Estimating Driver Workload with Systematically Varying Traffic Complexity Using Machine Learning: Experimental Design

Udara E. Manawadu(✉), Takahiro Kawano, Shingo Murata, Mitsuhiro Kamezaki, and Shigeki Sugano

Waseda University, Tokyo, Japan
{udara,t_kawano,murata,sugano}@sugano.mech.waseda.ac.jp,
kame-mitsu@aoni.wasead.jp

Abstract. Traffic complexity is one of the factors affecting driver workload. In order to study the relationship between traffic complexity levels and workload, a designed experiment is required, especially to vary traffic flow parameters systematically in a simulated environment. This paper describes the experimental design of a simulator study for developing a computational model to estimate the behavior of driver workload based on traffic complexity. Driving simulators allow creating and testing different traffic scenarios and manipulating independent variables to improve the quality of data, as compared to real world experiments. Physiological responses such as heart rate, skin conductance, and pupil size have been found to be related to workload. By adapting a data-driven method, we integrated electrocardiography sensors, electro-dermal activity sensors, and eye-tracker to acquire driver physiological signals and gaze information. Preliminary results show a positive correlation between traffic complexity levels and corresponding physiological responses, performance, and subjective measures.

Keywords: Driving simulation · Driver workload · Intelligent vehicles

1 Introduction

Driver workload can be identified as the impact on the driver resulting from his or her engagement with the driving tasks, and it is a subjective parameter. Demand, on the other hand, is an objective parameter that depends on the specific driving task. Therefore, driver's mental workload is a consequence of the characteristic demands of driving task [1]. Fatigue and drowsiness are indicators of low mental workload, while stress indicates high workload. Both high and low workload has found to be related to accidents. Driver mental workload is influenced mainly by the highly dynamic characteristics of driver, vehicle systems, and the environment.

Data collection in real world experiments (naturalistic driving), also known as passive data collection, may lead to many problems when creating a computational model [2]. Due to the simultaneous changes of multiple factors, the observed changes in a dependent variable may not be caused by it, but still correlated with independent

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variables. This will result in interactions that are difficult to classify into individual effects. Also, in situations where observations are dependent, the model may consider them to be independent. On the other hand, designed experiments can overcome these problems. The experimental environment and independent variables are actively manipulated to improve the quality of information and to eliminate redundant data, in a designed experiment. In addition, data collection is usually done with great care and attention to acquire sufficient information to accurately estimate model parameters.

2 Background

2.1 Workload Measures

In order to quantify driver workload levels, three different metrics can be used [3]. They are physiology, performance, and subjective measures. Commonly used physiological measures include heart rate variability, skin conductance level, and pupil diameter. Performance measures are steering entropy, lane position, pedal operation. Subjective measures include questionnaires and rating scales.

2.2 Traffic Complexity

Driver workload is sensitive to traffic complexity [4–6]. A field study involving driving routes having only two traffic levels: high, and less demanding, was reported in [4]. In [5], authors reported that subjective driver workload rating has a linear upward trend with increasing traffic flow in a simulator-based study. In [7] traffic situation data from onboard geographical database were used in estimating current driver workload in a field study.

2.3 Machine Learning Approaches

Computational models can be built to classify cognitive load within and across individuals. Machine learning techniques have been applied to vehicle dynamics (performance) and driver physiological data to recognize elevated cognitive workload periods for evaluating in-vehicle user interfaces [8, 9]. Support vector machines (SVMs) have been used to detect cognitive distraction in real-time using gaze movement and vehicle performance data [10]. In a simulator-based study, SVM was successfully used to recognize driver cognitive distraction based on vehicle dynamics and eye movement data [11]. Predicting future values of driver mental workload is the key objective of our study. Therefore, we need to study time series data in order to predict the future behavior based on knowledge of the past. Nonparametric, nonlinear machine learning models use past data to learn stochastic dependency between past and the future of an observable variable. Artificial neural networks (ANNs) can outperform classical statistical methods, and can be successfully used for modeling and forecasting nonlinear time series [12]. As other machine learning frameworks, using probabilistic methods such as hidden Markov models (HMMs) and dynamic Bayesian networks (DBNs) is also possible.

3 Experimental Design

3.1 Driving Scenarios

We designed two experimental scenarios: turning right at an intersection, and merging onto highway. In the turning scenario (Fig. 1), in order to vary the traffic complexity in each scenario, we defined two variables: oncoming traffic volume, which is the no. of vehicles crossing the intersection in a unit time, and the pedestrian and cyclist density. The experiment consists of the traffic situations shown in Table 1. We use a pseudo-random order in presenting the nine traffic situations for each participant. In the merging scenario, the independent variables are; traffic density (vehicles/km) in the main lane, which is the no. of vehicles included in a road segment of unit length at a given time, and the mean speed (km/h), which is the average speed of all vehicles in the main lane segment at a given time.

