An Adaptive Multimodal Interface for Collaborative Control of Human-Centered Automated Vehicles

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Waseda University

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Research on Intelligent Machines

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To my ever-loving parents and brother

"The future is what we create"

SUMMARY

The advent of intelligent vehicles with driving automation systems are changing the driver-vehicle relationship that is more than 100 years old. Vehicles that can operate in different levels of driving automation are increasingly being developed and tested in many countries including Japan. The SAE International has introduced six levels of driving automation that distinctively define the boundaries of driving automation, where level 0 means no automation and level 5 being fully autonomous in all situations. A vehicle capable of level 5 automation, with no human intervention is still far away. In the intermediate levels, the automated driving (AD) system will occasionally require the driver to take part in the dynamic driving task. Recent research focus on takeover scenarios where the AD system requests the human driver to take over control when it reaches a system boundary.

Although vehicles up to level 2 autonomy are currently commercialized, achieving level 5 autonomy (in which the vehicle is capable of driving on any type of road at any time of day and in any weather condition) is still a massive technological challenge. Except in level 5, all other levels require the presence of some sort of a vehicle control interface for the human driver/operator to take back control of the DDT either fully or partially at system boundaries, or when the driver desires to take control. Such situations include driver taking back control at the end of AD system operational design domain (ODD), roadwork, manual traffic diversions, severe weather conditions, and when system failure happens. Since in level 3 and 4, drivers do not need to constantly monitor the driving environment, taking back control within several seconds (7-10 s) could be safety critical. Being out of the control loop reduce situation awareness and can result in decreased performance and reduced safety. Moreover, increasing driving automation will transform the role of driver into an observer or a mere passenger, and that will result in lack of driving pleasure and reduced flexibility in controlling. To summarize, I identified two problems with the intermediate levels of driving automation: reduced performance and decreased safety due to low SA (out of the loop problem in takeover situations - only level 3), lack of driving pleasure and reduced flexibility in controlling (level 3 and above).

As a solution to both the above problems, I propose a collaborative driving method between human driver and AD system based on tactical level controlling of

DDT. I developed a prototype of a novel multimodal human-machine interface (HMI) system to realize collaborative driving in highly automated vehicles. In this study by proposing a collaborative control method using a novel bi-directional human-machine interface system. In our collaborative control approach, the human driver and AD system (agents) act as a team in conducting tactical-level driving tasks (e.g. lane changing, overtaking, turning, parking, etc.).

A collaborative control interface system will provide the medium for seamless interaction between the two agents at any time during a trip. From human factors point of view, collaborative control has many advantages. From a technical point of view, such control method could overcome the system limitations in perception and motion planning by integrating human driver in the loop. In this study, I developed a multimodal HMI system consisting of a touchscreen, haptic, and hand-gesture based interfaces. Multimodal interfaces (MMIs) have advantages such as improved recognition, faster interaction, and situation-adaptability, over unimodal interfaces. Purpose of HMI: facilitate intent communication between driver and AD system in real-time, support shared situation awareness, enhance bi-lateral understanding of intents and actions AD system and driver. Each interface, coupled with the AD system facilitate context-adaptive interaction by providing dynamic visual, audio, force and tactile feedback to the driver, thus realize effective bi-directional interaction, as opposed to uni-directional interfaces used in related works for takeover scenarios.

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AD – Automated Driving

ADAS – Advanced Driver Assistance Systems

DS – Driving Simulator

DVI – Driver-Vehicle Interface

HMI – Human-Machine Interface

HRI – Human-Robot Interaction

MMI – Multimodal Interface

OLI – Operational Level Input

SLI – Strategical Level Input

TLI – Tactical Level Input

TOR – Takeover Request

LIST OF APPENDICES

1 INTRODUCTION

This chapter begins with an introduction to automated vehicles and the technologies behind them. By illustrating how the driver-vehicle relationship evolved through the history of automobile, here I state the importance as well as the challenges in designing a new driver-vehicle interaction for highly automated vehicles. This chapter formulates the main research questions addressed in this dissertation: (1) lack of driving pleasure and reduced flexibility in controlling in AD mode, and (2) decrement of driver performance and safety due to low SA in takeover situations. The chapter concludes describing the organization of the rest of the thesis.

1.1 Automated Vehicles

Vehicles equipped with automated driving (AD) systems are radically changing the fundamentals of the conventional driver-vehicle relationship. With increasing automated features available in passenger vehicles such as highway autopilot, automated valet parking, automated lane change, pedestrian recognition, the tasks and roles of the driver are also getting reshaped and redefined [1], [2]. Many leading automotive companies have announced mass production of autonomous passenger vehicles by year 2020 and have demonstrated several prototype vehicles as well as shown in Fig. 1.1. In 2014, technology company – Google (Waymo, since 2016) demonstrated their prototype of an autonomous vehicle that has no conventional vehicle controllers such as the steering wheel, accelerator and brake pedals [3]. The role of a human in a vehicle with highly automated features could change from being the driver to a user or just a passenger during a single trip.

Vehicles enabled with automated driving can bring many advantages to societies and economies. Among them, improved safety is a key benefit. It has been found that human error is the cause for 90% of the road traffic accidents that result in 1.3 million fatalities and 50 million injuries annually, worldwide [4], [5]. Speeding, driving under influence, and distracted driving are major risk factors contributing to human error. Automated driving can save lives by eliminating or attenuating human error. In addition, AD will increase productivity, and lower workload by allowing drivers to engage in activities other than driving. Moreover, AD will increase mobility and access (of elderly or disabled) while improving comfort, energy and time efficiency, and traffic flow.

Although automated driving brings along many benefits, it can also come with drawbacks, mostly related to the interaction with humans. Recent prototypes of automated vehicles often have no driver control interfaces, as shown in Fig. 1.1. Some of the prototypes like Nissan IDS concept have transforming vehicle controllers that retract into the dashboard while in autonomous mode [6]. In a recent study involving 1,000 new car buyers in the U.S. revealed that lack of driver control in automated

Figure 1.1 Recent prototypes of automated vehicles

vehicles was a major concern among 72% of the respondents [7]. Lack of driver control in turn, results in lack of driving pleasure. Moreover, a simulator-based study comparing individual driving experience in automated vehicles and manual human-driven vehicles showed that drivers preferred to have authority to control lateral and longitudinal motions of automated vehicles. Further, lack of driver control reduces the adaptability of automated vehicles in highly dynamic traffic environments. In addition, when automated vehicles encounter system limitations, they require some human input to successfully deal with such situations. Increasing degree of automation is found to reduce operator performance due to out-of-the-loop control. Since the drivers do not need to continuously monitor the road environment in highly automated vehicles, they may lack situation awareness. This can be safety-critical, especially in case of control transition from AD system to human driver. Thus, out of the loop performance is also a key drawback in automated vehicles.

To understand how the driver-vehicle relationship would change with increasing driving automation, it is important to understand the different levels of automation related to on-road motor vehicles.

1.2 Levels of driving automation

The society of automotive engineers (SAE) has published a taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (J3016) [8]. It provides detailed definition for six levels of driving automation by illustrating the specific roles of primary actors of driving task (i.e. human driver, and driving automation system) in each level.

Table 1.1 User roles in an automated vehicle (SAE J3016)

	No *Driving Automation*	**Engaged Level of *Driving Automation***				
	0	**1**	**2**	**3**	**4**	**5**
In-*vehicle* User	*Driver*			*DDT fallback-ready user*	*Passenger*	
Remote User	*Remote Driver*			*DDT fallback-ready user*	*Dispatcher*	

The dynamic driving task (DDT) refers to all the real-time operational and tactical functions required to operate a vehicle. DDT includes the subtasks of lateral vehicle motion control via steering, longitudinal vehicle motion control via acceleration and deceleration, monitoring the driving environment by object and event detection and response (OEDR), and maneuverer planning, etc. The specific conditions under which a given driving automation system is designed to operate is defined as operational design domain (ODD). An ODD maybe limited to a specific geographic, roadway, environmental, traffic, speed and temporal limitations.

SAE's levels of driving automation can be divided into two: lv. 0 -2 (eyes-on) where (human) driver performs part or all of the DDT, and lv. 3 – 5 (eyes/mind-off) where the automated driving system performs the entire DDT. Below, I present a brief description of each level of automation.

Level 0, where no driving automation is available, the driver performs the entire DDT including OEDR and DDT fallback. This level maybe considered as pure manual driving. In level 1, the driving automation system performs either the lateral or the longitudinal vehicle control subtask of the DDT while the driver performs the remainder of DDT. This level is known as driver assistance, and a system such as either adaptive cruise control (ACC) or lane keep assist (LKA) may perform part of the DDT. Level 2, also known as partial automation lets the system take control of both the lateral and longitudinal motion control subtasks of the DDT. However, the driver still needs to conduct OEDR and DDT fallback. It is important to note that driver needs to constantly monitor the road environment and be ready to take control (DDT fallback) in a system limitation or ODD limitation, without any advance warning (Eyes on).

From level 3 and up, the system fundamentally conducts the entire DDT and OEDR, and driver does not require to monitor the road environment. In level 3, known as conditional automation specifically, the driver needs to respond and conduct the DDT fallback given a request to intervene. Known as high driving automation, level 4 conducts the entire DDT, OEDR, as well as fallback of the DDT without any expectation that a user will respond to a request to intervene. Level 4 vehicles can achieve minimal risk condition even if the driver is not available to respond. Level 5, known as full driving automation is capable of conducting the entire DDT, OEDR and fallback of DDT unconditionally. The key difference in level 5 compared to level 4 is that in level 5, there is no limitation to the ODD, thus they can operate without any human input given any geographical or weather condition.

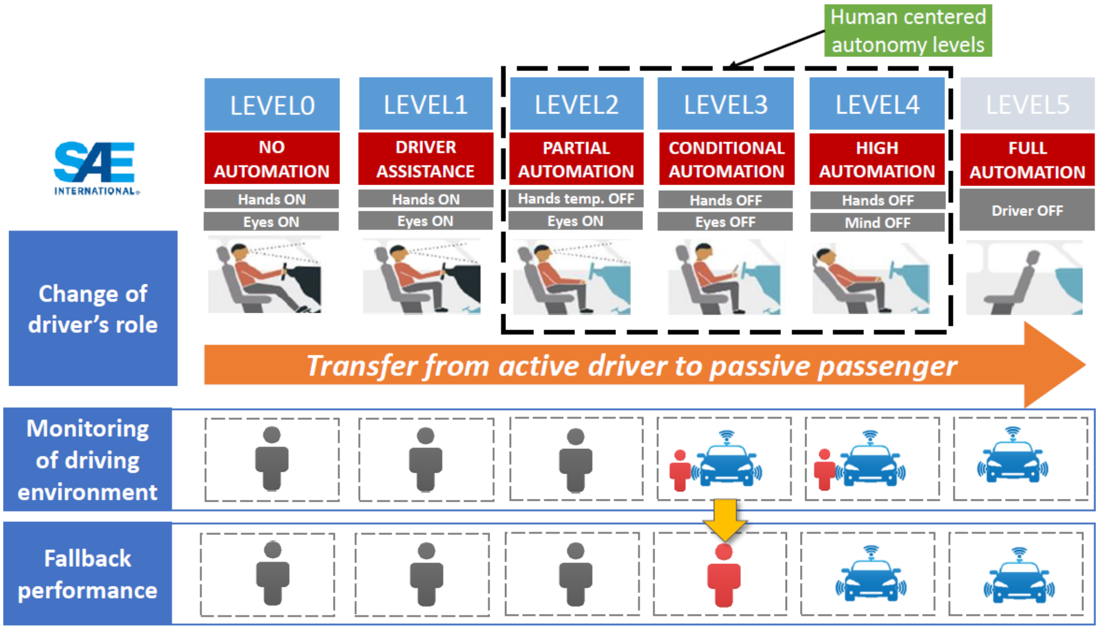


Figure 1.2 SAE levels of driving automation

The role of the user transforms with the increasing automation levels. In levels 0 to 2, the role is conventional ‘driver’. In level 3, the driver becomes DDT fallback-ready user. In level 4 and 5, the driver/user becomes a mere passenger. A vehicle equipped with a level 4 or 5 automated driving system, may also include the functionality to control it in lower levels of automation. In such vehicles, and also in level 4 vehicles moving from one ODD to another, we could see the transformation of the roles of user from active driver to passive passenger and vice versa, in a given trip.

It can be assumed that it would take decades of research and development to realize level 5 full-autonomy, given the current state of the art. However, with the existing technology, it is possible to achieve conditional autonomy with the human driver in the control loop. Therefore, automation levels that rely on human input at some point, can be categorized as human-centered autonomy levels. The human input may come from the user/driver in the vehicle or from a remote operator via teleoperation. Vehicles operating in these intermediate autonomy levels may be seen as human co-existing ‘personal robots’ that collaborate with humans to achieve a common goal. To bring the advantages of automated driving to our society as early as possible, human-centered autonomy levels can play a vital role, and therefore, it is important to address the human factors issues related to those levels.

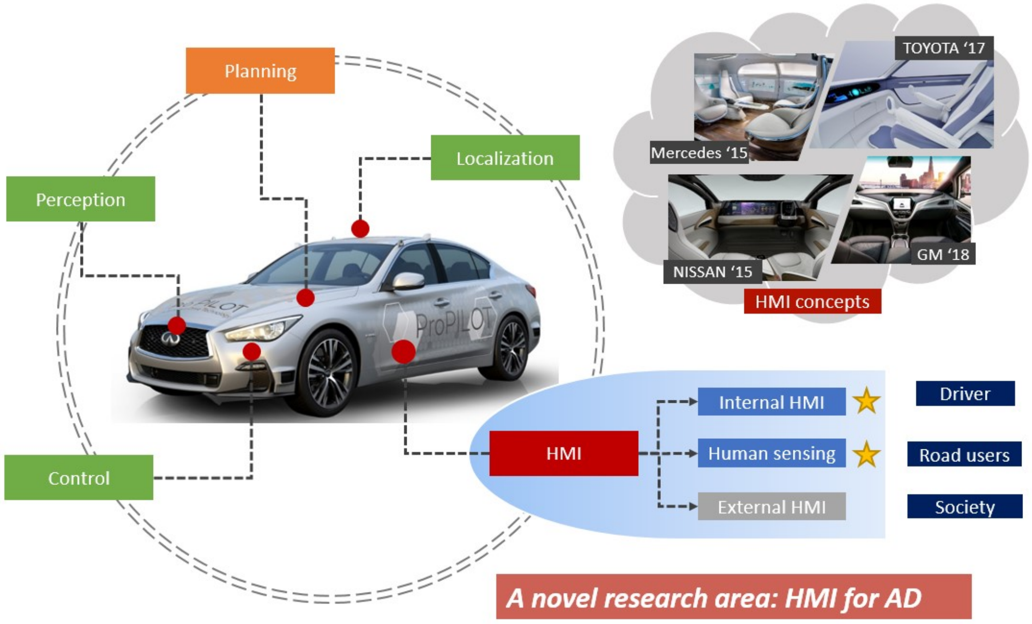


Figure 1.3 HMI - a novel research area in automated vehicles

In the next section, I introduce the key components of an automated driving system.

1.3 Key elements of automated vehicles

An automated driving system fundamentally requires to recognize and understand its environment, make judgments on control actions, and operate the lateral and longitudinal controls of the vehicle. In addition, if it is operating in human-centered autonomy levels, it requires to cooperate with human operators. This section presents the key components of automated vehicles to achieve the above requirements.

