Classification of Automated Lane-Change Styles by Modeling and Analyzing Truck Driver Behavior: A Driving Simulator Study

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This work was supported in part by the Hino Motors Ltd., and in part by the Grant-in-Aid for Early-Career Scientists from the Japan Society for the Promotion of Science under Grant 21K17781.

Zheng Wang and Muhua Guan contributed equally to this work.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Office for Life Science Research Ethics and Safety, Graduate School of Interdisciplinary Information Studies, University of Tokyo, under Application no. 18-09.

Abstract

Lane change is a highly demanding driving task. A number of traffic accidents are induced by erroneous maneuvers. An automated lane-change system has the potential to reduce the driver workload and improve driving safety. A challenge is to improve the driver acceptance of the automated system. From the perspective of human factors, an automated system with different styles would improve user acceptance, because drivers could drive with different styles in different driving scenarios. This paper proposes a method to design different lane-change styles for automated driving by analyzing and modeling truck-driver behavior. A truck driving simulator experiment with 12 participants was conducted to identify the driver-model parameters. The lane change styles were classified into three types: aggressive, medium, and conservative. The proposed automated lane-change system was evaluated by another truck driving simulator experiment with the same 12 participants. Moreover, the effects of different lane-change decision-making styles on the driver experience and acceptance were evaluated from the perspectives of both the ego truck and surrounding vehicles. The evaluation results demonstrate that different lane-change decision-making styles can be distinguished by drivers. Overall, the three styles were evaluated by the human drivers as being safe and reliable. The main contribution of this study is that it provides the insights into the design of an automated driving system with different driving styles. Furthermore, these observations can be applied to commercial automated trucks.

Index Terms

Intelligent transportation systems, human factors, automated driving, human–machine systems, driving styles.

I. INTRODUCTION

Automated driving has attracted significant attention because it has substantial potential for reducing driver workload and improving driving safety. There is an even more urgent need for automated truck driving owing to the labor shortage and aging problem of truck drivers [1], [2]. Lane change is a highly demanding driving task that induces a tremendous number of traffic accidents [3]. Therefore, the development of automated lane change systems has generated wide interest [4], [5].
According to SAE “Levels of Driving Automation” Standard [6], before fully autonomous driving is available in the market, drivers would be required to monitor the driving environment and take charge of the driving task when necessary for Automation Levels 2 and 3. Considering this, it is important that drivers perceive the automated driving system as safe and comfortable so that the system would be accepted from the perspective of human factors [7]. Thus, the problem here is to improve driver acceptance of automated driving systems.

Human-centered automation has been demonstrated to reduce the likelihood of human–machine miscommunication and improve cooperation [8]. An automated driving system designed for an average driver would be conservative for certain drivers considering safety issues. Therefore, a personalized driver model has been developed and applied to driver-automation systems [9], [10], [11]. A variety of driver models have been developed considering specific requirements and different applications [12], [13], [14]. In recent years, owing to the increasing amount of available data, many data-driven methods have been developed to design human-like automated driving systems [15], [16], [17], [18], [19]. In [16], driving behaviors were extracted from expert human drivers using the deep learning method. These were applied to an autonomous vehicle to successfully reproduce proactive driving behaviors. The support vector machine is another commonly used data-driven method. It was developed to capture the lane-change decision behavior of human drivers [18]. It was integrated into a model predictive control framework to develop a personalized automated driving system. Human-like automated driving systems have been observed to help drivers accept these systems [20]. This is because these systems help the driver feel more involved in driving tasks. In addition, this sense of involvement could reduce driver distraction and inattention during automated driving [21] and shorten the response time for a take-charge request during a critical event [22].

Adaptable automation has been proposed to improve driver acceptance of automated driving systems. It plays an important role in the human-centered approach for automated system design [8], [23], [24]. Drivers prefer to select different types or levels of automation in different driving scenarios to achieve better performance [23], [25]. In conclusion, drivers expect automated driving systems to operate as they do [9], [26], [27], although they tend to evaluate their own driving styles as being aggressive [26]. As individual drivers have different driving styles [28], [29], drivers with an aggressive driving style may prefer a relatively more aggressive automated driving system. Even for the same driver, a more aggressive driving style is preferred when he/she is in a hurry. Considering this, users/drivers should be capable of adjusting the driving style of automated vehicles to improve their driving comfort [30]. For the lane-change decision-making phase, a time-efficient recognition method was used to automatically label the decision-making data into three styles: moderate, vague, and aggressive, and the identification accuracy and stability were verified [31]. A moderate driver was found to prefer more conservative lane changes, an aggressive driver preferred risky lane-changing maneuvers, and a vague driver preferred an intermediate approach. For the lane-change maneuver phase, a dynamic model was proposed to reflect the driver control strategies of adjusting longitudinal and latitudinal acceleration with different driving styles including slow and cautious and abrupt and aggressive [32]. Although these effectively designed systems can provide different driving styles, the problem of evaluating their effect on driving experience (e.g., from the perspective of ego and surrounding vehicles) was not addressed further by these studies.

In addition, the above-mentioned research was focused mainly on passenger cars. Limited attention has been paid to trucks. Considering the high workload of truck drivers and economic costs, it is necessary to develop automated driving systems for trucks [33]. The vehicle dynamics of a truck are significantly different from those of a passenger car because of the truck’s length, size, weight, and maneuverability. Moreover, truck drivers are generally well trained and are competent in achieving rapid and smooth lane-changes in most scenarios [34]. Compared with other frequent driving behaviors on highways, lane changes are more complex and challenging for both human drivers and automatic driving systems.

