Preliminary Study of Tactical-Level Interaction for Highly-Automated Vehicles: Its Application to Touchscreen Interface

Mitsuhiro Kamezaki, *Member, IEEE*, Udara Eshan Manawadu, *Member, IEEE*, Masaaki Ishikawa, and Shigeki Sugano, *Fellow, IEEE*

***Abstract*—In automated vehicles, drivers are only required to input high-level control commands as opposed to lower-level commands in manually driven vehicles. The conventional driver-vehicle interfaces (DVIs) such as steering wheel and pedals that function in operational level, thus, may not be utilized in higher levels of automation. A DVI that allows the driver to input tactical-level control commands, i.e., lane change and turning, by easily understanding a situation, would be potentially required for automated vehicles. We thus propose tactical-level-interaction (TLI) for lateral and longitudinal controlling of highly automated vehicles. In this study, we developed a touchscreen-based DVI prototype that allows the driver to use simple touch gestures to input tactical control commands. The screen displays an augmented map including the ego vehicle rendered from the top view. The driver can instantly input a set of lateral commands by location-based TLI, e.g., lane changing, by designating a desired location on the map, e.g., lane, by double-tapping and swiping. Situational awareness is enhanced, for e.g., when approaching an intersection, by using visual and auditory prompts. We performed experiments using a simulator to evaluate TLI compared with the operational- (OLI, level 0) and strategical-level interaction (SLI, level 4). The results show that TLI offers both the flexibility of OLI as well as the comfort of SLI, and drivers prefer to use all three interaction methods depending on the driving environment.**

***Index Terms*—Tactical-level interaction, driver-vehicle interface, automated vehicle, variable spatiotemporal resolution.**

Manuscript received 10 April 2020; revised 4 October 2020 and 24 November 2021; accepted 14 January 2022. Date of publication 25 January 2022; date of current version 20 March 2023. This work was supported in part by JSPS KAKENHI under Grant 16K06196 and in part by the Research Institute for Science and Engineering, Waseda University. *(Corresponding author: Mitsuhiro Kamezaki.)*

Mitsuhiro Kamezaki is with the Research Institute for Science and Engineering (RISE), Waseda University, Shinjuku-ku, Tokyo 162-0044, Japan (e-mail: kame-mitsu@aoni.waseda.jp).

Udara Eshan Manawadu and Masaaki Ishikawa are with the Department of Modern Mechanical Engineering Graduate School of Creative Science and Engineering, Waseda University, Shinjuku-ku, Tokyo 162-0044, Japan (e-mail: udara@sugano.mech.waseda.ac.jp; ishikawa@sugano.mech.waseda.ac.jp).

Shigeki Sugano is with the Department of Modern Mechanical Engineering, Waseda University, Shinjuku-ku, Tokyo 169-8555, Japan (e-mail: sugano@waseda.jp).

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by Ethics Review Committee on Research with Human Subjects of Waseda University.

This article has supplementary material provided by the authors and color versions of one or more figures available at https://doi.org/10.1109/TIV.2022.3145391.

Digital Object Identifier 10.1109/TIV.2022.3145391

I. Introduction

Vehicles equipped with automated driving systems are radically changing the fundamentals of the driver-vehicle relationship. With increasing automated features available in passenger vehicles such as highway autopilot [1], traffic-jam assist [2], automated valet parking [3], automated lane change [4], scene understanding [5], [6], path planning [7], [8], and so on, the tasks and roles of the driver are reshaped and redefined. The role of a human in highly-automated vehicles could change from being the driver to a user or just a passenger. The SAE International's taxonomy on Levels of Automation (LoA) J3016 (2016) [9] provides an idea on the tasks and responsibilities of the driver in each LoA, as shown in the upper part of Fig. 1. There are six levels from no automation (LoA 0) to full automation (LoA 5). This classification system is based on the amount of driver involvement in the dynamic driving task (DDT) and attentiveness required. According to this, in LoA other than 5, the automated driving (AD) system will still allocate some or all of the driving tasks to the driver.

LoA 1, where advanced driving assistance systems are present, still requires the human to perform the DDT including Object and Event Detection and Response (OEDR) as well as vehicle motion control. LoA 2, where the AD system performs part of the DDT, requires the human to monitor the driving environment and to conduct OEDR. LoA 3, where the system performs the entire DDT including OEDR, requires the human to conduct a fallback performance of the DDT and does not require the driver to monitor the environment. However, it expects him/her to takeover control in situations where the AD system fails to function or when the vehicle encounters a mechanical fault [10]–[12]. This can be a serious safety issue since drivers would lack situation awareness, due to engaging in other activities like using a smartphone, napping, and even lack competence (due to degrading driving skills resulting from 'not driving' for a long time). Higher LoA usually reduces human control, but this could lose flexibility and driving pleasure that drivers can experience in manual driving (LoA 0 and 1).

The relationship between drivers and highly-automated vehicles will imply the need of reconsidering a driver-vehicle interaction. The characteristics of required tasks for the drivers in LoA 2+, such as performing DDT and its fallback, indicate that a driver-vehicle interaction that allows the driver to easily

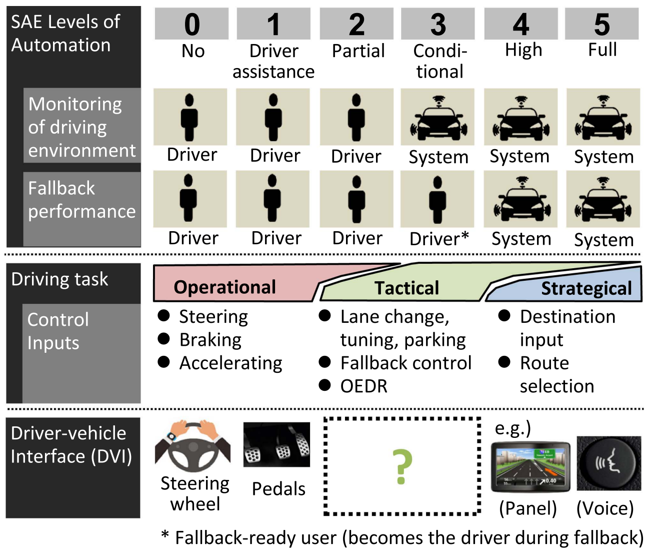

Fig. 1. Relationship among SAE levels of automation (LoA), driving task (operational, tactical, and strategical-level), and driver-vehicle interfaces (DVIs).

understand a driving situation and instantly command a control input consisting of a series of lateral and longitudinal motion, i.e., tactical-level interaction (TLI) (Fig. 1), would be essential [13]. However, the functionality of conventional driver-vehicle interfaces (DVIs), e.g., steering wheel and pedals were not considered for tactical-level command since they were originally derived from driving tasks in LoA 0 and 1, i.e., operational-level interaction (OLI). For instance, TLI such as ‘turn right at the next intersection’ or a strategical-level interaction (SLI) such as ‘designating a destination from a map’ cannot be input by using traditional steering wheel and pedals. Thus, a novel interaction method that effectively engages in controlling vehicles in LoA 2–4, that is, TLI and SLI, will be necessary. AD systems increase safety and comfort (easiness), but they somewhat limit the flexibility of control and driving pleasure due to the reduction of the amount of interaction between the vehicle and driver [14]. From the above as well, it is important to define a new interaction method to have a balance between the above parameters by introducing new DVIs that will help the seamless transition of driver’s roles according to LoA.

However, this is a very challenging task because DVIs for vehicle control have not undergone any momentous change since the invention of the modern automobile. Some researchers have developed DVIs such as a haptic steering wheel [15] and pedals [16], a cooperative shared control [17], a haptic switch display [18], a vibrotactile seat-display [19], and a head-up/down display [20], and moreover, they have proposed a conceptual DVI for LoA 4 [21], such as a brain-machine interface [22]. However, they have not focused on ‘controlling’ automated vehicles by ‘a tactical-level input method’. In response to such potential (hypothetical) needs for highly automated vehicles, we propose a tactical-level-input (TLI) method to input ‘tasks’ as a set of lateral and longitudinal control, e.g., overtaking, lane changing, and parking, which can vary the spatiotemporal resolution of the input. We adopt the TLI method to a touchscreen as a prototype DVI. A touchscreen can be a bidirectional interface that enables location-based commands (direct task input) and conveys more information to the user in a short period of time (increased situation awareness), compared to other interface types such as voice, gesture, etc.

This paper is structured as follows: Section II explains the concept and requirements for a new TLI-based DVI. Section III describes the development of a touchscreen interface. Section IV describes the experiments and Section V presents the results and analysis. Section VI describes the discussion. Section VII summarizes findings and discusses future works.

II. Re-Design of Driver-Vehicle Interaction

We analyzed hypothetical requirements for a driver-vehicle interaction for highly-automated vehicles and introduced the design concept of a new control input method and DVI.

A. *Levels of Driver-Vehicle Interaction in Automated Vehicles*

The driving task is divided into three levels of time-based control hierarchy; strategical, tactical, and operational [23]. At the strategical level, a driver plans a route and determines goals, at the tactical level, the driver selects appropriate maneuvers to achieve short-term objectives, and at the operational level, the driver translates these maneuvers into control operations. Adequately performing driving tasks in each level enables the vehicle to reach a destination safely and efficiently. Currently, a driver conveys the intent via steering wheel/pedal, and this regards the OLI method. As increasing LoA, an agent who performs driving tasks would shift from the driver to AD system. We thus analyzed input methods that correspond to tactical and strategical levels while clarifying an intent conveyance method (DVI) and AD system capability (minimum LoA). The general idea of control methods is summarized in Fig. 2.

1) Operational Level Input Method: A driver makes a general plan, selects appropriate route and speed, and controls lateral and longitudinal parameters in real time. This command is realized by using the steering wheel and pedals. We call this ‘operational-level input (OLI) method’, which usually lasts from 0.5 to 5 seconds. OLI requires an AD system with LoA 0+. OLI has advantages, such as flexibility and driving pleasure, but for novice and elderly drivers, it may be difficult to accurately and immediately perceive the driving environment and adjust many parameters in a given short time window according to the situation, e.g., a dense-traffic intersection [24].

