations of driving (straight and curves), without a secondary task, and performing the secondary task while the simulator was in the parked condition. Then, the participants practiced dual-task situations of driving while performing a secondary task at the same time. During the actual test, the participants were instructed to drive

[4]In the experiment, each subject only received one or two of these messages to maintain their current speed.

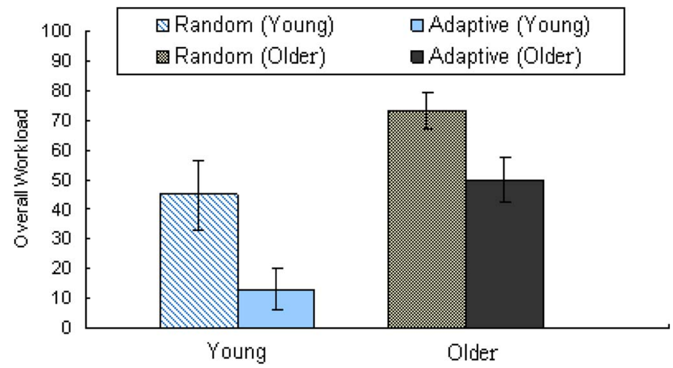


Fig. 17. Comparison of the overall workload between the random and adaptive conditions (the error bar shows 1 ± SD of the overall workload rating).

with System A (random condition) or System B (adaptive condition), with the order varying based on the group in which they were assigned. After the participants finished all of the driving conditions (two speeds and two curvatures) in the random or the adaptive condition, they were asked to complete the NASA-TLX form to report their subjective workload.

E. Experimental Result

1) Subjective Workload: Fig. 17 shows the comparison of the overall workload ratings measured in the NASA-TLX index between the random and adaptive conditions. A mixed-factor (between and within-subject) analysis of variance showed that the main effect of the system (random versus adaptive) on the overall workload was significant $(F(1,14) = 30.61, p < 0.01)$. In addition, the main effect of age on the overall workload was significant $(F(1,14) = 21.09, p < 0.01)$, but the age–system interaction was not significant $(F(1,14) = 0.35)$. Within each age group, there was a significant difference in the overall workload between the random and adaptive conditions (young group: $F(1,7) = 26.57$, $p < .01$; older group: $F(1,7) = 4.67$, $p < .05$).

The comparison of the workload ratings in the six subscales between the random and adaptive conditions is presented in Fig. 18. The main effect of the system was significant for the workload ratings on each of the six subscale/dimensions of NASA-TLX (MD (mental demand): $F(1,14) = 18.01$, $p < 0.01$; PH: $F(1,14) = 6.95$, $p < 0.05$; TD (temporal demand): $F(1,14) = 30.21$, $p < .01$; PE (performance): $F(1,14) = 8.73$, $p < 0.01$; EF (effort): $F(1,14) = 30.97$, $p < 0.01$; and FR (frustration): $F(1,14) = 28.30$, $p < 0.01$). In addition, the main effect of age was also significant for each of these dimensions (MD: $F(1,14) = 15.28$, $p < 0.01$; PH: $F(1,14) = 12.07$, $p < 0.01$; TD: $F(1,14) = 11.09$, $p < 0.01$; PE: $F(1,14) = 17.52$, $p < 0.01$; EF: $F(1,14) = 27.26$, $p < 0.01$; FR: $F(1,14) = 43.97$, $p < .01$). The age–system interaction was not significant (MD: $F(1,14) = 0.96$, $p > 0.05$; PH: $F(1,14) = 0.01$, $p > 0.05$; TD: $F(1,14) = 0.70$, $p > 0.05$; PE: $F(1,14) = 0.15$, $p > 0.05$; EF: $F(1,14) = 0.96$, $p > 0.05$; and FR: $F(1,14) = 0.003$, $p > 0.05$). In the young group, multivariate analysis of variance (MANOVA) found that there is a significant difference in the workload rating between the random and adaptive conditions on the TD $(F(1,7) = 24.93, p < 0.01)$, PE $(F(1,7) = 6.36, p < 0.05)$, EF $(F(1,7) = 5.79, p < 0.05)$, and FR $(F(1,7) = 21.81, p <$

