Development and evaluation of driving speed controller for lane merging considering surrounding driver’s intention toward stress-free driving

Masato Kawaguchi, Anh Tuan Tran, Hiroyuki Okuda and Tatsuya Suzuki

Department of Mechanical Systems Engineering, Nagoya University, Chikusa, Nagoya, Japan

ABSTRACT
A model predictive controller to perform a lane-merging task is proposed. We consider a hierarchical control structure that consists of an inner and outer control loop. The inner loop is an adaptive cruise controller that gives the acceleration command to the autonomous merging car to follow the designated speed and maintain a relative distance from the preceding vehicle while satisfying the constraints based on explicit optimal control. The outer loop determines the car in the main lane that the autonomous car should follow to maximize the acceptance and clarity of the decision-making of the human drivers in the main lane. The proposed system is implemented on the merging car in a driving simulator, and the human driver evaluates the merging car while driving in the main lane. The validity of the proposed system was determined through objective and subjective evaluations by human drivers.

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1. Introduction
Advanced driver-assistance systems (ADAS) and autonomous driving (AD) are expected to play an important role in improving safety and comfort and reducing not only the physical but also the mental burden of driving. Although the use of ADAS has gradually increased in this decade, the understanding and acceptance of ADAS and AD systems are necessary for their widespread adoption. The systems must be designed to be human-friendly, not only for the driver but also for surrounding traffic and pedestrians to achieve widespread acceptance.

One of the most stressful driving tasks for drivers and other traffic is lane merging at highway junctions. Smooth merging requires careful observation, and the driver must interact and cooperate with other cars in the surrounding [1]. Hence, it is necessary to consider human behaviour in the system design to reduce the stress of the surrounding agents. Many researchers have investigated driving behaviour at highway junctions. In general, human behaviour can be regarded as a combination of decision-making and motion. Therefore, it is natural to express merging behaviour as a combination of decision-making and acceleration, as shown in previous studies [2–6]. Although these studies attempted to understand the behaviour of the driver in the merging car, the behaviour of those in the main lane was not analysed. Okuda et al. attempted to construct a piecewise driver model that utilizes a soft-max function to understand driver behaviour [2]. The model was also used to predict the decision-making and acceleration of other car drivers. The term “decision entropy” of the driver was proposed to quantify the stress caused by the driver’s decision-making.

In the controller design for the lane-merging task, traditional approaches focused on the safety index derived from physical safety without taking into account mental stress, as proposed in [7–9]. In [10], Okuda et al. proposed a driving-speed controller for the merging vehicle based on randomized model predictive control (RMPC) by considering the acceptance of the merging action by the surrounding vehicles. First, the decision-making characteristics of the main lane drivers on whether to accept or reject the merging from the highway ramp, and the corresponding speed control behaviour for each decision state, were modelled from measurements using a switched dynamical model.

As a stochastic switching function was used to express the decision-making, the stress of decision-making was quantified and minimized according to the idea that drivers get stressed when they do not have clear decisions, i.e. the decision entropy is large. Minimization of the decision entropy to determine the driving speed in the negotiation step was achieved by applying nonlinear model predictive control based on RMPC, which resulted in long computation time.

To solve this problem, Tran et al. [11] integrated an adaptive cruise control (ACC) controller and safety constraints based on the analytical optimal control theory to determine the driving speed and decision-making method used to select the gap for a merging car to cut into. The proposed method considered the
decision entropy of main lane drivers, which was calculated from the optimal input and predicted state trajectory by the driver model. The optimal gap for merging was selected according to the predicted cost function, which includes the decision entropy. This approach could significantly reduce the computing power required for real-time computation. However, the manner in which the proposed method could reduce the mental workload of drivers was not evaluated subjectively.

This paper evaluates the effectiveness of the proposed method in [11] aimed at reducing mental stress in a highway merging scenario. The experiment is carried out using a driving simulator. The proposed method is applied to a merging car to determine the driving speed and where the car should merge, test drivers in the main lane, and evaluate the behaviour of the merging car. The test driver’s acceptance of the merging car’s behaviour is subjectively evaluated.

The paper is organized as follows. Section 2 reviews the control design of the proposed lane-merging speed controller. Section 3 describes the method to determine where to merge according to the MPC.

The validation method for the proposed system is introduced in Section 4, and the results are discussed in Sections 5 and 6.

2. Review of the adaptive cruise control design method and the driving behaviour at a highway junction

In this section, the ACC design method proposed in [12] and the driver behaviour model at a highway junction introduced in [2] are briefly summarized.