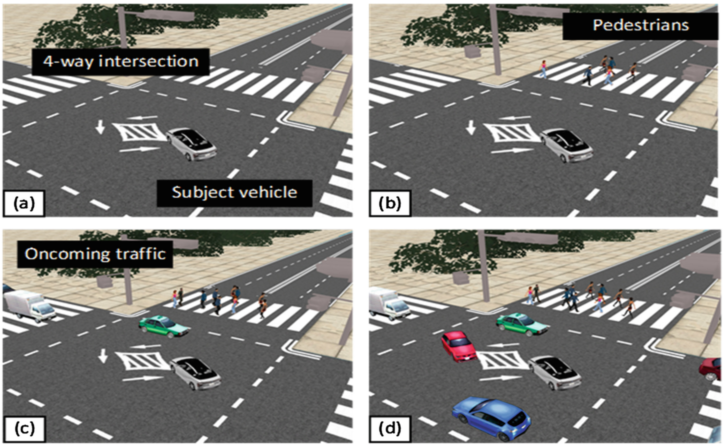

Fig. 1. Traffic complexity levels implemented in simulator

Table 1. Experimental conditions: turning

		Pedestrian density (ped./hour)		
		0	240	360
Traffic flow (vehicles/hour)	0	A	B	C
	360	D	E	F
	720	G	H	I

3.2 Procedure

The proposed procedure for experiments is as follows. First, brief the participants regarding above steps and ask them to practice the turning and merging maneuvers in the simulator without other traffic or pedestrians. Then attach the sensors and ask them to drive along a straight road with minimal traffic and ensure good signals acquisition from the sensors. This is also to obtain baseline values of their physiological signals, and driving characteristics. After that, for the experiment, drive along an urban route consisting of the above traffic situations. Soon after making each maneuver (turning right, merging), participants input their perceived mental workload rating (1 to 5) using a touchscreen interface (Fig. 2).

Fig. 2. Experimental setup

4 Preliminary Results

A preliminary experiment which includes only turning maneuvers was conducted to confirm the acquisition of proposed physiological and performance data, and to check for drawbacks in methodology and experimental design. In this section, we present the initial results obtained from one participant. One male of age 21 years with 3 years of driving experience participated in the experiment. He had corrected to normal vision and previous experience in a driving simulator. For the clarity of understanding traffic complexity levels, we classify the nine traffic conditions in to three levels (level 1: A, D, G pedestrian density = 0; level 2: B, E, H ped. density = 240; level 3: C, F, I ped. density = 360, see Table 1). Data recorded at higher sampling rates were resampled at 50 Hz. Figure 3 shows the subjective score of perceived mental workload at each traffic situation. It can be seen that with the increase of traffic complexity, perceived mental workload increases correspondingly. Figure 4 shows the skin conductance level and a positive relation with subjective mental workload can be observed, especially in higher traffic complexity levels. The heart rate variability data and pupil diameter data, however, did not show clear positive trends with subjective workload score. We assume that is due to measurement errors and noise. As a performance measure, we calculated the standard deviation of steering angle (Fig. 5). It showed positive correlation with increasing traffic complexity as well as subjective workload except in one situation (I).

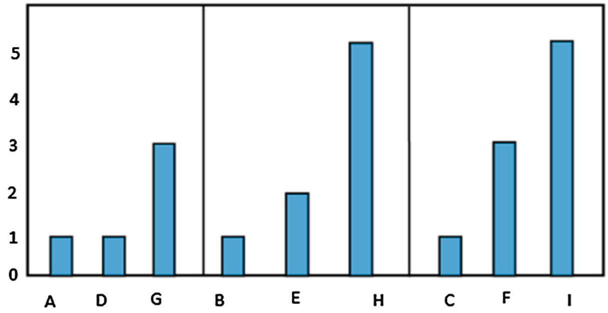

Fig. 3. Subjective mental workload score

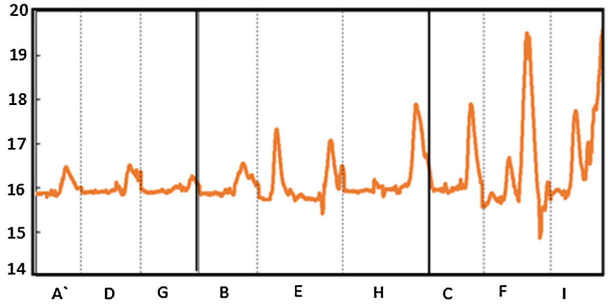

Fig. 4. Skin conductance (μS)

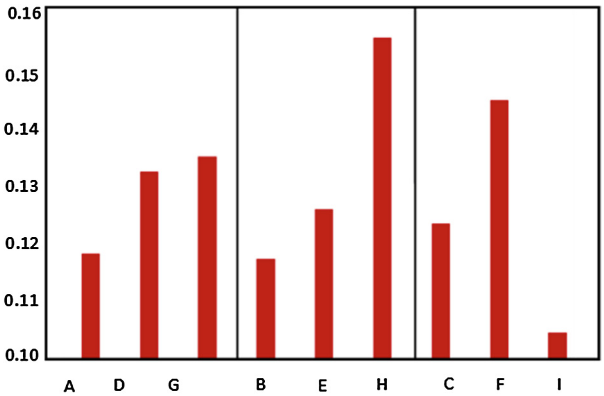

Fig. 5. SD of steering angle (degrees)

5 Conclusion

In this paper, we presented the experimental design of a driving simulator-based study with systematically varying traffic complexity levels. We conducted driving experiments to validate our experimental design. Driver physiological and performance data showed correlation with traffic levels and subjective workload scores. Future works include conducting experiments with different drivers to acquire a sufficiently large dataset to develop a time-series prediction model using machine-learning methods.

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