2) Strategical Level Input Method: A driver may only input the destination, traveling time, routes, and driving mode (e.g., eco, sport, etc), if the AD system could perform both operational- and tactical-level tasks. This command is expected to be realized by using a voice communication system or specialized car navigation system although they have not been commercialized. We call this ‘strategical-level input (SLI) method,’ which can last from minutes to days. SLI would require an AD system with LoA 4+. SLI has advantages in comfort (easiness) and safety, but only SLI will not be sufficient since current AD systems cannot deal with unexpected events, e.g., route change and sudden roadwork

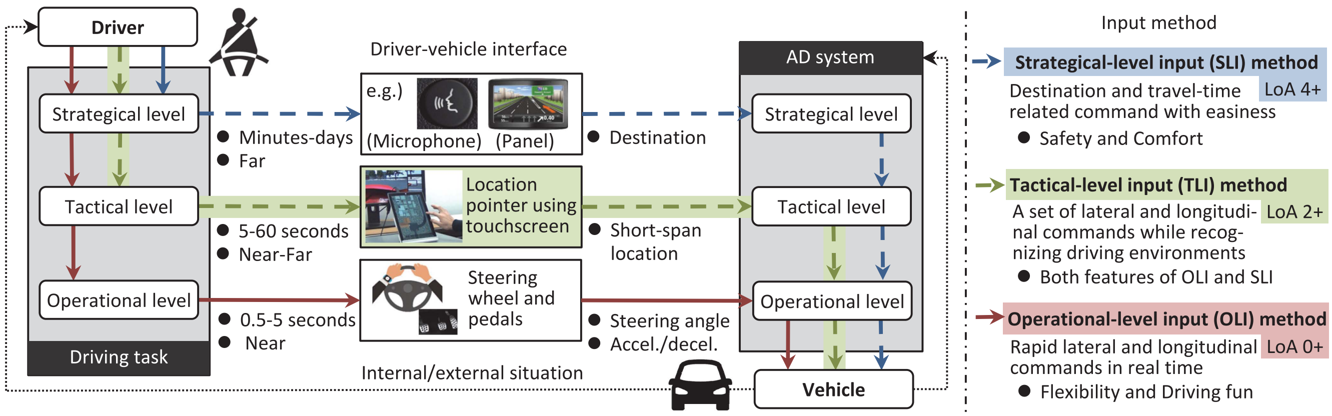

Fig. 2. General idea of vehicle control method that makes three levels of driving tasks correspond to the input method, such as OLI, TLI, and SLI. TLI and SLI inevitably requires higher capability of AD system. Considering requirements for TLI, this study proposes a touchscreen-based DVI that allows the driver to instantly command a tactical task, by designating a desired location on the map while enhancing situational awareness. .

[11]. Also, SLI would decrease driving pleasure due to the lack of interaction with vehicle control.

3) Tactical Level Input Method: A driver may perform part of the DDT, monitor the driving environment, and conduct OEDR or fallback performance of the DDT, based on driving task performed in strategical level, if the AD system could perform operational-level tasks. We call this 'tactical-level input (TLI) method', which can last from 5 to 60 seconds. TLI would require an AD system with LoA 2+. TLI is located at the medium level. (TLI is relatively more indirect than OLI and more direct than SLI), so TLI would compensate for the drawbacks of these two methods. TLI can allow the driver to input vehicle motions to be executed in reserve, as short-term future states, adjusting the input range spatially and temporally. This enables the reduction in the number of inputs than OLI and more flexible input than SLI, which provides TLI with features of both OLI and SLI. In summary, TLI should allow a driver to command a set of lateral and longitudinal controls, e.g., lane changing and parking, but DVIs for TLI have not been proposed.

B. Potential Advantages and Significance of TLI Method

As stated above, the TLI method, which allows the driver to control future states of the vehicle in a short spatiotemporal range while the AD system conducts the DDT ensuring safety, would be important for automated vehicles with LoA 2+. The potential advantages and significance of TLI over OLI and SLI are listed in Table I. For TLI, environmental information could be perceived in real time by both the driver and AD system and could be used to make control decisions to input the vehicle's future state. The decision and control are collaboratively made by the intent of both parties. TLI would thus give the driver the flexibility to control the vehicle compared with fully-automated SLI while ensuring utmost safety by constant monitoring and intervention by the system compared to OLI. Actually, AD systems focusing on tactical-level driving tasks have been proposed such as tactical lane change [25] and enhanced map for lane-level navigation [26]. However, they just dealt with a single DDT and did not focus on a systematic approach for 'designing DVIs for controlling highly automated vehicles.' Note that many studies on LoA in various human-machine systems have been conducted such as multiple unmanned aerial vehicles [27], but there are few studies on the TLI method [28].

TABLE I
POTENTIAL ADVANTAGES AND SIGNIFICANCE OF TACTICAL-LEVEL INPUT

Item	Descriptions
Driver workload	• Reduce driver workload compared with OLI due to decreasing input granularity
Capability	• To have more control over vehicle compared with SLI – In case of a sudden change of destination – Need to pull over at a point of interest – During emergency situation (passenger health condition) – In unexpected road and traffic conditions – To experience driving pleasure
Driver-vehicle collaboration	• Seamlessly change between levels of automation • Learn to drive safely and efficiently to empower user • Shared/collaborated control to takes the advantage of both human driver and autonomous decision making processes • Fulfill mobility requirements of elderly and handicapped, who cannot use conventional controllers • Safely maneuver vehicle in case of automation failure

C. Requirements of DVI to Command TLI

A DVI should be designed according to the driver-vehicle interaction to be achieved. We thus analyze DVIs for OLI, TLI, and SLI, respectively (Fig. 2). The OLI, which requires real-time lateral and longitudinal inputs, is realized by using the steering wheel and pedals. In contrast, the SLI, which requires the destination and travel-time-related commands, is expected to be realized by using a voice interaction system, etc. TLI requires a set of lateral and longitudinal inputs while recognizing the forehand driving environments of the driver. Tesla Motors use the turn signal switch as a DVI to input a lane-change command [29]. However, our TLI method should enable many input types situation-adaptably, such as turning at the second intersection, so traditional DVIs will not be suitable for realizing the full benefits of TLI. To achieve these requirements, first, we define a set of lateral and longitudinal commands as a tactical task, and then regard the tactical task as a command of a short-span future location of the vehicle. To command the vehicle's future state, we use a touchscreen displaying a map including the ego vehicle rendered from the top view. The touchscreen can convey the intent of inputs from the driver to the system, results, e.g., approval or denial to the input, and suggestion from the system to the driver, by using visual and auditory prompts. To summarize, in this study, a TLI method will be realized by using a touchscreen that allows the driver to instantly command a tactical task, e.g., lane changing, by designating a desired location on the map, e.g., the lane (the center of Fig. 2).

III. Development of Touchscreen Interface for TLI

We developed a touchscreen-based DVI for commanding TLI on the basis of requirements stated in the previous section.

A. Requirements and Related Parameters

1) Location-Based Input Using Touchscreen: There are many candidates for DVIs such as voice, hand gestures, etc. [30], [31]. In this study, we adopted the TLI method to a touchscreen because a screen can not only receive much information from driver but also convey them to AD system, and driver can comprehend that information in a very short time (at a glance), compared to voice and gesture interfaces. In addition, drivers would be familiar with using the touchscreen in smartphones and car navigation systems. Thus, we can expect that the acceptability of such an interface is high. The important point when using a touchscreen in vehicles is to allow the driver to precisely touch a location with reliability. We carefully design the DVI to ensure the above properties, but the acceleration and oscillation make precise touches difficult and they may result in miss-recognition. In this pilot study, we thus focus on investigating the effectiveness of our TLI method.

2) Bidirectional Interaction With Comfort and Robustness: A new DVI should enable bidirectional interaction, to collaboratively perform DDTs. The DVI thus provides the driver with feedback on the input commands, information of the driving environment, and suggestions from the system, by using visual and auditory prompts. A touchscreen should display an overview map, with an adjustable field of view depending on the situation, to comfortably command short-span future states of the vehicle. The DVI should also have an input-correction function for robust inputs. Moreover, the DVI should be located by considering human factors, e.g., angle of vision, reachable region, and difficulty in accurate positioning of the fingertip, when the vehicle is moving.

B. Touchscreen-Based DVI

We developed a touchscreen interface implemented in a Microsoft Surface Pro 3 (Fig. 3(a)). The interactive graphical user interface was developed using Unity [32], which is software for creating three-dimensional contents. We used a 27-inch LCD to display the virtual environment from the driver's point of view (Fig. 3(c)). The computer for the driving simulator [33] wirelessly connects with the touchscreen to update the vehicle

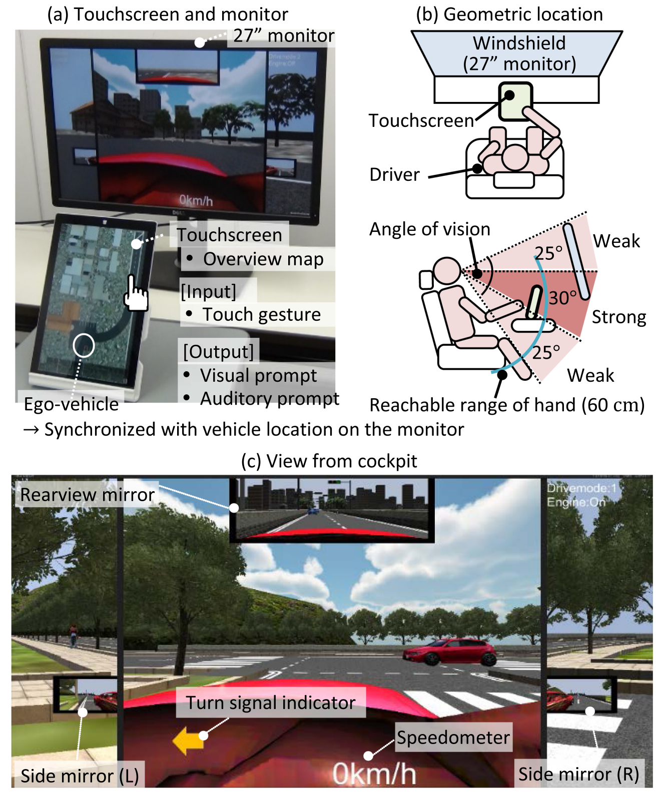

Fig. 3. (a) Touchscreen interface and monitor to display view from cockpit. (b) Geometric location of interface and monitor considering cognitive ability and ergonomics. (c) Reproduced view from cockpit made by using Unity. .

position and overview map in real time. Considering the human's angle of vision and reachable region of the fingertip, the touchscreen is located in front of the driver to allow the driver to watch both the simulator screen and touchscreen at the same field of view (Fig. 3(b)).