1.3.1 Perception and localization

Various sensor types are used in automated vehicles for perception and localization. Radar is one of the most used automotive sensor for object detection and tracking. It is a cheap sensor and works well even in extreme weather conditions. The downside of radar is its low resolution compared to LIDARs. With extremely accurate depth information and much higher resolution than radars, LIDAR provide 360 degrees of visibility. However, they are usually expensive than radars. On the other hand, cameras provide longer range, very high resolution and much more information, being relatively cheaper. Recent advancements in deep learning, and growth of annotated driving data have contributed in the wide use of cameras in AD systems. However,

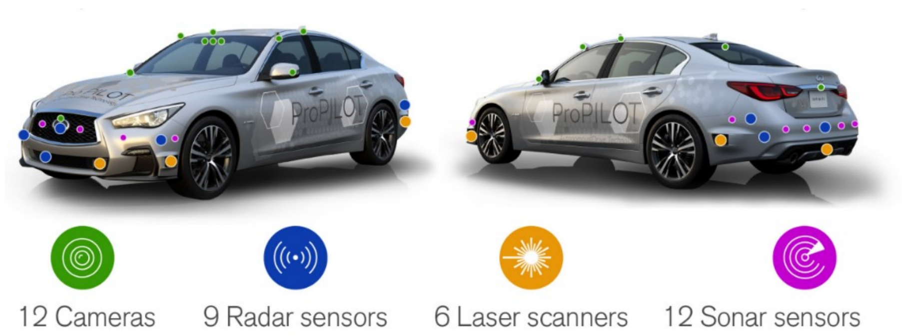


Figure 1.4 Sensory modules on Nissan ProPILOT AD system

cameras are usually bad at depths estimation and do not perform well in extreme weather conditions, and susceptible to ambient light conditions. Sensor fusion helps in overcoming drawbacks in each sensor type and improving overall environmental perception. Combined with GPS, high definition maps and fused sensor information, an AD system can localize itself with sufficient accuracy.

1.3.2 Judgment, scene understanding

Accurate detection of objects is necessary for safe operation of automated vehicles. Especially, when operating in urban environments, scene understanding is much more challenging compared to highways. Past approaches in object detection involved cascades classifiers with Haar-like features [9]. Recent advancements in deep learning [10] helps in accurate and robust detection, recognition, and classification of objects. Semantic segmentation, where each pixel is assigned to an object-class has also received much attention recently [11], [12].

1.3.3 Path planning

Autonomous path planning has received much attention in the research community and has advanced with growing driving data and improved algorithms. Previous approaches include optimization-based control. Deep reinforcement learning is widely used in path planning recently. It gives the ability to deal with uncertainty, sensor calibration problems, or lack of prior map information [13], [14] [15].

At present, both policy-based and learning-based approaches are used in path planning. Both approaches have pros and cons, but the black-box nature of deep learning-based approach is a major disadvantage for its acceptance by regulators (i.e. governments).

1.3.4 Human-machine interface

The human-machine interface (HMI) is also an integral component of an AD system. It can be divided into two: internal HMI and external HMI. Internal HMI communicates with the driver/user and passengers of an automated vehicle. Through an effective HMI, the AD system and driver can communicate the intents of each other. The external HMI communicates with other road users such as pedestrians, cyclists and other vehicles. The people who interact with automated vehicles may come from all walks of life. Therefore, the AD HMI must play an important role to increase the acceptance of automated vehicles into the society. More details on the requirements of an HMI for automated vehicles is presented in Chapter 2.

Detecting and predicting the state of the driver is an important research area in the domain of automated vehicles. Driver emotions, cognitive workload, drowsiness, and situation awareness are key components of driver state [16]–[24]. I present a discussion on driver state estimation in Appendix A1.

The current state of development of automated vehicle technologies suggest that still there are considerable limitations in sensing, scene understanding and artificial intelligence. Thus, one can reasonably assume that level 5 autonomy is still very far away in the future. However, by adopting human-centred autonomy levels and keeping the human in the control loop can bring the advantages of automated vehicles as early as possible.

1.4 Driver-vehicle interaction

Since the early stages in the evolution of automobile, driver-vehicle interaction has been an important topic. In conventional human-driven vehicles, it is mainly about controlling the direction and speed of the vehicle by the driver. The steering wheel and pedals have been essential components of human-machine interface throughout the history of modern automobile. It is important for the drivers to know about the state of the vehicle including but not limited to travelling speed, fuel level, engine temperature, and engine rpm. Signal lights, head lights, brake lights, wipers, honk etc. are also necessary parts of the human-machine interface, and many knobs, buttons and controllers are used in vehicles to operate each of those systems [25]–[27].

Rapid growth of driver information systems has resulted in increased utilisation of embedded computers and telematics systems inside vehicles. Adaptive digital meters, satellite navigation systems, audio/visual players connected to internet, and smartphone connectivity etc. are being increasingly available in modern vehicles. Infotainment systems that are a combination of information and entertainment systems are taking up a central role in driver-vehicle interaction in modern vehicles. These in-vehicle systems are being developed to;

1. Enhance road safety
2. Make transportation more efficient by saving time and fuel
3. Make driving more pleasurable
4. Make drivers and passengers more productive

In the recent years ‘connected cars’ offer their owners to control certain functions remotely via internet. Through a mobile application, users can unlock/lock their cars, turn on the air conditioner, and even can turn on the engine remotely.

As vehicles become more and more automated, and capable of operating in varying degrees of automation, many aspects of the interaction between the driver and vehicle also undergo drastic changes. Figure 1.3 shows driver-vehicle interfaces in some autonomous vehicle prototypes. Efforts have been made to create new devices and methods in the form of concept to control vehicles as shown 1.5.

Since the conventional steering wheel and pedals would become obsolete above level 3, it is important to investigate on novel methods that can be used to replace those conventional interfaces. Automated vehicles (and concepts) from Waymo and GM have no conventional steering wheel or pedals. On the other hand, several other concepts from Nissan, etc. have transforming steering wheels that goes inside the dashboard when in AD mode, to allow more space inside the cabin. Moreover, automakers have shown concepts like Mercedes F016 that has rotatable front seats allowing to create a lounge-like environment inside the cabin while in AD mode.

Advances in hardware and software enable technology to build ever more advanced and complex systems. However, we must not forget that it is vital to make these systems easy to understand and operate for their human users.

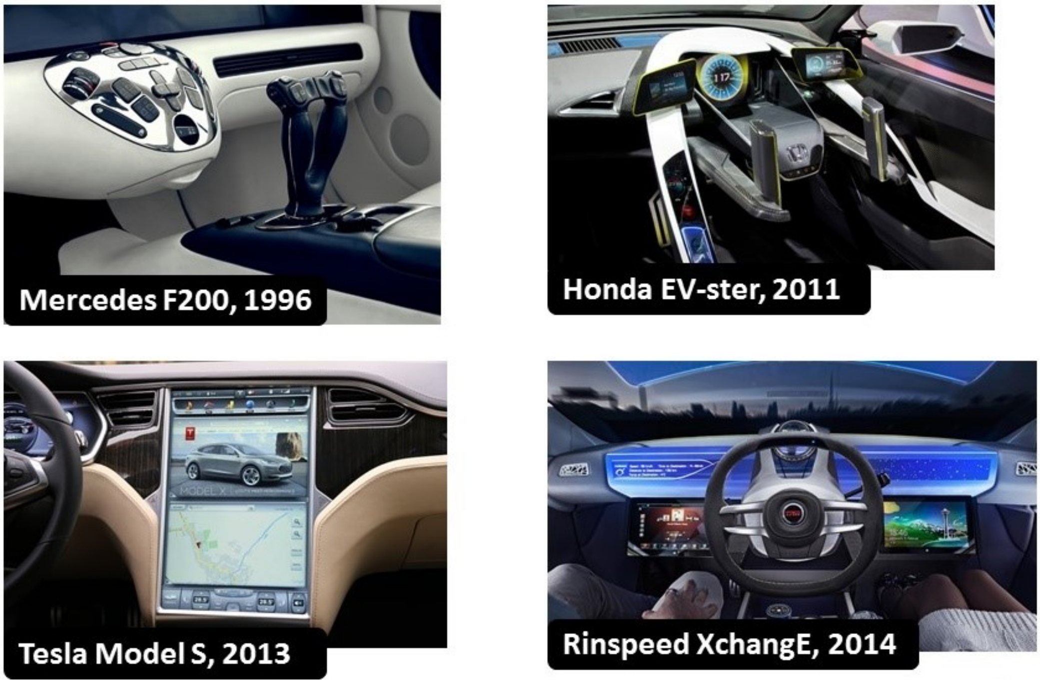


Figure 1.5 Some of the revolutionary driver-vehicle interfaces

With contrasting concepts like above, essentially, questions like “what kind of vehicles would we drive in future?”, and “how to *drive* such kind of vehicles?” would inevitably arise.

1.5 Research Questions

One of my previous studies comparing individual driving experience in human-driven and autonomous (lv. 4) vehicles have shown that removing drivers from the control loop in AD mode will result in lack of driving pleasure and reduced flexibility in controlling [28]. It revealed that experienced drivers preferred to drive manually in roads with less traffic. A key recommendation of that study was future automated personal vehicles should have a means of switching between AD mode and manual driving, and an effective interface system should assist the control transition. Moreover, a recent study showed that 72% of the new car buyers are concerned about lack of driver control in automated vehicles [7]. Driving pleasure and controllability are inherent characteristics of manual driving, thus, losing them would be a downside in conventional AD systems. It would, in turn, affect the social acceptance of automated vehicles.

On the other hand, intermediate levels of automation require a vehicle control interface for the human driver/operator to take back control of the DDT either fully or partially at system boundaries [29]–[31]. Such situations include scheduled takeovers i.e., driver taking back control at the end of AD system operational design domain, or unscheduled takeovers such as roadwork, manual traffic diversions, severe weather conditions, and system failure. In addition, drivers may want to switch to manual driving from AD whenever they desire. Since in level 3 and 4, drivers do not need to constantly monitor the driving environment, taking back control within several seconds could be safety critical. Previous research has shown that being out of the control loop reduce operator situation awareness (SA) and result in decreased performance and reduced safety [32]–[35]. To summarize, I identified two research questions with the intermediate levels of driving automation:

(1) Lack of driving pleasure and reduced flexibility in controlling in AD mode, and

(2) Decrement of driver performance and safety due to low SA in takeover situations.

This research addressed the above research questions and proposed a collaborative control method along with a multimodal human-machine interface system to control highly automated vehicles.

1.6 Collaborative Control

As a solution to both the above research questions, I propose a collaborative control method between human driver and AD system based on tactical level controlling of DDT.

Driving tasks can be categorized under three levels of driver control; strategical, tactical, and operational (described in detail in Chapter 2). This hierarchy is adapted to differentiate the levels of driving automation for the present study. In strategical level (lv. 4, 5), the driver inputs long-term commands such as the destination and route, and the vehicle conducts entire DDT. In tactical level driver can input medium-term control commands such as overtaking, lane-changing, speed controlling, merging, turning, and parking. In this level, the vehicle conducts the DDT with in accordance with driver intention. In operational level (lv. 0, 1), driver controls the steering angle and speed in real-time. By adopting tactical level input (TLI) method for controlling in AD can provide the driver with flexibility and driving pleasure associated with manual driving, while ensuring safety and comfort of automated driving.

Collaborative control enables the human driver and AD system to work together to achieve a common goal. Human drivers and automation systems have their own strengths and weaknesses. For instance, humans are strong in judgment, adaptation, inference, intuition and morality. However, they have weaknesses such as long response time, narrow information bandwidth, endurance, and inconsistency. On the other hand, automated driving systems have strengths such as faster reaction, persistency, consistency, and predictiveness. Among their weaknesses are low adaptability, limited ODD, susceptibility to system failure, and limitations in judgment and inference. Thus, through collaborative control, human driver and AD system can perform better together, than acting alone. Collaborative control will bring the following important benefits:

1. Extend the operation limits of automated driving system and human driver
2. Provide an effective mechanism for control flexibility and situation adaptation
3. Enable natural, effective, and seamless driver-vehicle interaction
4. Promote driving pleasure even in AD mode

1.7 Thesis Organization

This thesis proposes a collaborative control method for human-centered automated vehicles. In the following chapters, I present the underlying theory and framework of collaborative control based on tactical-level input. I describe the requirements for a collaborative control method and a novel multimodal human-machine interface for automated vehicles. I conducted several experiments using a driving simulator to validate the effectiveness of the proposed control method and the interface system. Through experimental results I prove that collaborative control based on tactical-level input is widely accepted by the drivers. Moreover the multimodal interface proved to be an effective HMI for collaborative control. The thesis is structured as follows.

In chapter 2, I present the requirement and theoretical framework for collaborative control. I discuss the related works in horse-metaphor, direct control and supervisory control. Then I introduce tactical-level input for automated vehicles as a method of collaborative control. Finally, this chapter highlights the requirement for a human-machine interface to facilitate collaborative control and suggest design guidelines.

To demonstrate the proposed control method and evaluate the human-machine system, a driving simulator capable of simulating automated driving, and connecting arbitrary interfaces is necessary. Chapter 3 describes the development of a virtual reality driving simulator that provide the experimental platform for the main work of this thesis.

Chapter 4 presents the development of the situation adaptive multimodal HMI system. The HMI system consists of touchscreen, hand-gesture, and haptic interfaces. This chapter provides design requirements for each modality and the overall HMI system by referring to the theoretical framework of collaborative control method. Chapter 5 presents the experimental evaluation of the HMI system as well as the control method and documents the results of a driving experiment involving 20 drivers.

In chapter 6, I discuss the human-factors issues related to control transitions of automated vehicles. I evaluated how collaborative control method with the multimodal HMI work in practice for unscheduled takeover scenarios in automated vehicles. This chapter documents the experimental design and results of the simulator-based experiment. In chapter 7, I discuss the strengths and weaknesses of the collaborative control method and HMI system, summarize the contributions of my research and identify directions for future research.

Following the main text, appendix A describes a driver state estimation and prediction system for automated vehicle applications, along with an experimental evaluation.

1.8 Summary

This chapter provided an introduction to automated vehicles by presenting the key elements of a driving automations system, and state of the art. By briefly discussing the evolution of driver-vehicle interaction and presenting recent trends in development, this chapter provided insights into the future of human-machine interface/interaction in automated vehicles. It described the levels of driving automation in detail and highlighted the importance of human-in-the-loop control for highly automated vehicles. Finally, this chapter formulated the research questions addressed in this research and described the organization of the thesis.

2 Tactical Level Input for Collaborative Control

This chapter first explores the conventional control methods in human-automation systems. Then it describes the three levels of driving task: strategical, tactical, and operational. Adapting the classic three-levels of vehicle control to automated vehicle domain, this chapter proposes collaborative control based on tactical level input (TLI) for highly automated vehicles. I then discuss related systems and control models used in automation domain including h-metaphor, shared control and compare them to collaborative control method. This chapter concludes with a set of guidelines for designing human-machine interfaces for collaborative control.

2.1 Three Levels of Driving Task

Automated vehicles are drastically changing the conventional relationship between the driver and vehicle. Such vehicles are transforming the role of the user from and active driver to a passive passenger with increasing levels of automation. To answer questions like “how to drive future automated vehicles?”, first, it is important to understand the essential components of the overall act of driving.

The task of driving can be divided into three levels of control hierarchy; strategical, tactical, and operational [36]. 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 in real-time.

Adequately performing driving tasks in each level enables the vehicle to reach a destination safely and efficiently. In conventional human-driven vehicles, a driver conveys the control intention via steering wheel and pedals, and this is regarded as operational-level input method. With increasing levels of automation, the principal agent which performs driving tasks would shift from driver to AD system. In an ideal AD system operating in level 5, input required from human driver would be only in strategical level, i.e., input of a destination. However, as explained in Chapter 1, reduced driver control in automated vehicles result in lack of driving pleasure and can lower user acceptance. Moreover, limitations in automation capabilities could hinder the social acceptance due to overreliance of automated systems. Consequently, by increasingly allowing the human driver to make inputs other than in strategical level, could result in high driver acceptance, and early adoption of automated vehicles to our societies.

