Predicting the Effects of Time-Gaps for Adaptive Cruise Control (ACC) on Bus Driver Performance

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Abstract. Researchers have a deal of attention to the effects on driver performance when driving with assist systems. This article describes modeling approach to simulate the effects of time-gaps for adaptive cruise control (ACC) on bus driver's performance. A concept model was built with the knowledge of modularization, parameterization, and parallel processing. By running the model, the predictions for the effects of five levels of time-gaps were collected in two measures, mean gap and minimum gap. Predictions from the model were validated by the experiment with a verified fix-based bus driving simulator in authors' previous studies. Through the modeling approach, this research provides a theoretical and accurate way to assess effects of time-gaps. To apply this approach to the evaluation on other driving assist systems (e.g. collision warning systems & navigation systems) is the next topic for authors to work on.

Keywords: Adaptive cruise control (ACC); Driver performance modeling approaches; Time-gaps.

1 Introduction

Driving is an intently operation between human and vehicle. Drivers can control the vehicle directly, give orders indirectly, or only supervise the situation according to information display. Depending on the numbers and complexity of tasks the driver needs to pay attention to, driver's behavior and performance may change. Therefore, driving assist systems are greatly developed for driver's convenience and driving safety (to reduce driver's workload and increase performance). One such helpful system is the adaptive cruise control (ACC), which has been optionally attached to some passenger cars in the market (e.g. Toyota Camry 2010; Lexus 2009, and Mercedes 2008). ACC is the enhanced cruise control that keeps a pre-selected time-gap (gap divided by speed) between the lead and the driver's vehicle. Some studies have evaluated subjective and objective effects of ACC with different measures (Sato, et al., 2006; Suzuki & Nakatsuji, 2003; Törnros, et al., 2002), by experimental results. In author's previous research, time-gap is indicated as the key factor for safety, and proper time-gap settings can lead to better performance and can compensate the in-vehicle distraction (Lin, et al., 2009; Lin, et al., 2008). To predict the effects of time-gap with computational modeling methods is the primary objective of this research.

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A modeling approach for driving with assist systems should be created carefully. Researchers used to develop various driver behavior models with some modeling methods, such as the driver's action modeling with COSMODRIVE (Bellet & Tattegrain-Veste, 1999), lane-change detection with model tracing methodology (Salvucci, et al., 2007), cellular phone dialing effects with ACT-R (Salvucci & Macuga, 2002), and driver's workload with QN-MHP (Wu & Liu, 2007). This research purposes to realize a conceptual model in the first place and an integrated modeling approach is used to combine and arrange several subtasks into one.

2 Literature Review

2.1 Driver Performance Modeling

Driving is a common but complex task that involves multiple critical subtasks. In order to know how people perform in these tasks, many models have been developed to describe (conceptual) and simulate (computational) driver's behavior. Conceptual models are the foundation of computational ones, and can also help the components and procedure of the driving task be understood such as the Risk-based model (Van der Molen & Bötticher, 1988). As to computational models, two categories are usually included, cognitive and performance models, based on their objectives. Cognitive models are used to simulate the mental statement of human beings, such as perception, memorizing, decision making, anticipating, or option selecting (e.g. COSMODRIVE (Bellet & Tattegrain-Veste, 1999; Tattegrain-Veste, et al., 1996)). These kinds of models are to develop artificial cognitive systems that can represent human's cognitive activities.

Nowadays, some well-developed computational models have both features of cognitive and performance models, that can simulate the whole procedure of the driving task (e.g. ACT-R driver behavior model (Salvucci, 2006), QN-MHP (Tsimhoni & Liu, 2003), SmartAHS (Delorme & Song, 2001)). These models are structured by cognitive models and implemented as performance models. For instance, in the ACT-R driver model, it is based on the ACT-R cognitive architecture (Anderson & Lebiere, 1998), which works with chunks of declarative knowledge and production rules that operate the knowledge. Generally, a human driver model should be put into practice, based on input variables, cognitive processing speed, and how drivers evaluate performance.