The two-dimensional overview map including the ego vehicle is displayed on the screen (Fig. 4). The interactive region is 16.9 $\times$ 25.4 cm in size and can show a road environment of 110 $\times$ 160 m, to provide sufficient time to recognize, judge, and act a command (determined from the result of iterative exploratory experiments). The map is controlled to keep the ego vehicle on the screen constantly heading in the direction toward the top of the screen with an offset of 30% of the height of the screen below the horizontal centerline, corresponding to an offset of 50 m. This is for expanding the visible area to check roads ahead and to provide sufficient temporal and spatial resolution for the 5–15 seconds before input. The touchscreen allows the driver to use fundamental touch gestures, including single tap, double tap, pan, swipe, rotate, pinch, and spread. If the input is mistaken, the driver can tap the input-cancel button. To facilitate understanding of the current situation and the result of input, we implemented visual and auditory prompts.

C. Location-Based TLI Method

As stated in Section I, we assume that the vehicle has an AD system to enable self-navigation and collision avoidance, corresponding to LoA 2–4. To provide users with a consistent,

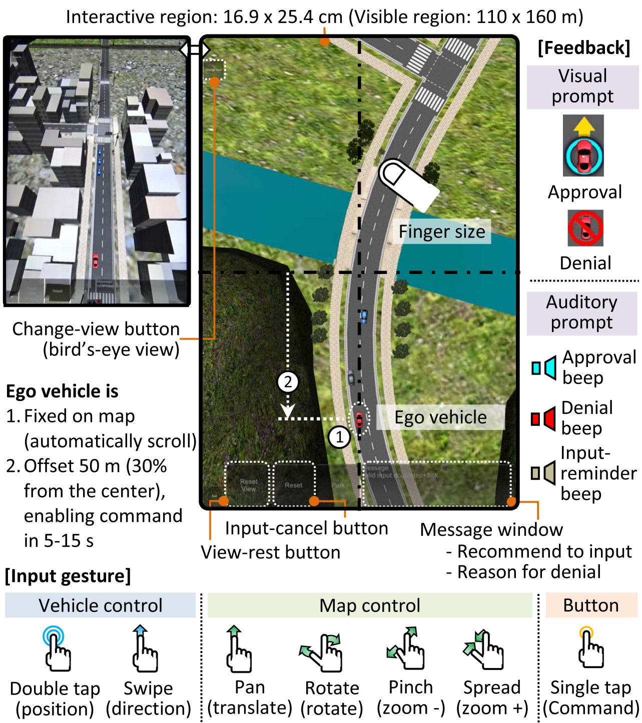

Fig. 4. Interactive touchscreen-based DVI for TLI. Relationship among touch gestures, tactical tasks, and map configuration was designed to facilitate robust command and situational awareness.

intuitive experience with DVI, we followed the accepted conventions for touch gestures from Android/iOS developer guidelines for human-interface design [34]. As illustrated at the bottom of Fig. 4, we implemented three categories of gesture interaction; vehicle control, map control, and button pressing.

1) Commands for Vehicle Control: The relationship between touch gestures and tactical tasks should be designed considering intuitiveness, reliability, and robustness. For vehicle control, we created a common input method, which allows the driver to designate a point on a location to go (Fig. 5(a)). To designate the desired vehicle location, e.g., lane and parking spot, we adopted a compound gesture by combining double tap and swipe gestures to avoid miss-inputs, that is, the driver double-taps at the desired location on the screen (reliability) then swipes in the direction to proceed (intuitiveness) (Fig. 5(a-2)). When the driver touches a traversable area on the screen, a residual (ghost vehicle) image appears at the touched location and an approval beep is given to the driver (Fig. 5(a-3)). If the area is not traversable, a denial marker appears with a beep. After the approval, the vehicle is controlled by the AD system (Figs. 5(a-4, 5)). The visual prompt disappears when the vehicle arrives at the designated point, and then the vehicle continues to travel along the current road (Fig. 5(a-6)). These compound touch gestures can apply to all TLIs (scenarios). For turning at an intersection, the driver designates the road to be traveled (Fig. 5(b)). For changing lanes, the driver designates the lane to enter (Fig. 5(c)). In parking, the driver touches the desired parking space and designates the direction by using the swipe gesture (Fig. 5(d)). This DVI allows sequential commands e.g., turning right at the next intersection and then turning left at the second intersection, by sequential touch inputs.

2) Supporting Functions for Robust Input: To assist the driver in making accurate inputs with less effort, we implemented an automatic map control system (Fig. 5(e)). The vehicle is shown fixed on the screen while the map is shown relative to the vehicle. However, a moving map could make it difficult to precisely input the desired location. Thus, in regions where drivers could possibly give input, such as at an intersection or interchanges at highway approaches (in this study, 80 m before to provide enough time to input (6 s)), the map remains fixed, and also the DVI provides a reminder beep and comments via the message window (e.g., recommend to input). Moreover, considering the tendency of low accuracy to point out the desired location on a screen, especially while the vehicle is moving, we set an acceptable margin (road width) of input error and the system automatically corrects the input. For map control, the size and viewpoint of the map can be changed by swipe, rotate, pinch, and spread gestures. Map control is a prevalent task in smartphones and car navigation systems. We thus adopted the same touch gestures to our interface for map control (the bottom of Fig. 4). Moreover, the view angle (bird's-eye view) can be changed by using the change-view button for understanding a surrounding driving environment. The above map parameters can be reset by using the reset-view button. If no input is received from the driver, the vehicle is controlled to continue to travel along the current road by the system.

3) Seamless Connection From TLI to SLI: For SLI, the driver may command the final destination for the vehicle, as stated in Section II. The proposed DVI can apply to SLI by touching the destination from the map displayed on the touchscreen interface. The tasks required on the way to get to the destination, such as avoiding obstacles and negotiating intersections, are automatically conducted by the AD system.

IV. Experimental Conditions

This section explains the experimental design and describes the driving route used for experiments which was created in a virtual environment consisting of several scenarios and events.

A. Virtual Reality Driving Simulator

We developed a driving simulator with sufficient functions to evaluate our method [33]. We prepared two types of DVIs. A Logitech G27 steering wheel with accelerator and brake pedals was used for OLI. The proposed touchscreen was used for TLI and SLI. A virtual environment and scenarios, including road modules, road signs, traffic lights, vehicles, and pedestrians were created by using Unity (Fig. 6). We implemented the ego vehicle as a mid-sized sedan with an automatic transmission. The vehicles, pedestrians, and traffic lights were controlled by scripts. We implemented triggered control points for traffic control and created a sensor script to enable rule-based control for the motion of other vehicles.

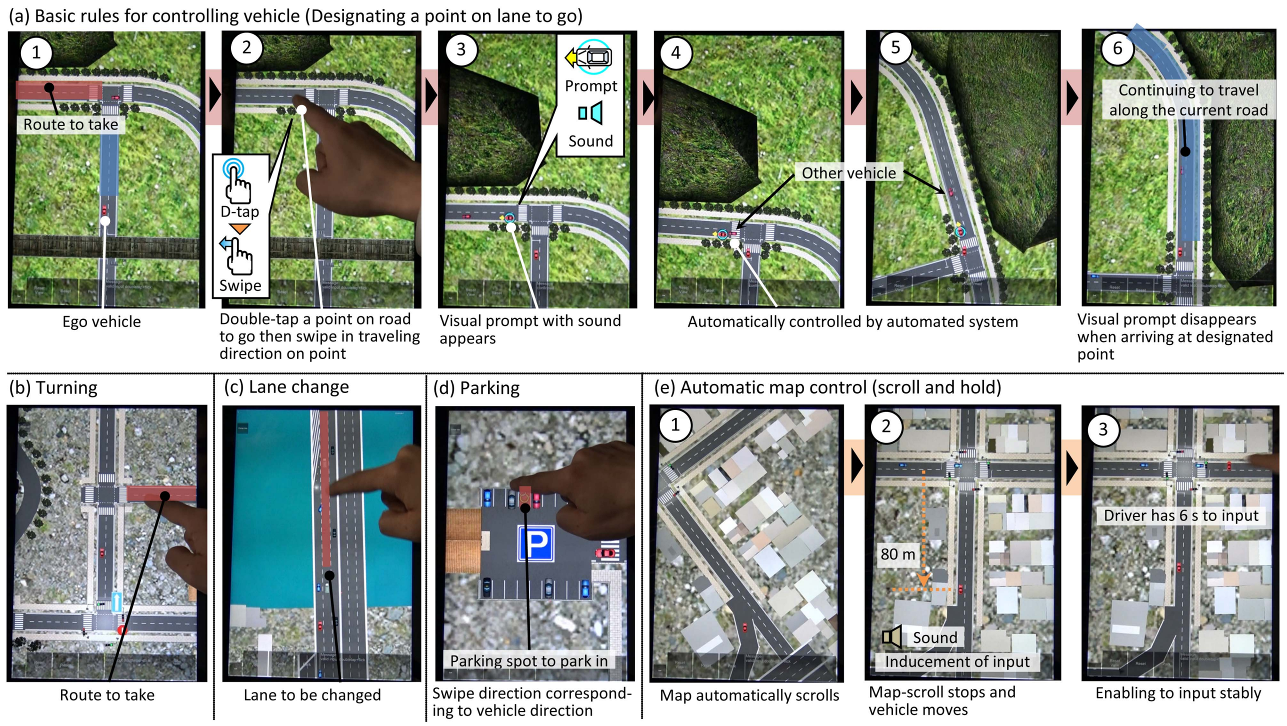

Fig. 5. Location-based TLI method. (a) Basic inputs for controlling vehicle, that is, driver designates a point of lane or parking spot to go by double-tap and swipe in traveling direction in order to avoid miss input. For example, (b) lane to take for tuning, (c) lane to be changed for lane change, and (d) parking spot to park for parking, is designated, respectively. (e) Automatic map control for facilitating input and situational understanding.