The general idea of a three-level input method is summarized in Fig. 2.1. Below I will describe the control hierarchy of driving task in more detail by considering strategical level, operational level, and tactical level.

2.1.1 Strategical Level

A driver may only input the destination, traveling time, what routes to take, and driving mode (e.g., eco, sport, etc), if AD system could perform the rest of the driving task, i.e., both operational- and tactical-level tasks. In an automated vehicle, such inputs may be made through touchscreens or voice-based HMIs. I call this ‘strategical-level input (SLI) method’, which can span from minutes to days. A vehicle that need only strategical-level input from the human driver would generally require an AD system that can operate in levels 4 and 5. Strategical-level input has advantages, such as comfort (easiness) and safety, but SLI only will not be sufficient in unexpected situations, e.g., route changes, sudden roadwork, and in extreme weather conditions in level 4 AD systems. In addition, allowing drivers to make strategical level input only, would decrease driving pleasure due to reduced driver interaction with vehicle.

2.1.2 Operational Level

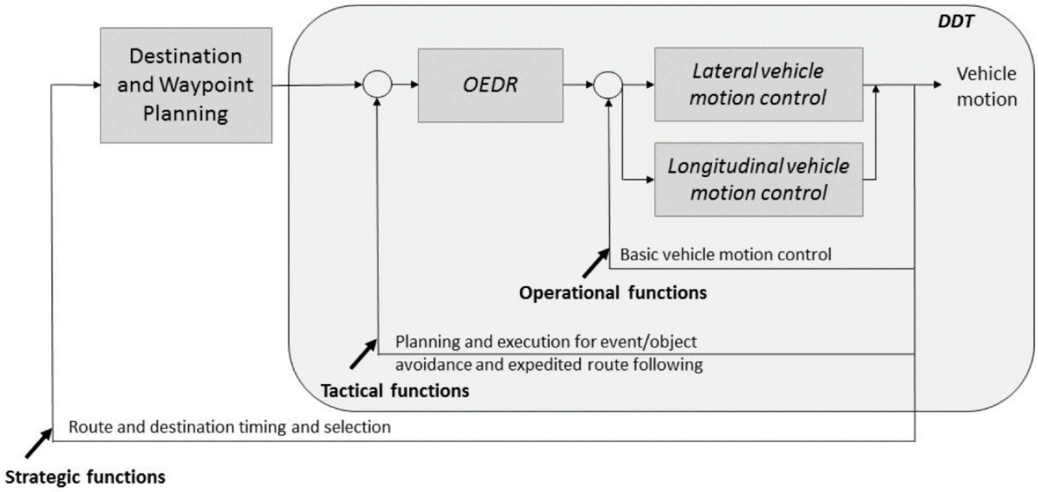


Figure 2.1 Schematic view of driving task (SAE J3016)

After driver made a general trip plan and decided a destination, appropriate route (waypoints) and travel time, he or she conduct the dynamic driving task by controlling lateral (steering) and longitudinal (acceleration and braking) parameters in real-time. This type of control is realized by using steering wheel and pedals in conventional human-driven vehicles. This is known as 'operational-level input (OLI)', which usually spans from 0.5 to 5 seconds. Depending on the design of AD system, and if the vehicle has conventional controllers (i.e. steering wheel and pedals) it may allow drivers to use OLI in levels 3 and below. OLI has advantages, such as flexibility of controlling and driving pleasure. However, depending on individual driver characteristics and their workload sensitivity, it may be difficult to accurately and immediately perceive driving environment and adjust many parameters in a short time window in different traffic situations, e.g., a dense-traffic intersection. Thus, I suggest personal vehicles capable of AD should have a way of switching between manual driving and automated driving when the driver desires to.

2.1.3 Tactical Level

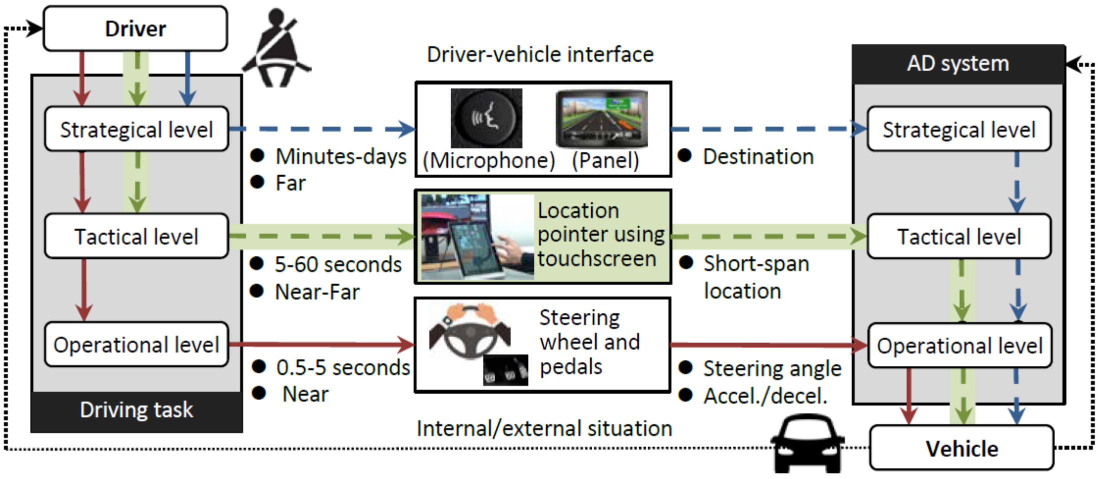


Figure 2.2 Overview of hierarchical driving task

In Michon's hierarchy of driving task, tactical level lies in between strategical and operational levels. In order to realize high-level trip goals that are set in strategical level (i.e., arriving at a set destination following a desired route within a desired time), a vehicle may need to make different maneuvers in dynamic traffic environments. Such maneuvers may include overtaking, lane-changing, turning, accelerating/decelerating, merging into highway and parking etc. Given that operational level driving tasks being conducted by the AD system, driver may input tactical level commands if necessary or when desired. I call this 'tactical-level input (TLI) method'. Tactical level maneuvers can span generally from 5 to 60 seconds. TLI would require an AD system capable of operating in levels 2 and above. TLI is in the intermediate level, which relatively makes operational level input more abstract and strategical level input more detailed compared to TLI. Thus, TLI would potentially 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 as desired. This enables the reduction in the number of inputs compared to OLI and more flexible and situation-adaptive input in contrast to SLI. This characteristic, most importantly, enables TLI to integrate features of both OLI and SLI. To sum up, tactical level input in an automated vehicle can allow a driver to command a set of lateral and longitudinal controls, e.g., lane changing and parking, while the AD system conducts the more cumbersome and real-time operational level control.

Table 2.1 Advantages and significance of TLI

Item	Descriptions
Driver workload	• Reduce driver workload compared with OLI due to decreasing input granularity
Capability	• To have more control over vehicle − In case of a sudden change of destination − Need to pull over at a point of interest (PoI) − 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

2.2 Advantages and Significance of TLI Method

As stated above, TLI method, which allows the driver to control lateral and longitudinal motions of the automated vehicle in a short spatiotemporal range while the AD system conducts the DDT ensuring safety, would be important for automated vehicles operating in levels 2 and above. The potential advantages and significance of TLI over OLI and SLI are listed in Table 2.1.

In TLI, information on the environment could be perceived in real time by both the driver and AD system, and could be used to make control decisions to input the future state or maneuvers of the vehicle. For example, if the driver/user of an automated vehicle operating in AD mode would want to change the travelling speed, or travelling lane he or she can use TLI to communicate intent to the AD system. Then, if the user input is valid and legal to execute, the AD system conducts the operational level driving tasks to achieve the tactical level control command. If the user input is invalid or illegal due to traffic constraints and rules, AD system gives feedback to the user. Since the AD system is responsible in conducting the operational level control, safety of automated driving is ensured. Without TLI, if drivers desire to control the maneuvers of the vehicle, they would have to use OLI, which is conducting the dynamic driving task manually (with some driver assist), usually associated with higher driver workload. Therefore, the proposed TLI could reduce driver workload associated with controlling the vehicle in OLI, while giving them the option, freedom, and flexibility to control the maneuvers of the automated vehicle.

Enabling tactical-level input in automated vehicles would increase their flexibility to adapt to various situations in the dynamic traffic environment. For instance, unscheduled roadwork or accidents in urban environments may involve manual traffic diversions, and persons using hand gestures to control traffic. Current AD systems are not capable of performing well in such complex and unstructured situations, and would require human intervention. In such situations, using TLI could be conveniently used rather than taking back control in OLI, which might be unsafe due to reduced situation awareness of drivers. Moreover, in case of a sudden change of destination, or if user/driver desired to make a brief stop at point of interest (i.e., a convenient store, ATM, restaurant, shopping mall, sightseeing spot, etc.) TLI could be effectively and easily used to control vehicle maneuvers such as turning, lane-changing, stopping, and parking.

Users of automated vehicles are diverse. People who are physically handicapped, and are unable to use conventional vehicle controllers (i.e. steering wheel, pedals) would benefit greatly from AD. However, in situations, including the ones described above, TLI with a suitable human-machine interface could be utilized to improve the mobility experience and requirements of such users. Therefore, TLI has a huge potential in helping in extending the advantages of automated driving to a diverse range of users.

To sum up, TLI creates a new interaction space between automated vehicle and its user/driver. While ensuring the safety and convenience of automated driving, it brings the flexibility and adaptability of manual driving. Although there exist human-machine interfaces to input strategical-level and operational-level commands in existing systems, there is a need for a novel interface for tactical level input. In the next section I discuss the requirements of an HMI system for TLI.

2.2.1 Requirements of an HMI for TLI

A human machine interface should be designed according to the driver-vehicle interaction to be realized. I thus analyze HMIs for OLI, TLI, and SLI, respectively, as shown in Fig. 2.4. Operational level control, which involves continuous lateral and longitudinal inputs in real-time, is realized by using steering wheel and pedals. On the other hand, strategical level control, which includes destination and travel-time related inputs, is expected to realize by using HMIs such as voice or touchscreen interfaces. Tactical level input includes a set of lateral and longitudinal commands that require a novel HMI system for its effective use. The AD system of Tesla Motor called AutoPilot, uses the turn signal switch as an HMI to input lane-change command. However, the TLI method proposed in my dissertation needs to enable many input types while adapting to different situations, such as turning at the second intersection, as well as parking. Consequently, such conventional (existing) HMIs will not be sufficient to realize the full benefits of TLI.

To use TLI in certain takeover situations effectively, an HMI system should fulfill information needs of the driver to enhance situation awareness. The status of the AD system (e.g. availability of TLI, request to intervene, etc.), information about its environment are important for the driver to make an informed control input. Looking from a human-robot interaction (HRI) perspective, [37] provides a set of guidelines to improve situation awareness in human-robot systems. In designing the HMI and HRI in our study, therefore, we adopted the following guidelines; providing a map to show robot's path, providing fused sensor information to lower the cognitive workload, and providing spatial information to make operator aware of robot's immediate surroundings.

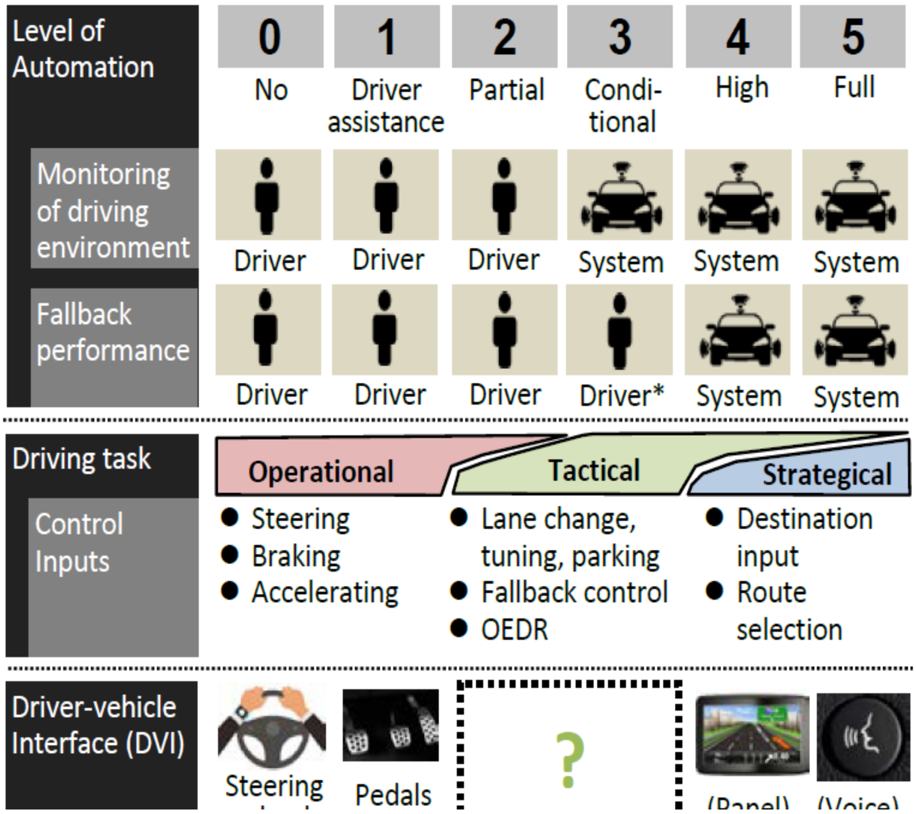


Figure 2.3 Requirements of HMIs in different levels of automation

To realize these requirements, first, I defined a set of input functions that can be mapped to a finite set of vehicle maneuvers. Then, a set of guidelines for designing human-machine/robot interaction was listed. Fundamentally, the interface system should convey information of inputs from the driver to the AD system, and system responses, e.g., approval or denial of driver input, and/or suggestion from the AD system to the driver in an effective and efficient manner.

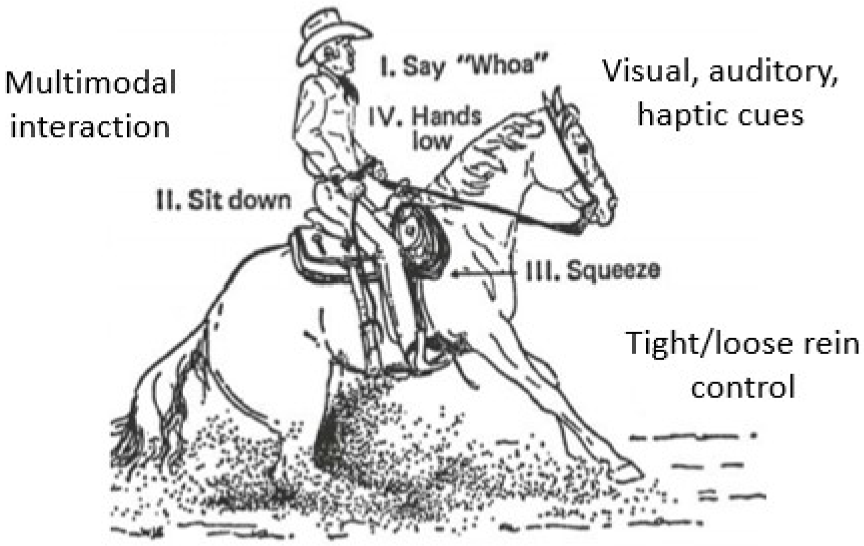


Figure 2.4 Human-horse system (Miller, 1975)

Relationship between driver and vehicle in highly-automated vehicle would imply the necessity of reconsidering the existing human-machine interactions and interfaces. The characteristics of required task for the drivers in levels 2 and above, such as performing DDT and DDT fallback, indicate that a HMI that allows the driver to easily understand a driving situation and immediately command a control input consisting of a series of lateral and longitudinal motion, i.e., tactical-level command as shown in Fig 2.3 would be essential. However, the functionality of conventional HMIs such as steering wheel and pedals would not be suitable (optimized) for tactical-level command inputs because they have been originally derived based on driving tasks in levels 0 and 1, i.e., operational-level command inputs. For instance, a tactical-level command such as 'turn right at the next intersection', or a strategical level command such as 'selecting a destination from a map' cannot be input by using a conventional steering wheel and pedals, as they are designed to control a vehicle in real-time. Thus, a novel DVI that facilitates effective driver-vehicle interaction in levels 2–4, that is, tactical- and strategical-level input methods, will be necessary. AD systems increase the safety and comfort, but they somewhat limit the flexibility of controlling, and driving pleasure due to the reduction of the amount of interaction between the vehicle and driver. From the above viewpoint as well, it is important to define a new method of interaction to have a balance among the above parameters by introducing new human-machine interface that will help the seamless transition of driver's roles according to LoA.