2.2 Components in the Model Simulation Cycle

A model simulation intends to generate a sequence of behaviors as humans do, and outputs by these behaviors will give feedback which can activate next stimuli and form a cycle. In the sequence, stimuli will be perceived and comprehended (in cognitive architecture and through memory storage), so that the responses and motions can be properly controlled. How our model simulation works is interpreted in this section.

Stimulus input and perception. The environmental stimuli are from the external world, and models always begin here. In driving models, inputs (stimuli) are generated from the driver's surroundings, by the in-vehicle interface and the outside world. In-vehicle interface takes all the information represented in the vehicle, such as the navigation information (route planning, electronic maps), vehicle conditions (speed, rpm, oil level, engine temperature), multimedia displays (radio, CD player), or communication devices (cellular phone, wireless). The outside world involves the road factors (gradient, curvature, surface, lane numbers), traffic conditions (traffic flow, density), and weather. The input of environmental stimuli will trigger the functions of perceiving stimuli.

Cognitive architecture. In cognitive architecture, knowledge, performance, and learning are included (Anderson & Lebiere, 1998). The knowledge determines what rules should to be triggered with the greatest gain and the performance will generate the actions of the rules. Learning can affect the knowledge and performance by adding new knowledge into memory or practice to enhance existing knowledge. Further, memory is an important component in cognitive architecture. Long-term memory affects the accuracy of perception and the decision making process. Short-term memory is the temporary storage room for what were perceived. In the modeling process, memory continuously interact with the performance to give proper commands to body parts. The performance module has the tactical process and operational process. The tactical process is a complicated part in the performance module. How a driver makes a decision and how he thinks over the current situation are not based on the state of the world, but on the mental representation from perception. From the mental cognition, decisions will be made by rules from the long-term memory, as the ACT-R (Anderson & Lebiere, 1998) and COSMODRIVE (Tattegrain-Veste, et al., 1996) do. These rules provide strategies, priorities, or conditions for (multiple) tasks. The relationship between tactical module and long-term memory is established by driver's knowledge, experience, and skills. Then the outputs of the tactical process are commands for the operational process, to move, control, or respond.

Motor control. The operational module will control the vehicle in two dimensions or operate the in-vehicle task interface. Because different body parts and accuracy are necessary for each task, the action time will also differ. The movement time of some body parts has been observed and estimated according Fitt's Law (Fitts, 1954), such as the one-finger typing movement time (MacKenzie, 2003), using head-controlled computer input devices (Radwin, et al., 1990), and using scrolling and hierarchical lists (Cockburn & Gutwin, 2009). For motions, several critical functions for manual control should be referred and applied in this study. These functions are based on experiments, observations, physiological theories, and HCI theories.

3 Method

In this section, the scenario and environments for drivers were based on author's previous studies (Lin, et al., 2009; Lin, et al., 2008), which was the same scenario for simulation. The concept model was illustrated, coming with the tactical and operational process simulation. Finally, the simulation results were put into comparison with empirical data.

3.1 The Concept Model

To realize a human driver model, in general, there are five common components: environment, perception, memory and rules, tactical process, and operations. The process flows as the following brief (also see Fig. 1). External environment triggers the perception to receive the stimuli from the outside world (Parameterization 1). Then the stimuli will be encoded to meaningful information, which is so-called mental representation (e.g. perceive the brake light of the lead vehicle as a warning signal). The information is temporarily stored in driver's short-term memory (as the factual knowledge) and passed to the tactical process (Parameterization 2). In the tactical process, the decision making is based on the factual knowledge and ruled by the skill knowledge (Parameterization 3), so that the strategy and anticipation can be developed. How to operate, control, and react will be determined and the commands are sent to the operational process (Parameterization 4). All responses and body movements occur here, and will finish the modeling cycle. The learning function, which feed the operational results back to driver's knowledge (Parameterization 5), is involved in the model, but will not be realized in this research.