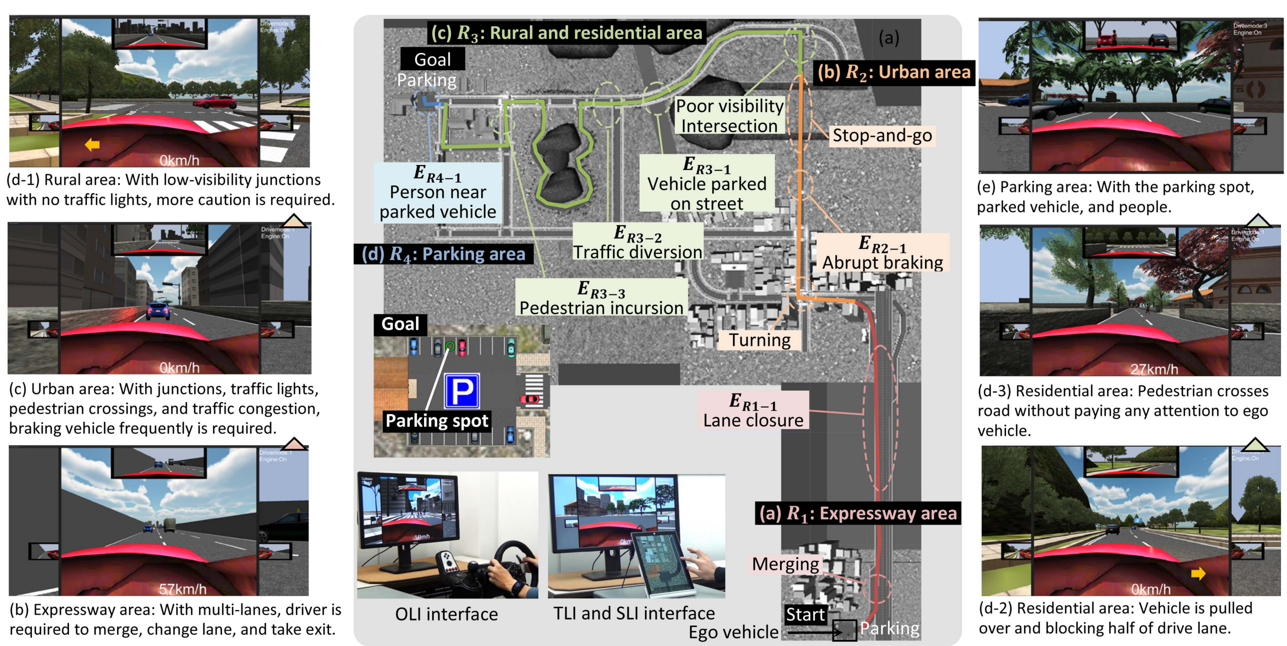

Fig. 6. (a) Driving course with four areas, such as (b) expressway, (c) urban, (d) rural and residential, and (e) parking areas, involving several events, which required different types of recognition, judgment, and operation of the driver and system.

B. Model of Automated Vehicle

1) Navigation: We used Unity's navigation system to navigate automated vehicles. Unity creates a data structure consisting of road components represented by convex polygons, called the navigation mesh which describes the road surfaces where the vehicle can traverse. A-star algorithm [35] is used to find a path from the start point to goal. Then, the sequence of polygons describing the path is created and the automated vehicle agent steers from one polygon to the next in the sequence to reach

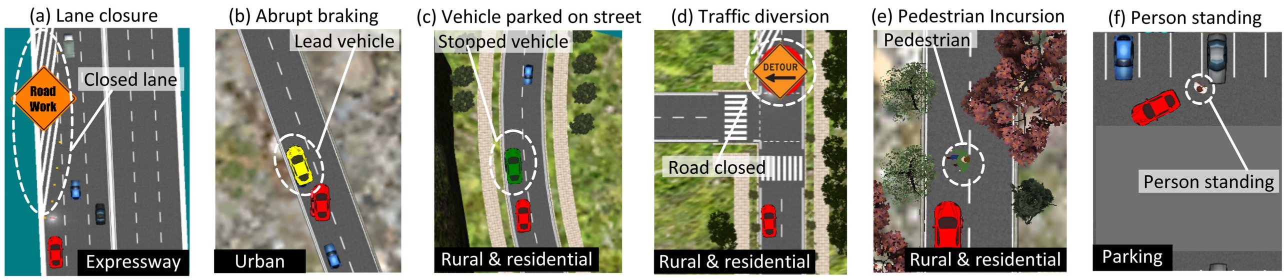

Fig. 7. Scripted scenarios and events, including (a) one lane is closed, (b) lead vehicle suddenly stops, (c) parked vehicle on street, (d) sudden traffic diversion, (e) pedestrian crosses road without paying any attention to ego vehicle, and (f) a person standing next to dedicated parking spot.

TABLE II
ROAD PROPERTIES IN FOUR AREAS INCLUDING SPEED LIMIT, NUMBER OF LANES, AND LENGTH

Property	Exp. way (R_1)	Urban (R_2)	Rural & res. (R_3)	Parking (R_4)
Speed limits km/h	80	40	40	10
No. of lanes	6	2	2	N/A
Length km	0.7	0.5	0.8	N/A

the goal. Automated vehicle identifies the dynamic obstacles, e.g., other vehicles and pedestrians, and avoids them by using reciprocal velocity obstacles (RVO). The sequence of polygons from the start to goal is locally adjusted and updated while the vehicle is moving.

2) Acceleration/Deceleration Profile: We created a headway variable for the automated vehicle to maintain with the lead vehicle. This distance was decided based on the speed limit of the road (Table II) and the braking deceleration and brake force of the vehicle. The headways for each area were chosen considering the level of protection needed and the effects on ambient traffic. We use Unity's ray casting to continuously monitor the distance to the lead vehicle as well as to other surrounding vehicles (in 360 °) at 100 Hz and use this data for the calculation of the speed to maintain a desired headway.

3) Steering Control: As the automated vehicle model, we implemented virtual path segments consisting of reference points. For example, there is a predefined curved path that the vehicle moves along when it changes lanes, turns at an intersection, or passes a slower vehicle (avoiding static/dynamic obstacles). We created these paths to make the movement of the automated vehicle appear more fluid.

C. Scenario and Events

To evaluate the proposed TLI method, the virtual environment should consist of several scenarios and events to represent many situations that drivers encounter in the real world. We created a driving route having a length of 2 km , including an expressway area (R_1), urban area (R_2), rural and residential area (R_3), and parking (R_4), as shown in Fig. 6. In addition, we designed several events that drivers experience in each area, as shown in Fig. 7. The properties (the speed limit, number of lanes, and length) of each area are listed in Table II.

1) Expressway Area: In this area, which had three lanes in each direction, the driver had to merge into traffic, change lanes, and take an exit. As the event, one lane was closed due to roadwork (Fig. 7(a)). The vehicles moving in this lane were required to merge into the lane to the right.

2) Urban Area: This area had intersections controlled by traffic lights, pedestrian crossings, railroad crossings, and traffic congestion that caused the driver to brake and/or stop the car frequently. As the event for this area, the lead vehicle braked suddenly, and the driver had to overtake it (Fig. 7(b)).

3) Rural and Residential Area: This area had less traffic, but it had intersections with no traffic signals and low visibility, so the driver had to be more cautious. As the event, a car had pulled over and blocked half of the lane (Fig. 7(c)). The driver needed to wait for oncoming traffic to pass before going around the parked car. Moreover, due to a sudden traffic diversion, drivers had to take a bypass road as indicated by road signs (Fig. 7(d)). We also triggered an unexpected incursion of a pedestrian into the path of the ego vehicle (Fig. 7(e)). The driver had to brake immediately to avoid hitting the pedestrian.

4) Parking Area: The parking lot consisted of parked vehicles and people. There was a dedicated parking spot for the ego vehicle (Fig. 7(f)). As the event, a person was standing close to the dedicated parking spot, requiring the driver to be much more cautious to avoid hitting her.

D. Experimental Conditions

The purpose of experiments is to clarify differences in driving performance and experience among three input methods and to confirm our hypothesis, that is, TLI can offer both the flexibility of OLI as well as the comfort of SLI.