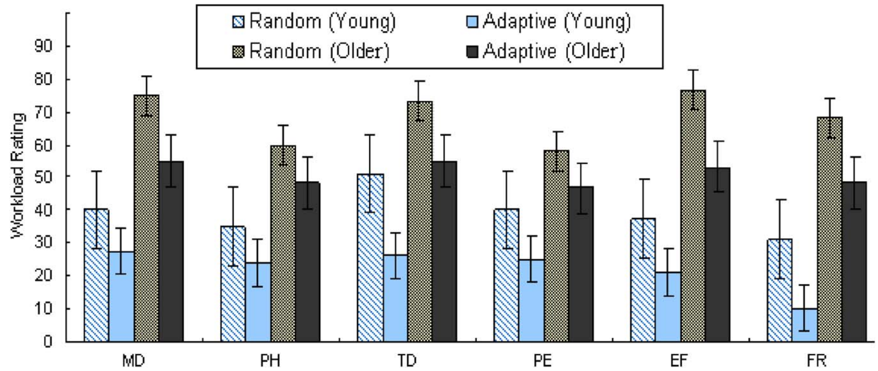


Fig. 18. Comparison of the six workload ratings in NASA-TLX between the random and adaptive conditions (the error bars show $1 \pm$ SD of the workload rating).

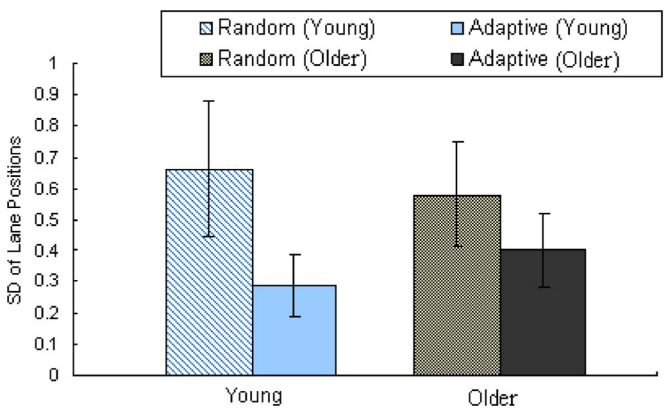


Fig. 19. Comparison of the SD of the lane position between the random and adaptive conditions (the error bars show $1 \pm$ SD of the SD of the lane positions).

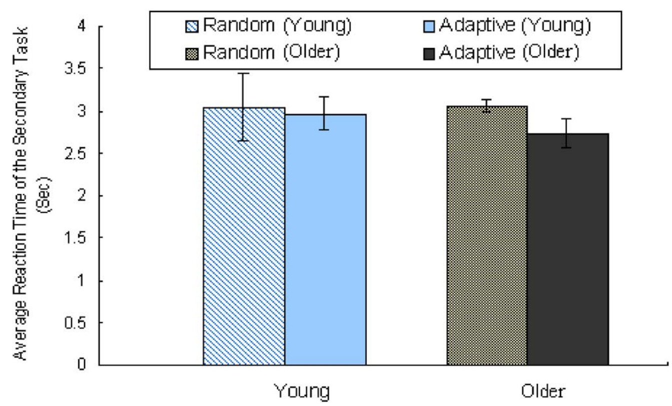


Fig. 20. Comparison of the mean RT of the secondary tasks between the random and adaptive conditions (the error bars show $1 \pm$ SD of the mean RT of the second task).

$0.01)$ subscales. In the older group, MANOVA found that there is a significant difference in the workload rating between the random and adaptive conditions on the EF subscale $(F(1,7) = 7.50, p < 0.05)$.

In other words, the adaptive system significantly reduced the subjective workload in both the younger and older age groups, as reflected in both the overall workload and the six subscales of the NASA-TLX.

2) Performance in Driving and Secondary Task: In terms of driving performance, the main effect of the system on the SD of the lane positions was also significant (mixed-factor analysis of variance, $F(1,14) = 33.37, p < 0.01)$. The main effect of age was not significant $(F(1,14) = 0.012)$. The system–age interaction was significant $(F(1,14) = 7.3, p < 0.05)$. The adaptive condition significantly reduced the SD of the lane positions for both the young $(F(1,7) = 20.50, p < 0.01)$ and older driver groups $(F(1,7) = 5.91, p < 0.05)$ (see Fig. 19).

Fig. 20 shows the comparison of the average RT of the secondary task between the random and adaptive conditions (the error rate of the secondary task is less than 1% in both conditions; mixed-factor analysis of variance $F(1,14) = 10.29$, $p < .05)$. The main effect of age was significant $(F(1,14) = 7.54, p < 0.05)$. The system–age interaction was significant $(F(1,14) = 5.01, p < 0.05)$. The prototype of the adaptive system significantly reduced the average RT of the secondary task in the older group but not in the younger driver group (older driver group: $F(1,7) = 24.12, p < 0.01$; younger driver group: $F(1,7) = 0.54)$.