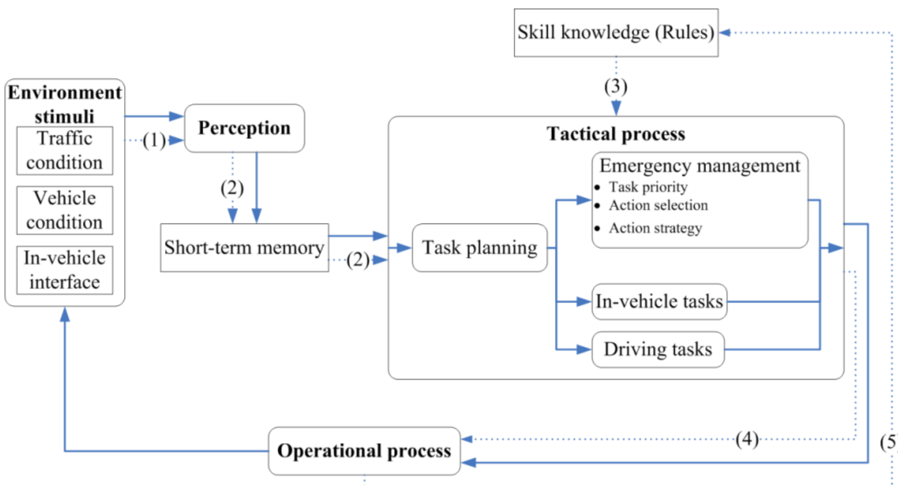

Fig. 1. Structure of the concept driver model. The solid lines represent the flow of the simulation; the dotted lines represent the process of parameterization.

3.2 Tactical and Operational Process Simulation

Comparing to the environment and perception components, memory and tactical process were relatively complicated and affected how the model works greatly. In the component of tactical process, subjects did the mental representation and made decisions for their operations. This model assumed that there were two phases in tactical process, task planning and operation preparation. The former represented how the driver was aware of the current situation and determine what task should be done in this moment. And the latter included handling the general driving tasks, in-vehicle tasks, and the response to emergency situations.

Task planning. In the scenario, drivers were asked to avoid dangers with controlling the brake pedal when the emergency occurred. It was observed that the cue for drivers to determine the reaction for emergency was the current gap. Due to that bus drivers' subjective acceptance for pre-selected time-gaps in the pilot study were the ones over 1.60 s, time-gaps of 1.76 s and above would only be selected to this simulation. It was found out that there was a relationship between the current time-gap which was determined to brake and the pre-selected time-gap settings, as shown in Eq. (1). The polynomial fitting line was shown in Fig. 2, with R^2=.9437. This function was used to simulate that the subject would decide to brake or keep working on general driving and in-vehicle tasks.

$$\text{The current time-gap determined to brake} = -0.1737x^2 + 1.6696x - 0.6902,\quad \text{where } x = \text{pre-selected time-gap (1.76 s to 2.40 s).} \tag{1}$$

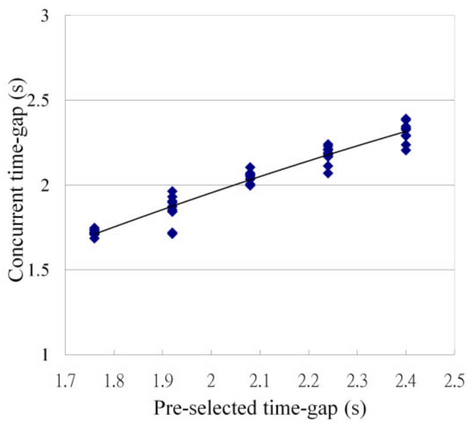

Fig. 2. Function to determine the reaction for emergency

Emergency management. When the driver's emergency management module was triggered, it was assumed that the priority to avoid the danger would be put to the first place at once. After the driver made up his mind to brake, the next step was to set up how the brake would be controlled. The braking movement time, representing the time interval from the brake pedal just moving until completely pushing-down, also has something to do with the pre-selected time-gap, as shown in Eq. (2). The shorter the braking movement time was, the more urgent the situation could be. The polynomial fitting line with R^2 of .9916 was in Fig. 3.