Thus, they better convey the differences among the different driving styles. Therefore, the aim of this study was to design and evaluate an automated lane-change system with different decision-making styles by analyzing and modeling truck-driver behavior. The hypothesis was that the different lane-change decision-making styles (including aggressive, medium, and conservative) can be distinguished by drivers from the perspective of ego and surrounding vehicles. Meanwhile, the driver acceptance of the system reliability could be demonstrated. The observations of this study are likely to be applicable to commercial automated trucks.

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The remainder of this paper is organized as follows. Section II introduces an automated lane-change model of truck drivers. Section III presents the design of an automated lane-change system with different lane-change decision-making styles. It uses the driver-model parameters identified from a driving simulator experiment. Section IV presents the evaluation of the designed automated lane-change system by conducting another driving simulator experiment and the evaluation results. Discussions on the system design and evaluation are presented in Section V. Conclusion and future work are described in Section VI.

II. MODEL OF AUTOMATED LANE CHANGE

A discrete lane-change model based on gap acceptance, which refers to the space between the ego vehicle and the surrounding vehicles needed for a safe lane change, is presented in this section. The lane-change process has
three phases: the car-following phase, lane-change decision-making phase, and dynamic-control phase. According to Balal et al.’s review on lane-change parameters [35], inter-vehicle distances and velocities are the most often considered parameters in modeling the lane-change decision-making processes of drivers. Therefore, in this study, the modeling of the lane-change decision-making of truck drivers was based on gap acceptance, which considers distances, velocities, and accelerations.

A. RELATED WORK
Lane-change tasks are demanding and require information on the surrounding vehicles. Previous research has classified the lane-change task of trucks into two subcategories: mandatory lane-change and discretionary lane-change [36]. This study addresses discretionary lane-change by using a discrete decision model based on gap acceptance [37], [38].

B. LANE-CHANGE SCENARIO
The lane-change scenario is shown in Figure 1. Here, four trucks run on two adjacent lanes. At a certain moment, the vehicle $C_1$, which runs in front of the ego vehicle $C_0$, begins to decelerate. Meanwhile, $C_2$ and $C_3$ continue to run at a constant speed. After the deceleration, $C_1$ continues to run at a speed lower to those of $C_2$ and $C_3$. To maintain a higher driving speed, $C_0$ attempts to perform a lane change by detecting the distance to the surrounding vehicles. If the gap acceptance to the surrounding vehicles is satisfied, $C_0$ would undertake a lane change to enter between $C_2$ and $C_3$.

Otherwise, it would continue to perform the car-following task behind $C_1$.

During the car-following phase, $C_0$ detects the distances to the surrounding vehicles $C_1$, $C_2$, and $C_3$, which are indicated by $X_1$, $X_2$, and $X_3$, respectively (see Figure 2 (a)). In addition, the speeds of the vehicles are denoted by $V_0$, $V_1$, $V_2$, and $V_3$, respectively.

At time $t_1$, $C_0$ starts to perform a lane-change maneuver. At $t_2$, the center of gravity of $C_0$ reaches the lane boundary, as shown in Figure 2 (b). The distance from $C_0$ to $C_1$ at this time is denoted as $D_1$. At $t_3$, the lane change maneuver is completed when $C_0$ reaches the target lane and its yaw angle becomes $0^\circ$, as shown in Figure 2 (c). The distances from $C_0$ to $C_2$ and $C_0$ to $C_3$ at this time are denoted as $D_2$ and $D_3$, respectively.

C. CAR-FOLLOWING PHASE
$C_0$ continues to follow the lead vehicle $C_1$ until a lane-change decision is made and a maneuver is performed. If the gap acceptance is not satisfied, $C_0$ continues to perform the car-following task. In this paper, an adaptive cruise control-based car-following model is presented. It automatically adjusts the vehicle speed to maintain a safe distance from the lead vehicle, as shown in Figure 3. In the car-following model, it is necessary to ensure that $D_1$ is always larger than the threshold of safety for $D_1$ (denoted as $S_1$). Thereby, $C_0$ can change lanes whenever the gap acceptance of $D_2$ and $D_3$ is satisfied. In addition, when $V_0 > V_1$, the distance from $C_0$ to $C_1$ decreases gradually. If $C_0$ starts to decelerate when $D_1 = S_1$, $D_1$ becomes less than $S_1$. Thus, the deceleration process of $C_0$ with the variation in distance to $C_1$ was also considered. During this process, $C_0$ decelerates at a constant value $a_d$. The relationship between $D_1$ and $S_1$ is given by the following equation:

$$D_1 > \frac{V_0^2 - V_1^2}{2a_d} - \frac{V_0 - V_1}{a_d} + S_1$$ (1)
If the gap acceptance to surrounding vehicles is satisfied (which is described in the next section), \(C_0\) stops following \(C_1\) and changes lanes.

**D. LANE-CHANGE DECISION BASED ON GAP ACCEPTANCE**

The thresholds of safety for \(D_2\) and \(D_3\) are denoted as \(S_2\) and \(S_3\), respectively. If \(D_1 > S_1\), \(D_2 > S_2\), and \(D_3 > S_3\), \(C_0\) would change lanes. A flowchart of the lane-change decision is shown in Figure 4. Although Figure 4 presents the temporal order in which the logical judgments are run in the program and hardware, the three logical judgments are logically concurrent, indicating that there is no logical priority among them.

