Driver Workload Estimation System for Smart Vehicles

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***Abstract* -** Recent technological advances have enabled a wide variety of information systems to be integrated into a vehicle in order to increase safety, productivity, and comfort. However, improperly deployed technology can increase driver's workload and, consequently, degrade safety. Especially, potential information overload problems may become acute among older drivers who are the fastest growing segment of the driving population. Thus identification of a driver's workload and spare capacity is crucial in the design of intelligent vehicles. With this knowledge, the in-vehicle information systems (IVIS) can provide timely and affordable information when the driver has the spare capacity to understand and respond it.
This paper presents an empirical approach for estimating driver's workload using driving performance, visual attention, and physiological indices. Moreover, the feasibity of diagnosticity to distinguish the type of driving workload was tested and a simple diagnositicity algorithm was proposed using a steering wheel angle and a lane position. In order to collect driving data, the participants drove through highway and were asked to complete a series of auditory and visual tasks in a driving simulator. The trade-off between driving performance and secondary task complexity levels was evaluated by analyzing driving performance, eye movement, physiological signals. As a result, potential measures of driver workload are suggested to classify the type of workload and estimate drivers' cognitive workload. It is expected that these measures can be used for a prior indication of driving performance degradation.

Keywords: Driving Workload, Workload Assessment Measures, Workload Diagnosticity, Cognitive Workload Estimation, Intelligent Vehicle

1 Introduction

The growing introduction of new technologies inside vehicles generates additional information that drivers have to manage at the same time. Their use can interfere with the driving activity and induce performance decrements. Thus, voice recognition is widely used by vehicle manufacturer to reduce potential driver distraction. However, voice recognition also increases cognitive workload, even though it allows drivers to control various infotainment systems and other comfort features, while keeping their hands on the steering wheel and eyes on the road ahead.
Diversion of attention to secondary tasks is one of the largest contributors to inattentive driving and, consequently, to accidents [1]. According to car accident statistics, driver distraction is an important safety problem. Between 13% and 50% of crashes are caused by driver distraction [2]. Therefore, an understanding of driver's workload is essential in the design of intelligent vehicle. Workload can be measured in a variety of ways, including: driving performance based measures, subjective measures, and by physiological measures. However, no single measure presents complete effects of the workload. Furthermore, the effects observed depend on the types of workloads. Visual and cognitive distractions are two major types of driver workload. Both can degrade driving performance. Visual distraction is straightforward and can be measured by the duration and frequency of glances away from the roadway ahead. However, the effects of cognitive workload are very subtle and are not monolithic. Therefore, two major criteria for assessing workload should be considered. One is sensitivity which means ability to discriminate between levels of workload, and the other is diagnosticity which means ability to distinguish between types of workload [3].
This study aims to suggest methods to distinguish the type of driving workload and to discriminate high cognitive workload from low.

2 Driver workload and measures

2.1 Driver workload and in-vehicle tasks

According to the final report of Driver Workload Metric Project [4], driver workload is defined as the competition in driver resources (perceptual, cognitive, physical) between the driving task and a concurrent subsidiary task, occurring over the task's duration, as manifested in degraded lane keeping, longitudinal control, object-and-event detection, or eye glance behavior. Another studies show that operating or talking on a mobile phone while driving results in increased workload and greater levels of frustration, particularly when the conversation is complex or highly emotional [5] and operating a route guidance system while driving also increases workload [6]. Figure 1 presents typical in-vehicle tasks that have been classified by the input and output modalities needed to perform the task [4]. As shown in the classification, driver workload can be assigned into two categories, i.e. visual and cognitive, although there are more complex tasks which require both visual and cognitive demand.

2.2 Measuring driver workload

Approaches to measuring driver workload are: subjective ratings, driving performance methods, physiological methods, and eye movement methods. Diving performance method is unobtrusive and practical for everyday monitoring, and is able to detect driver workload with decent performance while engaged in secondary tasks [3, 7]. However, it has limited ability for classifying workload into complexity levels, especially with cognitive workload. Physiological indices are more sensitive than performance measures for detecting cognitive workload [8] Lenneman found that heart rate and blood pressure have been shown to increase with escalating cognitive workload. However, there is currently little knowledge regarding a definitive relationship between changes in standard physiological parameters and workload has not been established in the driving literature [9]. Eye movement method uses fixation identification and changes in visual attention [10]. Reimer suggested that the centralization of gaze observed with increased cognitive workload thus the changes in gaze dispersion could be used as drivers' cognitive workload indicator. All the approaches have advantages and disadvantages and no single measure presents complete effects of the workload. In this study, all of three objective methods were analyzed and suggested a potential combination of indices.