2.1. Adaptive cruise control design method

The ACC problem in [12] on following a leading vehicle can be considered and modelled as follows:

\[
\begin{bmatrix}
\dot{d}
\
v
\end{bmatrix} = \begin{bmatrix}
v_L - v \\
-c_1 - c_2 v^2
\end{bmatrix} + \begin{bmatrix}
0
\
u
\end{bmatrix},
\]

where \(d\) denotes the relative distance between the two vehicles (m), \(v_L\) denotes the leading vehicle’s velocity (m/s), \(v\) denotes the following vehicle’s velocity (m/s), \(c_1\) is the coefficient of friction, \(c_2\) is the coefficient related to the aerodynamic drag (m/s\(^2\)), and \(u\) is the acceleration command (m/s\(^2\)). The ACC problem (1) can be written in the form of an output regulation problem [12,13] as follows:

\[
\begin{bmatrix}
\dot{x}
\
\dot{w}
\
\dot{z}
\end{bmatrix} = \begin{bmatrix}
f(x, w) + g(x)u \\
\tilde{S}w \\
e = h(x, w)
\end{bmatrix},
\]

where \(x = [d v]^T\) denotes the state; \(w = [d_{com} v_L]^T\) denotes the exogenous signal, which includes reference signals and/or disturbances; \(e = h(x, w) = d_{com} - d\) denotes the tracking error; and \(z\) is the integration of \(e\) which deals with the steady-state offset when disturbances or modelling errors exist. In general, the exogenous signal \(w\) is not constant. However, \(w\) is assumed to be a step input signal with an arbitrary magnitude to simplify the problem. Therefore, \(S = 0\) is assumed. One can verify that the relative degree of (1) is 2 [14]. Thus, the following cost function is considered to design the optimal controller for the ACC problem [12,13].

\[
J = \frac{1}{2} \int_0^\infty \begin{bmatrix}
\tilde{e}
\zeta
\end{bmatrix}^T Q_e \begin{bmatrix}
\tilde{e}
\zeta
\end{bmatrix} dt,
\]

where \(\tilde{e} = [e \dot{e}]^T\), \(\zeta = [\bar{e}]\), subject to

\[
\begin{align*}
d_{min} & \leq d \leq d_{max}, \\
\nu_{min} & \leq \nu \leq \nu_{max}, \\
u_{min} & \leq u \leq u_{max}.
\end{align*}
\]

Here, the \(Q_e, Q_\nu, R_e\) are the weighting parameters in the cost function. It is necessary to solve a Hamilton–Jacobi equation to solve the constrained optimal control problem [12,13,15]. In [12], a method was proposed that calculated several optimal control input candidates corresponding to various scenarios of active constraints based on the centre-stable manifold method [13,16]. Subsequently, an algorithm was developed to obtain the “probably true” optimal control input candidate at each time \(t\). Since the designed ACC controller consists of polynomial functions, it is convenient to utilize this as a low-level controller, whereas the higher-level ones are designed for different tasks. For the sake of convenience, the ACC controller is expressed as follows:

\[
\tilde{u} = u_{\text{ACC}}(x, \nu, w, \gamma),
\]

where \(\gamma = [d_{min} d_{max} \nu_{min} \nu_{max} u_{min} u_{max}]^T\) is the vector of constraints. Note that, the ACC controller (4) only consists of polynomial functions, and thus requires minimum computation time.

2.2. Driving behaviour at a highway junction

In the merging scenario at a highway junction, the consensus between the drivers in the main lane and merging lane is very important to ensure a safe and smooth merging action. It was observed in [2,17] that the human driver in the main lane first decides whether to accept or reject the merging vehicle cutting in front of his/her vehicle, and then acts accordingly. Then, the authors predicted the driving behaviour of the drivers in the main lane using two models. The first is the acceptance model, which represents the decision of the driver in the main lane to accept or reject the merging vehicle cutting-in ahead of him/her. The second is
the motion model, which represents the deceleration or acceleration of the car in the main lane according to the decision of the driver.

2.2.1. Acceptance model of the vehicle in the main lane

In [2,17], Okuda et al. introduced an acceptance model to predict the decision of the driver in the main lane. Three states of decision (SOD), \( X = 1, 2, 3 \), were considered in the model. \( X = 1 \) implies that the main lane driver "ACCEPTs" the merging car cutting-in ahead of it; \( X = 2 \) means that the main lane driver "REJECTs" the merging car; and \( X = 3 \) represents the "UNDECIDED" state in which the main lane driver is unsure whether to accept or reject the merging car. Based on the observed data, \( \phi(t) \), the probability of each SOD at time \( t \) in the acceptance model, \( P( X(t) = s | \phi(t), \eta_s ) \) where \( s \in \{1, 2, 3\} \), was estimated using logistic regression; \( \eta_s \) denotes the parameter of the driver model. The decision of the driver was determined by the SOD with the highest probability. In the remainder of the paper, the probability \( P( X(t) = s | \phi(t), \eta_s ) \) is written in a more compact and equivalent form \( P_s(\phi(t), \eta_s ) \) for simplicity. The decision-making (acceptance model) of the driver \( t \)th at time \( t \), \( X'(t) \) was estimated as in (5). The observed data \( \phi(t) \) is summarized in Table 1 and depicted in Figure 1.