$$\text{The braking movement time} = -0.4018x^2 + 2.1786x - 1.6122,\quad \text{where } x = \text{preselected time-gap (1.76 s to 2.40 s).} \tag{2}$$

Vehicle control. To simulate the primary driving task, it was simple because the driver only needed to steer under the assist of ACC. It is assumed that the action of steering would transfer 2° the most in 100 ms, which was observed and collected from the raw data of the pilot study. Therefore, the steering angle would be randomly applied between 0° and 2° to keep the vehicle in the middle lane.

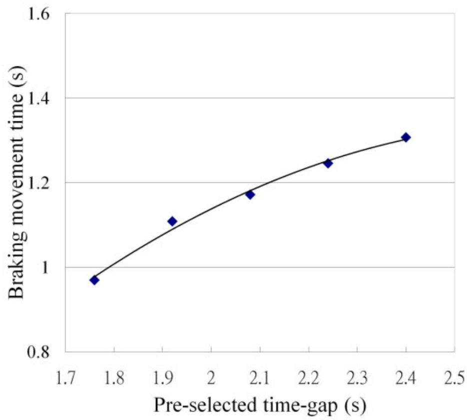

Fig. 3. Function to set up the braking movement time

4 Results

In Fig. 4, the results for both the model simulation and the human drivers (empirical data) were shown. The gray bars meant the results by simulation, and white bars represented empirical data. Also, the comparisons of regressions were shown in Fig. 5 (solid regression lines: simulation results; broken regression lines: empirical results).

4.1 Mean Gap

The model predictions for mean gap showed that as selecting longer time-gaps, the mean gap had obvious increase, no matter driving with or without in-vehicle tasks (Fig. 4). The correlation between simulation and empiric was very high, with the $R > .96$. However, tests indicated that the difference between simulation and empirical results were significant in the no task condition ($F(1,90) = 18.486$, $p < .001$). The difference could be seen in Fig. 5, the linear regression fitting of model prediction and human data. The slope was similar and the difference between regressions was due to the intercept.

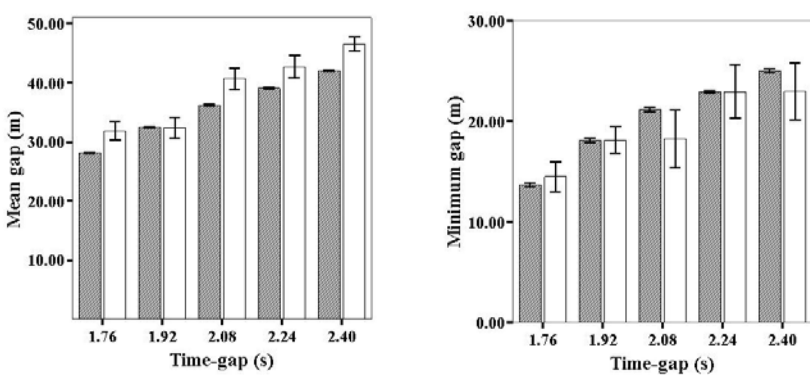

Fig. 4. Means and standard errors from the model simulations and empirical data

4.2 Minimum Gap

The next measure was the minimum gap. Comparing to the human data (as shown in Fig. 4), the overall patterns were similar. The model not only conformed to the basic rank-order effects of variant time-gaps, simulated results were also almost the same to the experimental ones in some conditions. These two types of results were highly correlated ($R > .94$). The difference between them was not statistically significant ($F(1,90) = .606$, $p = .438$). From Fig. 5, two regression lines were close to each other. There was only a little difference existing at the greater time-gap settings.