\(D_1\), \(D_2\), and \(D_3\) are calculated by predicting the relative distances to the surrounding vehicles at times \(t_2\) and \(t_3\) if a lane change is performed. Their respective thresholds are used to prevent collisions during lane changes. \(D_1\), \(D_2\), and \(D_3\) are expressed as

\[
D_1 = X_1 + V_1(t_2 - t_1) - \left( V_0(t_2 - t_1) + \frac{1}{2}a_x(t_2 - t_1)^2 \right)
\]

\[
D_2 = X_2 + V_2(t_3 - t_1) - \left( V_0(t_3 - t_1) + \frac{1}{2}a_x(t_3 - t_1)^2 \right)
\]

\[
D_3 = X_3 - V_3(t_3 - t_1) + \left( V_0(t_3 - t_1) + \frac{1}{2}a_x(t_3 - t_1)^2 \right)
\]

where \(a_x\) is the constant longitudinal acceleration during the lane-change maneuver, which is explained in the next section.

**E. DYNAMICS CONTROL PHASE DURING LANE-CHANGE MANEUVER**

Longitudinal and lateral accelerations are two important parameters for the dynamic control phase during the lane-change maneuver. It is assumed that the longitudinal acceleration \(a_x\) is constant during the lane-change maneuver. The lateral acceleration \(a_{y12}\) is constant during the first half of the lane change maneuver (from \(t_1\) to \(t_2\)), and \(a_{y23}\) is constant during the second half of the lane-change maneuver (from \(t_2\) to \(t_3\)). These are expressed as

\[
a_x = \frac{V_{t3} - V_{t1}}{t_3 - t_1}
\]

\[
a_{y12} = \frac{2l_1}{(t_2 - t_1)^2}
\]

\[
a_{y23} = \frac{2l_2}{(t_3 - t_2)^2}
\]

where \(V_{t1}\) and \(V_{t3}\) are the longitudinal speeds of \(C_0\) at \(t_1\) and \(t_3\), respectively. \(l_1\) and \(l_2\) are the lateral distance variations of \(C_0\) from \(t_1\) to \(t_2\) and from \(t_2\) to \(t_3\), respectively.

**III. DESIGN OF AUTOMATED LANE-CHANGE SYSTEM**

A truck driving simulator experiment was conducted to obtain the driving data. These were used to identify the parameters of the proposed lane-change model. The identified parameters were classified into three types to represent different lane-change decision-making styles: aggressive, medium, and conservative.

**A. DRIVING SIMULATOR EXPERIMENT**

1) PARTICIPANTS

Twelve professional truck-drivers (11 males and 1 female) participated in the experiment. Their ages ranged from 26 to 60 years (mean = 42.9, SD = 8.2). All the participants had valid Japanese driver licenses for heavy vehicles. Their driving experience ranged from 2 to 26 years (mean = 14.6, SD = 8.2). The experiment was approved by the Ethics Committee of the Interfaculty Initiative in Information Studies, The University of Tokyo.

2) APPARATUS

The experiment was conducted in a truck driving simulator. It consisted of a real truck cabin, two rear-view mirrors, and a 140° field-of-view driving-scene visualized by four projectors (see Figure 5). The two rear-view mirrors were
emulated using two monitors to present the rear environment. The visual scene was updated at a rate of 120 Hz. The truck driving simulator also had a six six-degree-of-freedom motion platform. The platform was capable of providing real driving sensations to the drivers, including the feeling of acceleration, braking, turning, and vibration caused by rough roads. Within the cabin, the cockpit of a real truck was replicated by providing automatic transmission, a brake pedal, an accelerator pedal, a shift handle, an actuated steering wheel, and a dashboard. Raw data on driving performance were recorded in the host computer of the driving simulator at a sampling rate of 120 Hz.

3) SCENARIO

The driving environment was a two-lane highway with an emergency lane on the left, as shown in Figure 6. The driving scenario for the lane-change task is shown in Figure 7. There were totally six trucks, and the body length of each truck was 12 m. There were two vehicles in the left lane of the highway: a lead vehicle (corresponding to $C_1$ in Figure 1) and an ego vehicle (corresponding to $C_0$ in Figure 1). There were four trucks with different gap distances in the right lane of the highway. The gap distance was defined as the distance between the rear end of the leading vehicle and the front bumper of the following vehicle. Raw data on driving performance were recorded in the host computer of the driving simulator at a sampling rate of 120 Hz.

A pilot experiment was conducted to determine the gap-distance setting among the vehicles in the right lane. According to its results, a gap distance of 40 m was considered to be short for a professional driver to perform a lane change, whereas that of 70 m was considered to be adequate. Therefore, in the formal experiment, four vehicles ran in the right lane with gap distances of 50, 60, and 70 m. These gap distances were permuted and combined to yield six experimental conditions, as shown in Table 1. In addition, the distance between $C_2$ in the right lane and $C_1$ in the left lane was set to 55 m. During the driving task, the participants were asked to follow the lead vehicle $C_1$ and not fall behind $C_2$. Thereby, the first gap-distance between $C_2$ and $C_3$ can be considered for the lane-change decision.