\[
P_s(\phi^i(t), \eta_s^j) = \begin{cases}
\exp\left(\eta_s^T \phi^i(t)\right) & \text{if } s \in \{1, 2\}, \\
1 + \sum_{j=1}^{2} \exp\left(\eta_j^T \phi^i(t)\right) & \text{if } s = 3,
\end{cases}
\]

\[
\phi^i(t) = \left[1 \ d_{M,i} \ v_{M,i} \ a_{M,i} \ d_{i-1} \ d_{C,i} \ L_w\right]^T,
\]

\[
X'(t) = \arg \max_{s=1,2,3} P_s(\phi^i(t), \eta_s^j),
\]

where \( i \) denotes the vehicle/driver index in the main lane, \( \eta_s^j \) is the driver model's parameter of the \( i \)th vehicle, and \( j \) denotes the SOD index. The authors also introduced the term “decision-making entropy” to describe the vagueness of the decision-making of the driver. The decision-making entropy \( S(t) \) is defined as

\[
S'(t) = - \sum_{i=1}^{3} P_s(\phi^i(t), \eta_s^j) \times \log_2 P_s(\phi^i(t), \eta_s^j).
\]

It can be seen that the \( S'(t) \) has small value if \( P_s(\phi^i(t), \eta_s^j) \) is close to 0 or 1. This means when the driver is more certain of his decision, the decision-making entropy is reduced. This term can be used to design a harmonic lane-merging controller at a highway junction by considering the interaction between human drivers.

2.2.2. Motion model of the vehicle in the main lane

After deciding whether to accept or reject the merging vehicle, the human driver in the main lane will control the car accordingly. This motion control can be approximated using a switched proportional-derivative (PD) controller. Refer to [10,17] for further details. The output of the switched PD controller \( u_{PD}(t) \) at time \( t \) for the \( i \)th driver is expressed as

\[
u_{PD}(t) = \begin{cases}
f_{acc}(\phi^i(t)) & \text{if } X(t) = 1, \\
f_{rej}(\phi^i(t)) & \text{if } X(t) = 2, \\
f_{und}(\phi^i(t)) & \text{if } X(t) = 3,
\end{cases}
\]

\[
f_{acc}(\phi^i(t)) = g(d_{acc}, \min(d_{i-1} - 1, d_{M,i})),
\]

\[
f_{rej}(\phi^i(t)) = g(d_{rej}, d_{i-1} - 1, d_{i-1} - 1)),
\]

\[
f_{und}(\phi^i(t)) = g(d_{und}, d_{i-1} - 1, d_{i-1} - 1)),
\]

where \( f_{acc}, f_{rej}, \) and \( f_{und} \) denote the acceleration/deceleration of the \( i \)th mainstream vehicle when the SOD of the driver is "ACCEPT," "REJECT," and "UNDECIDED," respectively. The corresponding reference distances of the switched PD controller are \( d_{acc}, d_{rej}, \) and \( d_{und} \), respectively.

Driving data collected from the driving simulator [2,17] was used to identify the parameters \( \eta_s^j(s = 1, 2) \) in the acceptance model and \( d_{acc}, d_{rej}, \) and \( d_{und} \) in the motion model. The mean values of these parameters are listed in Table 2. The gains \( k_p \) and \( k_d \) in the switched PD controller were assumed to be –0.15 and –0.005, respectively.

| Table 1. Observed data for estimating the SOD. |
|-----------------------------------------------|
| \( d_{M,i} \) | Distance between Car i and Car M |
| \( v_{M,i} \) | Relative velocity between Car i and Car M |
| \( a_{M,i} \) | Relative acceleration between Car i and Car M |
| \( d_{i-1} \) | Distance between Car i and Car \( i-1 \) |
| \( d_{C,i} \) | Distance between Car i and the merging lane's endpoint |
| \( L_w \) | Distance from A to B (length of the recognizable area) |

Figure 1. Lane-merging task diagram.
In this section, a lane-merging controller is designed based on the ACC controller described in Section 2.1. This controller takes into account the behaviours of drivers in mainstream vehicles to reduce their stress or decision-making burden when the autonomous vehicle is merging into the main lane.

The lane-merging controller contains two control loops. In the inner loop, the vehicle acceleration is controlled by the ACC controller to follow a preceding vehicle at a specific distance while satisfying system constraints. In the outer loop, the optimal target vehicle in the main lane is determined for the merging vehicle to follow to minimize the cost function that includes the decision-making entropy of all drivers in the main lane. Figure 2 illustrates the control diagram of the merging vehicle. In the figure, $x'$, $v'$, and $a'$ denote the position, velocity, and acceleration of the $i^{th}$ vehicle in the main lane, respectively. The optimal target vehicle that the merging vehicle should follow is denoted by the superscript $i^*$. The merging vehicle is denoted by the superscript $M$. The lane-merging task has two phases: reaching phase and merging phase.

### 3.1. Reaching phase

The reaching phase begins when the merging vehicle starts detecting the mainstream vehicles until the merging consensus between vehicles is reached. In this phase, the optimal target vehicle for the merging vehicle is calculated to minimize the cost function containing the decision entropy.