1) Procedures: First, every participant was briefed about the driving simulator, each input level, and the automated vehicle model. Then, the participants used the training track to practice driving in each input level until they got used to them (about 20 min each). We then explained the driving route and objective, which is to get to the destination as quickly as possible while obeying road rules. For the experiment trials, we asked the participants to drive on the driving course, using three input methods. OLI adopted the steering wheel and pedals, and TLI and SLI adopted our touchscreen interface, but for SLI, it was used only to select the final destination. They drove with each input method, and we randomized the order of trials. OLI, TLI, and SLI were implemented to a vehicle with LoA 0, 2, and 4, respectively, although there are many possible combinations

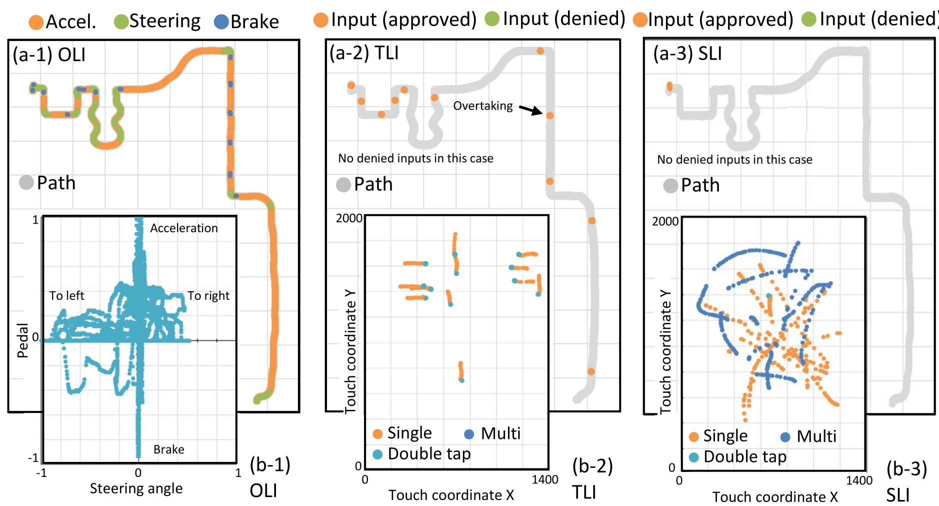

Fig. 8. (a) Overview map including path of ego-vehicle and input/output information and (b) command map in the entire trip for each input method. (a-1) acceleration, steering, and brake inputs, (a-2) approved and denied inputs for TLI, and (a-3) approved and denied inputs for SLI. (b-1) normalized steering angle (left/right) and pedal input (acceleration/brake) for OLI, (b-2) coordinates of single-, multi- touch, and double tap on touchscreen for TLI, and (b-3) coordinates of single-, multi- touch, and double tap on touchscreen for SLI. There were no denied inputs in this case.

among input method, DVI, and LoA. As a preliminary study, we adopted the most basic combination (Fig. 2).

2) Participants and Evaluation: 12 healthy participants (1 female, 21–24 years old, mean age of 22.6 years) participated in the experiment. In this preliminary study, we chose young participants who were familiar with using a touchscreen interface. They possessed a driving license, had normal or corrected to normal vision, and received monetary compensation for their contribution. In each trial, we recorded the task completion time, and mean heart rate using a wearable heart rate monitor (HR500-U, OMRON), as objective performance. In general, the mean heart rate is positively correlated with mental workload/stress [36], [37]. After completing each trial, we asked the participants to evaluate their experience using NASA-TLX subjective workload assessment tool [38]. After completing all three trials, they were given a computer-based questionnaire that was designed to evaluate driver experience and preference for each input method. Participants were also asked to support their answers by explaining the reasons for their choices. A variety of questions and subjective workload were able to use as subjective acceptance. This study was approved by Ethics Review Committee on Research with Human Subjects of Waseda University. Written informed consent was obtained from each study participant.

V. Results and Analysis

In this section, we explained the experimental results from the quantitative and qualitative evaluation of driving experience for OLI, TLI, and SLI methods.

A. Overview of Characteristics: Results of Inputs and Outputs

Fig. 8 shows an example of the overview maps including the path of ego-vehicle and input/output information and command map in the entire trip for each input method. As Figs. 8(a-1) and (a-2) show, OLI always required drivers to simultaneously input lateral and longitudinal commands. On the other hand, As Fig. 8(b-1) shows, TLI required drivers to input only when the drivers needed to change lane to go, so the number of commands was significantly lower than that of OLI, as Fig. 8(b-2) shows. We also found in R_2 that overtaking command was input once. SLI only requires drivers to designate the final destination, so the command was just once as shown in Fig. 8(a-3). However, map control was required before designating the destination, as shown in Fig. 8(b-3).

To analyze the easiness (effort) of each input method, we summarized the statistical data of input/output for each input method in Table III. We first calculated the mean total input time T. For OLI, T corresponds to the mean task completion time (323 s) because drivers always need vehicle control as stated above. For TLI, T can be obtained as the products of the mean time spent for one input t_i and the mean total number of inputs N. From the result, t_i was 2.48 s ($SD = 0.33$ s) and n_i was 9.58 s ($SD = 2.02$ s), so T was 23.8 s ($SD = 3.16$ s), which means that the input time for TLI was 7.37% of OLI. For SLI, in addition to designating the final destination, map control requires. The mean total time spent for map control T_M was 8.26 s (3.27 s) and N for SLI was 1, so T was 10.74 s ($SD =$ 3.50 s). Then, to analyze the system response, we calculated the approval rate R_A and denial rate R_D from N, the mean total number of approved inputs N_A and denied inputs N_D. From the result, R_A was 100 for OLI, 98.6 % ($SD = 0.0332$) for TLI, and 100% (0) for SLI. R_D was 0 for OLI, 1.39% ($SD =$ 3.32) for TLI, and 0 (0) for SLI. The reason for denial (only two times) for TLI was that a driver touched a location except for a dedicated parking spot for the ego vehicle. Note that the success rate R_S was 100% for all input methods. N ($SD = 2.02$) for TLI means that drivers could voluntarily change lanes to go,

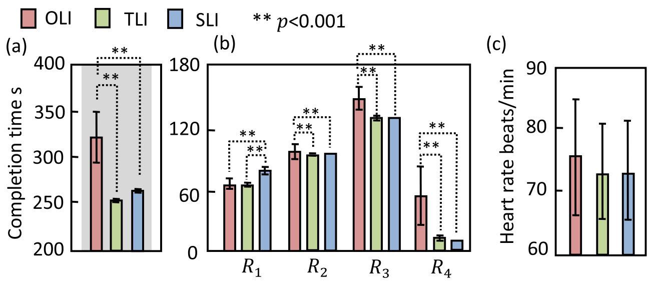

Fig. 9. Quantitative results, including (a) mean completion time for entire trip, (b) mean completion time for each region, and (c) mean heart rate.

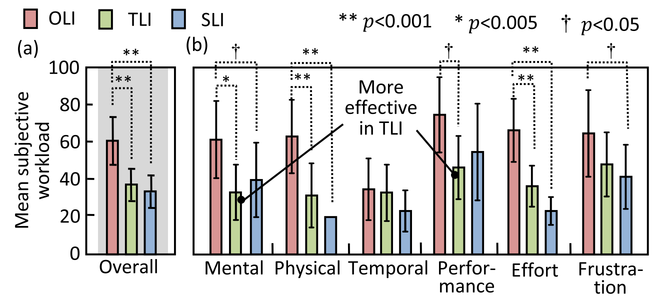

Fig. 10. Mean subjective workload using NASA-TLX which has six subscales: mental, physical, temporal, performance, effort, and frustration.

TABLE III
STATISTICAL DATA OF INPUTS AND OUTPUTS

	OLI	TLI	SLI
Total input time T s	323 (26.6)	23.8 (3.16)	10.74 (3.50)
Total number of inputs N	n.s.	9.58 (2.02)	1 (0)
Total number of approved inputs N_A	n.s.	9.41 (1.78)	1 (0)
Total number of denied inputs N_D	n.s.	0.167 (0.389)	0 (0)
Success rate R_S %	100	100 (0)	100 (0)
Approval rate R_A %	100	98.6 (0.0332)	100 (0)
Denial rate R_D %	0	1.39 (3.32)	0 (0)
Total time spent for map control T_M s	n.s.	0 (0)	8.26 (3.27)

n.s.: those values are not defined in OLI.

TABLE IV
RESULTS OF ANOVA AND POST-HOC TESTS IN COMPLETION TIME

	ANOVA: $F(2, 33)$		Post-hos test (p value)		
	F value	p value	OLI–TLI	OLI–SLI	TLI–SLI
Entire trip	61.5	< 0.001	< 0.001	< 0.001	n.s.
R_1	73.7	< 0.001	n.s.	< 0.001	< 0.001
R_2	14.6	< 0.001	< 0.001	< 0.001	n.s.
R_3	32.9	< 0.001	< 0.001	< 0.001	n.s.
R_4	55.5	< 0.001	< 0.001	< 0.001	n.s.

n.s.: $p>0.05$

in particular in the highway (R_1). These results would indicate that vehicle control using TLI method was feasible and TLI (also and SLI) method could make the drivers input easier and more flexible.

B. Objective Performance Data

1) Task Completion Time: Fig. 9(a) shows the mean completion time in the entire trip. We found that the OLI method ($M = 323.2$ s, $SD = 26.6$ s) spent more time than TLI ($M = 254.6$ s, $SD = 3.50$ s) and SLI methods ($M = 265.3$ s, $SD = 3.71$ s). To reveal statistical differences among input methods, we performed a one-way analysis of variance (ANOVA) and post-hoc tests using the Bonferroni correction. The test results were listed in Table IV. We found from the table that the mean completion time differed significantly among input methods, $F(2,\, 33) = 61.5$, $p<0.001$. The post-hoc test revealed significant differences ($p<0.001$) between OLI–TLI and OLI–SLI, respectively. We then analyzed the completion time for each area (R_1–R_4), as shown in Fig. 9(b) and Table IV. The completion time for OLI was the highest in R_2 , R_3, and R_4 (SLI was the highest in R_1, since it spent time to point to a destination). It was especially much higher in R_4 and R_3, meaning that the vehicle control in those areas was difficult than that in other areas. We confirmed from the results that TLI and SLI which introduced an automated control system offered more efficiency than OLI, and TLI had the same efficiency as SLI despite the concern that TLI that requires inputs from the driver might degrade the efficiency compared with SLI. This is because TLI could allow the driver to input vehicle motions to be executed 'in reserve'.

