A Discussion on the Consistency of Driving Behavior across Laboratory and Real Situational Studies

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Abstract

This study investigated the degrees of consistencies in driving behavior when operating a real system (real car), a virtual system (high fidelity driving simulator), and a laboratory system (computer driving game). The same tendency of behavioral consistencies was confirmed among the three systems: i.e., the steering operation demonstrated the highest behavioral consistencies, followed by the acceleration and braking operations, respectively. The individuality of driving behavior emerged more in the braking and acceleration operations than in the steering operation. The same tendency for behavioral consistencies of braking, acceleration, and steering operations was confirmed in each of the three systems.

Keywords: behavioral consistency; driving behavior; individual differences; virtual environments

Introduction

In studies of human factors, analyses of human behavior are usually conducted in actual environments using observational methods. However, advances in computer technology are now facilitating experiments on human factors by using various simulators because they provide a convenient and safe method for assessing human behavior. Thus many studies about human behavior in serious situations that may lead to accidents have been performed, such as people driving cars, operating airplanes, controlling industrial plants (e.g., dos Santos et al., 2008; Kemeny, 2003; J. D. Lee et al., 2002; Metzger & Parasuraman, 2001; Parasuraman et al., 1996; Wickens & Alexander, 2009). Driving simulators in particular have played an important role in automobile human factors research for more than three decades. Various studies using driving simulators have examined not only basic characteristics of driving behavior but also applied investigations of those effects of drinking and aging that relate to social problems because using automobiles is a major part of our daily lives (e.g., H. C. Lee et al., 2003; Mets et al., 2011; Pradhan et al., 2005; Rizzo et al., 1997).

However, virtual systems cannot simulate real systems completely. Therefore, many researchers agree that an examination of their validity is a crucial component in any study. The validity of driving simulators has previously been evaluated through a comparison of behavior when driving real cars and simulators (e.g., Törnros, 1998; Godley et al., 2002; Underwood et al., 2011; Shechtman et al., 2009; Mayhew et al., 2011). Previous studies have discussed both commonalities and specificities in the distributions of specific errors or characteristics of specific behaviors when operating real and virtual systems. Such discussions have an essential assumption of the consistency of behavioral characteristics when driving vehicles. However, we do not know to what human driving behavior is consistent. In the present study, we examined behavioral consistency (BC) when driving vehicles on road and using simulators.

The purpose of this study is to reveal the degree of BC by analyzing three basic operations of driving behavior: braking, acceleration, and steering operations. First, we investigate the BCs for the three operations when driving a real car. Then, we study the BCs in two other types of systems: a virtual system as a high fidelity driving simulator and a laboratory system as a low fidelity driving simulator (similar to a computer driving game). The following outlines our basic strategies for the investigation.

Imagine a situation in which drivers repeatedly drive on a specific course. The BC within each participant shows the degree of consistency in individual behavior when repeatedly driving on the same course. We also calculate the BCs across participants, demonstrating the degree of consistency in the general characteristics of human behavior independent of each participant's individuality. We refer to the former as the intrapersonal BC and the later as the interpersonal BC.

In our analyses, the interpersonal BC is treated as the baseline because it reflects the generality of BCs across participants. The intrapersonal BC is predicted to exceed the interpersonal BC. In this study, by comparing the inter- and intrapersonal BCs, we attempt to answer the following two research questions.

RQ1 To what degree is driving behavior, characterized by the three basic operations of braking, acceleration, and steering, consistent across individuals in the real system? Is the tendency observed in the real system confirmed in the two types of simulation systems?

RQ2 To what degree is individual behavior more consistent than behavior across individuals in the real system? Is the greater consistency of individual behavior in the real system confirmed in the two simulator systems? In other words, to what degree are the intrapersonal BCs greater than the interpersonal BCs in each system?