#### 3.1.1. Problem formulation

The optimization problem to determine the target vehicle is formulated as follows:

**Given:** $x_A$, $x_B$, $x_C$, $d_{com}$, and initial values of all vehicles

**Find:** target vehicle number $i^*(k|t)$, $k \in \{1, 2, \ldots, K\}$ which minimizes:

\[
J_{\text{cost}} = r_1 J_1(k|t) + r_2 J_2(k|t) + r_3 J_3(k|t) + r_4 J_4(k = K|t)
\]

\[
J_1(k|t) = \sum_{k=1}^{K} \begin{bmatrix} \hat{e}(k|t) \\ z(k|t) \end{bmatrix}^T \begin{bmatrix} Q_e & 0 \\ 0 & Q_z \end{bmatrix} \begin{bmatrix} \hat{e}(k|t) \\ z(k|t) \end{bmatrix}
\]

\[
J_2(k|t) = - \sum_{k=1}^{K} \sum_{s=1}^{3} P \left[ X_{i}^{k+1} \right] s(k|t) = s|\phi^{i+1}(k|t), \eta_i \}
\]

\[
J_3(k|t) = \sum_{k=1}^{K} \left[ X_{i}^{k+1} \right] s(k|t) = s|\phi^{i+1}(k|t), \eta_i \}
\]

subject to:

**dynamics of the vehicles in the main lane :**

\[
x'(k+1|t) = x'(k|t) + v'(k|t) \Delta t, \quad i \in \{1, \ldots, N\}
\]

\[
v'(k+1|t) = v'(k|t) + a'(k|t) \Delta t, \quad i \in \{1, \ldots, N\}
\]

\[
a'(k|t) = u_{PD}(t), \quad i \in \{2, \ldots, N\}
\]

\[
a^*(k|t) = 0
\]

**dynamics of the merging vehicle :**

\[
x'^{M}(k+1|t) = x'^{M}(k|t) + v'^{M}(k|t) \Delta t
\]

\[
v'^{M}(k+1|t) = v'^{M}(k|t)
\]

\[
+ (-c_1 - c_2 v'^{M}(k|t)^2 + a'^{M}(k|t)) \Delta t
\]

\[
a'^{M}(k|t) = u_{ACC}(x(k|t), z(k|t), w(k|t), \gamma_c)
\]

\[
x(k|t) = \left[ \begin{array}{c} x'^{M}(k|t) - x'^{M}(k|t) \\ v'^{M}(k|t) \end{array} \right] \]

\[
w(k|t) = \left[ \begin{array}{c} 0 \\ v'^{M}(k|t) \end{array} \right]
\]

\[
e(k|t) = h(x(k|t), w(k|t))
\]

\[
z(k+1|t) = z(k|t) + e(k|t) \Delta t
\]

\[
d_{ref}(k|t) = d_{com}, \quad v_{ref}(k|t) = v'^{M}(k|t)
\]

where $K = 50$ is the number of predicted steps, $d_{com} = 20$ (m) is the reference distance of the ACC controller, $\Delta t = 0.1$ (s) denotes the time step, and $N = 4$ denotes the total number of vehicles in the main lane. It can be observed that the relative distance, velocity, and acceleration constraints do not appear explicitly in the problem formulation (9) as these constraints are taken into account when calculating the acceleration of the merging vehicle in the ACC loop. The merging vehicle and mainstream vehicles are in separate lanes in the reaching phase. Therefore, it is not necessary to examine the constraints on the relative distance at this moment. Thus, in the vector of constraints $\gamma_c$, the constraints of $x_1$ can take arbitrary and sufficiently large values, i.e., $x_{1_{\text{min}}} = -1000$ (m) and $x_{1_{\text{max}}} = 1000$ (m). The velocity constraints are $x_{2_{\text{min}}} = ...$
17 (m/s) and \(x_{\text{max}} = 25\) (m/s), while the acceleration constraints are \(u_{\text{min}} = -1.5\) (m/s\(^2\)) and \(u_{\text{max}} = 1.8\) (m/s\(^2\)). When the autonomous vehicle starts merging with the mainstream vehicles, the values of \(x_{\text{max}}\) and \(x_{\text{min}}\) are changed to ensure the safe distance between vehicles. In the cost function (9), the term \(J_1\) denotes the cost for the merging vehicle to follow the \(i^{th}\) car in the prediction horizon. The term \(J_2\) denotes the decision-making entropy of the \((i+1)^{th}\) vehicle, which is the one behind the \(i^{th}\) car. The term \(J_3\) describes how long the \((i+1)^{th}\) vehicle stays in the REJECT state. This cost function was derived based on the idea that when the autonomous vehicle merges into the main lane between vehicle numbers \(i\) and \(i+1\), the SOD of those two vehicles are REJECT and ACCEPT, respectively.