2) Comfort: Fig. 9(c) shows the mean heart rate (beats/min). We observed that the mean heart rate for OLI ($M = 76.7$, $SD = 9.64$) was highest because it always required the drivers to keep their attention on the road. The lower mean heart rate for TLI ($M = 73.2$, $SD = 7.69$) and SLI ($M = 73.4$, $SD = 8.33$) implied lower physical and mental burden. A one-way ANOVA showed that mean heart rate did not differ among input methods ($F(2,\, 33) = 0.563$, $p = 0.575$), but we might be able to say from the results that TLI and SLI which introduced an automated control system offered less stress than OLI, and TLI had the same stress as SLI despite the concern that TLI that requires inputs from the driver might increase the stress compared with SLI. This is because TLI could allow the driver to input vehicle motions to be executed 'when only necessary,' as shown in Fig. 8(b-1).

C. Subjective Evaluation

1) Workload: Fig. 10(a) shows the overall mean subjective workload obtained from NASA-TLX. We found that TLI and SLI had less workload than OLI. We performed a one-way ANOVA and post-hoc tests using the Bonferroni correction, and the test results were listed in Table V. The results showed that the mean overall workload differed significantly among input methods, $F(2,\, 213) = 36.9$, $p<0.001$. The post-hoc test revealed the significant differences ($p<0.001$) between OLI ($M = 61.1$, $SD = 12.6$)–TLI ($M = 37.5$, $SD = 8.83$) and OLI–SLI ($M = 33.9$, $SD = 9.01$), respectively. This result can support objective performance data. We then analyzed the workload for each subscale, as shown in Fig. 10(b) and Table V. We found that TLI had less workload in all subscales over OLI, and in mental (related to fatigue) and performance over SLI.

TABLE V
RESULTS OF ANOVA AND POST-HOC TESTS IN SUBJECTIVE WORKLOAD

	ANOVA: $F(2, 33)$		Post-hos test (p value)		
	F value	p value	OLI–TLI	OLI–SLI	TLI–SLI
Overall	36.9 *	< 0.001	< 0.001	<0.001	n.s.
Mental	6.88	< 0.005	< 0.005	<0.05	n.s.
Physical	24.2	< 0.001	< 0.001	<0.001	n.s.
Temporal	1.80	n.s.	n.s.	n.s.	n.s.
Performance	5.10	< 0.05	< 0.05	n.s.	n.s.
Effort	34.8	< 0.001	< 0.001	<0.001	n.s.
Frustration	4.20	< 0.05	n.s.	<0.05	n.s.

$*$ $F(2, 213)$, n.s.: p>0.05

1) *Mental:* OLI that required the drivers to keep their attention on the road required more mental workload compared to TLI (p<0.005) and SLI (p<0.05). SLI was slightly higher than TLI due to less flexibility of path planning.
2) *Physical:* Drivers for TLI and SLI interacted only with the touchscreen using fingers. OLI that requires to use their legs and hands continuously thus required more physical workload compared to TLI (p<0.001) and SLI (p<0.001).
3) *Temporal:* It was high in order of OLI, TLI, and SLI, since OLI required all the vehicle control in real time while SLI required to input the final destination at the beginning, and TLI required inputs of vehicle motions when necessary.
4) *Performance:* Many drivers mentioned that they were not satisfied with their operation in OLI due to lack of driving skills. TLI was statistically lower than OLI (p<0.05), due to the flexibility in vehicle control while ensuring safety.
5) *Effort:* SLI with a fully-automated control system required the lowest effort compared to OLI (p<0.001) and TLI. The effort for TLI was much lower than that for OLI (p<0.001), due to fewer control inputs needed.
6) *Frustration:* There was a significant difference between OLI–SLI (p<0.05). Some drivers mentioned that their frustration in TLI and SLI was higher than OLI, due to their advanced driving skills and experience.

2) Questionnaires for Preference: We asked the participants to choose the best input methods after all trials. Fig. 11(a) shows the statistical results of the driver's preference evaluation for each input method for the entire trip and each area. The input method chosen by most drivers was OLI (50%) in the expressway area (R_1), TLI (58%) in the urban area (R_2), OLI (42%) in the rural area (R_3), and TLI (83%) for the parking area (R_4). To reveal the independence of the distributions for each area, we performed Pearson's Chi-square test. The results revealed that the preference for input methods was not equally distributed in the different regions, $\chi^2(6, N = 48) = 11.36$, p<0.1. Then, to identify conditions with statistical differences, we performed the residual analysis and the results revealed that OLI for R_1 and TLI for R_4 were statistically larger than others (p<0.05), and OLI for R_4 was statistically smaller than others (p<0.05). We found that the preferred input method varied depending on the area of interest and no one preferred OLI in R_4.

3) Discussion in Driving Experience: As a discussion, we here equally divided participants into two groups, including the novice (< 2 years) and experienced ($\geq$ 2 years), based on the driving experience. The breakdown was 6 (0–2 yrs), 2 (2–4 yrs), and 4 (4–8 yrs). Fig. 11(b) shows the statistical results of preference for each input method for the entire trip and each area for two groups. The graph for the entire trip shows that the novice drivers preferred automated vehicles (TLI: 33% and SLI: 17%), while the experienced drivers preferred controllable vehicles (OLI: 70% and TLI: 30%). This tendency can be also observed in each area. The experienced drivers preferred OLI in R_1 and R_3 and TLI in R_2 and R_4. In contrast, the novice drivers preferred TLI in R_1–R_4. This tendency was basically consistent across the drivers. We confirmed that drivers preferred the different input methods depending on driving environments, and the preference could be changed in the driving experience. Note that the analysis result indicated that TLI can be used regardless of the complexity of driving environments and individual driving skills. This result of analysis quite matches that TLI only requires a small number of inputs, as shown in Fig. 8(a-2). We performed Chi-square tests for each area, and the results showed that the preference for three input methods only in R_1 was not equally distributed between two groups, $\chi^2(2, N = 12) = 5.667$, p<0.1, and the residual analysis revealed that OLI in the experienced was statistically larger and OLI in novice was statistically smaller than others (p<0.05). The Chi-square tests revealed that distributions in other areas did not statistically differ between the two groups.

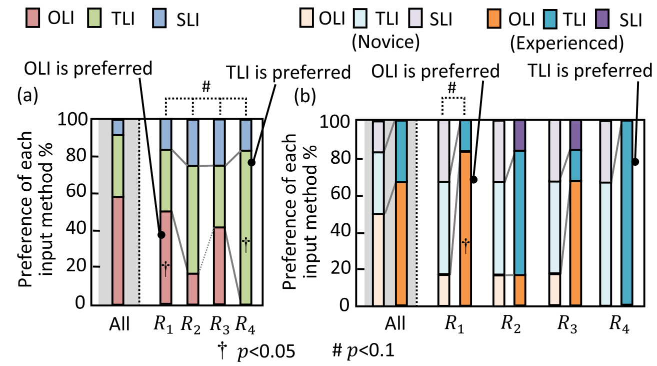

Fig. 11. Preference evaluation for choosing the best in three methods for entire trip and each area. (a) All drivers and (b) novice and experienced drivers.

D. Preference Analysis

To clarify reasons for preferences/non-preferences revealed in the previous section, we analyzed the results of questionnaires and free descriptions, by referring to text mining techniques [39]. We first defined five dominant keywords including workload, driving skill, flexibility, reliability, and driving pleasure, which were derived from the advantages of OLI and SLI. High flexibility and high driving pleasure are expected to be preferred reasons for OLI, and low workload and irrelevant driving skill are expected to be preferred reasons for SLI. The non-preferred reasons are the opposite of the above. High workload and relevant driving skill would be non-preferred reasons for OLI, and low flexibility and low driving pleasure would be non-preferred reasons for SLI. Note that the reliability may be changed if the driver has confidence in his/her driving skill. By referring to a hypothesis in this study, TLI would have the preferred reasons

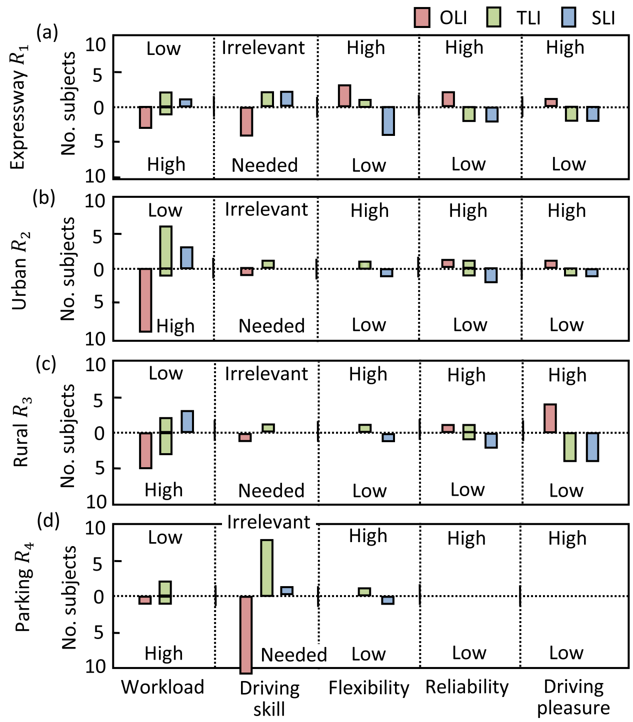

Fig. 12. Statistical results of reasons for preference (upper bars) and non-preference (lower bars) about workload, driving skill, flexibility, reliability, and driving pleasure for each area (a)–(d).