Multi-layered experimental platform

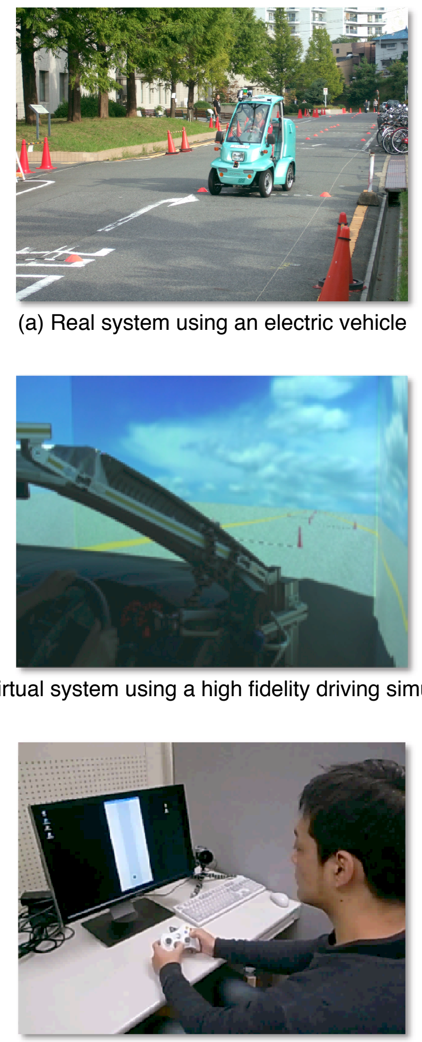
In this study, to determine BCs within various systems, we constructed an innovative experimental platform consisting of three different types of systems: the real system using an electric vehicle, the virtual system using a high fidelity driving simulator, and the laboratory system implemented as a driving game(Figure 1).

The systems

Real system We used an instrumented vehicle called COMS from Toyota Auto Body as the real system (Figure 1(a)). We equipped COMS with various sensors to record participant behavior, car dynamics, and environmental data. For participant behavioral data, manipulations of the steering wheel and brake/acceleration pedals were recorded. The car dynamics data were obtained from speed, acceleration, and angular velocity triaxial sensors. These data were collected at 2000 Hz. Three video cameras were mounted on the COMS in three different positions: front, downward, and face views. The front view camera captured the road conditions. The downward view camera was directed at the road surface and recorded road tags that identified where and when COMS passed specific course points. The face view camera captured the participants' facial expressions and steering control. Time codes were synchronized with the logged sensor and video data.

Virtual system A vehicle motion simulator called carSim from Mechanical Simulation Corporation was used as the virtual system (Figure 1(b)). The virtual system shared many characteristics with the real system, such as the front field of view that was 180° on three screens and the driver's cockpit with the same interior as a real car. The manipulations of the steering wheel and brake/acceleration pedals were recorded as participant behavioral data. These data were collected at 100 Hz.

Laboratory system In the laboratory system, stimuli were presented to the participants on a 21-inch computer screen similar to a typical laboratory setting (Figure 1(c)). The laboratory system was different from the other two systems in many ways. For example, the road configuration was shown from a top-down view and the vehicle controlled by the participants was depicted as a black dot. The car dynamics provide simple reactions for participant inputs. The participants controlled the black dot using a gaming pad controller. When the participants input right or left on the steering control, the dot moved in the corresponding direction by pixels on the basis of the input time. Furthermore, the accelerator/braking operations increased/decreased the dot velocity. The participant operation data were collected at 25 Hz.



(a) Real system using an electric vehicle

(b) Virtual system using a high fidelity driving simulator

(c) Laboratory system using a driving game

Figure 1: Multi-layered experimental platform

Driving course

The participants controlled their vehicles on an experimental driving course. The course consisted of three physical configurations: sharp curves, gentle curves, and straight lines (Fig-

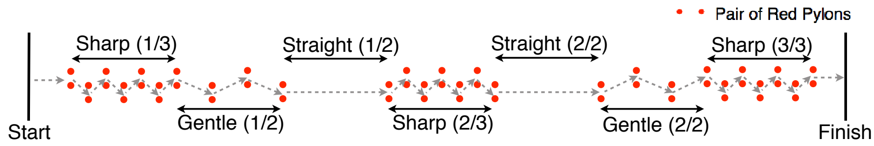


Figure 2: Overview of the driving course

ure 2). The driving courses used for each vehicle were similar and based on the vehicle's size.

Method

Participants

Study participants included twenty-one adults (11 males and 10 females) whose ages ranged from 31 to 55 (mean = 49, SD = 3.0). For the study to capture stable vehicle control, they were required to have over ten years of driving experience and currently drive a car more than ten days a month.

Task

The experimental task assigned to the participants was to drive the vehicles toward the finish line using each system. They were instructed to drive as rapidly as possible and improve their lap times across the trials while maintaining driving safety.

Procedure

The participants engaged in the task using each system as a within-participants design. The order of the experiments was counterbalanced between participants whenever possible.

For each system, the participants were involved in a practice and an experimental session. The practice session comprised of eight trials and the experimental sessions had six trials.