VIII. Discussion

To reduce driver workload in multitasking, a prototype of a new AWMS (QN-MHP AWMS) was developed in this paper. The QN-MHP AWMS was composed of two components: a QN-MHP-based driver model estimating driver workload in different driving situations and an MC to change the rate of messages from the in-vehicle systems. Given the information of a secondary task (e.g., the processing time at the perceptual, cognitive, and motor stages), the QN-MHP AWMS adaptively changes the rate of messages based on the driving conditions (e.g., the current driving speed and the road curvatures) and the characteristics of the driver (e.g., age). The experimental study validated the potential effectiveness of the system in reducing the workload measured by NASA-TLX in terms of overall workload, as well as the workload rating at the temporal demand, performance, effort, frustration, and effort subscales. The driving performance was also improved by using this AWMS.

There are two possible applications for the proposed system: First, to reduce driver workload, design engineers of in-vehicle systems can use the QN-MHP AWMS to modify their design at the early stage of development of various in-vehicle systems. The QN-MHP AWMS lets the user estimate the driver workload when drivers are manipulating different user interfaces of in-vehicle systems. Engineers can estimate the level of driver workload and performance based on road situations (e.g., curvature), drivers' age, message properties from the in-vehicle systems change in terms of modalities (the processing time at the perceptual part), message difficulty (the processing time at the cognitive part), and motor execution time. Engineers can also set the absolute (workload "redline") and differential thresholds of the simulated workload (e.g., M_{WL}) to determine the optimal design of the messages and whether the proposed design can produce a workload that is higher than the "redline."

Second, the QN-MHP AWMS might be implemented into vehicles with the development of computer technologies. Even though the current QN-MHP AWMS needs a simulation software installed on a computer, the simulation results of the QN-MHP and the suggested optimal message rates can be approximated by relatively simple algorithms; these algorithms can be implemented into microcomputers in vehicles, particularly vehicles with special duties (police vehicles, ambulance vehicles, etc.). The MC in the experiment in this paper can also easily be replaced by the software in the in-vehicle microcomputers, because it only needs to read information for the vehicle speed and the angles of the steering wheel from the bus line (a parallel circuit that connects the major components and sensors in a vehicle). Global Positioning Systems can also be used to measure road curvatures and speed on the next road section so that the QN-MHP AWMS can estimate the driver workload a few seconds in advance.

There are several limitations of this paper that need to be examined in future research. First, because the focus of the QN-MHP AWMS is to reduce driver workload, it is only suitable for nonurgent messages of in-vehicle systems (when delaying messages for a few seconds is allowable, e.g., messages from e-mail systems and messages related to traffic congestion). For urgent messages that require immediate driver response, e.g., forward collision warning messages, no extra delays are allowed. In fact, this limitation applies to many adaptive workload systems, because the extra delay or suppression of messages may delay drivers' responses to all of these nonurgent messages (however, it is possible to add an option in the QN-MHP AWMS so that users can disable the message delay function). Second, the current adaptive system developed in this paper only focuses on the rate of two types of messages with equal priority. New algorithms are needed to manage messages with different priorities, including the order and length of these messages, but the QN-MHP AWMS may still serve as a platform for designing and optimizing the other properties of the information presented to drivers. Third, this paper only tested the adaptive part of the QN-MHP AWMS under four driving conditions (current speed $\times$ road curvature) and one characteristic of drivers (age). Future modeling and experimental studies are expected to add more driving conditions (e.g., traffic density, intersections, road curvature in the next few seconds, route planning and selections, and weather conditions) and driver characteristics (e.g., driving experience) into the simulation and empirical validations of the system. Previous published work of the QN-MHP has considered aging [the variable A (aging factor) in (1)–(3)] as one of the major factors in predicting driver workload, and this has already built a foundation for testing the adaptive system incorporating three sources of information (driving conditions, information from the in-vehicle systems, and driver characteristics) at the same time.

In summary, we are extending the current approach in both modeling different driving tasks and applying the model to design intelligent in-vehicle systems to improve transportation safety. Our comprehensive computational model of the driver workload not only offers theoretical insights into driver workload but is also a step toward developing a proactive ergonomic design and multipurpose analysis tools for tasks in transportation.

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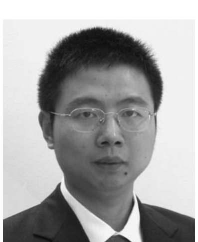

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