Since there is a nonlinear cost function and switched systems owing to the switching behaviour of \(u_{\text{ACC}}\) and \(u_{\text{D}}\), it is necessary to use a hybrid MPC solver, which can sometimes require a large computation time. An alternative approach is to use the RMPC method [18], which can deal with nonlinear and/or stochastic MPC problems by calculating a “probably true” optimal solution. It generates several random control input samples and selects the control input sample that minimizes the given cost function. This RMPC method was used in [17] to calculate the velocity profile of the merging vehicle to perform the lane-merging task. However, to cover the whole admissible velocity region, a large number of random samples may be required, which requires high computing power. To address this issue, instead of generating random velocity profile samples, we generated the target vehicle index samples that the merging vehicle should follow in the prediction horizon. Furthermore, it is preferred that the autonomous vehicle not switch its target frequently. Thus, we assumed that the merging vehicle follows the same target vehicle in the prediction horizon. This assumption decreases the required number of samples, thus minimizing the computation time. It should be noted that the merging vehicle can still control its acceleration and velocity to any value inside the admissible domain.

### 3.2 Merging phase

Before merging with the mainstream traffic flow, a consensus must be reached between the merging vehicle and the other vehicles in the main lane. Note that the acceptance model presented in Section 2.2 is a useful tool to predict the decision-making of mainstream drivers within the framework of predictive control. As it is not practicable to acquire the precise driver model for each individual in the main lane, an average model was used to estimate the decision-making of all drivers in the main lane. Therefore, a mismatch between the actual and predicted decisions of the driver is sometimes unavoidable.

The decision process to initiate the lane merging is shown in Figure 3. After the optimal following target vehicle is selected by the scenario-based MPC described in the previous section, the acceptance by the driver in the car \(i^* + 1\) who is driving behind the following target \(i^*\) of the merging car is evaluated by the following condition:

\[
P_2^{i^*+1} < 0.5 \lor \beta \times d_{\text{rej}} \leq x^M(t) - x^{i^*+1}(t),
\]

where \(P_2^{i^*+1}\) is the probability that the driver in car \(i^* + 1\) rejects the merging, and \(d_{\text{rej}}\) is the following distance of the driver in car \(i^* + 1\) when the driver rejects the merging. The coefficient \(\beta\) was set to 0.9 by trial and error.

If this condition is not satisfied, then the next following target is switched to the next car by increasing \(i^*\) by one.

The constraint expressed in (11) is considered to evaluate the safety of the merging behaviour. The first condition in (11) implies that the merging car is allowed to move toward the lateral direction for the lane merging only after passing point \(x_B\). The second condition in (11) ensures the safety gaps between the merging car and cars \(i^*\) and \(i^* + 1\).

\[
[x^M(t) > x_B] \land [x^{i^*+1}(t) + d_{\text{rear}} < x^M(t) + d_{\text{front}} < x^{i^*}(t)]
\]

If the safety condition is satisfied, then a simple constant-lateral-speed controller is enabled to gradually change the driving lanes. If the safety condition is not satisfied, then the merging car continues following the target vehicle without lateral motion. The lateral
speed \( u^y_M(t) \) is expressed as follows:

\[
  u^y_M(t) = \begin{cases} 
  -1 \text{ m/s} & \text{if (11) is satisfied}, \\
  0 \text{ m/s} & \text{otherwise}.
  \end{cases}
\]  

(12)

Note that this decision process and MPC-based optimal target selection are executed in each control cycle.

4. Validation of proposed method

4.1. Experimental setup

Figure 4 shows the driving simulator (DS) used in the experiment. The DS can provide a front view of over 180° and a side view to see the merging vehicle. A real car dashboard was installed in the DS, and the visual was computed by reflecting the geometric field-of-view to obtain the realistic view using the game engine, Unity (Unity Technologies). The ego car behaviour is computed by the vehicle dynamics simulator, Carsim (Mechanical Simulation Corp.) in the DS. The outline of the driving environment for the target merging scenario created in the DS is shown in Figure 5. It was assumed that there is one merging car in the merging lane and five cars in the main lane. The leading car (Car 1) drives at a constant speed of 80 km/h automatically. The other cars in the main lane, except for the third car, are controlled by the driver model proposed in [10]. This driver model changes the following distance from the car in front depending on the decision to accept or reject the merging car cutting-in ahead of the car. See [10] for details on the driver model. The subjects drove the third car following Car 2 and adjusted the driving speed to either let the merging car cut-in ahead of the car or not. Subsequently, the driver evaluated the merging behaviour of the merging car after accomplishing the merging trial. Twenty drivers participated in this experiment.

The position and driving speed of all cars were measured in real time. The driver’s decision (accept or reject) and its timing were also observed by operating a turn signal. Lane change was prohibited and the driver must avoid collision by adjusting his driving speed.