This is a very challenging task because HMIs for vehicle control have not undergone any momentous change since the invention of the modern automobile, and the existing conventional HMIs are deeply linked to the conventional driver-vehicle interaction. Some researchers have developed HMIs such as a haptic steering wheel and pedals, a cooperative shared control, a haptic switch display, a vibrotactile seat-display and information support system, and moreover, they have proposed a conceptual HMI design for level 4, such as a brain-machine interface. However, they have not focused on 'controlling' automated vehicles by tactical-level input method.

2.3 Related works

Interaction between automation and humans have been widely studied in aviation, marine, robot teleoperation, and related domains. However, there is only a limited number of studies in the automated vehicles domain. Among them, horse-metaphor, shared control, and collaborative control are key interaction system models. This section describes each of the above models and compares them with collaborative control.

2.3.1 Horse metaphor

The horse-metaphor, or h-metaphor is the concept of horseback riding that can be applied to the driver-vehicle interaction in automated vehicles [38]. This concept can be simplified as follows. Horses have intelligence to sense and avoid obstacles and path planning. Similarly, autonomous vehicle will drive safely avoiding obstacles. Horse provide multimodal feedback through visual, auditory, and haptic channels, and it helps the rider to be aware of the state of the horse, or simply what it is doing. In automated vehicles, through multimodal feedback (mainly haptic), driver can know the state of the vehicle. Horse might be aware of the rider state and engagement and may act accordingly. Similarly, automated vehicles could sense driver state and engagement and adjust its behavior. In overall, adopting the h-metaphor concept in designing the human-machine interaction will promote safer and natural interaction in human-centered automated vehicles.

It is important to note that like a horse, the AD system acts as a safety net and always supports the driver to avoid crashes. This concept enables seamlessly variable

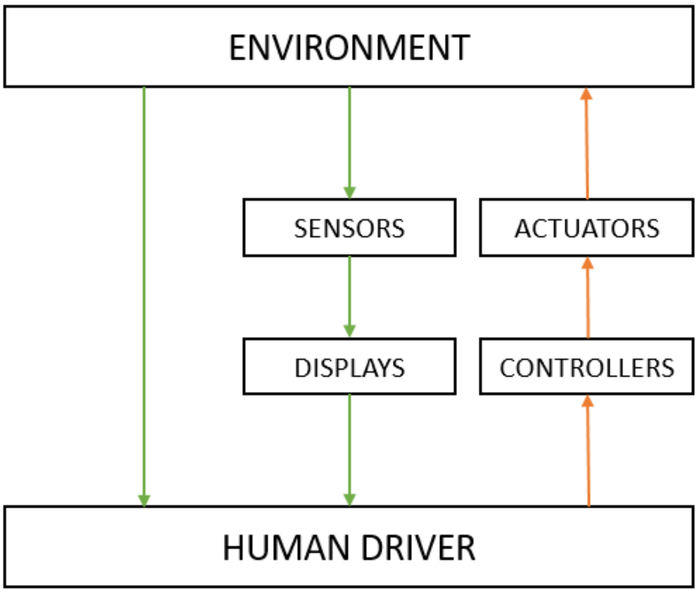


Figure 2.5 Direct control system model

levels of automation. To realize this concept, an intelligent, adaptive human machine interface with multimodal feedback that resembles the intelligence and visual-audio-haptic feedback of the horse, is required. Moreover, this concept promotes development of driver-vehicle relationship through cooperation.

2.3.2 Direct control

As a classic system model to operate mobile robots, direct control has been in wide use in the domain of robotics. In direct control, the human operator perceives the environment through his own senses and/or the human machine interface, makes control decisions, and executes maneuvers. Thus, the primary responsibility of perception, planning, and action is with the human (Fig. 2.5). The vehicle/robot system may assist the human in perception and actuation. Although this system model has an advantage of using human intelligence in making control decisions, it can bring along major drawbacks. Mainly, the system performance has a direct relationship with human operator's capabilities. System performance is directly affected by operator workload, skills, knowledge, and sensory-motor limits. This is similar to operational-level control of vehicles.

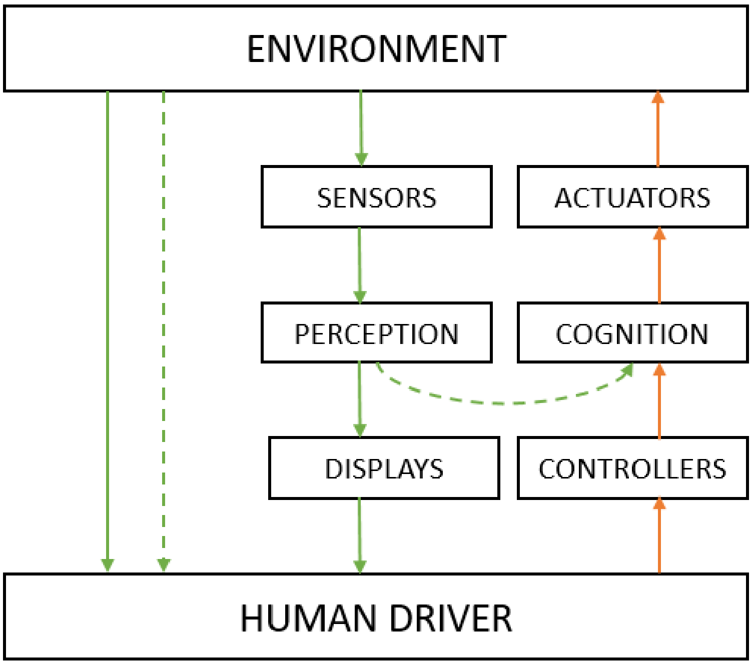


Figure 2.6 Supervisory control system model

2.3.3 Supervisory control

The interaction between human operator and automation system, in supervisory control, can be thought of as supervisor-subordinate like interaction [39]. In mobile robot teleoperation [40]–[42], supervisory control involves an operator dividing a task or a problem into a several sub-tasks in sequence. Then, the robot system is expected to execute the sequence of subtasks ‘autonomously’, or on its own. Of course, the extent of the control task executed by the robot depends on its level of autonomy. Conventionally, once the human operator has given control to the robot system (i.e. subordinate), he or she monitors the task execution through an HMI, paying the role of a ‘supervisor’. There are two main branches of supervisory control: traded control, and shared control.

In traded control, human irregularly control the robot system, similar to direct control by being in the control loop. In shared control, both the automated system and human operator achieve a single operational task through a single operation input. Shared control allows the human to control some variables while, in the same time, leaving the controlling of other variables to the robot system. Shared control has been studied in control authority transfers in automated vehicles.

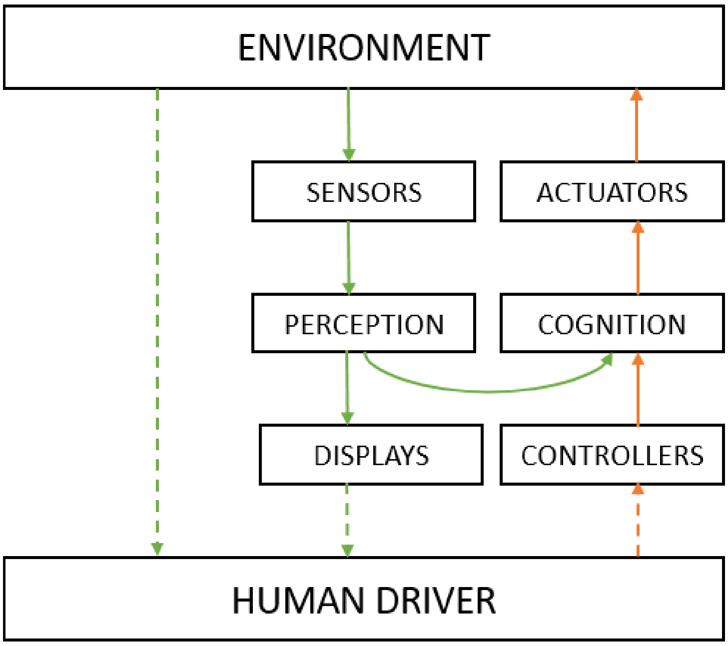


Figure 2.7 Autonomous control system model

In order to a shared control model to be effective, clear division of tasks is vital. It may need clear set of rules or instructions of *who* does *what,* and *when*. Therefore, supervisory control inherently requires substantial training for human operators. Moreover, when the robot systems are operating in dynamic and unstructured environments, the uncertainties that are essentially part of such environments are a huge challenge for a structured/rule-based supervisory control system.

2.3.4 Autonomous control

An autonomous robot system can be defined as a system capable of performing tasks or actions independent of an external control. In autonomous control, generally, a human operator gives a high-level, abstract input, (e.g., destination, goal) to the robot, and the autonomous system will perform perception and planning to act on the dynamic environment to achieve the set goal(s) independently. Overall system performance is thus, is constrained by the appropriateness of robot's level of automation in the environment where the robot is embedded in.

In order to realize safe, effective, and robust autonomous control, a robot system needs sufficiently advanced computational resources, both in terms of hardware and software. As stated earlier, there are major technological challenge to overcome in realizing fully autonomous control like SAE level 5. Moreover, even if a robot system is capable of autonomous control in a controlled environment, human factors problems such as lack of situation awareness, and deficient out-of-the-loop performance would still exist.

2.3.5 Limitations in conventional models

Conventional system models described above have been used successfully in many different robotics/automation applications. However, since they inherently assume a supervisor-subordinate relationship between human and the robot, there are many limitations arising from that. Below I highlight such limitations from the perspective of driver-vehicle interaction in automated vehicles.

In direct control, the driving task can be performed only if the human driver is in the control loop. Therefore, the overall performance is constrained by driver-subjective parameters such as workload, skills, and experience.

In supervisory/shared control, a clear distinction between the roles of human driver and automated system is necessary. As a result, significant training may be required for a human driver to understand the control boundaries and duties of each agent in a variety of situations.

The users of automobiles are diverse; thus, their skill levels, sensory-motor capabilities, and experience vary significantly. Since the levels of skills required for

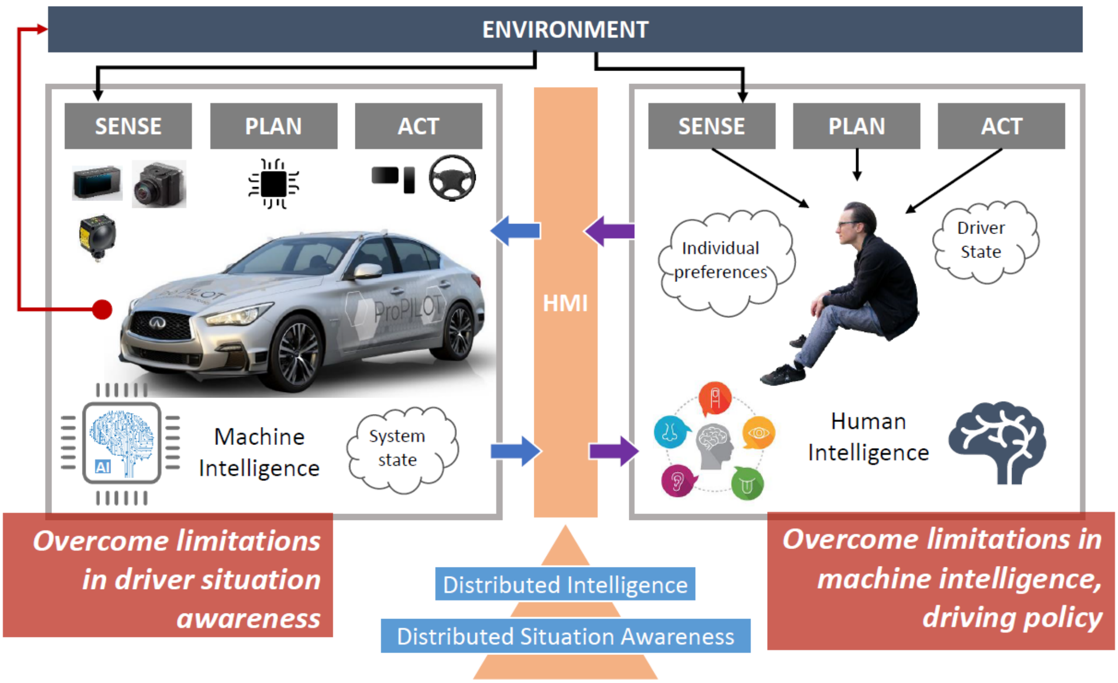


Figure 2.8 Overview of collaborative control in automated vehicles

direct control and shared control are high, accommodating a wide range of users become a major challenge. Besides, the conventional control models do not address the need of dynamically adjusting the level of autonomy to reflect driver/operator needs or to compensate for operator weaknesses.

2.4 Significance of Collaborative control

In collaborative control, the automated system and human operator acts together to achieve more than a single operational task. In contrast to shared control, human-system cooperation in collaborative control spans through a broader spectrum. A tactical-level input based collaborative control can address the limitations in both AD system and human driver through collaboration. In systems where only fully-automated driving and manual driving (direct control) options are available, if the AD system encounter difficulties, it will ask the driver to take control manually, or else come to a stop, or worse case, it would continue performing sub-standardly. However, through collaborative control with TLI, perception, cognition, and operation aspects can be seamlessly shared between driver and AD system, thus both agents can compensate for inadequacies of each other.

Moreover, collaborative control with TLI creates a new interaction space between driver and vehicle that did not exist until this study. In contrast to supervisor-subordinate control or direct control, TLI enhances the driver-vehicle interaction by making both agents teammates. Control decision or performance is collaboratively made by considering the intention of both agents. 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. Although AD systems capable of conducting tactical-level driving tasks have been developed, there was not enough focus on practical approach for designing human-machine interfaces and interaction for highly automated vehicles to realize the benefits of collaborative control. Note that although many studies on human-automation interaction in various kinds of human-machine systems have been conducted such as multiple unmanned aerial vehicles, mobile robot teleoperation, there are few studies on TLI method, as well as in the automated vehicles domain. Consequently, considering the research gap stated above, this thesis explores the new type of interaction between humans and automated vehicles created through collaborative control and tactical level input, and facilitated by a situation-adaptive HMI system.