Each condition was repeated two times. Therefore, each participant drove for a total of 12 trials (including six trials with different conditions, followed by six repeated trials). The order of the experimental conditions presented to the participants was partially counterbalanced using a Latin square [39].

4) PROCEDURE

On the day of the experiment, the participants were asked to sign a consent form after the experimental contents were explained. Then, they completed a questionnaire on their personal information and driving experience. Subsequently, they entered the driving simulator and adjusted their seat to achieve a normal driving position. The participants were asked to follow Japanese traffic rules and drive as naturally as feasible. Before the experiment started, the subjects were

| TABLE 1. Experimental conditions for system design. |
|--------|--------|--------|--------|--------|--------|
| Cond. 1 | Cond. 2 | Cond. 3 | Cond. 4 | Cond. 5 | Cond. 6 |
| 1st gap (m) | 50 | 50 | 60 | 60 | 70 | 70 |
| 2nd gap (m) | 60 | 70 | 70 | 70 | 50 | 60 |
| 3rd gap (m) | 70 | 70 | 60 | 70 | 50 | 60 |

| TABLE 2. Experimental conditions for system evaluation. |
|--------|--------|--------|--------|--------|--------|
| Cond. 1 (Aggressive) | Cond. 2 (Medium) | Cond. 3 (Conservative) |
| Scenario A | Trial A1 | Trial A2 | Trial A3 |
| Scenario B | Trial B1 | Trial B2 | Trial B3 |
| Scenario B | Trial B1 | Trial B2 | Trial B3 |
informed that the ego truck in the experimental scenario was of the same model as the other trucks and that all were 12 m in length. The participants performed two practice trials of the driving task to familiarize themselves with the driving simulator and the lane-change task.

After the practice trials, the participants were permitted to rest for 5 min. After the rest, the formal experimental session started, wherein the participants performed 12 trials. They were instructed on the three gaps in the right lane at the beginning of the formal session. However, they were not informed about the order in which the three gaps would occur. The entire experiment required approximately 120 min per participant.

5) MEASUREMENT

The relative distance of the ego vehicle to the surrounding vehicles and the speed of the vehicles during the driving task were measured. The longitudinal acceleration and lane-change duration of the ego vehicle were also measured.

B. IDENTIFIED PARAMETERS

The parameters of the proposed lane-change model (described in Section II) were identified from the measured data. These included the relative distances to surrounding vehicles, longitudinal acceleration, and lane-change durations. The distribution of the parameter values (including those of $D_1$, $D_2$, $D_3$, $(t_2-t_1)$, $(t_3-t_1)$, and $a_x$) are shown in Figure 8.

The identified parameters were used to design the automated lane-change system. The designed system was evaluated by another driving simulation experiment, which is described in Section IV. The lateral acceleration during the lane-change maneuver was assumed to be constant, as shown in Equations (6) and (7). $a_{y12}$ and $a_{y23}$ represent the lateral accelerations from $t_1$ to $t_2$ and $t_2$ to $t_3$, respectively. Through a trial-and-error process, we determined the steering wheel angles to be input to control the vehicle during the automated lane-change maneuver, to obtain the desired lateral acceleration.

C. CLASSIFICATION OF LANE-CHANGE DECISION-MAKING STYLES

Three styles of lane-change decision-making were considered in this study: aggressive, medium, and conservative. The classification was achieved by selecting the 25th, 50th, and 75th percentiles, respectively, of identified parameters, namely, the relative distances to surrounding vehicles ($D_1$, $D_2$, and $D_3$). The hypothesis was that the selection of the 25th, 50th, and 75th percentiles can make the lane-change decision-making styles distinguishable by drivers and that the three styles can be evaluated as safe and reliable by them. On the one hand, although the selection of gaps with larger differences in percentile (e.g., 10th, 50th, and 90th)
between different styles could make it more convenient for drivers to distinguish these, it could also result in the perception of the gaps as being unsafe and unreliable. This is particularly so for the aggressive style. On the other hand, the selection of the gaps with smaller differences in percentile could hinder drivers from distinguishing the different lane-change decision-making styles.

In addition to the identified parameters of \( D_1 \), \( D_2 \), and \( D_3 \), the automated vehicle accelerated in the longitudinal direction at a constant value of 0.10 m/s\(^2\) during the lane change maneuver phase. This is the average value of \( \alpha \) from the identified results. The automated vehicle accelerated in the lateral direction at a constant value of 0.21 m/s\(^2\) from \( t_1 \) to \( t_2 \) and decelerated at a constant value of 0.28 m/s\(^2\) from \( t_2 \) to \( t_3 \) according to Equations (6) and (7), respectively. As mentioned in Section III-B, the steering wheel angle was controlled to obtain the desired lateral acceleration.

IV. EVALUATION OF AUTOMATED LANE-CHANGE SYSTEM

Another driving simulator experiment was conducted to evaluate the design of the automated lane-change system with three lane-change decision-making styles. Subjective evaluations of system performance were obtained from participants. This subjective experiment was designed with the hypothesis that the three different lane-change decision-making styles of proposed model can be distinguished by drivers from viewpoint of ego and surrounding vehicles. It consisted of two scenarios: Scenarios A and B. In Scenario A, the designed system was evaluated from the perspective of the automated vehicle \( C_0 \). In Scenario B, the designed system was evaluated from the perspective of a surrounding vehicle.