Data treatment

In this study, we analyzed the BCs quantitatively. We defined the BCs of the braking, acceleration, and steering operations as similarities between feature vectors of each operation. In the real system, behavioral data of two participants were treated as missing values because of equipment trouble. In the virtual system, three participants could not participate for personal reasons. Furthermore, in the experimental session using the virtual system, all trials of two participants and four trials of four participants were treated as missing values due to 3D sickness.

Feature vectors Here, we summarize the definitions of feature vectors. For example, the feature vector of a braking operation is calculated as follows.

(1) The time-series data of a braking operation in a trial were divided into 26 sections. Each section corresponded to the region between two pairs of adjoining red pylons (see Figure 2).

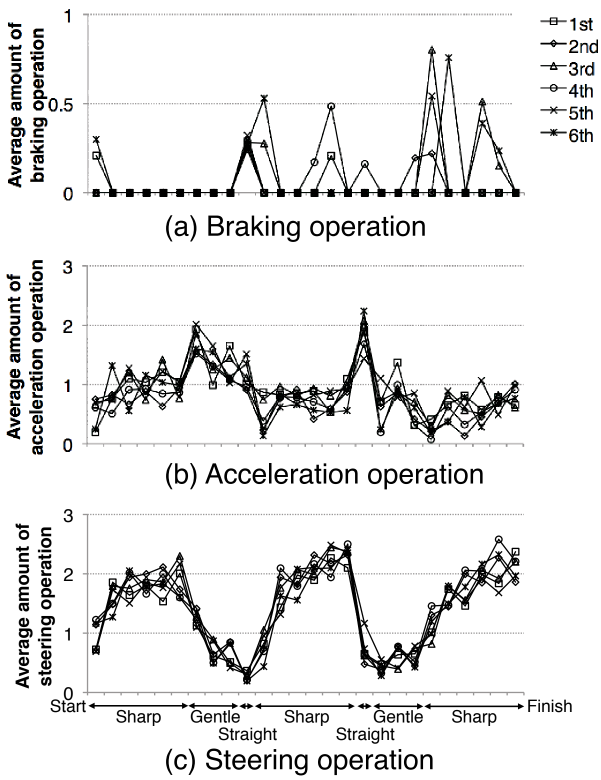


Figure 3: Examples of feature vectors in the real system

(2) The average amount of a braking operation in each section was calculated.

(3) The series of 26 data points corresponded to a feature vector of a braking operation in each trial (see examples in Figure 3 (a)).

We calculated 6 vectorial data for each operation from all participants.

Behavioral Consistency as Similarity between Feature Vectors The BCs in each operation were calculated as an average of the similarity between two feature vectors using Pearson's product-moment correlation coefficient (Expression 1). The vector components of x and y in Expression 1 correspond to 26 data points each, as shown in Figure 3. Combinations of the feature vectors x and y are as follows from the viewpoint of the participant factor.

$$S_p(\mathbf{x},\mathbf{y}) = \frac{\sum_{i=1}^{26}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{26}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{26}(y_i-\bar{y})^2}} \tag{1}$$

Interpersonal BCs To discuss RQ1, the interpersonal BCs within each system were calculated to determine to what degree driving behaviors are consistent across individuals in the real system and whether such tendency observed in this system is confirmed in the other two systems. Specifically, first, one participant (Participant 1) was selected, and the correlation coefficients were calculated between the feature vectors of Participant 1 and those of another participant (Participant 2). Each had six feature vectors in each of the three operations of braking, acceleration, and steering; therefore, 18 (= (6 x 6)/2) combinations were considered for the calculation. The average of the correlation coefficients among the 18 combinations was calculated. Second, in a similar manner, by repeating the calculation of the average of correlation coefficients between Participant 1 and the others, the average amount, defined as the correlation coefficient of Participant 1, was calculated. Finally, the interpersonal BCs within each system were calculated, defined as the average of the correlation coefficients of all participants (Participants 1–21).

Intrapersonal BCs To discuss RQ2, we calculated the intrapersonal BCs within each system to determine the degree to which individual behavior is more consistent than behavior across individuals in the real system and whether the greater consistency of individual behavior in this system is confirmed in the other two systems. Specifically, the correlation coefficients of one participant were calculated using 15 (= (6 x 5)/2) combinations and the average of the correlation coefficients among the 15 combinations was calculated. The intrapersonal BCs within each system were calculated, defined as the average of the correlation coefficients of all participants (Participants 1–21).