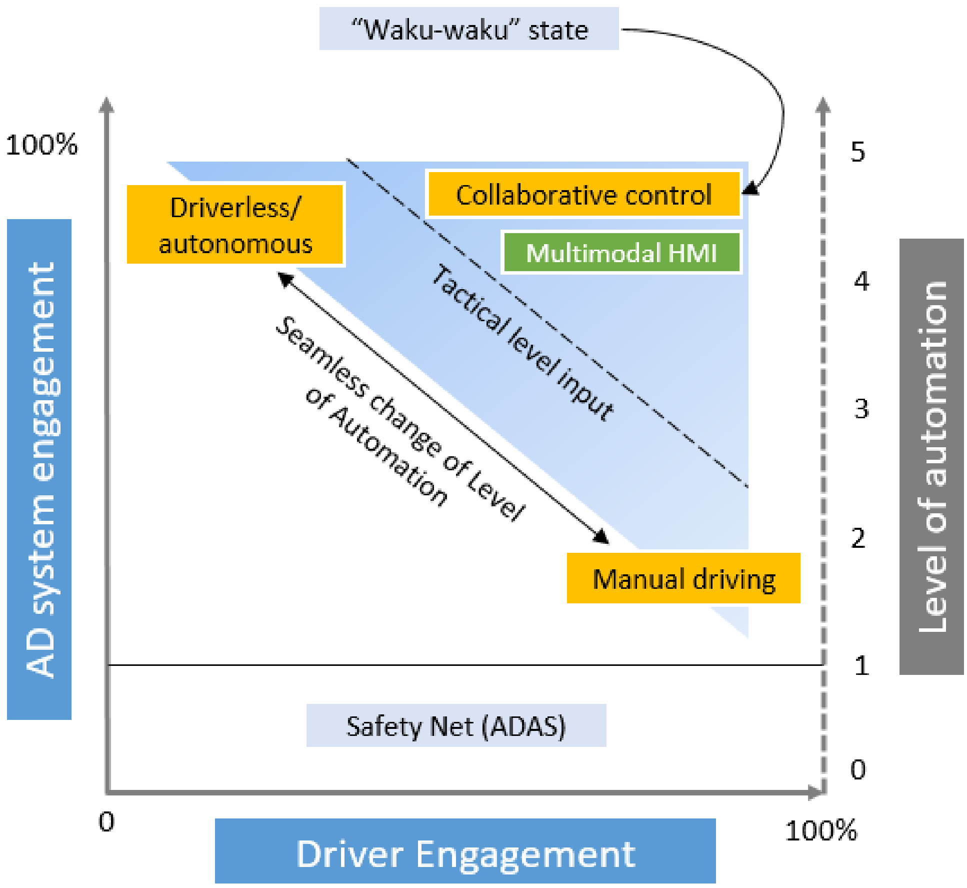


Figure 2.9 Significance of collaborative control

Need of a common "language" for the new type of interaction between humans and automated vehicles.

2.5 Summary

Increasing levels of automation in vehicles changes the traditional relationship between the driver and vehicle. By presenting the fundamentals of the hierarchy of driving task, this chapter introduced the novel use of tactical-level input in automated vehicles. Comparing with conventional human-automation control system models such as direct control, supervisory control, and autonomous control, the advantages and significance of a collaborative control method based on tactical level control was presented. This chapter also addressed the design requirements of an appropriate human-machine interface system to realize collaborative control through tactical level input, and serves as a guideline for designing interfaces and interactions for human-centered automated vehicles. From the next chapter onward, I present and describe the various steps in system design. In the following chapter, I discuss the development of virtual reality driving simulator that serves as the central platform in designing, prototyping, and evaluating the human-machine interfaces as well as interactions.

3 Development of a Driving Simulator

Driving simulators offer the flexibility to create and test many different traffic scenarios safely, efficiently, and economically as opposed to conducting experiments in real world. To serve as an experimental platform for my study, I built a driving simulator using Unity Engine, consisting of a 2 km long driving route, a training track, as well as many traffic scenarios including highway, urban, sub-urban, and parking areas. This chapter describes the development of the driving simulator, its autonomous vehicle model, as well as the events and driving scenarios. It also presents the results of an experiment I conducted to validate the simulator. In this experiment, I evaluated the preference for autonomous driving between novice and experience drivers using the simulator.

3.1 Introduction

When it comes to evaluating driver experience in automobiles, it is better to conduct real-world experiments using instrumented vehicles on actual roads or test tracks. However, conducting such experiments poses many challenges, including liability issues, consistency and reproducibility of experimental conditions, safety of drivers, other road users and experimenters, and the considerable time it takes to plan and conduct the experiments [43]. In contrast, driving simulators offer repeatability, consistency, safety, and excellent flexibility in terms of authoring scenarios and creating extreme events in a controlled environment. These scenes and events can then be repeated identically for each participant, which is nearly impossible to do in real-world situations.

Owing to their advantages and significance, virtual reality simulators have been applied in the field of disaster response work involving construction machines [42], [44]. In addition, it is cost-effective and time-efficient to conduct driving experiments using a simulator. Driving simulators with motion platforms and real vehicle cabins as well as 360-degree view are recommended for human-in-the-loop experiments. However, such driving simulators can be expensive to own and operate. Therefore, I used free and opensource software packages and off-the-shelf hardware components to create a driving simulator that has sufficient functionality to conduct human-in-the-loop experiments and evaluate driving experience and arbitrary HMIs, as shown in Fig. 3.1.

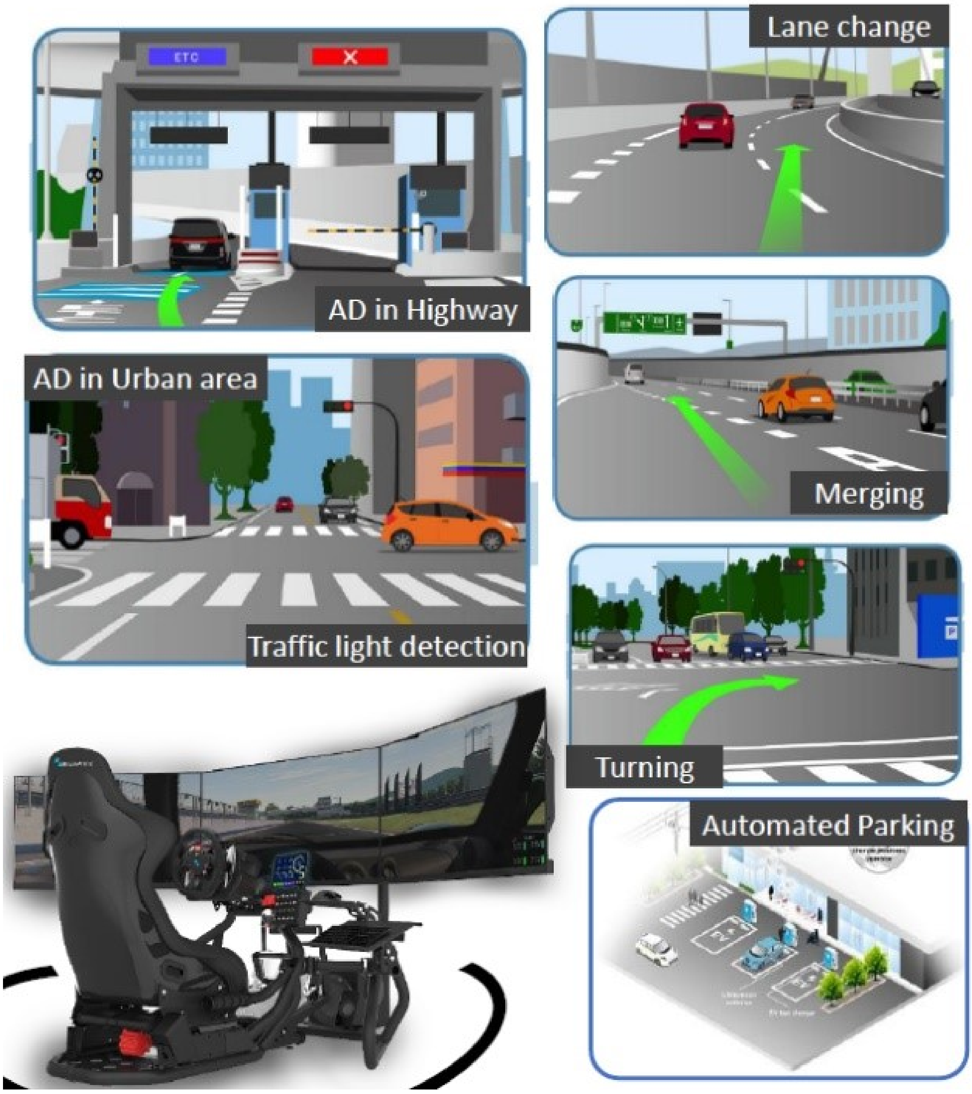


Figure 3.1 Simulator features

Table 3.1 Simulator specification

Components	Properties
Field of view	150°
Visual output	Left, right, and front view on 27-inch 2-D LCD monitor, Surface Pro 3
Auditory output	2.1 channel stereo speaker system
Control interfaces	Logitech G27 racing wheel, Surface Pro 3
Motion platform	None

The purpose the simulator is to replicate autonomous driving and manual driving in a simulated environment for evaluating user experience. This chapter describes a preliminary experiment, using both novice and experienced drivers in autonomous and conventional driving situations, that was conducted to evaluate the effectiveness of the simulator for user experience studies.

3.2 Development of Simulator

In this section, I describe the requirements and specifications of a driving simulator to evaluate driving experience in autonomous and conventional driving, and I describe the development of the simulator. The simulator specifications are listed in **Table 3.1**.

3.2.1 Requirements of the simulator

In the recent years, driving simulators have been developed and used for various purposes. Their applications include: performing research on traffic safety, examining the efficacy of driver training programs, evaluating risks and benefits of in-vehicle information systems (IVIS), testing and training in advanced driver assistance systems (ADAS), investigating the impact of alternative traffic control devices, identifying the acute and chronic effects of medications, checking the fitness to drive of patients with visual, cognitive and motor impairments, and to simulate full vehicle dynamics [43]. Most of the existing driving simulators have been developed focusing on precisely simulating conventional driving (manual driving) and the evaluation of driver assistance technologies, thus, they do not meet the purpose of my study.

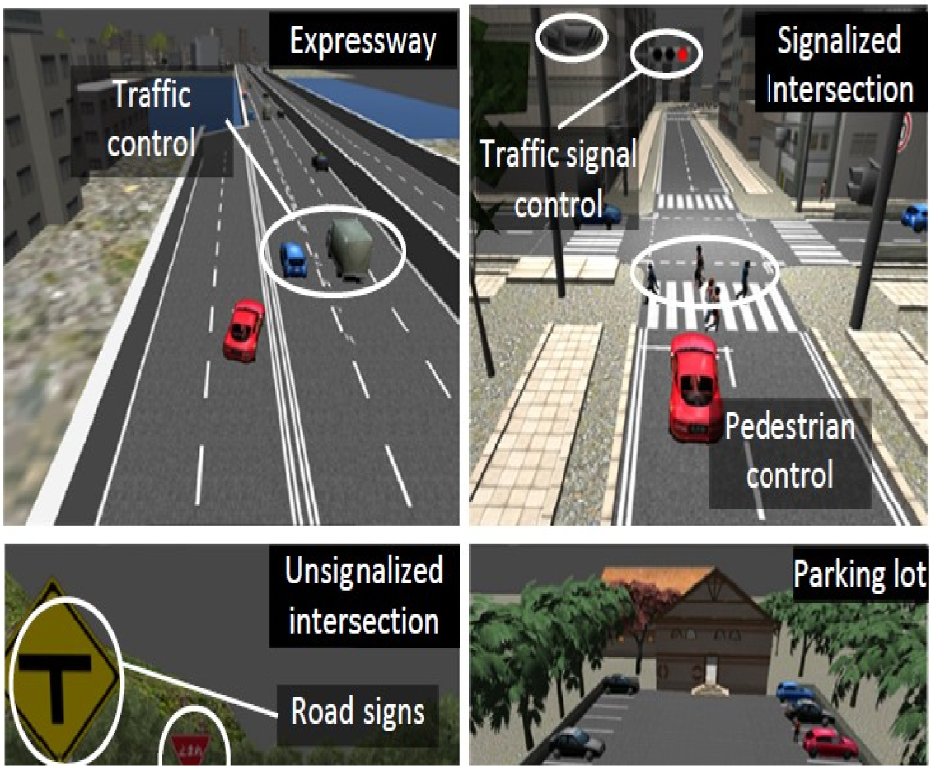


Figure 3.2 Virtual environment

Below, I describe in detail the features and functions that required to be implemented in a driving simulator to meet the aims of this study. These features and functions make this simulator a unique and an effective platform for evaluating driving experience in varying levels of automation, including conventional manual driving, partial and highly automated driving, and fully automated driving.

3.2.1.1 Reproduction of autonomous and dynamic behavior

First, it is required to create a vehicle model that is capable of automated driving up to level 5, having the essential capabilities of dynamic path planning and dynamic obstacle avoidance. Moreover, features such as traffic light and traffic sign detection, pedestrian detection are important to include in the vehicle model. On the other hand, the simulator backend should have features such as high-frequency, low signal-to-noise ratio data acquisition in real-time, triggered control points in virtual environment, weather effects, as well as dynamic visual and audio responses, such as in acceleration, braking and even collision.

3.2.1.2 Creation of arbitrary scenarios and events

It is necessary for the simulator to have functionality to allocate various object types including, but not limited to other vehicles, pedestrians, cyclists, intersections, railroad crossings, and traffic lights in its virtual environment. Moreover, it is necessary to create real-world traffic scenarios and events that could reproduce the naturalistic driving experience as much as possible.