A total of 48 merging situations were tested for each subject. Informed consent was obtained by explaining the risks and merits of participation, and a privacy policy was implemented before commencing the experiment; only consenting subjects participated in the experiment. In each trial, the control method for a merging car was randomly selected from three methods: “Constant speed,” “ACC,” and “ACC + DE.” The “Constant speed” controller maintains its driving speed at 80 km/h. The merging car initiates merging when it reaches 350 m and completes it at 410 m regardless of the relative positions or velocities of the other cars in the main lane. The black solid line in Figure 6 shows the trajectory of the merging car controlled by the ‘Constant speed’ controller.

For the “ACC” controller, a scenario-based prediction is made based on the proposed ACC, and the following target is selected by minimizing the tracking error and w.r.t. reference distance from the selected car in the main lane WITHOUT considering the decision entropy. The merging car speed was controlled by proposed ACC to follow the target car in the main lane, and merging was initiated when the safety condition (11) is satisfied.

In other words, “ACC” controller specifies the following target which is the easiest to follow and merges without considering the decision models of other cars.

However, the “ACC + DE” controller described in Section 3 selects the following target to minimize the proposed cost function by considering the decision-making characteristics of the drivers in the main lane.

4.2. Subjective evaluation

Three methods were compared based on the evaluation using the questionnaire shown in Table 3. The questionnaire contains four questions. The first three questions rate the “Sense of safety, “ “Sense of incongruity,”
Table 3. Questionnaire on acceptability.

1. How safe was the driving?
   □ Safe □ Somewhat safe □ Rather unsafe □ Unsafe

2. Did you feel the incongruity of the merging car behaviour?
   □ Yes □ If anything, yes □ If anything, no □ No

3. Did you feel being considered by the merging car?
   □ Yes □ If anything, yes □ If anything, no □ No

4. Is driving in this trial easier compared with the previous trial?
   □ Yes □ If anything, yes □ If anything, no □ No

Note: This questionnaire was translated; the original one was provided in Japanese language.

Table 4. The initial conditions of the merging cars.

| Index of trials | 1   | 2   | 3   | 4   | 5   | 6   | ... | 48 |
|-----------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Control method  | 3   | 1   | 3   | 2   | 2   | 3   | ... | 3  |
| Initial position, m | −8  | −2  | 2   | −6  | 0   | −2  | ... | −6 |

and “Consideration,” respectively, in the absolute rating scale. The fourth question, related to “Comfort,” is a relative rating scale and the answer is selected by comparing the comfort of the current trial with the previous one sequentially.

4.3. Tested scenarios

The initial conditions of each trial were changed, as shown in Table 4, so that the merging car merges either ahead or behind the subject’s car. In the table, the “Control method” indicates the selected method: 1 denotes “Constant speed,” 2 denotes “ACC,” and 3 denotes “ACC+DE.” A total of 48 trials were carried out, i.e. 16 trials were conducted for each control method. The initial positions indicate the initial distances between the merging car and ego car (Car DS) at the nose edge, and were chosen from −8 m to 4 m for each method in a similar manner. The initial speed of the merging car depends on that of Car DS. The driver models are the average driver models obtained in [2].

5. Experimental results

5.1. Measured driving data

Examples of the measured data profiles are shown in Figures 7–10. Figure 7 shows the positions and decisions of the cars in the main lane at time $t = 11$, 13, 15, and 17. The colour of the cars in the main lane shows the decision state of the drivers as predicted by the driver models used in the experiment. Note that the colour of the third car shows the measured decision state but not the estimated one since the car is driven by a human driver. The markers in light blue, green, and red denote the cars driving with the decision states “UNDECIDED,” “ACCEPT,” and “REJECT,” respectively. Figures 8 and 9 show the velocity and acceleration of all cars measured in 1 of 48 trials of driver 12. The velocity profile of the merging car (Car M) depicted by the red solid line shows that the velocity constraints are satisfied by applying the proposed method.

Figure 10 shows an example of the decision state transition profile of driver 12, which was measured using the turn signal. In this trial, the driver rejected the merging car that was cutting in front of the ego car, and accelerated to shorten the following distance to the leading car.
5.2. Questionnaire results

Two examples of the subjective evaluation results of 20 drivers are shown in Figures 11 and 12. The average of all 20 drivers are shown in Figure 13.

Figures 11 and 12 illustrate the average of the “Sense of safety,” “Sense of incongruity,” and “Consideration” evaluations of drivers 9 and 18, respectively. As the “Sense of incongruity” is a negative index, “Natural movement,” which is the opposite index of the “Sense of incongruity,” was used in the evaluation to turn it into a positive index. A larger value shows a positive evaluation from the subjects in all indexes in these figures. Figure 14 shows the results of “Comfort” calculated by Scheffe’s paired comparison method. The averaged evaluation values of all drivers, relatively aggressive drivers, and relatively conservative drivers are shown in Figure 14 from left to right, respectively. The definition of these groups is provided in a latter discussion. These results are analysed and discussed in the next section.

6. Analysis and discussion

This section describes the validation of the proposed method from subjectivity and objectivity evaluations based on the results shown in the previous section.