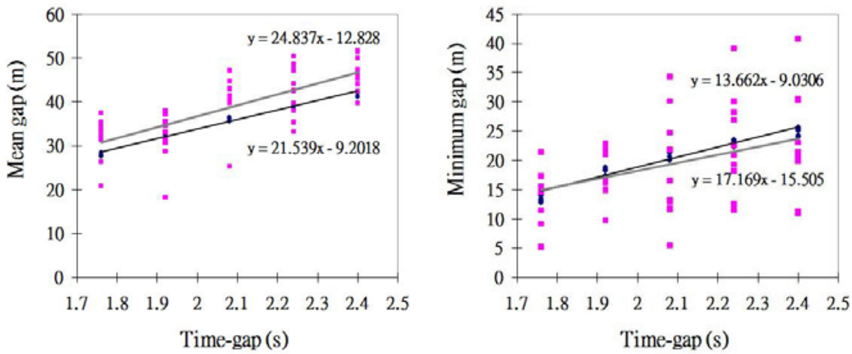

Fig. 5. Linear regressions for model simulation results and empirical data

5 Discussions

In this research, this modeling approach is a conceptual, computational, modular, and simple way to predict effects on driver's performance. The process of modeling in this research follows the following steps: modularization of information processing, building conceptual model with modules and parameter flows, task analysis, simulation, and validation. At the step of modularization, human's behavior is separated into several parts to analyze. For each part, different modules work on their own functions and cooperate as a network. Modules in this study have the same characteristic as what QN-MHP (Feyen, 2002) and ACT-R (Anderson & Lebiere, 1998) stand that modules will work on concurrent activities in parallel.

This human driver model was demonstrated to predict the effects of time-gaps and in-vehicle tasks on driving performance. Several theorem, rules, and observations were referred to construct the model. In the results of model validation, three measures had explained how the model prediction fits the experimental results, respectively. However, a phenomenon occurred that the model works better for driving with in-vehicle tasks, than without task. It may be due to some unnecessary movements when driving. As what ACT-R driver model (Salvucci, 2006) or GOMS (Card, et al., 1983) did, drivers' behavior was assumed to be a fixed sequential movements. But the driver might have some improper actions or unexpected manners, such as trance, daze, impatience, boredom, or even dropping off, especially when they have redundant mental resources. In other words, the positive efficiency from ACC is to save drivers' workload, but it also results in drivers' negligence and omission. These kinds of unimaginable movements and manners are impossible to simulate with modeling approaches. In this research, some subjects indeed have those situations, so that the gap between simulation and empirical data exists.

As to simulating the manual in-vehicle task, the results can accurately predict effects on driver performance. In the experiment, drivers were asked to control the panel for same tasks with identical functions, so their behavior would be more consistent. It is a benefit for modeling because there will be more situations under control. Now it is a simplified model, and validated with ACC evaluation experiments. More measures should be applied to make the validation more complete. Further, some limitations, including internal functions of modules, assumptions, and efficiency of simulation, need to be improved continuously. More general functions in modules must be developed for more cases, such as turning, backing, or overtaking. To improve the efficiency, finite state machine (FSM) and process flow diagram have been applied popularly in simulation (Delorme & Song, 2001; Liu & Özgüner, 2007). These information techniques can systematically represent all the steps, conditions, restricts, and outputs, which enable the process to go smoothly.

6 Conclusions

To create a model for driver behavior simulation, we have searched some other models with different vehicle types, driving scenarios, and modeling techniques. We gather the similarities of these models, including the concept of modularization, queue time, and cognitive architecture, applying to the bus highway driving scenario. This driver model can correctly predict driving performance of mean gap, minimum gap and forward collision rate, especially when drivers need to work on secondary in-vehicle tasks. For auto manufacturers, this modeling approach is very helpful for the phase of ACC prototype evaluation. The interaction of ACC and other vehicle-equipped interfaces, such as navigation devices or some semi-automated assist systems, can be assessed quickly, economically, and accurately. To simulate in other driving scenarios, a task analysis should be performed to develop a new process of behavior for the driving task. Through the way we did, developers can predict and compare the difference among interfaces. Most important of all, by the model simulation, interfaces which are rigorously analyzed will be fewer, so that more efforts can be put into some more complicated field studies.

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