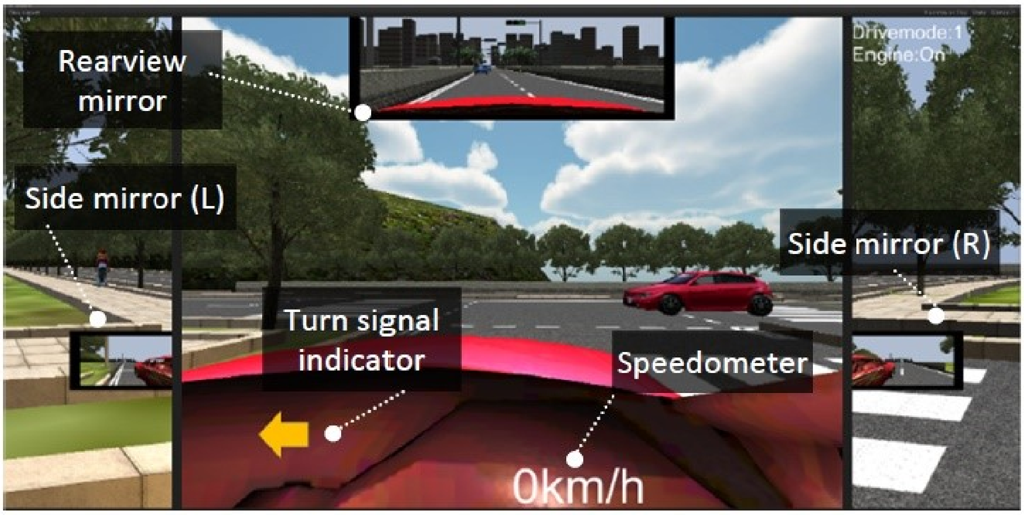


Figure 3.3 Driver's view

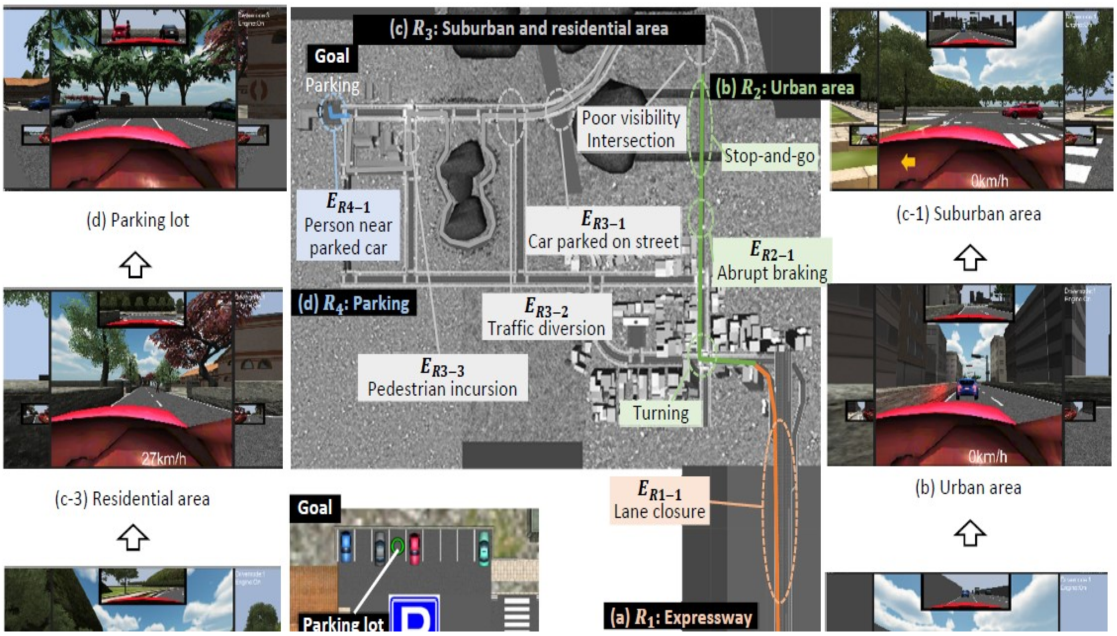


Figure 3.4 Driving route with four regions

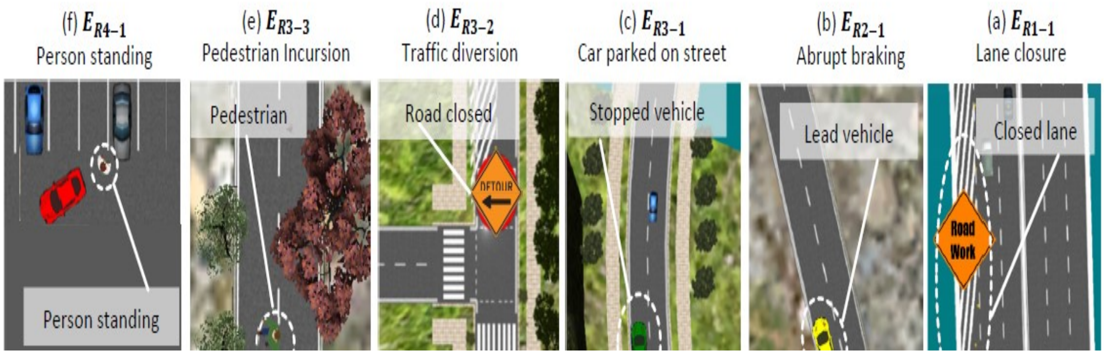


Figure 3.5 Scripted events and scenarios

3.2.1.3 Connection to arbitrary control interface

To realize the main goals of my study, the driving simulator need to be able to connect to different human-machine interfaces. Therefore, in addition to conventional vehicle controllers, e.g., the steering wheel, accelerator, and brake pedal, the simulator should have the functionality to easily connect and accommodate many HMI prototypes, via USB or CAN bus.

3.2.2 Virtual environment

Table 3.2 Properties of regions

Property	Expressway (R_1)	Urban (R_2)	Sub. & 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

Table 3.3 Triggered events

Area	Event
Expressway	Lane closure
Urban	Abrupt braking of lead vehicle
Suburban & Res.	Stopped vehicle, traffic diversion, pedestrian incursion
Parking	Person sitting next to parking spot

To create the virtual driving environment of the simulator, I used the free content-creation engine, Unity [45]. It is popular for creating interactive three-dimensional (3D) content, such as games and animations for PC, mobile as well as web platforms. Compared to using conventional graphics environments/libraries such as OpenGL [46], using Unity's rich Application Program Interface (API) and its Assets Store significantly reduces development time. Moreover, many high-level tutorials are widely available for beginners as well as for advanced users. Scripting languages such as C# and JavaScript is used for create interactions, and Unity supports a wide range of application programming interfaces (APIs).

3.2.2.1 Creation of vehicles, roads, and other objects

For creating the virtual environment with many different traffic scenarios and events, I used free 3-D models available in the Unity Assets Store. These models include road modules, road signs, traffic lights, vehicles, people, trees, and buildings, as shown in Fig. 3.2. The ego-vehicle, which the drivers or automation system would control, was designed with a 5-speed automatic transmission system and a 2-litre gasoline engine. The suspension damping values, center of gravity, and turning radius were set to the standard values of a midsized sedan. The engine sound and other ambient noises from the virtual environment were also simulated, and played through a 2.1 channel speaker system.

3.2.2.2 Reproduction of autonomous and dynamic behavior

When operating in AD mode, it is necessary to control the dynamic behavior of the ego-vehicle, other road users including vehicles, pedestrians, cyclists and also traffic control signals. The behavior and dynamics of above objects was controlled using scripts written in C# and JavaScript. Controlling traffic at intersections, and to implement various events, trigger points were implemented in strategic locations in the virtual environments using invisible box-colliders. A separate script called sensor-script replicates the behavior of Light Detection and Radar (LiDAR), radar, and image sensors to measure the distance between the subject vehicle and surrounding vehicles, road users, and obstacles. I used Unity's Raycast function in the sensor-script to get information about the types of obstacles around the vehicle. In addition, to implement fully autonomous driving behavior, I used Unity's navigation mesh data structure (NavMesh) with dynamic obstacle avoidance. I describe this in more detail in section 3.2.3.

3.2.2.3 Scenario authoring

I designed various driving routes and scenarios by combining the 3D models of road sections, traffic lights, vehicles, and people. As the experiment route (course), I created a driving route that was 2 km long and included an expressway, urban area, suburban and residential area, and parking lot. In addition, I designed several events that drivers experience in real-life driving. I describe these scenarios and events in detail in section 3.3. These different driving environments would replicate real-world driving situations and would result in creating a more realistic driving experience.

3.2.2.4 Reproduction of driver field of view

Three 4-K resolution monitors are used to display the virtual environment from the driver's point of view, including the views from the left and right windows. The views from the rear view and side view mirrors were also shown (Fig. 3.3). In addition, essential driver feedback components such as speedometer, turn signal indicators, were included along with a warning indicator that flashed when drivers exceeded the speed limit.

3.2.2.5 Simulator PC and data acquisition

For the simulation, I used a desktop computer with Windows 8.1, an Intel Core i7 processor, 16 GB RAM, and an Intel HD Graphics card. For data acquisition, vehicle telemetry including GPS coordinates, speed, and input from vehicle controllers (i.e., steering angle, brake, and accelerator pedal position or touch input coordinates that represent the driving behavior of each participant) can be recorded at a 100 Hz.

3.2.3 Autonomous vehicle model

In this section I describe the autonomous vehicle model and its design parameters.

3.2.3.1 Navigation

I used Unity's built-in navigation system for autonomous path planning through the virtual environment. It works as follows: first, Unity creates a data structure called the navigation mesh using the road network in the virtual environment. The navigation mesh describes the drivable road surfaces. This data structure consists of road components represented by convex polygons. After creating the data structure, each polygon is connected to a new surface laid on top of the existing road geometry. In this method, the A-star (A*) search algorithm [47] is used to find a path from the starting point to the goal. Then, a 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 the goal. While the automated vehicle is moving, the dynamic obstacles, such as other vehicles and passengers, are detected and identified, and it is capable of navigating without colliding with them. The sequence of polygons from the start to the goal is locally adjusted and updated while the agent is moving. Unity uses reciprocal velocity obstacles to predict and prevent collisions.

3.2.3.2 Acceleration/deceleration profile

To maintain a safe distance with the lead vehicle I created a headway variable for the automated vehicle. This distance was decided based on the speed limit of the road and the maximum 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. I used Unity's ray casting to continuously monitor the distance to the lead vehicle as well as to other surrounding vehicles. Ray casting measures the distance to objects surrounding (360 degrees) the autonomous vehicle at

100 Hz and sends this data for the calculation of the speed. The vehicle autonomously controls acceleration to maintain a desired headway using Unity's Raycast module.

3.2.3.3 Steering control

In the autonomous vehicle model, I 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). I created these paths to make the movement of the autonomous vehicle look more fluid.

3.3 Driving route and experimental conditions

In this section, I explain the driving route, which consisted of several scenarios and triggered events, in the virtual environment. I also describe the experimental conditions, including the procedure followed and information regarding participants.

3.3.1 Scripted events and scenarios

To analyze individual driving experiences, the virtual environment should consist of several scripted scenarios and events to replicate the varied conditions and situations that drivers encounter in the real world. In order to compare the driving experience among drivers, it is critical that the essential aspects of conditions be reproduced from trial to trial. I thus created a 2 km long driving route which included the following four regions of interest, as shown in Fig. 3.4. The four sections were an expressway, an urban area, a suburban and residential area, and a parking lot. There are also several triggered events implemented in each area. The properties (the speed limit, number of lanes, and length) of each region are listed in Table 3.2, and the triggered events are listed in Table 3.3.

3.3.1.1 Expressway area

In the expressway section with 3 lanes for each direction, the traffic scenarios required the drivers to merge into traffic, change lanes, and take an exit. As the event, one lane was closed due to roadwork, as shown in Fig. 3.5 (a). The vehicles moving in this lane were required to merge into the lane to the right.

3.3.1.2 Urban area

This area had signalized intersections, 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 was required to overtake it (Fig. 3.5 (b)).

3.3.1.3 Suburban and residential area

This area had less traffic, but it had un-signalized intersections with low visibility, so the driver had to be more cautious. As the event, a car had pulled over due to a mechanical problem, and it was blocking half of the lane, as shown in Fig. 3.5 (c). Moreover, there was a person standing by the stopped car. The driver was required to wait for oncoming traffic to pass before going around the parked vehicle. In addition, there was a sudden detour in this area (Fig. 3.5 (d)). Drivers had to take a bypass road as indicated by road signs. Furthermore, there is sudden incursion of a pedestrian into the path of the subject vehicle (Fig. 3.5 (e)). The driver had to immediately apply brakes to avoid hitting the pedestrian.

3.3.1.4 Parking area

The outdoor/open parking area consisted of parked vehicles and people walking around. There was a dedicated parking spot for the subject vehicle (Fig. 3.5 (f)). As the event, there was a person using a mobile phone standing close to the dedicated parking spot, requiring the driver to be much more cautious to avoid collision.

3.3.2 Preliminary experiment to evaluate simulator

As a preliminary evaluation of the developed driving simulator, I conducted a simple experiment to evaluate driving experience between novice and experienced drivers. Figure 3.6 (a) shows the speed variation of the two groups throughout the expressway section, and Fig. 3.6 (b) shows the steering angle variation of drivers in both groups in the suburban area. Figure 3.6 (a) shows that in general, variation of speed among novice drivers is high and unstable, whereas the experienced drivers maintained more stable speed. Figure 3.6 (b) shows that the steering control of both groups were similar. From these results, it could be said that novice drivers will have to improve their speed control skills. Using these data, one can get an idea of the differences in the driving skills of individuals. Such experiments using simulator could be conducted for driving skill evaluation and driver training as well.

3.3.3 Experimental design

This section describe the experimental conditions and procedure of the experiment conducted to assess the feasibility and effectiveness of the developed simulator. The objective was to evaluate driver experience in both automated driving and manual driving using the simulator.

3.3.3.1 Procedure

First, I briefed the participants on how to use the driving simulator in automated and manual driving modes using the corresponding interfaces. I explained how the behavior of automated driving system including path planning and decision making, such as how it would avoid collisions and navigate toward destination. Then I asked them to drive on the dedicated training track I created so that they could practice to control their speed, turn, brake, and observe traffic laws in the simulator. They practiced using both the conventional and automated driving methods. The training track consisted of straight roads, curves, and intersections. I then explained the actual driving route and objective, which was to get to the destination as quickly as possible while obeying traffic laws and road safety. For the first two trials (first set), the participants drove in manual mode, using the steering wheel and pedals. Then, they used automated driving to get from start to goal, along the same route as in the first trial. After they had a 15-minute break, I asked them to repeat the course (second set). The events mentioned in Section 3.1, were triggered during the second set of trials. However, I did not mention those events to the participants beforehand.

3.3.3.2 Participants

Twelve healthy people (11 males, 1 female), in the age range of 21 to 24 years (mean: 22.6, standard deviation: 0.86) participated in the experiments. Six of them had less than 2 years of driving experience. They were assigned to the novices group and the other six participants, who had 2 to 8 years of experience were assigned to the experienced group. In this context, I use the words ”experienced” and ”novice” only to refer to the two groups involved in this study.

3.3.3.3 Evaluation

I recorded the task completion time for each participant for every trial as a efficiency (time) index. As a safety index, I recorded the number of collisions (note that no collisions occurred during autonomous driving, as the car autonomously avoided any potential collision). In addition, using a wrist-based optical heart rate monitor, I measured the average heart rate for every trial as a physiological index. Finally, I asked the participants to assess their subjective workload using the NASA Task Load Index

(NASA-TLX) [48]. Moreover I designed a questionnaire to investigate their preferred driving method and reasons for preference as subjective usability indices.

3.4 Results

3.4.1 Quantitative results

Figures 3.7 (a) and (b) show the average completion time and average heart rate recorded for both novices and experienced drivers, respectively. When in automated driving mode, there was a reduction of approximately 18.3% in completion time. Average heart rate was also lower for both groups when in automated driving mode. Furthermore, the average number of collisions recorded for experienced and novice drivers were 1.67 and 3.67, respectively. The simulator registered a collision and incremented the collision counter, which served as a safety index, whenever the boundary of the subject vehicle overlapped with that of another vehicle, object, or person.

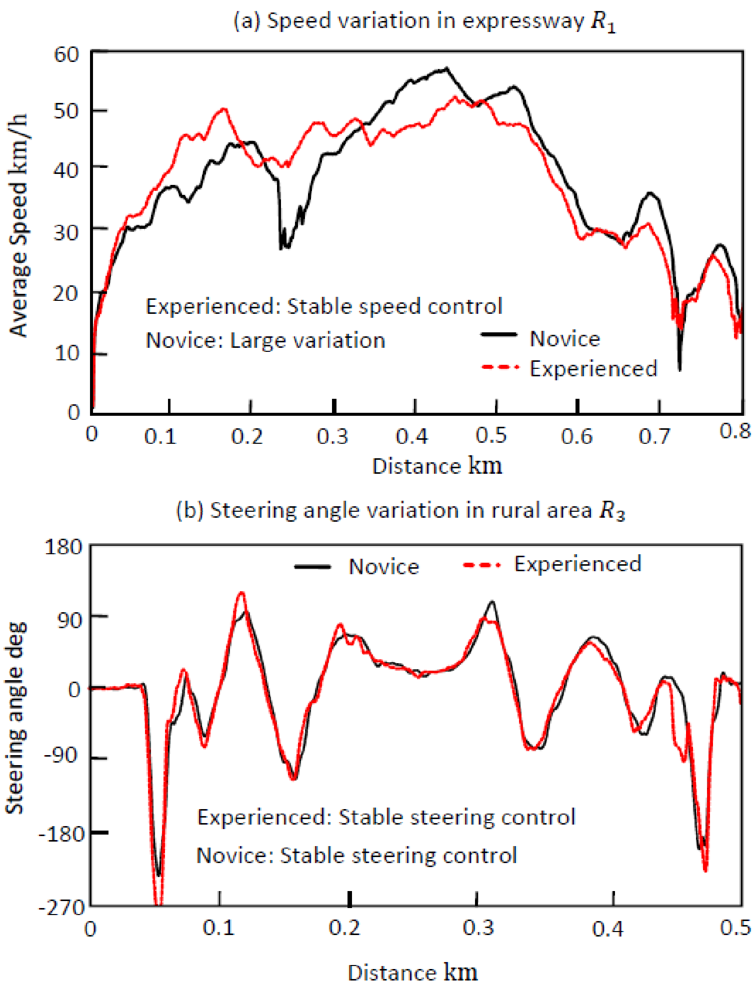


Figure 3.6 Vehicle telemetry data recorded by simulator

Figures 3.8 (a) and (b) show the subjective workload scores obtained using NASA-TLX (raw). This shows that in automated driving, both groups experienced a reduction in perceived workload for every parameter of NASA-TLX. The overall workload score for automated driving showed a significant reduction in both groups. It was 41.3% lower than for manual driving among novices, 49.1% lower for experienced drivers. Thus, it can be inferred from these results that automated driving is better than conventional driving in terms of time efficiency, safety, and subjective workload.

