Assistance Method for Merging by Increasing Clarity of Decision Making

Yuki Suehiro, Takahiro Wada, *Member, IEEE*, and Kohei Sonoda

***Abstract*—Merging into the flow of high-speed traffic on roadways, such as expressways, is a demanding driving task for non-expert drivers. The difficulty of merging is thought to arise from the difficulty of judging the location where the drivers should merge. In this paper, we propose a mathematical model of driver decision-making that can predict the location where the driver will merge. In addition, we demonstrate that the entropy of the judgment introduced based on the proposed model has the ability to describe the differences in skills of judgment in merging position as well as the difficulty of decision-making in a given situation. Furthermore, we propose a driver assistance method to decrease the difficulty of decision-making with respect to the merging position during the preparation phase based on the proposed decision-making model when the difficulty is judged as being higher than a given threshold. The proposed method recommends acceleration or deceleration to increase the clarity of judgment. Driving simulator experiments demonstrate that the proposed method reduces the difficulty of decision-making for merging and increases the ease of judgment at the early stages of merging preparation. In addition, the proposed method decreases mental demand without leading to an increase in the overall workload, that is, the weighted workload of NASA-TLX.**

***Index Terms*—Merging operations, decision making, driver assistance system, expressways.**

I. Introduction

Merging into the flow of high-speed traffic on roadways, such as expressways, is one of the most demanding driving tasks for novice drivers [1], [2]. There are drivers who experience difficulty in merging into expressways [2]. Studies report that the merging behavior includes continuous and parallel execution of cognition, decision-making, and operation [3], [4], and thus, some level of driving experience and skill is required to achieve safe and smooth merging. Therefore, an understanding of the tasks that need to be performed by drivers during the merging operation to identify the difficulty in merging and its countermeasures, is desired for drivers.

Previous studies have investigated driver behaviors in the merging operation including investigation of the difference in driving velocities across different age groups when merging into expressways [1]. There are many researchers building mathematical models of driver behaviors during merging operations that provide a deeper understanding. One among these is a driver decision making model that describes the relationship between the position or gap where a driver merges and the traffic situation of the main lanes as well as the status of the vehicle that the driver drives [4]–[7]. Most of the studies use regression models that model the merging gap as the explanatory variable and its relative relationship to the vehicles driving on the main lane such as relative positions and velocities. These analyses showed that the models successfully predicted the driver's behavior with some accuracy. Furthermore, based on the idea that continuous judgment and operation is one of the causes of the difficulty of merging, a method of quantifying the difficulty of merging was proposed based on a merging position judging model of the driver by [4], [6]. The above-mentioned studies are successful in describing the effect of driving experience on subjective difficulty in merging. Research has also been conducted on modeling decision making and control methods for merging based on automated driving [8]–[10]. In these, the focus is on the feasibility of automated merging rather than predicting the behavior of the driver. Furthermore, a mathematical model of the behavior of drivers of vehicles traveling on the main line has been derived [11]. As a driver-assistance method for merging, de Waard *et al.* [1] encouraged acceleration based on verbal advisory messages about velocity on the merging lane when the driver travels slowly, and demonstrated the effectiveness of this approach for elderly drivers.

Many advanced driver assistance systems (ADASs) such as adaptive cruise control, lane-keeping assist systems, and advanced emergency brake systems, have been developed to aim to reduce drivers' workloads and increase safety. Changes in drivers' behavior with the introduction of ADASs has been reported in [12]–[14]. In addition, studies have noted that the maintenance and growth of driving skills could be negatively impacted by the use of sophisticated ADASs [15]. Driving assistance, only when the drivers experience a difficulty in a given traffic situation, is thought to prevent the degradation of driving skills. Thus, it is necessary to identify the situation at which a driver's judgment is unclear and develop a driving assistance system to reduce the driver's workload.

Manuscript received December 25, 2017; revised April 26, 2018; accepted July 13, 2018. Date of publication December 13, 2018; date of current version February 22, 2019. *(Corresponding author: Yuki Suehiro.)*

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Digital Object Identifier 10.1109/TIV.2018.2886692

Fig. 1. The driving simulator.

Therefore, in the present study, the primary goal was to develop a mathematical model of driver decision making to predict the location where the driver merges and to quantify the difficulty of decision-making for given traffic situations. The second purpose was to propose a driver assistance system that helps decrease the difficulty of decision-making with respect to the merging position during the preparation phase based on the proposed mathematical model when the difficulty is judged as being higher than a given threshold. The proposed method recommends acceleration or deceleration to increase the clarity of judgment only when the driver experiences difficulty. The effectiveness of the proposed method was evaluated by performing driving simulator experiments.

The remainder of the paper is organized as follows. Section II describes simulator experiments to measure the driver's merging behaviors. In Section III, a mathematical model of drivers' decision-making is proposed that models where he/she merges and introduces a method to quantify the difficulty of decision-making. In Section IV, a driver assistance method is proposed to assist driver's decision-making about the merging operation. In Section V, the effectiveness of the proposed driver assistance method is investigated by performing driving simulator experiments. Preliminary versions of this paper were presented in [18] as conference proceedings where the fundamental idea and partial results were reported. In this paper, we have described additional analysis related to workload and obtained useful results to evaluate the proposed system and develop future assistance system.

II. Experiment 1: Investigation of Merging Behavior

A. Experimental Setup

Experiments were conducted to gather data on the merging behaviors of drivers by using the fixed-base driving simulator (DS) shown in Fig. 1. The DS comprises a steering wheel, accelerator, brake, rear-view mirror, and five 40-inch LCDs that display the driving environment to the participants. Three displays were placed on the right hand side of the drivers because it was assumed that merging into the main lanes was performed. Drivers could view the driving environment on the rear monitor via a rear-view mirror. The vehicle dynamics were calculated by using CarSim software (Mechanical Simulator Corp.) and were updated at 1000 Hz. Unity3D software (Unity Technologies Inc.) was used to generate driving situations.

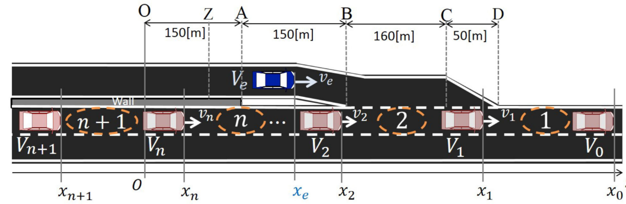


Fig. 2. The assumed merging environment.