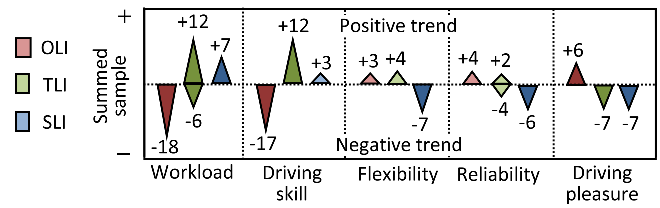

Fig. 13. Statistical results of reasons for preference (upper bars) and non-preference (lower bars) about workload, driving skill, flexibility, reliability, and driving pleasure for summed number of subjects.

TABLE VI
RESULTS OF CHI-SQUARE AND POST-HOC TESTS IN REASONS

	Chi-square test		Residual analysis *		
	χ^2 value	p value	OLI	TLI	SLI
Workload	$\chi^2(2, 43)$=26.8	< 0.01	< 0.01 (−)	n.s.	< 0.01 (+)
Driving skill	$\chi^2(2, 34)$=32.0	< 0.01	< 0.01 (−)	< 0.01 (+)	n.s.
Flexibility	$\chi^2(2, 14)$=32.0	< 0.01	n.s.	n.s.	< 0.01 (−)
Reliability	$\chi^2(2, 16)$=10.3	< 0.01	< 0.01 (+)	n.s.	n.s.
Driving pleasure	$\chi^2(2, 20)$=20.0	< 0.01	< 0.01 (+)	n.s.	n.s.

∗ +: positive, −: negative, n.s.: p>0.05.

for both OLI and SLI and mitigate (eliminate) non-preferred reasons for them. We manually extracted the five keywords and their usage contexts, i.e., positive or negative.

1) Analysis in Each Area: Fig. 12 shows statistical results of reasons for preference (upper bars) and non-preference (lower bars) about each keyword for each area (a)–(d).

1) Expressway R_1. Many drivers mentioned that OLI had higher flexibility in the speed and direction control of the vehicle (+25% of participants, positive opinion), but also had high workload (−25%, negative opinion) and relevant driving skills (−33%), e.g., merging, as disadvantages. For TLI and SLI, the drivers could drive easily, but SLI made the drivers feel the lack of flexibility (−33%).
2) Urban R_2. Many drivers mentioned that OLI was annoying to accelerate and apply brakes alternatively (−75%). The flexibility to enable to freely select the route was a reason for choosing TLI, and this appeared as low workload (+50%). Many drivers mentioned that the ability to cope with an abrupt event was a main advantage of TLI.
3) Rural R_3. The key reason for preferring OLI was the driving pleasure (+33%). In contrast, some drivers stated that SLI was easy due to fewer inputs required (+25%). In similar to R_2, OLI provided higher workload to some drivers (−42%). We also found that the importance of driving pleasure depended on the individual driver.
4) Parking R_4. Drivers mentioned that OLI needed precise operation (−92%), while more than half of drivers opted for TLI (+67%) because it did not require a high level of driving skills. SLI was not chosen because the drivers in TLI felt to command in parking, compared with SLI.

2) Analysis in Entire Trip: Fig. 13 shows the summed result in the entire trip. We performed Chi-square tests and the residual analysis, and the test results were listed in Table VI. The results show that all five keywords had different distribution (p<0.01). We found that TLI and SLI were preferred for difficult (parking R_4) and annoying tasks (stop and go traffic R_2). The results of the residual analysis show that OLI had a positive trend in reliability (p<0.01) and driving pleasure (p<0.01) and a negative trend in workload (p<0.01) and driving skill (p<0.01). SLI had a positive trend in workload (p<0.01) and a negative trend in flexibility (p<0.01), reliability (n.s.), and driving pleasure (n.s.). Moreover, TLI had a positive trend in driving skill (p<0.01) and no negative trends. These results confirmed that TLI had positive aspects of both OLI and SLI while compensating negative aspects of them, like our hypothesis. By combining data listed in Fig. 8(c), the results confirmed that TLI was more irrelevant to driving skill than OLI and more flexible than SLI, which means that TLI had advantages in both OLI and SLI.

E. Contributions and Limitations

As a preliminary study of advanced driver-vehicle interaction, we proposed a tactical-level input (TLI) method, implemented the TLI to a touchscreen interface, and evaluated TLI compared with OLI and SLI. The result of experiments showed that TLI had strong points of both OLI and SLI as well as mitigated weak points of both OLI and SLI. Moreover, we found that drivers who like driving and have much driving experience tended to choose OLI due to the fun of driving, and in contrast, drivers with less driving experience tended to opt for TLI and SLI. The contrition of this study would become a first but solid step to seek alternative DVIs in future intelligent automobiles. As the next step, on the other hand, we need to consider the system and evaluation design, to overcome the limitations of this study, as follows.

1) System Design: We found from the free description that the drivers desired an easier way of commanding that could lower the input time. This would be important because the temporal demand largely affects usability in terms of frustration and performance measures. We also found that the drivers desired to change longitudinal control parameters, i.e., speed and acceleration, in addition to the lateral control we implemented. This would be important to realize a more personalized and more flexible driving experience in highly automated vehicles. We will investigate other types of interfaces that allow drivers to rapidly command control inputs and change longitudinal control parameters, such as lever-type haptic or hand-gesture interfaces. These findings can be also one of the contributions to motivate designing DVIs in future intelligent automobiles.

2) Evaluation Design: The experiments were done by using only young participants, specific DVIs, and a virtual reality simulator. As the discussion part revealed that the novice and experienced drivers had different preferences, participant attributes (e.g., age, gender, and pro-driver or not) will largely change the response. Older participants, who are unfamiliar with a touchscreen interface, would bring different results in performance and preference [40] (actually, the young participants in this study did not require any special instructions and smoothly handled the interface). We should use diverse drivers for the experiments, but in this preliminary study, we tried to minimize differences derived from the variety, to focus more on evaluating the feasibility of the TLI method. Thus, we used only 21–24 years old participants. In the future, we will investigate it with various drivers, and a system that can adapt to personal preferences. Moreover, we adopted a touchscreen interface for TLI, so we will investigate different types of interfaces. Furthermore, we used a driving simulator due to the need for evaluating the methods in repeatable conditions, but the workload perceived by drivers will differ from that when driving a real car in real scenarios. In the future, we will evaluate the TLI method in a real car environment.

VI. Conclusion and Future Work

As one of the forms of future driver-vehicle interfaces (DVIs) for highly-automated vehicles, in this study, we proposed a tactical-level-input (TLI) method and developed a touchscreen interface that allows the driver to easily understand a situation and instantly input a control command for vehicles with automated driving systems. The screen displays an augmented map including the ego vehicle rendered from the top view. The driver can instantly command lateral control input(s) by TLI method, e.g., lane changing, by designating a desired location on the map, e.g., lane, by double tap and swipe. We performed experiments using a driving simulator to evaluate the TLI method compared with the operational- (OLI, level 0) and strategical-level input (SLI, level 4) methods. The results showed that the TLI method offered both the flexibility of OLI as well as the comfort of SLI. In-depth analyses showed that drivers preferred to use different interactions (level of automation/input method) for different traffic conditions and scenarios as well as their driving skills. This study contributes to indicating the feasibility of the TLI method and its application to a touchscreen interface, as one of the alternative DVIs in future intelligent automobiles.

For future work, a system that can adapt to personal preferences, regardless of the user's driving skills, experience, age, or physical disability is to be developed. It is also important to investigate different configurations of touchscreen interface (e.g., visible region) and different types of interfaces (e.g., haptic and hand gesture), and develop a different automatic map-control system and feedback methods that help the driver to learn and understand the status of the vehicle. Furthermore, we will evaluate the effectiveness in takeover situations.

References

[1] Nissan, "Nissan's new Serena ProPILOT technology makes autonomous drive first for Japanese automakers." [Online]. Available: https://global.nissannews.com/en/releases/160713-02-e

[2] BMW, "360-degree collision avoidance and fully-automated parking in multi-storey car parks." [Online]. Available: https://www.press.bmwgroup.com/usa/article/detail/T0198525EN_US/bmw0-innovations-at-the-2015-consumer-electronics-show-ces-in-las-vegas-360-degree-collision-avoidance-and-fully-automated-parking-in-multi-storey-car-parks?language=en_US

[3] Mercedes-Benz, "Mercedes-Benz intelligent drive." [Online]. Available: https://www.mbofnewton.com/mercedes-benz-intelligent-drive/

[4] Tesla, "Autopilot and full self-driving capability." [Online]. Available: https://www.tesla.com/support/autopilot

[5] S. Yang, W. Wang, C. Liu, and W. Deng, "Scene understanding in deep learning-based end-to-end controllers for autonomous vehicles," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 1, pp. 53–63, Jan. 2019.

[6] D. F. Llorca *et al.*, "Autonomous pedestrian collision avoidance using a fuzzy steering controller," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 390–401, Jun. 2011.

[7] X. Xu, L. Zuo, X. Li, L. Qian, J. Ren, and Z. Sun, "A reinforcement learning approach to autonomous decision making of intelligent vehicles on highways," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 50, no. 10, pp. 3884–3897, Oct. 2020.

[8] K. Chu, M. Lee, and M. Sunwoo, "Local path planning for off-road autonomous driving with avoidance of static obstacles," *IEEE Trans. Intell. Transp. Syst.,* vol. 13, no. 4, pp. 1599–1616, Dec. 2012.

[9] S. A. E. International, *(R) Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*, SAE Int. Standard J3016, Sep. 2016.

[10] Y. Chen, X. Zhang, and J. Wang, "Robust vehicle driver assistance control for handover scenarios considering driving performances," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 7, pp. 4160–4170, Jul. 2021.

[11] J. Nilsson, P. Falcone, and J. Vinter, "Safe transitions from automated to manual driving using driver controllability estimation," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 1806–1816, Aug. 2015.

[12] H. Hayashi *et al.*, "A driver situational awareness estimation system based on standard glance model for unscheduled takeover situations," in *Proc. IEEE Intell. Veh. Symp.*, 2019, pp. 718–723.