3.5 Discussion

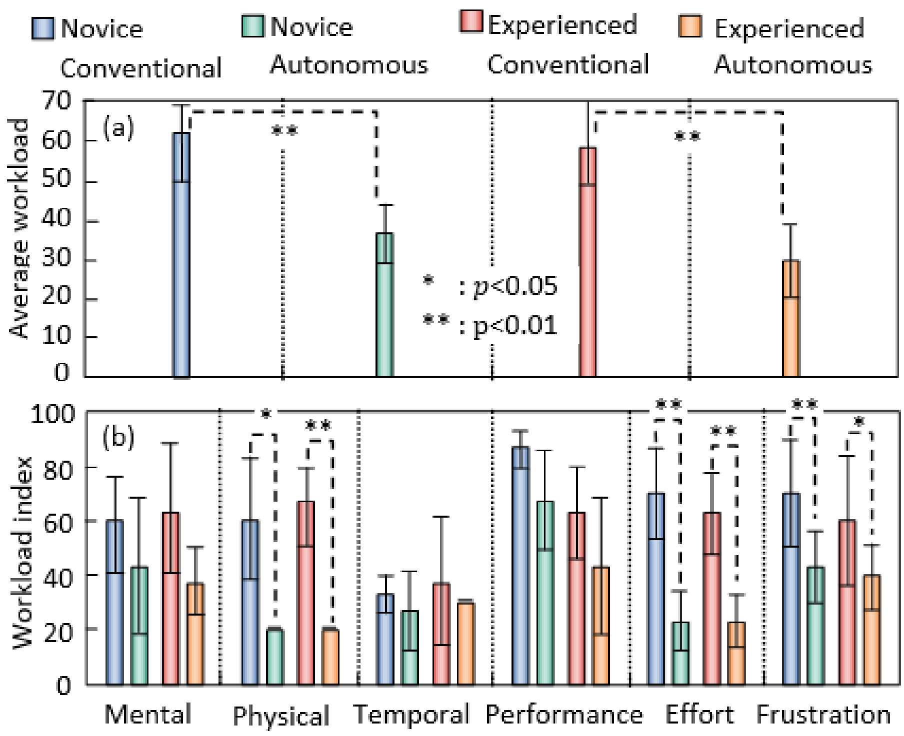


Figure 3.7 Subjective workload scores

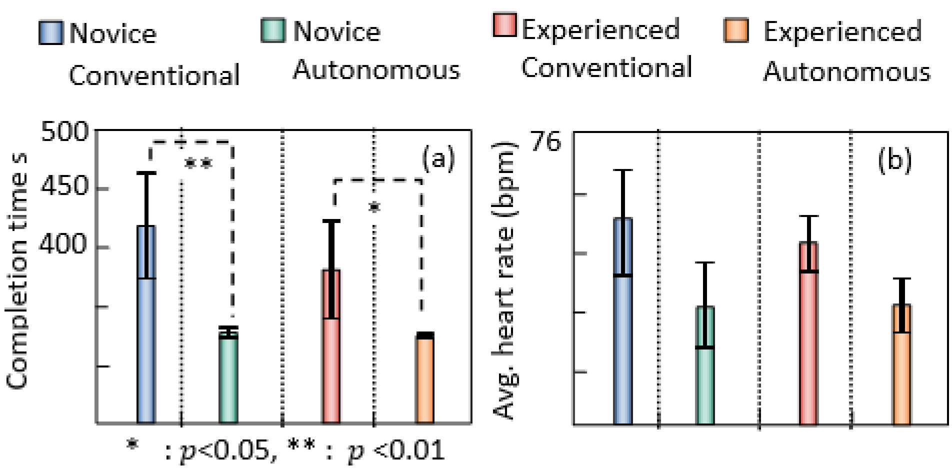


Figure 3.8 Completion time and average heart rate

The results show us that experienced drivers considered driving pleasure and flexibility in controlling the vehicle in conventional driving, while novices were concerned about the ease and safety of autonomous driving. It can be inferred that driver's confidence and experience influenced their preference for a particular method of driving in general. These results indicate that autonomous vehicles should be capable of varying the degree of automation according to the individual driver's experience and preference. The results also showed that the driving simulator has sufficient functionality to evaluate driver experience in both manual and automated driving. This experiment further helped in validating the data collection methods and user experience evaluation I adopted in the driving simulator experiments. Thus, the simulator is capable of conducting quality driving experiments.

3.6 Summary

In this chapter, I presented the requirements and development of a virtual reality driving simulator. Here I addressed the design requirements such as reproduction of autonomous and dynamic behavior, creation of arbitrary scenarios and events, and connection of different HMIs for driver experience evaluation. The virtual environment consists of four scripted scenarios and six triggered events to clarify the differences between autonomous and conventional driving modes. To evaluate the effectiveness of the driving simulator, I conducted a preliminary experiment to evaluate driving experience between manual driving and automated driving. Twelve participants (six experienced drivers and six novices) participated in the experiments by driving in both driving modes under different road and traffic conditions. Results confirmed the usability of the driving simulator as well as the effectiveness of data acquisition methods. In the following chapter, I describe the development of the multimodal HMI system for collaborative control.

4 A MULTIMODAL HMI FOR COLLABORATIVE CONTROL

In this chapter, I present the development of multimodal human-machine interface system for the proposed collaborative control method. A multimodal interface system has many advantages over its unimodal components. Among them are improved recognition, faster interaction, and situation-adaptability. The multimodal interface integrates the touchscreen, hand-gesture, and haptic modalities with the following objectives: enabling intent communication between driver and AD system in real-time, supporting shared situation awareness, and enhancing bi-lateral understanding of intents and actions AD system and driver. Each interface, coupled with the AD system facilitate context-adaptive interaction by providing dynamic visual, audio, force and tactile feedback to the driver, thus realize effective bi-directional interaction, as opposed to uni-directional interfaces. This chapter describes in detail the design of the multimodal HMI system.

4.1 Introduction

In the previous chapter, I presented the driving experiments conducted to evaluate and compare the individual driving experience in vehicles with full driving automation (SAE Level 5) and with no driving automation (Level 0). A qualitative evaluation revealed that drivers prefer to have tactical-level control over lateral and longitudinal motions while driving in level 5 [28], [49]. In chapter 2, I proposed novel level of driver-vehicle interaction for highly automated vehicles based on tactical level, in which drivers can input lateral control commands such as lane change, overtake, and longitudinal control commands such as acceleration and braking, and location specific commands such as parking. This chapter describes the development of a multimodal interface system to facilitate collaborative control using tactical-level input.

Multimodal interface (MMI) systems are capable of processing two or more combined user input modes, (i.e., touch, speech, gestures, and body movements) in a coordinated manner with multimedia output [50]. Such systems bring along many benefits into human-machine systems such as improved recognition and understanding, faster and intuitive interaction, and ability to adapt to different environment and users. When it comes automobiles, since they travel through highly dynamic environments, and their user groups are diverse, use of a multimodal interface system for vehicle controlling will bring significant benefits to drivers. A MMI will allow drivers to accomplish vehicle control tasks using a modality most appropriate to the driving situation, or a modality they are comfortable with or prefer. In the literature, there are many studies in the automotive domain investigating user interfaces with multimodal feedback [51], [52], but comparatively lesser number of studies on multimodal inputs [53]. Most of related studies focused on reducing driver distraction when performing secondary and tertiary tasks while engaged in manual driving in levels 0, or 1. There is also a lack of studies investigating the use of human-machine interfaces with multimodal input and feedback for tactical-level controlling of vehicles operating in levels 2 and above. Therefore, as a solution, I developed an HMI with multimodal input and feedback for highly automated vehicles with the objectives of: (1) facilitate highly efficient interaction (shorter input time, lower input error), and to (2) reduce driver workload.

4.2 Related Works on Multimodal Automotive Interfaces

When designing a multimodal system, it is essential to integrate complementary modalities that create a synergistic interaction where strengths of each modality are maximized to overcome weaknesses in others [54]. In this study, therefore, I integrated three modalities: a touchscreen with visual and auditory feedback, a hand-gesture interface with visual feedback, and a haptic interface with tactile and force feedback.

Known as a type of direct input devices, touchscreens are found to be better suitable for discrete, pointing, and ballistic types of tasks [55]. They perform better than rotary controllers in controlling in-vehicle functions [56]. Amount of information they can convey within a given time is generally higher than other modalities such as voice and gesture. Ability to adaptively change the information displayed, intuitive input by having clearly defined buttons and touch-areas, quick and direct methods to input commands (e.g. selecting a destination from a map), ability to easily upgrade with software updates are among key advantages of touchscreens. However, high visual attention, poor readability in direct sunlight, and lack of physical feedback are major drawbacks in touchscreen interfaces.

Hand gestures are a part of natural interaction among humans. A hand-gesture based interface, thus, would make the driver-vehicle interaction effortless and more intuitive compared to physical interfaces. Research on gestural interfaces in automotive applications have widely been aimed at improving safety by reducing driver's visual and cognitive demands associated with conducting secondary and tertiary tasks while engaged in driving (Levels 0, and 1), and most studies are based on non-intrusive, one-handed gestures [57], [58]. Since hand gestures can be made without visual engagement as opposed to touchscreens, and can convey information immediately in contrast with speech interfaces, they have numerous possible applications in vehicles. However, lack of direct physical feedback, and relatively high recognition errors are known disadvantages of gesture-based interfaces.

Haptic interfaces, on the other hand, can provide the user with active as well as passive feedback on input acknowledgement, and system status. Such interfaces can facilitate and enhance bidirectional interaction between the driver and automated vehicle, which is an important factor that contributes in increasing driver perception, situational awareness, and therefore, performance. By utilizing human haptic system, driver cognitive load could also be reduced, by supplementing other sensory channels such as visual and auditory [59]. Furthermore, haptic feedback is a better solution for environments that are noisy and distracting, compared to auditory or visual feedback. Several automotive manufacturers have demonstrated vehicles that have joy-stick-type haptic HMIs instead of conventional steering wheel and pedals [60], [61]. In addition, many studies investigated the use of tactile feedback for advanced driver assistance systems (ADAS), and in-vehicle infotainment systems (IVIS) [62]–[64]. However, use of haptic interfaces in controlling highly automated vehicles has not been investigated well enough. This thesis aims to contribute in filling this void.

In the following section, I present the details of the design and development of each interface type.

4.3 Development of Touchscreen HMI

I developed a touchscreen-based HMI for tactical-level input considering the requirements stated in the previous section. Here I provide the rationale of the design.

4.3.1 Requirements and related parameters

One major reason to use a touchscreen interface in this study is because it can not only receive input from driver but also convey much more information from AD system. Moreover, driver can comprehend that information in a very short time (at a glance), compared to voice or gesture interfaces. In addition, humans are generally familiar with using touchscreen interfaces in smartphones, tablet computers, and car navigation systems. As a consequence, one can expect that the acceptability of a touchscreen interface for tactical-level input would be high. The important point when using a touchscreen in vehicles is to allow the driver to precisely touch a location with reliability. I carefully designed the interface and interaction so as to ensure the above properties. However, it is important note that the acceleration (along 3-axes) and vibrations make precise touches more difficult, and moreover, these may result in input misrecognition and incorrect inputs.

4.3.2 Robust bidirectional interaction

In order to collaboratively perform DDTs, the human-machine interface should enable bi-direction interaction. The HMI 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. Moreover, the touchscreen interface displays an overview map, with adjustable field of view depending on the situation, in order to comfortably input tactical-level control commands. The HMI should also have an input-correction function for robust inputs. Furthermore, the location of HMI inside the cockpit should be decided considering human factors, e.g., angle of vision, reachable region, and difficulty in accurate positioning of the fingertip, when the vehicle is moving.

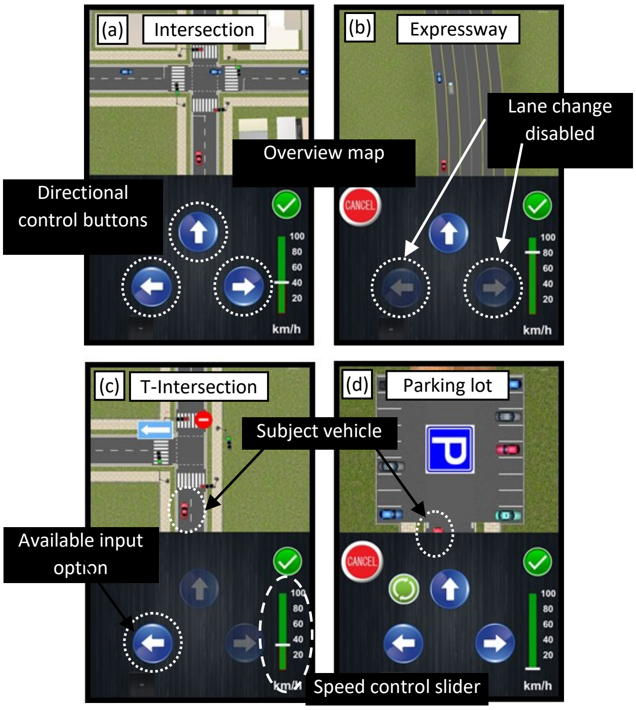


Figure 4.1 Touchscreen interface

4.3.3 Touchscreen-based driver-vehicle interface functionality

I implemented the touchscreen interface in a Microsoft Surface Pro 3 (Fig. 4.1). The interactive graphical user interface was developed using Unity engine. The driving simulator connects with the touchscreen using wireless communication to update the vehicle position and overview map in real-time. Considering human's angle of vision and reachable region of 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.

The top half of the screen displays a two-dimensional overview map of the vehicle and its surroundings while the overview map shows the surroundings of the vehicle including other vehicles and road layout. This information displayed on the screen in order to increase the driver's situation awareness. Drivers can move the map by panning, and zoom-in/out by pinching. The bottom half displays the lateral and longitudinal control buttons, as well as vehicle status. It consists of directional control buttons, speed control slider, and a confirmation button.

Driver can use the directional control buttons to input a turn, lane change, or an overtake command (Fig. 4.1). These buttons adaptively change their status between active (enable) and inactive (disable) depending on the options available to the driver.

Table 4.1 Technical specification of Leap Motion

Property	Value
Detection range	0.23 m^3, 25-600 mm above the sensor on +Y-direction
Sampling Frequency	200 Hz (max)
Accuracy	0.01 mm
Dimensions	13 mm x 30 mm x 76 mm
Connectivity	USB 2.0, 3.0

For example, in a certain part of the expressway, lane changing is prohibited. In this area, the lateral control buttons get disabled (Fig. 4.1 (b)). This will passively inform the driver of the road rules, and prevent the driver giving a wrong/illegal input. Drivers can change the travelling speed using the control slider. When the vehicle approaches the parking lot, the overview map displays the layout of the parking lot (Fig. 4.1 (d)) and drivers can tap an available spot and then tap the confirm button to park the vehicle. This interface provides visual and auditory feedback on acceptance or rejection of driver input.