B. Scenario

Fig. 2 shows the merging environment assumed on the expressways. The x-coordinate includes six points that are labeled as points O, Z, A, B, C, and D in Fig. 2. The ego vehicle V_e starts driving from point O ($x = 0$). The position of the ego vehicle is represented by x_e, and its velocity is expressed as v_e. Other vehicles $V_i (i = 1, 2, \ldots, n)$ exist on the main lane with x-coordinate position and velocity represented by x_i and v_i, respectively. Additionally, other vehicles V_0, 70 [m] ahead of V_1, and V_{n+1}, 70 [m] behind V_n, are located as shown in Fig. 2. In this study, $n = 6$ was used. The driver of the ego vehicle could recognize the other vehicles after passing point A, could merge after passing point B, and must merge the ego vehicle before passing point D. The relative distance and relative velocity of the ego vehicle and another vehicle V_i are denoted as eqs. (1) and (2), respectively.

$$\Delta x_{ei} := x_e - x_i \tag{1}$$

$$\Delta v_{ei} := v_e - v_i \tag{2}$$

The space between V_{i-1} and V_i is termed as the gap $i (i \in 1, 2, \ldots, n+1)$. The drivers definitely merge into one of gaps after the ego vehicle passes point B. In the study, the gap that is finally merged into by the driver is referred to as the merged gap.

C. Participants

Thirty male subjects with a driver's license who provided informed consent participated in the experiment. The ages of the participants ranged from 20 to 24 years (average = 21.9, SD = 1.16). The average driving experience of the participants was 2.5 years (SD = 1.2), and the mean driving frequency was 84.5 times annually (SD = 108.5). The participants were labeled P1 to P30 in ascending order of annual driving frequency. Participants were classified according to the annual driving frequency into the following groups: low-frequency group, which include P1-P15, and high-frequency group, which include P16-P30. The median (Inter Quartile Range) of the annual driving frequency for the low- and high-frequency groups were 2.0 (0.5, 8.0) and 156.0 (82.0, 234.0), respectively. Furthermore, the participants were provided with a pre-paid card to purchase books of value equivalent to 1000 yen as compensation.

D. Procedure

First, the participants were asked to provide personal information such as driving history and annual driving frequency. Subsequently, the participants were instructed to merge into the main lane as usual. Instructions on steering, acceleration, and braking behaviors were not provided. However, the following instructions were given to the participants.

- The participants were required to adjust the velocity of the ego vehicle to 80 [km/h] while passing point Z but no restriction was placed on the velocity after passing point Z.
- The participants were instructed to merge into the main line only after passing point B.

The participants drove for 20 trials, which corresponded to half of the experiment. This was followed by a small break of 10 min, and subsequently the remaining 20 trials were performed. All participants drove for the same number of trials in the same order. After every five trials, a participant was asked to respond to a questionnaire with respect to where the participant decided to merge. The questionnaire comprised eight questions. The result of the questionnaire is out of the scope of this study, and thus the details are omitted.

Additionally, the participants practiced on the DS for a period of time prior to commencing the experiment to get accustomed to using the DS. To generate varied situations of merging, the initial velocity of vehicle V_i $(i = 1, 2, \dots, n)$ at $x_e = 100$ was determined using eq. (3).

$$v_i = \alpha + \sum_{j=2}^{i=n} \Delta v_j, \tag{3}$$

where α is a scalar randomly selected from [70, 90] [km/h]. Scalar Δv_i is determined by random selection from $[-3, 3]$ [km/h]. The range of each of the vehicles V_{i-1} and V_i $(i = 2, \cdots, n)$ is determined by random selection from [20, 70] [m].

III. Classification of Merging Behaviors Using Logistic Regression Models

A. Driver's Decision-Making Model

The data vector related to the gap i at the vehicle position x_e is defined by eq. (4).

$$\boldsymbol{z}_i := [\ \Delta x_{ei-1},\ \Delta v_{ei-1},\ \Delta x_{ei},\ \Delta v_{ei},\ 1\ ]^{\mathrm{T}} \tag{4}$$

Vector $\boldsymbol{z}(x_e)$ is defined as $\boldsymbol{z} := [\boldsymbol{z}_1^{\mathrm{T}}, \boldsymbol{z}_2^{\mathrm{T}}, \dots, \boldsymbol{z}_n^{\mathrm{T}}]^{\mathrm{T}}$. A regression model that quantifies the probability of merging to gap i when the ego vehicle is located at x_e is defined using the observed data as follows.

$$p^{x_e}(\boldsymbol{z}_i) := (1 - {}^{F}p^{x_e}(\boldsymbol{z}_i))(1 - {}^{B}p^{x_e}(\boldsymbol{z}_i)), \tag{5}$$

where ${}^{F}p^{x_e}$ and ${}^{B}p^{x_e}$ denote the probabilities of merging into gap j when $j < i$ and $j > i$, respectively. The logistic regression models are given by eqs. (6) and (7).

$${}^{F}p^{x_e}(\boldsymbol{z}_i) = \frac{1}{1 + \exp(-({}^{F}\boldsymbol{a}^{x_e})^{\mathrm{T}}\boldsymbol{z}_i)} \tag{6}$$

$${}^{B}p^{x_e}(\boldsymbol{z}_i) = \frac{1}{1 + \exp(-({}^{B}\boldsymbol{a}^{x_e})^{\mathrm{T}}\boldsymbol{z}_i)} \tag{7}$$

Here, ${}^{F}\boldsymbol{a}^{x_e}$, ${}^{B}\boldsymbol{a}^{x_e}$ denote the regression coefficients. Note that a regression model was developed for each driver in this study.

B. Predicted Merging Gap

A merging gap was predicted by eq. (8) with a given data vector $\boldsymbol{z}_i$ $(i = 1, \dots, n+1)$.

$$\hat{i}_E(x_e) = \operatorname*{argmax}_j p^{x_e}(\boldsymbol{z}_j) \tag{8}$$

The predicted merging probability is expressed as $p^{x_e}_{\hat{i}_E(x_e)}(\boldsymbol{z}_{\hat{i}_E(x_e)})$ or $p^{x_e}_{\hat{i}_E(x_e)}$ for simplicity.

C. Prediction Accuracy

The accuracy of the predicted merging gap $\hat{i}^k_E(x_e)$ that was calculated from the predicted result in each trial k is defined as in eq. (9).

$$H_r(x_e) = \frac{1}{N}\sum_{k=1}^{N} \delta(\hat{i}^k_E(x_e), i^k_E) \tag{9}$$

$$\delta(a, b) := \begin{cases} 1 & (a = b) \\ 0 & (a \neq b), \end{cases} \tag{10}$$

where i^k_E denotes the gap at which the participant merges into a given experimental trial k.