6.1. Evaluation by driving safety

In general, the most important requirement for AD systems is driving safety. Firstly, driving safety is discussed from the driving data. In this experiment, the accidents, i.e. situations in which the merging car collided with another car, were observed. Most of the accidents occurred in the “Constant speed” condition because the “Constant speed” controller does not consider safety, but only considers driving at constant speed. The “ACC” controller also failed at safe merging in several trials in this experiment. Figure 15 shows an example of a driving scenario with an accident. Although the “ACC” controller followed the target car with both input and safety constraints, it does not consider the safe distance from the car behind the merging car because of the simplicity of the implementation.

Stopping at the end of the merging lane was not considered in the proposed system for same reason, and the merging car was forced to execute the merge when it reached the end of the merging lane. Therefore, the
merging car may collide with other cars if the human driver rejects the merging and does not notice that the merging car is approaching.

This implies that it is important to select the appropriate gap to merge in order to gain the acceptance of other cars and improve driving safety.

The number of trials in which collision was observed and accident rates in all trials of all 20 drivers, i.e., 320 trials for each condition, are listed in Table 5. The proposed “ACC+DE” controller had the best safety performance among the tested controllers.

Additional safety constraints will be considered to realize collision-free merging in future work.

6.2. Evaluation by subjective evaluation 1 to 3

Secondly, the results of the subjective evaluation from questionnaires 1 to 3 are discussed. In Figure 13, the average score obtained for the “Sense of safety” is consistent with the accident rate shown in Table 5. The proposed method realized the safest merging from both the subjective and the objective evaluations.

Figure 16 shows the ratio of resulting merging positions in all trials for each controller. Figure 16 shows that the “ACC+DE” controller frequently yields to the merging car compared with the other controllers. This implies that the proposed system has greater consideration of the cars driving in the main lane. Figure 17 shows how long it takes to make a decision from the time that the human driver sees the merging car. In Figure 17, it is shown that “ACC+DE” requires the shortest time for the driver to make a decision among the three tested controllers.

This implies that “ACC+DE” enables the drivers in the main lane to make a decision easily by adjusting their driving speed and selecting the appropriate position to merge. These advantages lead to the reduced stress of the drivers in the main lane. It was confirmed that the proposed “ACC+DE” controller can achieve the most considerate merging.

6.3. Evaluation by comfort

Thirdly, the result of the subjective evaluation of “Comfort” from questionnaire 4 is discussed based on Figure 14. In Figure 14, the averaged evaluation values of all drivers and the standard deviations are shown on the left. Here, the Student’s t-test was applied to check the significant difference between the “Constant speed,” “ACC,” and “ACC+DE.” The difference in the evaluation values between “ACC” and “Constant speed,” and between “ACC+DE” and “Constant speed” is significant at significance levels of 2% and 0.1%, respectively. This implies that the “ACC” and “ACC+DE” can realize more comfortable merging for the driver in the main lane compared with that at “Constant speed.” The difference between “ACC+DE” and “ACC” was not significant but tended to be significant at the significance level of 20% for all drivers.
Next, the drivers were divided into two groups: aggressive and conservative drivers. The top 10 drivers with longer following distances were classified as conservative drivers, while the others were classified as aggressive drivers. It was found that among aggressive drivers, the difference between “ACC” and “ACC+DE” tended to be significant with the significance level of 10%. Thus, the drivers in this group had to pay attention to the system to improve driving safety and to obtain acceptance. In contrast, a significant difference was not observed among conservative drivers. This result implied that the proposed system is useful and beneficial, especially when the merging car tries to merge into a position close to an aggressive driver in the main lane.

6.4. Evaluation by time to make a decision

Here we analysed the time it takes for the human driver to decide whether to accept or reject the merging car. Using the proposed method, the decision-making is expected to become easier for drivers in the main lane by considering the decision entropy in the cost function. Figure 17 shows the average duration from the time the driver sees the merging car to when the subject inputs his intention by operating the turn signal. Although a significant difference was not observed between “ACC” and “ACC+DE” for all drivers, the difference was significant among conservative drivers with a significance level of 20%. This implies that the proposed system can reduce the difficulty of the decision-making of conservative drivers by considering their intention.

6.5. Application of proposed method

Finally, the other application of the proposed method is discussed here. In this paper, the lane-merging scenario was selected to show the merit to consider the decision-making model and the decision entropy to get the acceptance and to reduce the time to reach a consensus. It is obvious that the proposed method can be applied not only to the lane-merging task but also the more general lane changing task. A lane change task can be regarded as the lane-changing task without the termination of the lane nor specific time limit to accomplish the task.

Another situation which the decision entropy is expected to play the important role is the intersection. In the intersection, the prediction of decision-making of the surrounding cars and/or the pedestrian, such as go/wait decision, are important to plan the ego-vehicle motion. Surrounding cars’ and pedestrians’ load to make a decision can be also considered by the decision entropy in order to realize the quick consensus decision-making.