Results

Behavioral consistencies within the real system

Figure 4 shows the results of the inter- and intrapersonal BCs when using the real system. A two-way within-participants ANOVA for the operations (braking, acceleration, steering) and participants (interpersonal, intrapersonal) factors showed significant main effects of the operation and participant factors ($F(2,36) = 76.35, p < .01; F(1,18) = 14.47, p < .01$; respectively). Moreover, a significant interaction was noted between these factors ($F(2,36) = 9.90, p < .01$). The detailed results of the simple main effects tests are presented in Figure 4.

These results are summarized as follows: (1) In the interpersonal BCs, significant differences were found among the three operations, with the interpersonal BC of the steering operation as the highest, followed by those for acceleration and braking operations, respectively. (2) In the intrapersonal BCs, this tendency was confirmed, and the intrapersonal BCs of the braking and acceleration operations were higher than their interpersonal BCs.

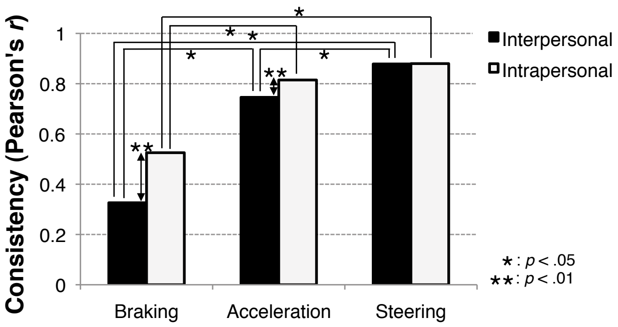


Figure 4: Behavioral consistencies within the real system

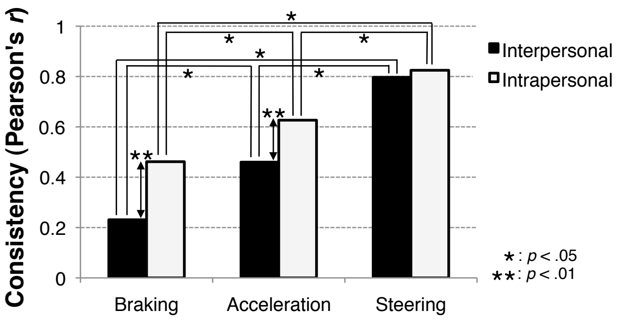


Figure 5: Behavioral consistencies within the virtual system

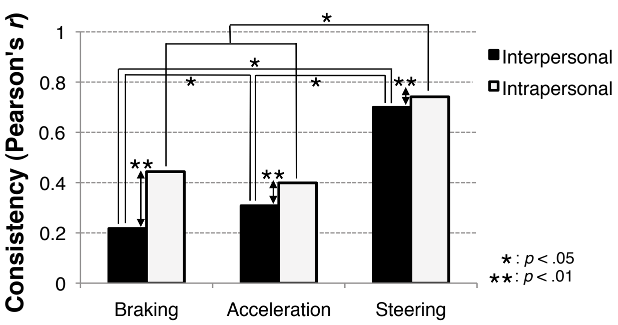


Figure 6: Behavioral consistencies within the laboratory system

Behavioral consistencies within the virtual and laboratory systems

Figures 5 and 6 illustrate the results of the inter- and intrapersonal BCs when using the virtual and laboratory systems, respectively. The two-way ANOVAs showed significant main effects for the operations and participants factors in each system (virtual: $F(2,30) = 103.71, p < .01; F(1,15) = 32.31, p < .01$, respectively, and laboratory: $F(2,40) = 61.56, p < .01; F(1,20) = 24.37, p < .01$, respectively). Moreover, significant interactions were observed between these factors (virtual: $F(2,36) = 9.90, p < .01$, laboratory: $F(2,40) = 7.97, p < .01$). The results of the simple main effect tests are shown in Figures 5 and 6.

These results for the virtual and laboratory systems were similar to those for the real system. In the interpersonal BCs, significant differences were noted among the three operations, with the interpersonal BC of the steering operation being the highest, followed by those of the acceleration and braking operations, respectively. This tendency was confirmed in the intrapersonal BCs, with the braking and acceleration operations higher than their interpersonal BCs. Only in the laboratory system was a significant difference found between the inter- and intrapersonal BCs of the steering operation. However, the effect size (Cohen's *d*) in the steering operation was relatively smaller than in the brake and acceleration operation (braking: 0.89, acceleration: 0.78, steering: 0.57).