A. DRIVING SIMULATOR EXPERIMENT

1) PARTICIPANTS

The participants of the previous experiment (described in Section III-A1) were recruited again to perform this driving simulator experiment.

2) APPARATUS

The truck driving simulator described in Section III-A2 was used. In this experiment, the driving speed and steering wheel angle of \( C_0 \) were controlled automatically.

3) SCENARIO A

The lane-change task in Scenario A is shown in Figure 9 (a). The participants performed as the driver of \( C_0 \) and evaluated the automated lane-change system. After \( C_1 \) decelerated, \( C_0 \) attempted to perform a lane change to the right lane if the gap acceptance was satisfied.

As described in Section III-C, three lane-change decision-making styles of automated lane-change were designed. Each lane-change decision-making styles (or driving condition) corresponded to a driving trial, as shown in Table 2. After calculating the acceptable gap distances for the aggressive, medium, and conservative models, we observed that these require gaps of approximately 42 m, 51 m, and 58 m, respectively. Considering that the speed at which \( C_0 \) starts to undertake a lane change always floats marginally, the gap distance between \( C_2 \) and \( C_3 \) was maintained at 45 m, 55 m, and 65 m for Trials A1, A2, and A3, respectively, to ensure that the three types of models performed lane changes when \( D_3 \) had the minimum required value.

As \( C_0 \) automatically performed the car-following and lane-changing tasks, the participants were asked not to operate the steering wheel and gas/brake pedal unless necessary. The participants were requested to pay attention to the relative distances to the surrounding vehicles to evaluate automated lane-change performance. To better investigate drivers’ evaluation of the distances to \( C_3 \) during lane changes, \( C_3 \) was set to maintain a constant distance to \( C_2 \). This design was applied in Scenario B as well.

A 3 × 3 Latin square [39] was used in the order design to counterbalance the order of experimental conditions within the participants.

4) SCENARIO B

In Scenario B, the participants performed as the driver of \( C_3 \) and evaluated the automated driving performance of \( C_0 \) from the perspective of a surrounding vehicle. Thus, \( C_3 \) became the ego vehicle, as shown in Figure 9 (b). The participants were required to control the steering wheel to stay within the lane, and the driving speed was controlled by an adaptive cruise control system to maintain a certain distance from the lead vehicle \( C_2 \).

As shown in Table 2, each group of trials (e.g., B11, B12, and B13) corresponded to a lane-change decision-making style condition (e.g., aggressive model). The difference between the three conditions was in terms of the automated driving style of \( C_0 \). The difference among the three trials in each condition (e.g., B11, B12, and B13) was in terms of the gap distance between \( C_2 \) and \( C_3 \). This was maintained at 45 m, 55 m, and 65 m for Trials B11, B12, and B13, respectively.

A 3 × 3 Latin square [33] was used in the order design to counterbalance the order of experimental conditions within the participants.
TABLE 3. Statistical analysis of subjective evaluation scores in scenario A.

| Question                                      | Aggressive M (SD) | Medium M (SD) | Conservative M (SD) | Friedman | A-M | A-C | M-C |
|------------------------------------------------|-------------------|---------------|---------------------|----------|-----|-----|-----|
| Q1: Lane-change safety                         | 2.92 (0.79)       | 3.08 (1.08)   | 3.83 (1.27)         | 0.019**  | 0.531 | 0.070* | 0.055* |
| Q2: Distance to vehicle ahead                   | 2.75 (0.62)       | 2.83 (0.58)   | 3.08 (0.29)         | 0.197    | 1   | 0.219 | 0.375 |
| Q3: Distance to vehicle ahead in target lane   | 2.42 (0.67)       | 2.75 (0.45)   | 3.08 (0.29)         | 0.011*   | 0.25 | 0.031* | 0.25 |
| Q4: Distance to rear vehicle in target lane    | 2.33 (0.49)       | 2.42 (1.00)   | 2.75 (0.62)         | 0.158    | 0.906 | 0.188 | 0.219 |

*p < 0.05, **p < 0.1.

5) PROCEDURE

The part of the experimental procedure before practice driving was similar to the experiment for system design, as described in Section III-A4.

In practice driving, the participants experienced the scenarios and familiarized themselves with the driving simulator, particularly with the automated driving system in Scenario A and the adaptive cruise control system in Scenario B.

After the practice, the participants were permitted to rest for 5 min. After the rest, the formal experimental session was started. Herein, each participant undertook Scenarios A and B in that order. In Scenario A, the participants were asked to complete a questionnaire after each trial. After the three trials in Scenario A, the participants were permitted to rest for 5 min. In Scenario B, the participants were asked to complete a questionnaire after each trial of each condition. After the three trials in each condition, the participants were asked to complete an overall questionnaire to evaluate each lane-change decision-making styles. The entire experiment required approximately 120 min per participant.

6) MEASUREMENT

The participants’ subjective evaluation of the designed automated lane-change system was measured.

In Scenario A, the following questions were asked after each driving condition:

Q1. Did you feel safe during the process of automated lane-change? From 1 (completely disagree) to 5 (completely agree).

Q2. How do you evaluate the distance to the front car during lane change? From 1 (very close) to 5 (very far).

Q3. How do you evaluate the distance to the right front car during lane change? From 1 (very close) to 5 (very far).

Q4: How do you evaluate the distance to the right rear car during lane change? From 1 (very close) to 5 (very far).