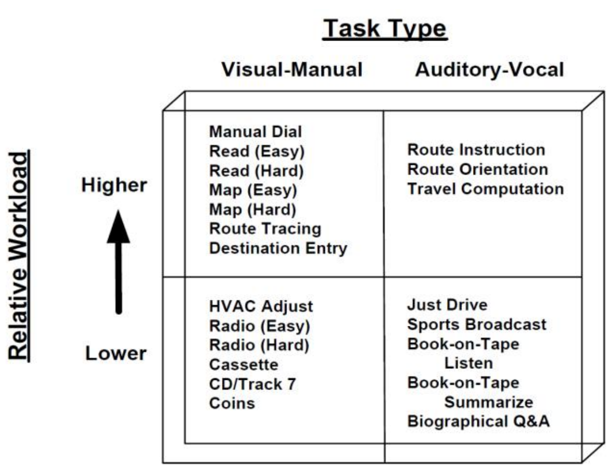


Figure 1. Typical in-vehicle tasks classification

3 Empirical approach for estimating driver workload

3.1 Experimental setup

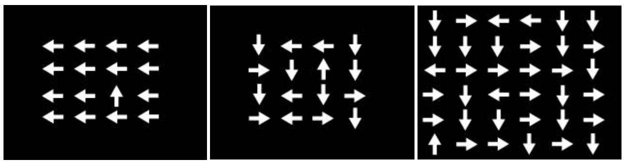
The experiment was conducted on the DGIST fixed-based driving simulator with STISIM Drive™ software (see Figure 2). Graphical updates to the virtual environment were computed using STISIM Drive™ based upon inputs recorded from the OEM accelerator, brake and steering wheel which were all augmented with tactile force feedback. The virtual roadway was displayed on a 2.5m by 2.5m wall-mounted screen at resolution of 1024 x 768. Feedback to the driver was also provided through auditory and kinetic channels. Driving distance, speed, steering, throttle, and braking inputs were captured at a sampling rate of 30 Hz. Physiological data and eye movement data were collected using the MEDAC System/3 (NeuroDyne Medical Corp., Cambridge, MA) and the FaceLAB 4.6 (Seeing Machines Ltd., Canberra, Australia) respectively.

3.2 Visual and cognitive workload

Both visual and cognitive workloads were designed for three levels of difficulty. For the cognitive workload during the simulated driving, the n-back task, an auditory delayed recall task, was used [7]. The n-back task requires the participants to say out loud the "nth" stimulus back in the sequence. The lowest level is 0-back, i.e. immediately repeating the last number presented. At moderate level (1-back) the next-to-last stimuli should be repeated, and the second-to-last stimulus for the most difficult level (2-back). The n-back was administered as a series of 30 second trials consisting of 10 single-digit numbers at an inter-stimulus interval of 2.1 seconds.
The task was given as a set of four trials per each level of difficulty for two minutes including introduction. The sequence of difficult level of the n-back task was randomly generated. Two minute rest was inserted between different levels of the n-back task.

Figure 2. The DGIST Driving Simulator

For the visual workload, the arrow search task, which only required visual processing demand and minimal cognitive processing, was used [11]. To create three levels of difficulty for the arrows task, three different arrangements of arrows were presented, each for 10s, forming a series of two minutes trials using 12 arrow pictures. On some occasions the upward pointing target arrow was present and on others it was not. The actual presentations of the displays are shown in Figure 3.



Level 0 Level 1 Level 2

Figure 3. Three levels of difficulty for the arrow task

3.3 Procedure

To analyze the effects of visual and cognitive workload on the driving behavior while driving, participants drove in good weather through 37km of highway twice, one for visual workload and the other for cognitive. Each driving takes about 20 minutes, and participants perform a secondary task, i.e. n-back task or arrow task at a specified segment. The order in which workloads were presented was balanced so that half of the participants drove under cognitive workload first.
Figure 4 shows the main experimental procedure for cognitive and visual workload task.

3.4 Data Analysis

Measures of driving performance, physiological arousal, and eye movement are listed on Table 1.