[13] R. Sukthankar, J. Hancock, and C. Thorpe, "Tactical-level simulation for intelligent transportation systems," *Math. Comput. Model.*, vol. 27, no. 9–11, pp. 229–242, 1998.

[14] E. R. Boer and M. Hoedemaeker, "Modeling driver behavior with different degrees of automation: A hierarchical decision framework of interacting mental models," in *Proc. Eur. Annu. Conf. Hum. Decis. Mak. Manual Control*, 1998, pp. 63–72.

[15] Z. Wang, R. Zheng, T. Kaizuka, K. Shimono, and K. Nakano, "The effect of a haptic guidance steering system on fatigue-related driver behavior," *IEEE Trans. Hum.-Mach. Syst.*, vol. 47, no. 5, pp. 741–748, Oct. 2017.

[16] M. Corno, "Design, analysis, and validation of a haptic-based driver support system for traction control," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 4, pp. 1849–1859, Dec. 2013.

[17] Y. Saito, M. Itoh, and T. Inagaki, "Driver assistance system with a dual control scheme: Effectiveness of identifying driver drowsiness and preventing lane departure accidents," *IEEE Trans. Hum.-Mach. Syst.*, vol. 46, no. 5, pp. 660–671, Oct. 2016.

[18] A. Amditis *et al.*, "Towards the automotive HMI of the future: Overview of the aide-integrated project results," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 3, pp. 567–578, Sep. 2010.

[19] S. M. Petermeijer, J. C. F. de Winter, and K. J. Bengler, "Vibrotactile displays: A survey with a view on highly automated driving," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 4, pp. 897–907, Apr. 2016.

[20] M. AblaBmeier, T. Poitschke, F. Wallhoff, K. Bengler, and G. Rigoll, "Eye gaze studies comparing head-up and head-down displays in vehicles," in *Proc. IEEE Int. Conf. Multimedia Expo.*, 2007, pp. 2250–2252.

[21] A. L. Kun, S. Boll, and A. Schmidt, "Shifting gears: User interfaces in the age of autonomous driving," *IEEE Pervasive Comput.*, vol. 15, no. 1, pp. 32–38, Jan.–Mar. 2016.

[22] L. Bi, X.-A. Fan, N. Luo, K. Jie, Y. Li, and Y. Liu, "A head-up display-based P300 brain–computer interface for destination selection," *IEEE Trans. Intell. Transp. Syst.,* vol. 14, no. 4, pp. 1996–2001, Dec. 2013.

[23] J. A. Michon, "A critical view of driver behavior models: What do we know, what should we do?," in *Human Behavior and Traffic Safety*, L. Evans and R. C. Schwing, Eds., New York, NY, USA: Plenum Press, 1985, pp. 485–520.

[24] D. Otte, M. Jänsch, B. Pund, and K. Duntsch, "Accident causation factor analysis of traffic accidents on the example of elderly car drivers using the causation analysis tool ACAS," in *Proc. Int. Tech. Conf. Enhanced Saf. Veh.*, 2013, pp. 1–10.

[25] S. Ulbrich and M. Maurer, "Towards tactical lane change behavior planning for automated vehicles," in *Proc. IEEE Int. Conf. Intell. Transp. Syst.*, 2015, pp. 989–995.

[26] D. Betaille and R. Toledo-Moreo, "Creating enhanced maps for lane-level vehicle navigation," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 4, pp. 786–798, Dec. 2010.

[27] J. Y. C. Chen, M. J. Barnes, and M. Harper-Sciarini, "Supervisory control of multiple robots: Human-performance issues and user-interface design," *IEEE Trans. Syst., Man, Cybern., Part C*, vol. 41, no. 4, pp. 435–454, Jul. 2011.

[28] T. B. Sheridan, "Adaptive automation, level of automation, allocation authority, supervisory control, and adaptive control: Distinctions and modes of adaptation," *IEEE Trans. Syst., Man, Cybern. - Part A, Syst. Hum.*, vol. 41, no. 4, pp. 662–667, Jul. 2011.

[29] IEEE Spectrum, "Tesla's robocar to driver: accept the liability, buster." [Online]. Available: http://spectrum.ieee.org/cars-that-think/transportation/self-driving/tesla-robocar-to-driver-accept-the-liability-buster

[30] G. McAllister, S. J. McKenna, and I. W. Ricketts, "Towards a non-contact driver-vehicle interface," in *Proc. IEEE Int. Conf. Intell. Transp. Syst.*, 2000, pp. 58–63.

[31] J. Zhuang, K. Geng, and G. Yin, "Ensemble learning based brain-computer interface system for ground vehicle control," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 9, pp. 5392–5404, Sep. 2019.

[32] Unity. [Online]. Available: http://unity.com

[33] U. E. Manawadu, M. Ishikawa, M. Kamezaki, and S. Sugano, "Analysis of individual driving experience in autonomous and human-driven vehicles using a driving simulator," in *Proc. IEEE/ASME Int. Conf. Adv. Intell. Mechatronics*, 2015, pp. 299–304.

[34] Gestures- Patterns- Material design. [Online]. Available: https://material.io/archive/guidelines/patterns/gestures.html#

[35] P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," *IEEE Trans. Syst. Sci. Cybern.*, vol. TOSSAC-4, no. 2, pp. 100–107, Jul. 1968.

[36] B. Mehler, B. Reimer, and Y. Wang, "Comparison of heart rate and heart rate variability indices in distinguishing single task driving and driving under secondary cognitive workload," in *Proc. Int. Driv. Symp. Hum. Factors Driv. Assessment, Training, Veh. Des.*, 2011, pp. 590–597.

[37] U. E. Manawadu, T. Kawano, S. Murata, M. Kamezaki, J. Muramatsu, and S. Sugano, "Multiclass classification of driver perceived workload using long short-term memory based recurrent neural network," in *Proc. IEEE Intelli. Veh. Symp.*, 2018, pp. 2009–2014.

[38] S. G. Hart and L. E. Staveland, "Development of NASA-TLX (task load index): Results of empirical and theoretical research," *Adv. Psychol.*, vol. 52, pp. 139–183, 1988.

[39] V. Gupta and G. S. Lehal, "A survey of text mining techniques and applications," *J. Emerg. Technol. Web Intell.*, vol. 1, no. 1, pp. 60–76, 2009.

[40] A. Sonderegger, S. Schmutz, and J. Sauer, "The influence of age in usability testing," *Appl. Ergonom.*, vol. 52, pp. 291–300, 2016.

Mitsuhiro Kamezaki (Member, IEEE) received the B.S., M.S., and Dr.Eng. degrees in mechanical engineering from Waseda University, Tokyo, Japan, in 2005, 2007, and 2010, respectively. From April 2010 to March 2013, he was a Research Associate with the Department of Modern Mechanical Engineering, Waseda University. From April 2013 to March 2018, he was an Assistant Professor with the Research Institute for Science and Engineering, Waseda University. Since April 2018, he has been an Associate Professor with the Research Institute for Science and Engineering, Waseda University. His interests include intelligent vehicle, human-machine interface, and human sensing. He is a Workshop Co-Organizer of In-cabin human-sensing and interaction in intelligent vehicles (HSIV) in IEEE Intelligent Vehicle Symposium. Dr. Kamezaki was the recipient of the ICROS Best Paper Award Finalist from the IEEE/RSJ IROS 2011 and Best Paper Award from the IEEE/ASME AIM 2016. He is a Member of the SICE, RSJ, and JSME.

Udara Eshan Manawadu (Member, IEEE) received the B.Sc. degree (Hons.) in mechanical engineering from the University of Moratuwa, Moratuwa, Sri Lanka, in 2013, and the M.S., and Ph.D. degrees from the Graduate School of Modern Mechanical Engineering, Waseda University, Tokyo, Japan, in 2015 and 2018, respectively. His research interests include driver-vehicle interaction, driver monitoring, human sensing, and human-machine interface systems. He was the recipient of the Award for the Best Paper in IEEE International Conference in Advanced Intelligent Mechatronics in 2016. He is a Member of the IEEE Intelligent Transportation Systems Society and has been an Associate Editor for the IEEE-IV Workshop on Human Sensing in Intelligent Vehicles since 2020.

Masaaki Ishikawa received the B.S. degree in mechanical engineering in 2015 from Waseda University, Tokyo, Japan, where he is currently a Graduate Student with the Department of Modern Mechanical Engineering. His research interests include human-machine interface systems, driving simulation, and driving automation systems. He is a Member of the Japan Society of Mechanical Engineers. He was the recipient of the Best Paper Award from the IEEE/ASME AIM 2016.

Shigeki Sugano (Fellow, IEEE) received the B.S., M.S., and D.E. degrees in mechanical engineering from Waseda University, Tokyo, Japan, in 1981, 1983, and 1989, respectively. From 1986 to 1990, he was a Research Associate with Waseda University. From 1993 to 1994, he was a Visiting Scholar with Mechanical Engineering Department, Stanford University, Stanford, CA, USA. Since 1991, he has been a Faculty Member with the Department of Mechanical Engineering, Waseda University, where he is currently a Professor. From 2014 to 2020, he was the Dean of the School/Graduate School of Creative Science and Engineering, Waseda University. Since 2020, he has been the Senior Dean of the Faculty of Science and Engineering, Waseda University. His current research interests include anthropomorphic robot, dexterous manipulator, and human-robot interaction. Dr. Sugano was the recipient of many awards, including the IEEE RAS Distinguished Service Award in 2008, IROS Harashima Award in 2016, Commendation for Science and Technology by the Minister of Education, Culture, Sports, Science and Technology in 2017, and ICRA2021 Best Paper Award in Cognitive Robotics in 2021. From 2006 to 2007, he was the Secretary of the IEEE Robotics and Automation Society (RAS). From 2008 to 2013, he was an AdCom Member of the IEEE RAS. From 2007 to 2012, he was the Editor-in-Chief of the *International Journal of Advanced Robotics*. He was the General Chair of the IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM) in 2003, and IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) in 2013.