With respect to all 40 trials, K-fold cross-validation was conducted to obtain the prediction accuracy. Additionally, $K = 10$ was selected in the study. Fig. 3 shows the transition in the prediction accuracy of all participants. The prediction accuracy increased with increase in the position of the ego vehicle. Furthermore, the prediction accuracy of the high-frequency increased faster than that of the low-frequency.

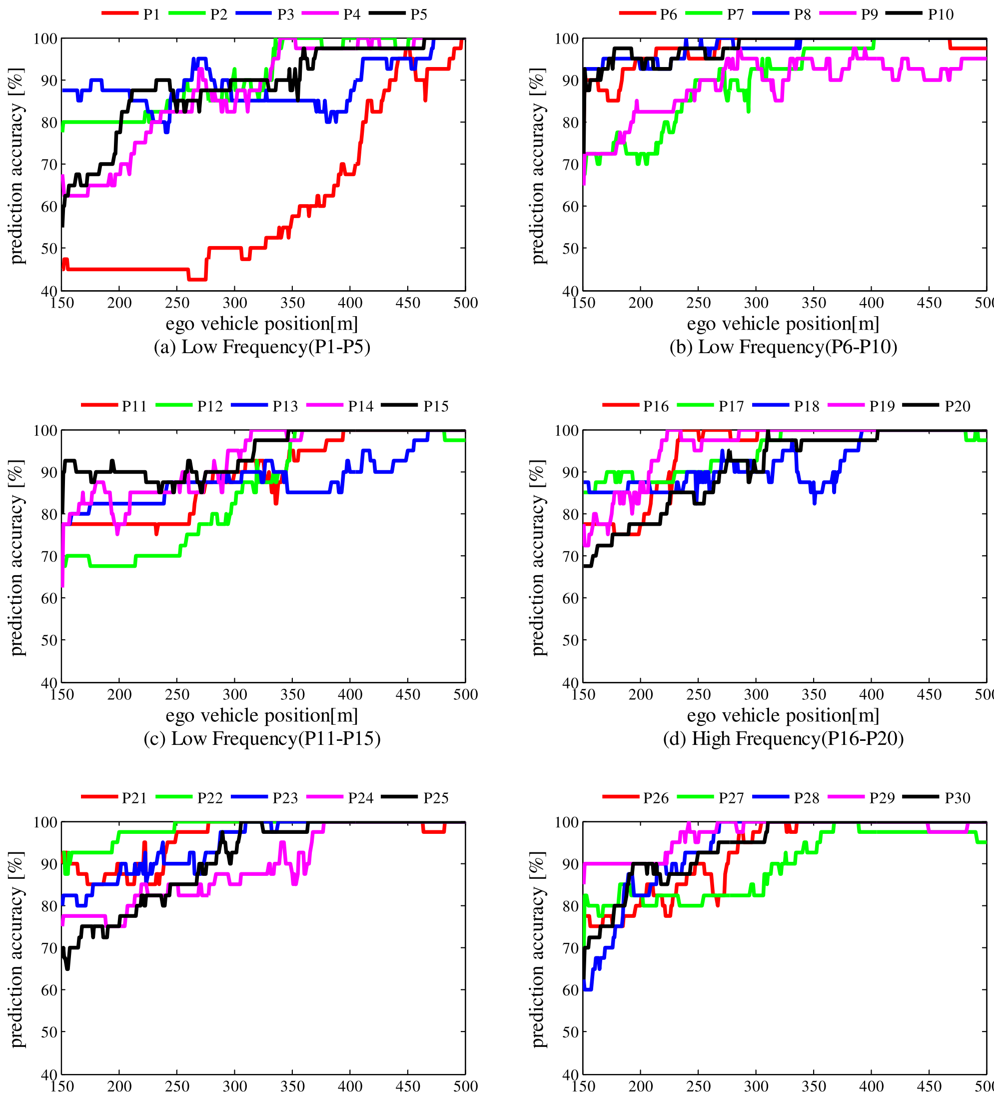
D. Judgment Entropy

The clarity or difficulty of judgment is determined by the judgment entropy [19], [20] because the predicted merging probability of the predicted merging gap is given by the model (eq. (5)). The judgment entropy $h(x_e)$ corresponding to the ego vehicle position is defined by eq. (11).

$$\begin{aligned} h(x_e) := -\int_{D_H} & p^{x_e}(\boldsymbol{z}) \log p^{x_e}(\boldsymbol{z}) \\ & + (1 - p^{x_e}(\boldsymbol{z})) \log(1 - p^{x_e}(\boldsymbol{z})) d\boldsymbol{z}, \end{aligned} \tag{11}$$

where $D_H := \{\ \boldsymbol{z} | \Delta x_{ei-1} \in [-10, 0], \Delta v_{ei-1} \in [-3, 3], \Delta x_{ei} \in [10, 20], \Delta v_{ei} \in [-3, 3]\ \}$.

Furthermore, integration of the judgment entropy from the ego vehicle position of x_e from a to b as defined by eq. (12) is



(a) Low Frequency(P1-P5)
(b) Low Frequency(P6-P10)
(c) Low Frequency(P11-P15)
(d) High Frequency(P16-P20)
(e) High Frequency(P21-P25)
(f) High Frequency(P26-P30)

Fig. 3. Prediction accuracy of all the participants.

called the integral judgment entropy H.