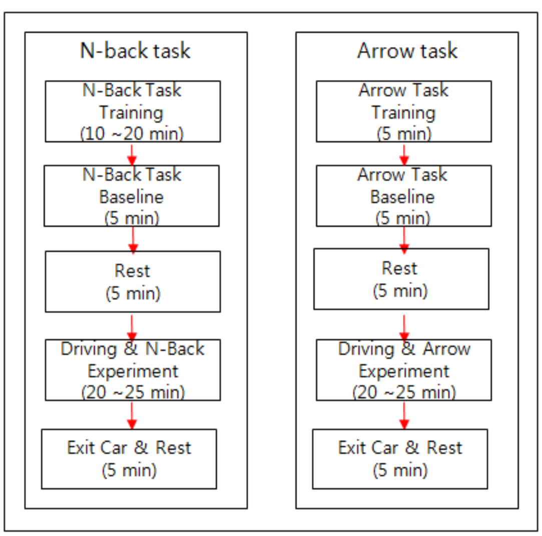


Figure 4. Main experiment flow

Table 1. Measures for driver workload

Methods	Measures	Descriptions
Driving Performance	AvVEL	Average velocity
	SdVEL	Standard deviation of velocity
	SRR	Steering wheel reversal rate
	SDLP	Standard deviation of lane position
Physiology	AvIBI	Average inter-beat interval
	SdIBI	Standard deviation of inter-beat interval
	AvHR	Average heart rate
	SCL	Skin conductance level
Eye Movement	SdGazeX	Standard deviation of gaze X
	SdGazeY	Standard deviation of gaze Y
	AvGazeX	average gaze X
	AvGazeY	average gaze y

Statistical analysis was computed using the Pearson correlation and the discriminant procedure in SPSS.

4 Classification and Estimation

4.1 Workload diagnosticity

Diagnosticity means ability to distinguish between types of workload. The best method to distinguish between visual and cognitive workload is watching the eye movement. However, this method requires additional camera based sensing system and complex image processing algorithm. In this paper, a simple diagnositicity method using driving performance is proposed. As shown in Figure 5, SRR (Steering wheel Reversal Rate) measures are increased as both visual and cognitive workload are increasing, but SDLP (Standard Deviation of Lane Position) measures show different direction according to

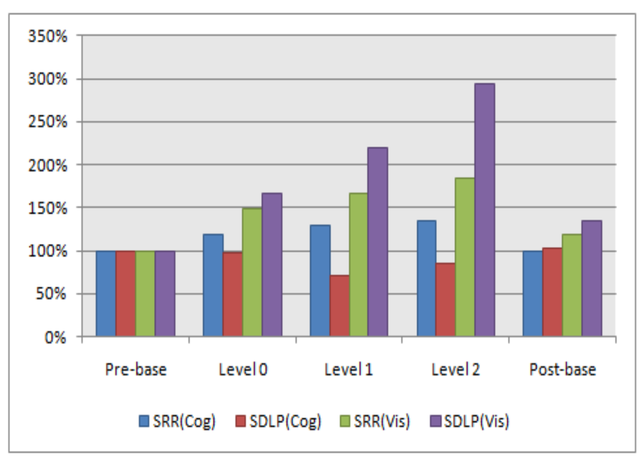


Figure 5. Comparison of steering performance

the type of workload. With this knowledge, we can infer the type of workload, i.e. visual or cognitive. For example, driver is under workload condition when the SRR is more than 20% higher than baseline value. When workload is occurred and the SDLP is decreased from its baseline, the type of workload will be cognitive.

4.2 Cognitive workload estimation performance

In order to select affective measures for estimating cognitive workload, correlations between difficult level of cognitive workload and collected measures, including driving performance, physiology and eye movement, was analyzed using the Pearson correlation procedure in SPSS. As shown in Table 2, the standard deviation of gaze X and Y in eye movement, and the average velocity and the steering wheel reversal rate in driving performance were significantly affected on the cognitive workload difficulty.

With these variables, the accuracy of discriminant ability was analyzed and the result of cognitive workload estimation accuracy was summarized in Table 3. As mentioned before, the difficult level of cognitive workload was hard to estimate due to its non-linearity. Thus the difficult levels were reduced to 3 levels by removing 1-back task level. Consequently, the reduced levels consist of non-workload, low workload (0-back), and high workload (2-back). The accuracy was increased by 67.8% with all measures. Moreover, the accuracy has remained 62.2% with driving performance measures only.

The results suggested that the driving performance measures can discriminate high cognitive workload from low.

Table 2. Correlations between difficult level of cognitive workload and various measures

Driving Performance	AvVEL	SdVEL	SRR	SDLP
	-.375**	.279**	**.366****	-.164
Physiology	AvIBI	SdIBI	AvHR	AvSCL
	-.188*	.098	.180*	.117
Eye Movement	SdGazeX	SdGazeY	AvGazeX	AvGazeY
	-.535**	**-.472****	-.239**	.102

Table 3. Comparion of estimation accuracy

No. of difficult levels	All measures in Table 2	Significant measures*	Driving performance measures**
4	53.3%	49.2%	49.2%
3	67.8%	64.4%	62.2%

*AvVel, SRR, SdGazeX, SdGazeY
** AvVel, SdVel, SRR, SDLP

5 Conclusions

In this paper, methods to distinguish the type of driving workload and to estimate cognitive workload were proposed. The experimental results show that a driver's cognitive status could be estimated with an average correct rate of more than 62%, which is encouraging considering the difficulty of cognitive workload estimation. Although 62% of accuracy is not enough to use in everyday monitoring, it is expected that the accuracy can be improved by applying more sophisticated algorithms and that these measures can be used for a prior indication of driving performance degradation.

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