The application should not be limited in the autonomous driving car control but also in the personal mobility context. The personal mobility (PM), such as the automated wheel chair and autonomous mobile robot in the mixed traffic scene, must pay attention to the pedestrians. In this context, PM often have to predict the decision-making of the pedestrian if the one is going to cross the driving path of PM. It is possible to get more acceptance from the pedestrians by reducing their decision-making load, and even it may be possible to control their decision indirectly by changing the ego vehicle behaviour according to the response prediction computed by the decision-making model.

Note that the observation of not only the behaviour but also the decision of the targeting agent is necessary in order to identify the prediction model. This drawback can be a problem in some application which the decision of the targeting agent cannot be measured directly nor indirectly.

7. Conclusion

This paper proposed an MPC lane-merging approach for automated lane merging at a highway junction. The lane-merging controller was designed using the stochastic driver model that predicts the decision of the driver in the main lane and the ACC, which calculates the optimal solution that meets constraints by an analysis solution. The proposed method also obtained higher evaluations of acceptability by 20 subjects. The results can be summarized as follows.

- The lane-merging controller design improved driving safety with reduced computational burden by utilizing the analytical solution of the optimal control problem with safety and input constraints. It obtained greater acceptance from other drivers by considering the intention of the driver in the main lane.
- The proposed system realized considerate driving by yielding the drivers driving in the main lane.
- A shorter decision-making time for a driver driving at a relatively long following distance was realized, while the system yielded to the main lane drivers.
- The merging car was sufficiently controlled from the viewpoint of comfort by the cost function, which was based not only on physical safety but also on the intention of the main lane driver for relatively conservative drivers.
- The proposed method improved the acceptance of the driver in the main lane driving at a short following distance by considering their intention and decision entropy.

There are several issues that remain to be addressed. A few collisions occurred when the merging car could not cut into the main lane because the car in the main lane would not yield to the merging car. This situation must be resolved to ensure driving safety and
reduce traffic congestion in the future. The evaluation of the proposed method in a real driving environment is another focus of future work.

Disclosure statement
No potential conflict of interest was reported by the author(s).

Notes on contributors

Masato Kawaguchi was born in Aichi, Japan, in 1994. He received a B.S. degree in Mechanical Engineering from Nagoya University, Japan, in 2018. His research interests are in the areas of the control system design considering the driver’s decision and its application to vehicle control.

Anh Tuan Tran received a B.E. degree in Mechanical Engineering from Hanoi University of Science and Technology, Hanoi, Vietnam, in 2012, and M.E. and Ph.D. degrees in Aerospace Engineering from Nagoya University, Nagoya, Japan, in 2015 and 2018, respectively. He is currently a postdoctoral researcher in the department of Mechanical Systems Engineering at Nagoya University, Nagoya, Japan, in the area of predictive control for autonomous driving. His research interests include nonlinear control theory, robust control, predictive control, and control applications for aerial and ground vehicles.

Hiroyuki Okuda was born in Gifu, Japan, in 1982. He received B.E. and M.E. degrees in Advanced Science and Technology from Toyota Technological Institute, Japan, in 2005 and 2007, respectively, and a Ph.D. in Mechanical Science and Engineering from Nagoya University, Japan, in 2010. He was a PD researcher with the CREST, JST from 2010 to 2012, and an assistant professor at the Green Mobility Collaborative Research Center in Nagoya University from 2012 to 2016. He was a visiting researcher of the Mechanical Engineering Department of U.C. Berkeley in 2018. Currently, he is an assistant professor at the Department of Mechanical Science and Engineering of Nagoya University. His research interests are in the areas of system identification of hybrid dynamical system and its application in the modelling and analysis of human behaviour, and human-centred system design of autonomous/human-machine cooperative systems. Dr. Okuda is a member of IEEE, IEEJ, SICE, JSAE, and JSME.

Tatsuya Suzuki was born in Aichi, Japan, in 1964. He received B.S., M.S., and Ph.D. degrees in Electronic Mechanical Engineering from Nagoya University, Japan, in 1986, 1988, and 1991, respectively. From 1998 to 1999, he was a visiting researcher of the Mechanical Engineering Department of U.C. Berkeley. Currently, he is a professor of the Department of Mechanical Systems Engineering, Executive Director of Global Research Institute for Mobility in Society (GREMO), Nagoya University. He has also been a Principal Investigator in JST, CREST in 2013–2019. He won the best paper award at the International Conference on Autonomic and Autonomous Systems 2017 and the outstanding paper award at the International Conference on Control Automation and Systems 2008. He also won the journal paper award from IEEJ, SICE, and JSAE in 1995, 2009, and 2010, respectively. His current research interests are in the areas of analysis and design of human-centric intelligent mobility systems, and integrated design of transportation and smart grid systems. Dr Suzuki is a member of the SICE, ISCIE, IEICE, JSAE, RSJ, JSME, IEEJ, and IEEE.

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