$$H := \int_a^b h(x_e)dx_e \tag{12}$$

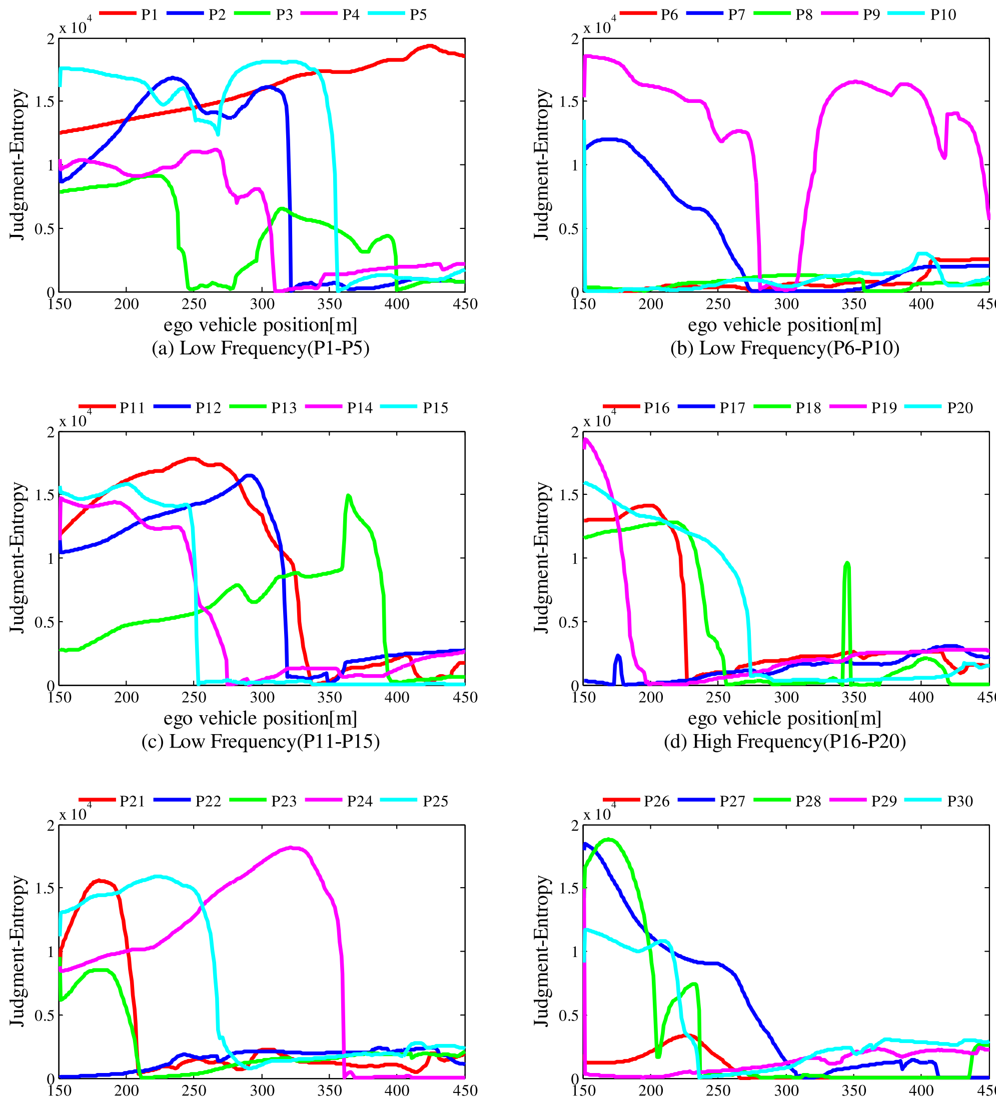
In this analysis, $a = 151$ and $b = 450$ were used. The larger values in judgment entropy $h(x_e)$ and integral judgment entropy H indicate that the driver's judgment is unclear during the merging operation.

Fig. 4 shows the transitions of the judgment entropy $h(x_e)$ of all participants. The judgment entropy decreased with increase in the position of the ego vehicle. Furthermore, the judgment entropy of the high-frequency decreased faster than that of the low-frequency. The average of the judgment entropy at $x_e = 250$ and $x_e = 300$ is shown in Fig. 5; here, the error bars represent the standard deviation. An independent t-test revealed that the judgment entropy of low-frequency was significantly larger than that of high-frequency at $x_e = 250$ and $x_e = 300$ ($p = 0.026,\ 0.044$). The average of the integral judgment is shown in Fig. 6, where the error bars indicate the standard deviation. An independent t-test revealed that the integral judgment entropy of the low-frequency was significantly greater than that of the high-frequency ($p = 0.046$).

These results strongly suggest that the judgment entropy at each ego vehicle position and integral entropy can describe the difference in judgment clarity according to the driving frequency.

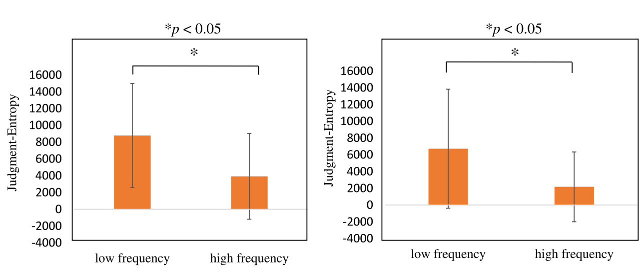
E. Discussion

The results of the prediction accuracy evaluation in Experiment 1, in which the prediction accuracy increases when approaching the merging area to reach a high of 91.7% (SD = 9.76%) at Point B ($x_e = 300$) and 98.8% (SD = 2.69%) at point C ($x_e = 460$), strongly demonstrates the validity of the proposed model in evaluating drivers' decision-making. In ad-



(a) Low Frequency(P1-P5)
(b) Low Frequency(P6-P10)
(c) Low Frequency(P11-P15)
(d) High Frequency(P16-P20)
(e) High Frequency(P21-P25)
(f) High Frequency(P26-P30)

Fig. 4. Judgment-entropy of all participants.



(a) $x_e = 250$ (b) $x_e = 300$

Fig. 5. Judgment entropy at $x_e = 250$ and $x_e = 300$.

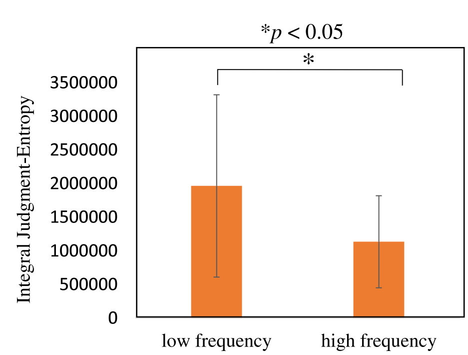


Fig. 6. Integral judgment-entropy.

dition, the fact that the judgment entropy derived from the proposed model of the high-frequency was significantly smaller than that at low-frequency for both $x_e = 250$ and $x_e = 300$ strongly suggests that the index has the ability to describe the difference in skills related to the merging position decision-making. Moreover, the integral judgment entropy, which is the integral of the judgment entropy for the ego vehicle position, showed a similar tendency, which strongly supports this conclusion. These results imply that the merging probability predicted by the model could reflect the difficulty/easiness of

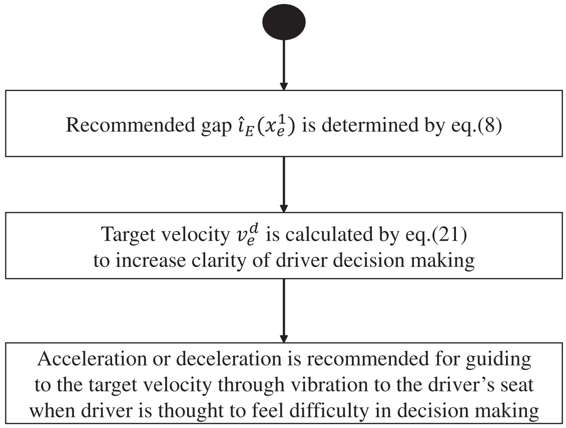


Fig. 7. Flow of determination of the assist mode.