In Scenario B, the following questions were asked after each driving trial. The questions differed depending on whether a lane change was performed or not.

The following questions were asked in the cases where the automated vehicle changed lanes:

Q1: Did you feel safe during the automated lane-changing of the lane-changing car? From 1 (completely disagree) to 5 (completely agree).

Q2: Please evaluate the distance to the lane-changing truck when the automated lane-changing system was started. From 1 (very close) to 5 (very far).

Q3: Please evaluate the distance to the lane-changing truck after lane-change. From 1 (very close) to 5 (very far).

The following questions were asked in the cases where the automated vehicle did not perform a lane change:

Q4: For this trial, the automated lane-changing system estimated the scenario to be dangerous. Therefore, no lane changes were observed. Do you agree with this assessment? From 1 (completely disagree) to 5 (completely agree).

In Scenario B, the following question was asked after each driving condition (which included three trials):

Q5: Do you perceive this automated lane-changing system to be reliable? From 1 (unreliable) to 3 (reliable).

B. DATA ANALYSIS

The subjective evaluation data were analyzed using the Friedman test and Wilcoxon signed-rank test. The Friedman test was used to compare the three groups (e.g., aggressive, medium, and conservative models) for statistical significance. The Wilcoxon signed-rank test was used to perform pairwise comparisons to determine which groups were significantly different from each other. Bonferroni correction was applied to control the family-wise error rate. The significance level was set at \( p < 0.05 \).

C. EVALUATION RESULTS

The performance evaluation results of the automated driving system from the perspectives of the automated vehicle (Scenario A) and a surrounding vehicle (Scenario B) are presented separately. The order in which the results are reported and figures are arranged is consistent with the order of the questions in the questionnaire.

1) FROM THE PERSPECTIVE OF AUTOMATED VEHICLE (SCENARIO A)

Figure 10 shows the subjective evaluation scores for each lane-change decision-making style model. Table 3 presents the mean value and standard deviation of the evaluation scores, and the results of the Friedman test and Wilcoxon signed-rank test. According to the Friedman test results, the effect of the different lane-change decision-making styles was significant for the subjective evaluation of lane-change safety and distance to the vehicle ahead in the target lane.
According to the results of Wilcoxon signed-rank test in Table 3 and the results shown in Figure 10 (a), the participants displayed a tendency to accord a higher level of safety to the automated lane-change system with the conservative model than with the aggressive or medium model. Moreover, the mean value of the evaluation scores was approximately three for all the three lane-change decision-making styles, which was the median value between unsafe and safe. This indicates that in general, the participants perceived the designed automated lane-change system to be acceptable based on safety criteria from the perspective of the automated vehicle.

The results of Wilcoxon signed-rank test in Table 3 and the results shown in Figure 10 (c) indicate that the distance to the vehicle ahead in the target lane for the aggressive model was significantly less than that for the conservative model. In addition, the distance to the vehicle ahead in the target lane tended to increase from the aggressive model to the medium model and to the conservative model.

As shown in Figure 10 (b), the distance to the vehicle ahead tended to increase from the aggressive model to the medium model and to the conservative model, although the difference was not significant. As shown in Figure 10 (d), this was also applicable to the distance to the rear vehicle in the target lane. According to the above results on the relative distance to surrounding vehicles, the three lane-change decision-making styles could be distinguished by the participants from the perspective of the automated vehicle.

2) FROM THE PERSPECTIVE OF SURROUNDING VEHICLE (SCENARIO B)

Table 4 presents the mean value and standard deviation of the evaluation scores, and the results of the Friedman test and Wilcoxon signed-rank test. According to the results, there was no significant difference among the three models of lane-change decision-making styles or between any two of the three models. This indicates that in terms of the relative distance, the participants did not distinguish the different decision-making styles from the perspective of the surrounding vehicle.

According to Table 4, the distance to the automated vehicle during lane change was evaluated by obtaining a mean score approximately equal to or larger than three, which was the median value between very close and very far. This indicates that the participants perceived the distance to be in line with their expectations or marginally longer. Thus, the automated lane-change system was acceptable with regard to the safe distance from the perspective of the surrounding vehicle.
TABLE 4. Statistical analysis of subjective evaluation scores in scenario B.

| Q1: Lane-change safety; Comparing Trials B12 and B22 | Aggressive M (SD) | Medium M (SD) | Conservative M (SD) | Friedman | A-M | A-C | M-C |
|--------------------------------------------------|-------------------|----------------|---------------------|----------|-----|-----|-----|
| Q2: Distance to automated vehicle when lane change starts; Comparing Trials B12 and B22 | 3.08 (0.52) | 3.33 (0.65) | - | - | 0.250 | - | - |
| Q3: Distance to automated vehicle when lane change ends; Comparing Trials B12 and B22 | 2.92 (0.52) | 3.00 (0.74) | - | - | 1 | - | - |
| Q1: Lane change safety; Comparing Trials B1s, B2s, and B3s | 3.58 (0.90) | 3.75 (0.75) | 3.75 (0.75) | 0.883 | 0.750 | 0.750 | 1 |
| Q2: Distance to automated vehicle when lane change starts; Comparing trial B1s, B2s, and B3s | 3.50 (0.52) | 3.50 (0.67) | 3.50 (0.67) | 0.956 | 1 | 1 | 1 |
| Q3: Distance to automated vehicle when lane change ends; Comparing Trials B1s, B2s, and B3s | 3.33 (0.49) | 3.25 (0.62) | 3.17 (0.67) | 0.444 | 1 | 0.625 | 1 |
| Q4: Agreement with decision to perform car-following rather than lane change; Comparing Trials B2s and B3s | - | 3.25 (1.22) | 3.42 (1.24) | - | - | - | 0.781 |

Figure 11 shows the subjective evaluation scores of the reliability of automated lane-change system. According to the results of the three lane-change decision-making styles, most of the evaluation scores were between two and three (reliable), and few participants selected one (unreliable). From the Friedman test results, there was no significant difference in system reliability among the three lane-change decision-making styles. This indicates that in general, the designed automated lane-change system was perceived as reliable by the participants from the perspective of the surrounding vehicle.