Discussion

In this study, we constructed a multi-layered experimental platform to determine the BCs of driving behavior on the bases of two factors: the operations (braking, acceleration, steering) and participants (interpersonal, intrapersonal).

In this section, we summarize the results of the experiments from the viewpoint of each research question and then discuss them.

Summary of Experimental Results

RQ1 asks to what degree driving behaviors are consistent across individuals in the real system and whether such a tendency is confirmed in the two different simulation systems. The results indicate that in the real system, the interpersonal BC of the steering operation was the highest, followed by those of the acceleration and braking operations, respectively. This tendency was confirmed in the virtual and laboratory systems.

RQ2 is as follows: To what degree is individual behavior more consistent than behavior across individuals in the real system, and is the greater consistency of individual behavior in the real system confirmed in the other two systems? The analyses demonstrate that the intrapersonal BCs of both the braking and acceleration operations were lesser than that of the steering operation but they were higher than the interpersonal BCs for each system.

Environmental Constraints

Experiment results reveal that the interpersonal BCs were different among the three operations in all systems: the interpersonal BC of the steering operation was the highest, followed by those of the acceleration and braking operations, respectively. This result suggests that each operation is regulated by different environmental constraints.

The higher environmental constraint on the steering operation than on the braking and acceleration operations might be caused by the arrangement of the driving course. Constraints based on driving course are recognized not only in the experimental setting but also in our daily driving situations. Our steering operations are strictly regulated by road configurations, whereas both acceleration and braking operations have high flexibility. That is, we usually do not out of traffic lanes, whereas the gas pedal or brakes can be used comparatively freely.

Additionally, there might be an interactive relation between the braking and acceleration operations. In some literature regarding the computational model of driver behavior based on cognitive architecture, the manipulation of vehicle controls has been defined as consisting of both lateral and longitudinal controls (e.g., Salvucci, 2006). The longitudinal control, or speed control, is achieved through coordination between the braking and acceleration operations, whereas lateral control is achieved by the steering operation. The mutually dependent relation between the braking and acceleration operations leads to an increase in their degrees of freedom. As a result, the BCs of the braking and acceleration operations might decrease more than that of the steering operation. Moreover, the velocity of the vehicle was mainly controlled by the gas pedal and not by the braking operation, causing different BCs for the braking and acceleration operations. In fact, as seen in the examples of feature vectors presented in Figure 3 (a) and (b), the frequency of the braking operation was substantially lower than that of the acceleration operation. Even though the participants typically controlled the vehicle velocity by using the gas pedal, in some accidental situations, they also had to press the brake to reduce the speed. As a result, the BC of the braking operation was lower than that of the acceleration operation.

Individuality and Behavioral Consistencies

In studies of driving behavior, an important research topic has been to identify the uniqueness of individual driving behavior in order to develop intelligent driver assistance systems customized for individual drivers. More specifically, identifying an individual's deviation from ideal behavior leads to predicting accidents and possibly preventing them (e.g., Igarashi et al., 2004; Wakita et al., 2005; Okuda et al., 2009).

The results of our experiments imply that the braking and acceleration operations are useful measures for identifying individual driver behavior because substantial differences were noted between the inter- and intrapersonal BCs. On the other hand, only a small difference was found in the steering operation because this operation was strongly regulated by the environmental constraints. Our experiments suggest that considering the generality and individuality of the environmental constraints in each operation is important when using behavioral data as personally identifying information.

Conclusion

In this research, we discussed the behavioral consistencies (BCs) within multiple systems—real, virtual, and laboratory systems—on a multi-layered experimental platform. The results showed that the BCs of the steering operation were the highest, followed by those of the acceleration and braking operations, respectively. The intrapersonal BCs (BCs within individuals) of the braking and acceleration operations were higher than the interpersonal BCs (BCs across individuals) in all systems. Further, this tendency was consistent in all three systems. In this paper, we discussed the behavioral consistencies within each system and the similarity of their tendencies among the three different types of systems. These findings lead to another research question: To what degree is human behavior similar across the different types of systems when comparing behavioral characteristics directly? This question can be investigated in future studies.

Acknowledgments

This research was conducted as a part of "Modeling and Detecting Overtrust from Behavior Signals," a study led by Kazuya Takeda. This took place within the "Creation of Human-Harmonized Information Technology for Convivial Society" project under the direction of Yoh'ichi Tohkura, Research Supervisor in the Core Research of Evolutional Science and Technology (CREST) program at the Japan Science and Technology Agency (JST).

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