merging under a given condition, i.e., a p-value close to 0.5 could represent difficulties in decision-making. Previous studies have proposed regression models for the merging decision-making [5]–[7]; however, none of these deal with the quantification of skills associated with decision-making in the merging operation. Thus, a major contribution of this paper is the first demonstration of the possibility of quantification of the skills associated with the decision-making of merging using judgment entropy. Notice that the judgment entropy used in this paper was originally introduced to describe the vagueness of the judgment on right-turn in left side traffic [19] and braking [20]. Ours is the first study to apply the judgment entropy to the merging operation.

IV. Assistance Method

A. Overview

We propose a driver assistance method that indirectly supports driver decision-making by tactilely presenting the target velocity to the driver. This provides guidance in a situation in which it is not easy to form a decision, and when a driver is thought to experience difficulties in merging. The details are provided in Section IV-C. As illustrated in Fig. 7, a target gap to be recommended is determined at position x_e^1; then, the target velocity of the ego-vehicle that increases clarity of decision-making is determined. Finally, driver assistance is provided by recommending a driving velocity by displaying the target velocity through seat vibration to the driver. The details are provided in Section IV-D.

B. Target Velocity Determination Method

First, the recommended gap $\hat{i}_E(x_e^1)$ at an ego vehicle position $x_e = x_e^1$ is determined by using eq. (8). In the rest of this paper, $\hat{i}_E(x_e^1)$ is abbreviated to $\hat{i}_E$ for simplicity as long as no confusion occurs.

Then, the predicted vector $\hat{\boldsymbol{z}}_{\hat{i}_E}(\hat{v}_e(x_e^2))$, which represents the state of the vehicles at the gap $\hat{i}_E$ at the ego vehicle position $x_e = x_e^2 (x_e^2 > x_e^1)$, is defined by eq. (13) as the function of $\hat{v}_e(x_e^2)$.

$$\hat{\boldsymbol{z}}_{\hat{i}_E}(\hat{v}_e(x_e^2)) := [\Delta\hat{x}_{ei-1}(x_e^2),\ \Delta\hat{v}_{ei-1}(x_e^2),\ \Delta\hat{x}_{ei}(x_e^2),\ \Delta\hat{v}_{ei}(x_e^2),\ 1]^{\mathrm{T}}, \tag{13}$$

where $\hat{v}_e(x_e^2)$ is an estimate of the ego vehicle velocity at x_e^2, defined later as the target velocity v_e^d. The scalar $\Delta\hat{v}_{ei}(x_e^2)$ is defined by eq. (14).

$$\Delta\hat{v}_{ei-1}(x_e^2) := \hat{v}_e(x_e^2) - \hat{v}_{i-1}(x_e^2) \tag{14}$$

Assuming that $\hat{v}_i(x_e) = v_i(x_e^1), \forall x_e \in [x_e^1,\ x_e^2]$, eqs. (15) and (16) hold.

$$\hat{x}_{i-1}(x_e^2) := x_{i-1}(x_e^1) + \hat{v}_{i-1}(x_e^2)T \tag{15}$$

$$\hat{x}_i(x_e^2) := x_i(x_e^1) + \hat{v}_i(x_e^2)T \tag{16}$$

T is the time taken by the ego vehicle V_e from x_e^1 to x_e^2. T is determined by eq. (17).

$$T = \frac{2}{v_e(x_e^1) + \hat{v}_e(x_e^2)}(x_e^2 - x_e^1) \tag{17}$$

Next, $\hat{p}_{\hat{i}_E}^{x_e}(\hat{v}_e(x_e^2))$, which denotes the predicted probability to merge into the recommended gap $\hat{i}_E$, is defined by eq. (18).

$$\hat{p}_{\hat{i}_E}^{x_e^2}(\hat{v}_e(x_e^2)) := \left(1 - {}^F\hat{p}_{\hat{i}_E}^{x_e^2}\right)\left(1 - {}^B\hat{p}_{\hat{i}_E}^{x_e^2}\right), \tag{18}$$

where $\hat{p}_{\hat{i}_E}^F$ and $\hat{p}_{\hat{i}_E}^B$ denote the probabilities of merging into gap j, which satisfy $j < \hat{i}_E$ and $j > \hat{i}_E$, respectively, as follows.

$${}^F\hat{p}_{\hat{i}_E}^{x_e^2} = \frac{1}{1 + \exp(-({}^F\boldsymbol{a}^{x_e^2})^{\mathrm{T}}\hat{\boldsymbol{z}}_{\hat{i}_E}(\hat{v}_e(x_e^2)))} \tag{19}$$

$${}^B\hat{p}_{\hat{i}_E}^{x_e^2} = \frac{1}{1 + \exp(-({}^B\boldsymbol{a}^{x_e^2})^{\mathrm{T}}\hat{\boldsymbol{z}}_{\hat{i}_E}(\hat{v}_e(x_e^2)))} \tag{20}$$

Finally, the target velocity at x_e^2 is determined by eq. (21).

$$v_e^d = \mathrm{med}\left\{\mathop{\arg\max}_{\hat{v}_e(x_e^2)\in[40,160]} \hat{p}_{\hat{i}_E}^{x_e^2}(\hat{v}_e(x_e^2))\right\}, \tag{21}$$

where $\mathrm{med}(\cdot)$ denotes the median of the given data set. We assume that clarity of the driver's decision making is high when $\hat{p}_{\hat{i}_E}^{x_e^2}(\hat{v}_e(x_e^2))$ is close to 1 or 0, while the clarity is low when $\hat{p}_{\hat{i}_E}^{x_e^2}(\hat{v}_e(x_e^2))$ is close to "0.5". Eq. (21) is derived to calculate the ego vehicle velocity that causes $\hat{p}_{\hat{i}_E}^{x_e^2}(\hat{v}_e(x_e^2))$ to increase toward 1.

C. Determination of Assist Mode

The driver assistance commences from the ego vehicle position $x_e = x_e^1 = 160$ and ends at point B ($x_e = x_e^2 = 300$).