V. GENERAL DISCUSSION

A. SYSTEM DESIGN

A discrete lane-change model for truck drivers based on gap acceptance is proposed, as described in Section II. Previous research on passenger cars [38] and trucks [36] established that the gap acceptance model is effective. Moreover, our validation study using numerical simulations demonstrated that the proposed model can yield safe automated lane-change and match the experimental results [40]. This indicates that the proposed model is capable of predicting driver lane-change behavior.

A relatively conventional method (i.e., the setting of different thresholds to classify different lane-change decision-making styles of the proposed model) was used in the model design. However, in practice, the model did not necessarily show lower efficiency or performance compared with models constructed with relatively novel or complex methods such as reinforcement learning or support vector machines. Nevertheless, these novel methods hindered the classification of different driving styles based completely on raw data and without manual prepossessing. Their preprocessing of data (i.e., tagging) always involves a certain degree of subjectivity. Otherwise, the setting of different thresholds would eventually be the simplest and most objective method for classifying driving styles even for these novel methods. In our future work, novel data-driven methods will be applied when more experimental data are available.

Furthermore, the use of novel methods such as machine learning requires a large amount of data to ensure performance. However, considering certain practical problems such as economic and time costs, it was difficult to recruit a larger number of professional drivers, particularly female ones. As remedies, the experiments were designed carefully, and the data were analyzed well using many effective methods such as the Latin square method and suitable statistical methods. Because the experimental participants were professional truck drivers, the data collected from the
experiments are reliable notwithstanding that the number of participants was 12. In the future work, more participants will be selected.

It has been contended that an automated system developed for all drivers must be conservative with regard to safety to address all types of driving styles [10]. In our study, based on the driver model parameters identified from the 12 participants, the lane-change decision-making styles were classified into three categories by selecting the 25th, 50th, and 75th percentiles of the relative distances to surrounding vehicles. Although previous research classified driving styles by adjusting the parameters in the driver model [32], our study provided a perspective on style classification by using experimental data collected from a group of drivers.

The evaluation results of the system design demonstrate that the use of the 25th, 50th, and 75th percentiles of parameters can enable drivers to distinguish the different driving styles while ensuring driver acceptance of the system reliability. However, the same model cannot be used to classify drivers’ different driving styles, which is a limitation of this current study. This may be because all of participants were professional truck drivers with years of driving experience, which results in a relatively small individual difference of driving behavior. Future studies would extend the current work by testing other percentile values of the parameters, particularly in the case of different driving scenarios.

While researching drivers’ lane-change behavior, it was observed that car-following, decision-making, and kinetic control during lane changes have a substantial influence on each other. A marginal variation in one of these may result in a completely different lane-change maneuver. A complete lane-change model should be an organic integration of all the three parts, or even more. However, in this work, both the acceleration process during lane change and the deceleration process during car-following were designed in a relatively simple and uniform manner. This was to eliminate the influence that these may exert on drivers’ evaluation of the lane-change decisions made by the designed models (the main purpose of our work was to design and test a lane-change decision-making model). Future work would develop an effective method to organically combine all the modules of a complete lane-change model.

As this study focuses on modeling the driver’s lane-change decision-making, we referred to and agreed with Balal et al.’s investigation of the parameters used in modeling the lane change decision [35], i.e., this study focuses on distance, velocity, and acceleration during the lane-change decision. However, there are many other factors that influence the driver’s subjective evaluations of a complete automatic lane-change system, such as lateral and yaw acceleration during lane-change kinetic control. Therefore, we will also investigate how different lane-change kinetic-control system influence the driver’s subjective evaluation of the system in future studies.

A rough comparison with another experimental study on passenger vehicles [41] indicates that trucks behave differently from passenger vehicles during the intermediate phase of a lane change, that is, trucks spend more time completing a lane-change maneuver with relatively smaller longitudinal and lateral accelerations. Although both experiments were focused on lane-change maneuvers on the highway, in addition to the vehicle types, the identities of the subjects differed. In other words, several factors may have contributed to the difference in lane-change maneuvers between the two experiments: body length, cruising speed, and whether the subjects were professional drivers. Therefore, the factors that influence the different lane-change maneuvers of different vehicle types will be investigated in future studies.