The state of the driver assistance system is determined from the relationship between the ego vehicle velocity v_e and target velocity v_e^d.

a) No velocity recommendation

The driver assistance system does not recommend either acceleration or deceleration, and implies that it is optimal to maintain the current velocity when eq. (22) is satisfied.

$$-2 < v_e^d - v_e < 2 \tag{22}$$

b) Recommendation of Acceleration
The driver assistance system recommends that a driver should accelerate when eq. (23) is satisfied.

$$v_e^d - v_e \geq 2 \tag{23}$$

c) Recommendation of Deceleration
The driver assistance system recommends that a driver should decelerate when eq. (24) is satisfied.

$$v_e^d - v_e \leq -2 \tag{24}$$

Please note that eqs. (22), (23), and (24) were determined by trial and error.

D. Presentation Method

The target velocity is displayed to the driver through the vibration of the vibrators that are embedded in the seat. There are two vibrators in front and two vibrators located at the shoulder, which can be controlled independently. The front and rear vibrators are vibrated in case of acceleration and deceleration, respectively. In our study, the amplitude of the vibrations was varied in three stages based on the error between the target velocity and current ego vehicle velocity. This is given as follows.

$$A := \begin{cases} 0 & |v_e - v_e^d| < 2 \\ A_0 & 2 \leq |v_e - v_e^d| \leq 10 \\ 10A_0 & |v_e - v_e^d| > 10 \end{cases}, \tag{25}$$

where A_0 is determined by trial-and-error.

V. Experiment 2: Evaluation of Driver Assistance Method

A. Purpose

Experiment 2 was performed to confirm the effectiveness of the proposed assist method. The proposed driver assistance system was implemented in the same DS that was used in experiment 1. Driver's behaviors with and without proposed system were compared to investigate the effectiveness.

B. Experimental Condition

There are two experimental factors: a two-level system condition as a between-subject factor and a two-level experimental phase condition as a within-subject factor. The two levels of system condition were without-assist and with-assist. In without-assist condition, participants merged into an expressway without any assistance while, in the with-assist condition, the proposed assistance method was used. Each group of participants experienced phase 1 that comprised 15 trials without the system. In phase 2, the participants in the without-assist condition experienced 15 trials without any assistance from the system while those in the with-assist condition experienced trials with the assistance. In phase 3, participants in both conditions experienced 15 trials without any assistance (Table I). Phase 3 was set to evaluate the after-effect of the assistance, which is another research theme. Therefore, we only analyzed phase 1 and phase 2 in this study.

TABLE I
Experimental Conditions

		Participants	
Phase	Trial	Without-assist	With-assist
phase1	1-15	No Assistance	No Assistance
phase2	16-30	No Assistance	Assistance
phase3	31-45	No Assistance	No Assistance

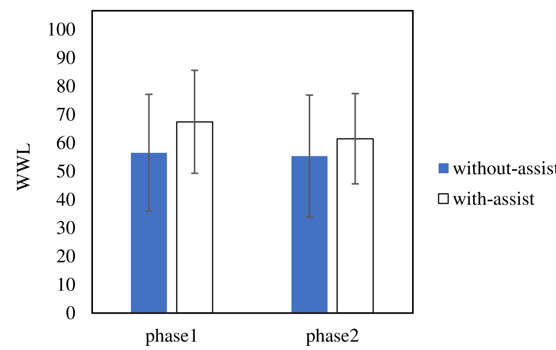


Fig. 8. WWL.

C. Participants

Twenty-four males with driver's license who provided informed consent participated in the experiment. The participant ages ranged from 21 to 24 years (average = 22.2, SD = 0.94). The average driving history of the participants was 3.0 years (SD = 1.0), and the mean driving frequency was 67.6 times annually (SD = 93.3). Additionally, the participants received pre-paid cards to purchase books of value equivalent to 1000 yen as compensation.

D. Procedure

Each participant participated in the experiment as shown in Table I. The with-assist group was provided with an explanation of the functioning of the driver assistance system prior to commencing phase 1, and the participants drove on the expressway with assistance several times to get accustomed to the system. The instructions for the participants were same as those in the merging behavior measurement experiment. The following guidelines were provided additionally to participants in the with-assist group.

- Vibration of the front and rear vibrators recommend that the driver should accelerate or decelerate, respectively. If the driver controls the ego vehicle velocity in a proper manner, then he/she can easily form a decision.
- There are three levels of vibrations generated. The driver assistance system recommends accelerating/decelerating more strongly if the vibrations are stronger. In the absence of vibrations, it is recommended that the current velocity should be maintained.

TABLE II
TWO-WAY ANOVA

	Assist		Phase		Interaction	
	F value	p value	F value	p value	F value	p value
WWL	$F(1,22) = 1.394$	0.250	$F(1,22) = 1.350$	0.258	$F(1,22) = 0.610$	0.443
MD	$F(1,22) = 0.008$	0.930	$F(1,22) = 10.020$	0.004^{**}	$F(1,22) = 12.870$	0.002^{**}
PD	$F(1,22) = 1.171$	0.291	$F(1,22) = 11.696$	0.002^{**}	$F(1,22) = 3.184$	$0.088^{\dagger}$
TD	$F(1,22) = 0.841$	0.369	$F(1,22) = 2.625$	0.119	$F(1,22) = 0.004$	0.953
OP	$F(1,22) = 0.815$	0.376	$F(1,22) = 4.517$	0.045^{*}	$F(1,22) = 2.214$	0.151
FR	$F(1,22) = 0.562$	0.462	$F(1,22) = 0.258$	0.616	$F(1,22) = 1.953$	0.176
EF	$F(1,22) = 0.053$	0.820	$F(1,22) = 0.388$	0.540	$F(1,22) = 1.383$	0.252
$p_{\hat{i}_E}^{250}$	$F(1,22) = 12.355$	0.002^{**}	$F(1,22) = 20.126$	0.000^{**}	$F(1,22) = 24.674$	0.000^{**}
$p_{\hat{i}_E}^{300}$	$F(1,22) = 18.881$	0.000^{**}	$F(1,22) = 82.389$	0.000^{**}	$F(1,22) = 66.442$	0.000^{**}
$h(250)$	$F(1,22) = 3.571$	$0.072^{\dagger}$	$F(1,22) = 0.068$	0.796	$F(1,22) = 3.919$	$0.060^{\dagger}$
$h(300)$	$F(1,22) = 5.849$	0.024^{*}	$F(1,22) = 0.380$	0.544	$F(1,22) = 4.242$	0.003^{**}

$^{**}: p < 0.01, ^{*}: p < 0.05, ^{\dagger}: p < 0.1$

- It is not mandatory to follow the recommendations of the driver assistance system.

The with-assist group was not informed that the driver's decision-making model used for the driver assistance system was a model for each individual.

After each of three phases, the subjective workload was assessed using the Japanese-language version of the NASA task load index (NASA-TLX) [21], [22] in which the weighted workload (WWL) was calculated as the weighted average of six subjective subscales: mental demand, physical demand, temporal demand, performance, frustration, and effort.

To generate a variety of situations involving merging, the behaviors of other vehicles were determined by a method similar to that used in experiment 1. α in eq. (3) was selected from $[\,85, 90\,]$[km/h]. The range of each of the vehicles V_{i-1} and $V_i\ (i = 2, \ldots, n)$ was determined by random selection from $[\,20, 30\,]$[m].

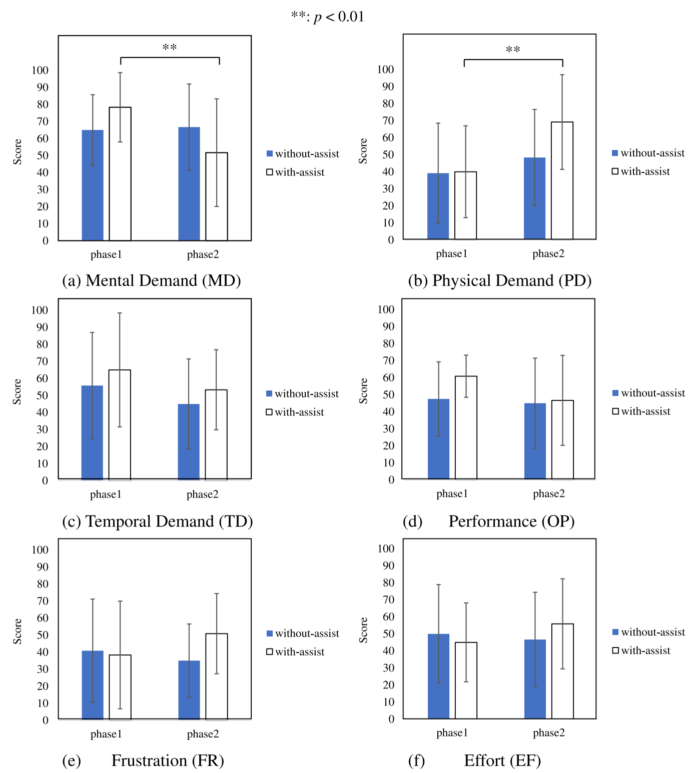
E. Results

1) NASA-TLX: The mean WWL of NASA-TLX for each phase is shown in Fig. 8; here, the error bars represent the standard deviation. The two-way ANOVA indicated that there were no significant main effects of phase and system conditions and their interactions (Table II).

Fig. 9 shows the average value of the score for each subscale of NASA-TLX in each phase. The two-way ANOVA for mental demand (MD) indicated that the main effect of phase condition and interaction were significant (Table II). The paired t-test for the with-assist condition showed that MD in phase 2 was significantly larger than that in phase 1 ($p = 0.004$). In contrast, the paired t-test for the without-assist condition indicated that there was no significant difference between phase 1 and phase 2 ($p = 0.586$).

The two-way ANOVA for physical demand (PD) indicated that the main effect of phase condition and interaction were significant (Table II). The paired t-test for the with-assist showed that PD in phase 2 was significantly larger than that in phase 1 ($p = 0.004$). In contrast, the paired t-test for the without-assist condition indicated that there was no significant difference between phase 1 and phase 2 ($p = 0.231$).

The each two-way ANOVA for each of temporal demand (TD), frustration (FR), and effort (EF) indicated that the main effects and their interaction were not significant (Table II).



(a) Mental Demand (MD) (b) Physical Demand (PD)
(c) Temporal Demand (TD) (d) Performance (OP)
(e) Frustration (FR) (f) Effort (EF)

Fig. 9. WWL ratings.

The two-way ANOVA for performance (OP) revealed that the main effect of phase condition was significant (Table II).

2) The predicted merging probability: The predicted merging probability $p_{\hat{i}_E}^{x_e}$ for the predicted merging gap was calculated for $x_e = 250$ and $x_e = 300$ by using the driver's decision-making model obtained in the merging behavior measurement experiment and the data obtained from the driving assistance experiment. The results are shown in Fig. 10. The bar indicates the average value of 15 trials, and the error bars represent the standard deviation.

(a) The predicted merging probability at $x_e = 250$

The two-way ANOVA by phase and system conditions indicated that the main effects of phase and system conditions and their interactions were significant (Table II). A paired t-test was conducted to compare the predicted merging probability (Fig. 10(a)) in phase 1 and phase 2. The results showed a significant difference in the average value of with-assist for

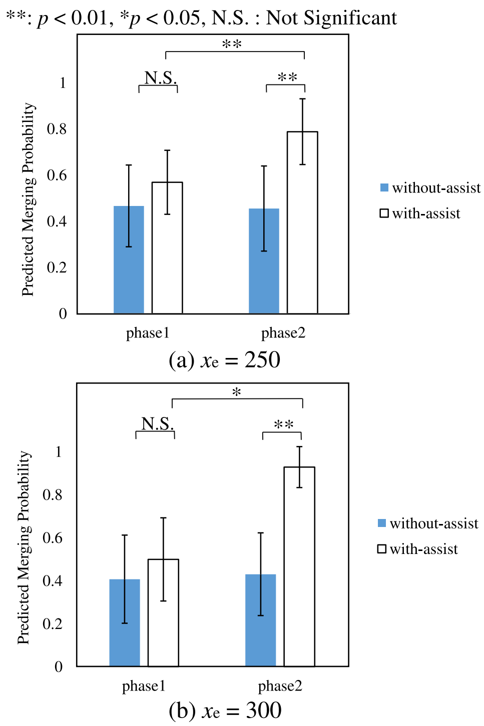


Fig. 10. Predicted merging probability.