B. SYSTEM EVALUATION FROM THE PERSPECTIVE OF AUTOMATED VEHICLE

The designed system was evaluated from the perspective of a driver in the automated vehicle. This is a common method used by researchers [9], [24]. In the subjective experiment, we recruited the same group of subjects as in the driving experiment based on the idea that the model built on the data collected from these 12 drivers should also be experienced and evaluated by them. Admittedly, there were external factors, such as the small number of professional truck drivers and the difficulty in recruiting subjects, as the experiment was conducted during the COVID-19 outbreak. However there was a long interval between the driving experiment and the subjective experiment, and the 12 drivers were sufficiently random and representative of the overall truck driver sample space. Therefore, the potential effect of recruiting the same subjects was controlled. We focused on the evaluation of the subjective perceptions of drivers with regard to the relative distance and driving safety. It has been observed that a more conservative driving style would yield a longer relative distance to the surrounding vehicles and the perception of a higher safety level by the drivers [32]. This is in accordance with our observations.

The statistical analysis of the evaluation results indicated that the different lane-change decision-making styles could be distinguished by the drivers. Given that drivers prefer to adjust the level or type of automation in different scenarios [23], it is likely that drivers would select a driving style that is appropriate to the driving scenario as long as the three decision-making styles can be distinguished. For example, experienced drivers tend to drive in a relatively aggressive manner [4]. Even for beginner drivers, a more aggressive driving style could be preferred when he/she is in a hurry. From the results shown in Figure 10 (a), there was a tendency for participants to perceive a higher level of safety for the automated lane-change...
with the conservative model than with the aggressive model. This indicates that a few drivers would have to achieve a trade-off between safety perception and lane-change efficiency by selection an appropriate model while using such a system.

As a human-like automated driving system helps drivers feel more involved in automated driving and accept the system, the perception of safety and involvement of the driver, or the so-called sense of agency, has been measured to evaluate automated driving systems [20]. A similar evaluation of the driver’s acceptance of the systems will be addressed in our follow-up study. Another extension of our study could be to conduct physiological measurements (heart rate, eye movement, EEG, etc.) [42], [43] to objectively evaluate a driver’s perception of the automated driving system.

In this stage of our work, the focus was on the distances between ego vehicles and surrounding vehicles when lane-change decisions are made, rather than the relative velocities. Relatively static scenarios were designed for our experiments to prevent the participants from being distracted by the likely effects of changing velocities. However, in most realistic driving scenarios, the rear vehicles in the target lane generally decelerate when their drivers realize the intentions of the lane-changing vehicle. In many cases, the speeds of the surrounding vehicles differ marginally from each other and even vary. This complicates the lane-change scenarios. Therefore, future work of our study would also consider the variations in speeds and even accelerations.

According to the collected driving data, drivers had similar mean lateral accelerations during lane changes. This may be because all the drivers were sufficiently trained to achieve rapid and smooth lane-changes in most cases. Therefore, we designed different types of models with identical lateral accelerations to eliminate the likely influence of different lateral accelerations on drivers’ evaluation of the distances. The acceleration and movement during lane changes were not investigated because these were nearly identical in all the trials.

C. SYSTEM EVALUATION FROM THE PERSPECTIVE OF SURROUNDING VEHICLE

In addition to the system evaluation from the perspective of an automated vehicle, this study evaluated the system from the perspective of a surrounding vehicle. This is one of the first investigations from this perspective. Although no significant difference in subjective evaluation was observed among different lane-change decision-making styles as shown in Table 4 (which is not in accordance with our hypothesis), this study provides certain guidelines for future studies.

The driver was placed in the vehicle of the target lane behind the automated vehicle. This was because an unsatisfactory lane-change normally causes the driver to feel frustrated and could cause a frontal crash [44]. It was anticipated that the participants could distinguish the distance from the automated vehicle when different lane-change decision-making styles were implemented. However, as shown in Table 4, the participants perceived that the distance was in line with their expectations or marginally longer. This indicates that the automated lane-change involved low risk. With regard to the results for reliability, as shown in Figure 11, the participants generally perceived the automated lane-change system to be reliable. In addition, the three lane-change decision-making styles yielded a similar level of reliability, which is in accordance with the results of the self-evaluation of the relative distance.

According to the results from the perspective of the automated vehicle (as shown in Table 3), there was no significant difference among the three lane-change decision-making styles with regard to the distance to the rear vehicle in the target lane. This is in accordance with the result from the perspective of the surrounding vehicle. A possible explanation for this could be that the current lane-change scenario was relatively simple because the driving speeds of the surrounding vehicles were constant. Thus, when the participants perceived the automated system to be reliable, their attention on the relative distance between the automated vehicle and rear vehicle was reduced. In future work, a more complex lane-change scenario with variation in driving speed would be designed.

VI. CONCLUSION

A truck driving simulator experiment with 12 participants was conducted to analyze and model truck driver behavior. Based on this, an automated lane-change system with different lane-change decision-making styles (aggressive, medium, and conservative) was designed. Another truck driving simulator experiment with the same 12 participants was conducted to evaluate the proposed automated driving system in terms of driver experience and acceptance.

The evaluation results indicate that the different lane-change styles could be distinguished by the drivers from the perspective of the automated vehicle, whereas the three styles were evaluated as being safe and reliable by the drivers from the perspectives of both the automated vehicle and surrounding vehicles. The main contribution of this study is that it provides insights into the design of an automated driving system with different driving styles. Furthermore, these observations can be applied to commercial automated trucks.

A limitation of the experiment is that only a subjective evaluation of the designed system was conducted in the current study. Future studies would address this limitation by including an objective evaluation.

ACKNOWLEDGMENT

This article solely reflects its authors’ opinions and conclusions and not Hino Motors.
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