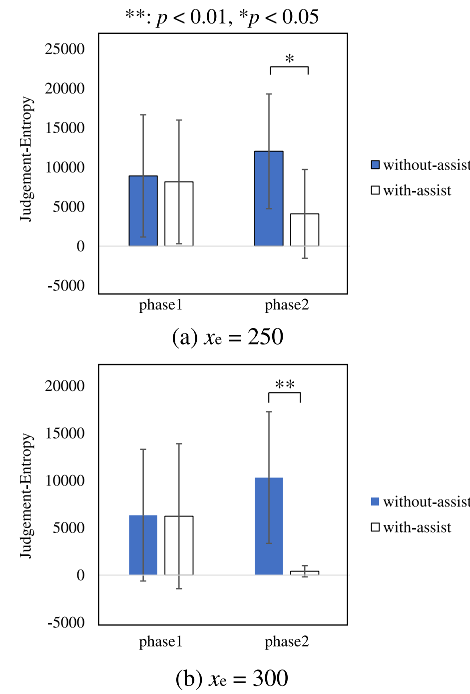


Fig. 11. Judgement-entropy.

phase 1 and phase 2 ($p = 0.000$). The difference in the average value of without-assist for phase 1 and phase 2 was not significant ($p = 0.754$). An independent t-test was conducted to compare the predicted merging probability (Fig. 10(a)) in the with-assist and without-assist cases. The results indicated a significant difference in the average value of phase 2 in with-assist and without-assist ($p = 0.000$).

(b) The predicted merging probability at $x_e = 300$

The two-way ANOVA by phase and system conditions revealed that the main effects of phase and system factors and their interactions were significant (Table II). A paired t-test was conducted to compare the predicted merging probability (Fig. 10(b)) in phase 1 and phase 2. The results indicated a significant difference in the average value of with-assist for phase 1 and phase 2 ($p = 0.011$). There was not a significant difference in the average value of without-assist for phase 1 and phase 2 ($p = 0.420$). An independent t-test was conducted to compare the predicted merging probability (Fig. 10(b)) in the with-assist and without-assist group. The results revealed a significant difference in the average value of phase 2 in the with-assist and without-assist ($p = 0.000$) cases.

3) Judgment Entropy: The judgment entropy $h(x_e)$ was calculated for $x_e = 250$ and $x_e = 300$ in phase 1 and phase 2 as shown in Fig. 11. Here, the bars indicate the average value of the groups, and the error bars represent the standard deviation.

(a) Judgment Entropy at $x_e = 250$

The two-way ANOVA for the judgment-entropy at $x_e = 250$ indicated that the main effect of system condition and interaction were significant (Table II). An independent t-test for phase 1 showed no significant difference of the judgment entropy $h(250)$ in the with-assist and without-assist groups ($p = 0.812$). However, an independent t-test for phase 2 revealed that the judgment entropy $h(250)$ of the with-assist was significantly smaller than that of the without-assist ($p = 0.007$).

(b) Judgment Entropy at $x_e = 300$

The two-way ANOVA of the judgment-entropy at $x_e = 300$ indicated that the main effect of system condition and interaction were significant (Table II). An independent t-test for phase 1 revealed that there was no significant difference of the judgment entropy $h(300)$ between the with-assist and without-assist groups ($p = 0.972$). However, an independent t-test for phase 2 revealed that the judgment entropy $h(300)$ of the with-assist was significantly smaller than that of the without-assist ($p = 0.000$).

F. Discussion

The fact that the predicted merging probability, which was approximately 0.5 in phase 1 and significantly increased to more than 0.8 in phase 2 only with-assist at both $x_e = 250$ and $x_e = 300$, strongly indicates that the proposed assist method successfully encouraged the drivers to control their velocities, thus simplifying the traffic situations such that the difficulty of decision making was thought to be decreased.

The fact that the insignificant difference of the judgment entropy in phase 1 among system conditions becomes significantly smaller in the with-assist condition than in the without-assist condition in the phase 2, implies that the clarity of the participants' judgment was significantly increased by introducing the proposed assist method.

The finding that there is no significant difference of WWL of NASA-TLX among system conditions suggests that there is no evidence that the overall workload was changed by introducing the proposed assist method. The results of the sub-categories of NASA-TLX, specifically that the MD significantly decreases and PD significantly increases by introducing the assist, implies that the cognitive load decreases when the assist is introduced while the physical control demand increases when controlling the vehicle velocity according to the assist system's recommendation. This leads to an interesting research question, specifically, how to determine the balance among sub-categories of workload when designing driver assistance system? This is an interesting and challenging future work. Techniques that decrease PD also constitute important future work. de Waard [1] proposed an assist method for merging operation in which assistance was provided using verbal advisory signals to encourage acceleration when a driver drove at a lower velocity than predetermined. The paper showed that the average velocity increased in the acceleration lane when the assistance was used by elderly people; however, improvement of the clarity of the driver's judgment was not evaluated. On the other hand, the assistance method proposed in the present study estimated the driver's clarity of judgment or the difficulty that the driver was thought to feel for every given situation, and provided instruction of acceleration/deceleration to improve the clarity of judgment. The contributions of this study include a novel driver assist method with the above-mentioned features and provides quantitative evidence that the easiness of judging the merging position and clarity of judgment increased.

VI. Conclusion

In this paper, we proposed a decision-making model for driver's merging position by predicting the merging gap with high accuracy. Additionally, it was demonstrated that judgment entropy based on the proposed model can quantify the differences in the decision-making skills of drivers and help evaluate the difficulty of decision-making in a given situation.

Furthermore, we proposed a driver assistance method that tactilely presents acceleration/deceleration recommendation to the driver, increasing their clarity of judgement by providing assistance when the system judges that the driver is experiencing difficulties in a given traffic environment. By evaluating the proposed system using driving simulator experiments, we confirmed that the system reduced the difficulty of decision-making for merging and increased the clarity of judgment during early stages of the merging preparation. In addition, the proposed method lowered cognitive load (MD subcategory of NASA-TLX) without leading to an increase in the overall workload (WWL).

The above-mentioned results prove the effectiveness of providing assistance for decision-making in a manner that does not directly dictate actions to the driver, and instead encourages actions that change the traffic environment such that the judgment becomes clear based on the skills and characteristics of judgment of an individual driver.

Future research directions include comparison of the proposed method with assistance methods that directly provide judgment results to the driver. Further, since the obtained results suggest that an increase in load might result owing to velocity control, the establishment of a method to realize reduction of control load should also be investigated.

Skill improvement of drivers was out of the scope of this study. Recent studies suggest that appropriate assistance can contribute to improvement of drivers' skill [15]–[17]. The type of assistance proposed in the present study, which assists decision-making of the driver only when it is thought to be necessary and encourages drivers to arrive at decisions by his/her own effort, is expected to support such skill improvement. This is an important topic for future study.

Acknowledgment

The authors would like to thank Clarion Co., Ltd. for providing equipments related to a seat with vibration function.

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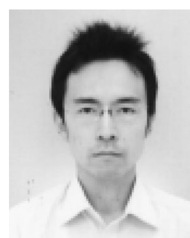

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