4.4 Development of hand-gesture HMI

Gestural interfaces are currently being developed for automotive applications focusing on reducing driver distraction. These interfaces place great emphasis on improving safety by reducing driver's visual and cognitive demands associated with conducting secondary driving tasks like operating the audio system, climate control system [57]. However, there is a lack of studies on using hand gesture interfaces for controlling vehicle maneuvers. Driving a vehicle manually, using hand gestures would be highly inconvenient, because of the many parameters (e.g., steering angle, speed) that need to be controlled in real-time. Therefore, one of the objectives of this study is to find out whether hand gestures can reasonably be used in an autonomous vehicle to conduct primary driving tasks, in tactical-level.

4.4.1 Gesture recognition technology

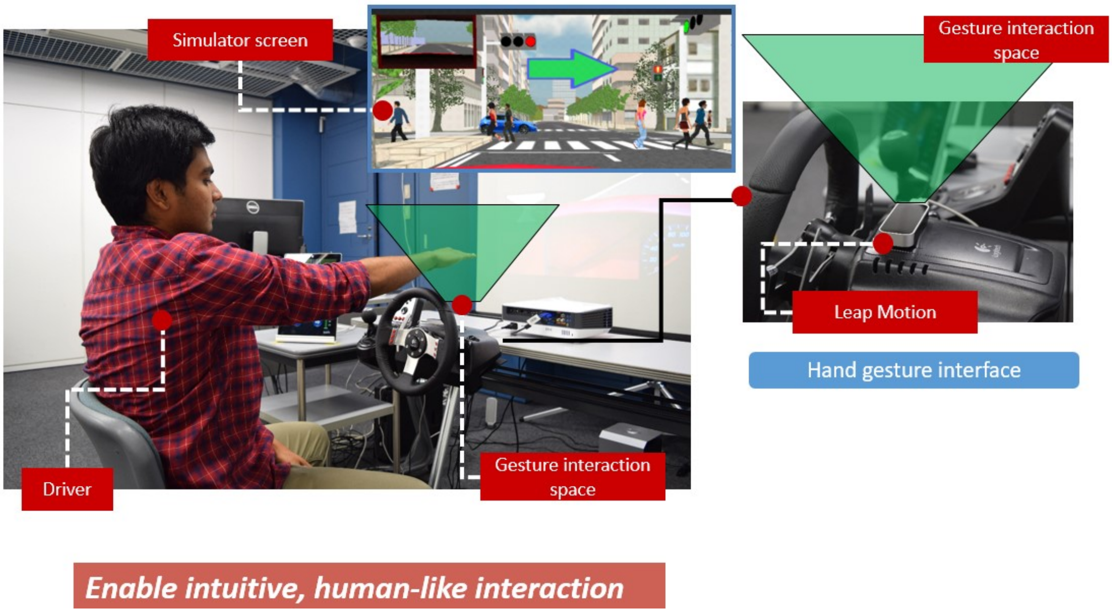


Figure 4.2 Hand-gesture interface overview

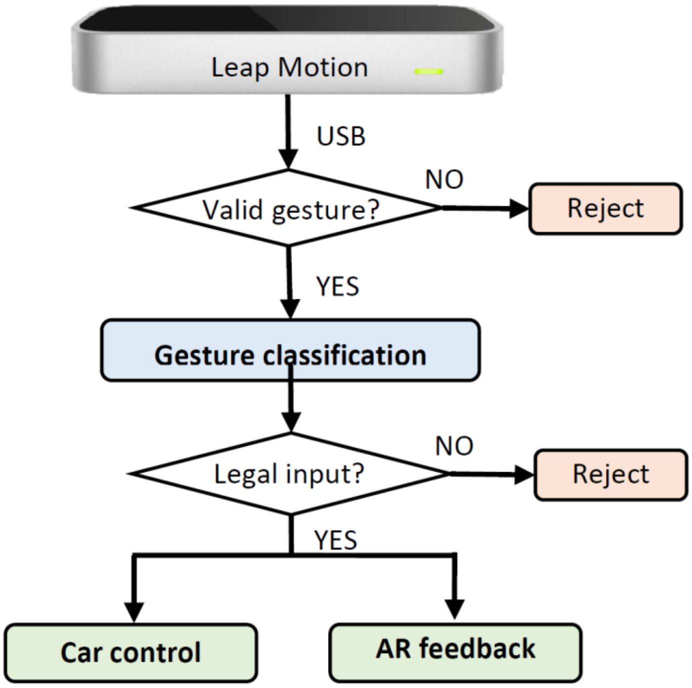


Figure 4.3 Information flow

For hand-gesture recognition, I used the Leap Motion Controller as a platform. Leap Motion Controller, as shown in fig. 4.3 and fig. 4.4, can determine the position of hands in three-dimensional (3D) space in real-time. It consists of two wide-angle infrared (IR) cameras and three IR LEDs [65]. It uses stereo vision principle for optical tracking. It generates a grayscale stereo image by tracking the IR light emitted by LEDs. However, there is not much information published on the emitting patterns or interferometry techniques it uses to generate this image. It can track hands within a 3D interaction space above the device. This space is in the shape of an inverted pyramid and it spans from 25 mm above the device to 600 mm in positive Y-direction. Technical specification of the controller is listed in Table 4.1. The sensory data (raw data), in the form of a grayscale stereo image, is streamed via USB to the computer after performing resolution adjustments locally, inside the controller. Leap Motion Service (software) that runs on the computer uses proprietary algorithms to process the streamed stereo images to reconstruct a 3D representation of the environment that it sees inside its interaction space. The resulting data is updated in an object-oriented application programming interface (API), as a series of frames consisting of all tracking information including positions, and velocities of the tracked hands.

I chose Leap Motion as the gesture recognition platform for the following reasons. It is unobtrusive in size with its small form factor, very portable and light weight, consumes less power, and cheaper compared to Microsoft Kinect [66] (another popular vision based motion recognition platform). It is also easy to use and non-intrusive (as a non-contact platform) compared with other devices that require the users to wear either gloves [67] or armbands [68] in order to input gestural commands. However, when the palm is tilted significantly with respect to X-Z plane, Leap Motion Controller fails to track a hand accurately [69]. To deal with this limitation, I defined our swipe gestures so that users will have to use a flat hand with their palm parallel to X-Z axis.

4.4.2 Integration with driving simulator

A dynamically loaded library (DLL) connects to Leap Motion service to provide tracking data in real time to the driving simulator. I created C# scripts in Unity to access the tracking data from Leap Motion API and to map and execute the primary driving tasks in the simulator (Fig. 4.3). However, Unity’s native coordinate system is different from that of Leap Motion’s. Therefore, it is required to use the Leap Unity extension script to convert the scale and coordinate system as well as to convert vectors and matrices from Leap API classes to Unity API classes.

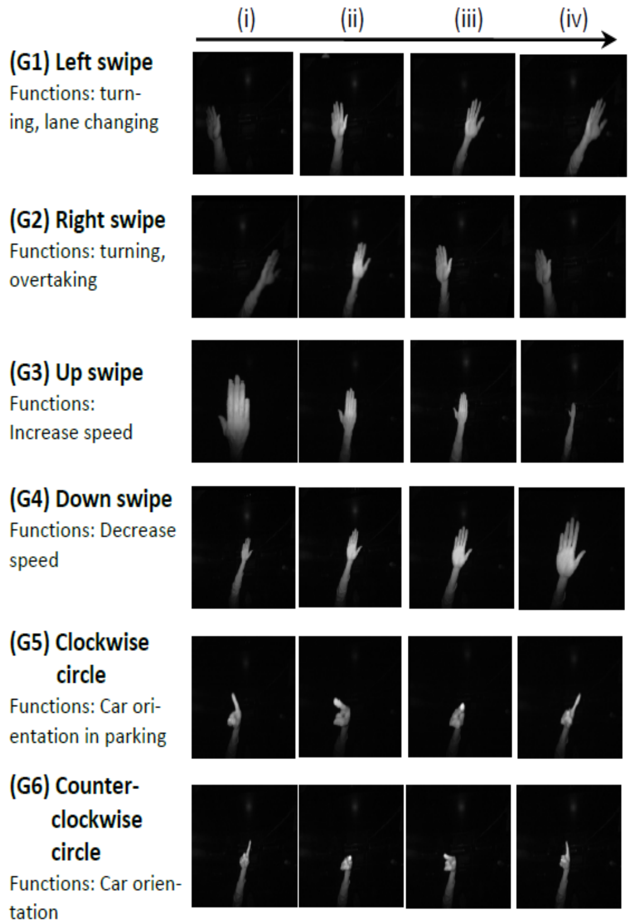


Figure 4.4 Relationship between control functions and gestures

4.4.3 Gesture interaction space

I placed the hand gesture sensor behind the steering wheel as shown in Fig. 4.3. Among the reasons for this placement were to avoid any unintended input resulting from hand movements of the driver or passengers, and to facilitate the use of either hand the driver is comfortable with. Human factors play an important role in determining the usability of an interface. The gesture interaction space lies within the standard range for operating hand controls of motor vehicles as outlined in Japanese safety regulations (article 10) and ISO 3958.

4.4.4 Control functions

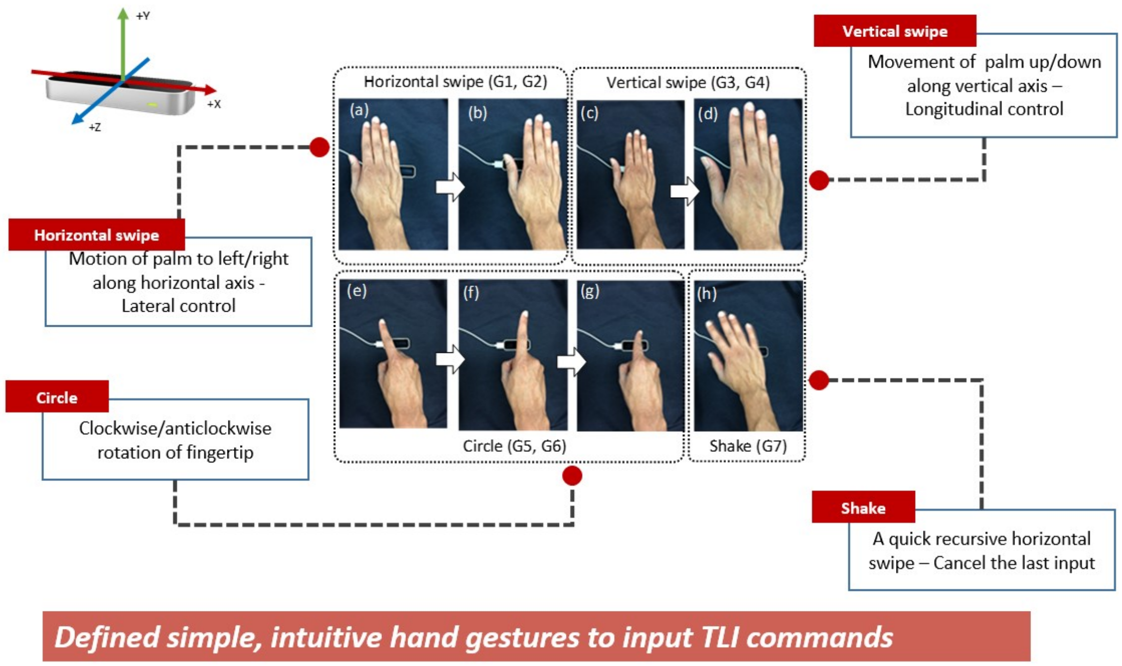


Figure 4.5 Hand-gesture types

For this experiment, I defined the following abstract control functions to be used in controlling a vehicle in collaboratively, with the objective of enhancing driver experience.

- Lateral control: turning, overtaking, merging, and lane changing.
- Longitudinal control: speed controlling
- Parking: selecting a parking spot, orientation of vehicle.

I defined the input functions for this interface so that drivers have the freedom to input the above commands using hand gestures. The autonomous vehicle control algorithms check the validity of input command based on the situation and traffic rules, and then maps the gesture input to the appropriate control function.

4.4.5 Gesture classification

I first defined a set of vehicle movements to improve the driving experience in an autonomous vehicle, as stated earlier, and related them to the set of hand gestures (G1 – G7). Figure 4.4 shows the grayscale image data of each gesture at four time steps ((i) to (iv)), captured by Leap Motion’s IR cameras. Out of the seven gestures, five are carried out using a flat hand parallel to X-Z plane (swipe gestures) and two are carried out using a pointing finger (circle gestures). Figure 4.5 shows the different hand

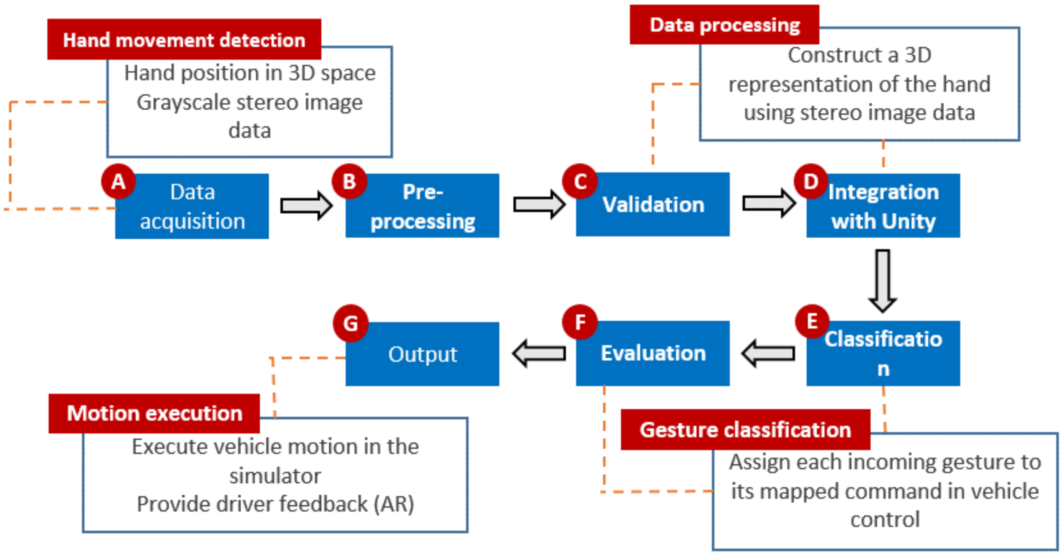


Figure 4.6 Gesture classification framework

movements required to make the gestures. The swipe gesture is defined as a straight line movement of the hand with fingers extended, and a circle gesture is defined as the circular motion of a fingertip. In natural human-human nonverbal interaction, people use hand gestures to indicate directional movements, and increase/decrease of a quantity. Therefore, to make the driver-vehicle interaction intuitive, swipes that are parallel to horizontal plane (XZ) were related to lateral controls while those are perpendicular to X-Z plane were associated with longitudinal control commands. It is also important for the gestures to be distinct from each other to avoid ambiguity and misrecognition. In order to differentiate horizontal (G1, G2) swipes from vertical (G3, G4) swipes, I compared the absolute values of the direction vector for each swipe input. To differentiate clockwise circle gestures from counterclockwise circle gestures, I compared the angle between the fingertip and the normal vector of the circle input. If this angle was less than 90 degrees, the gesture was defined to be in clockwise direction. In order to minimize hand fatigue, I used following recommended values for parameters to validate a gesture: minimum swipe length – 150 mm; minimum swipe speed – 1000 mm/s; minimum circle radius – 5 mm; and minimum arc length $1.5\times\pi$ radians.

4.4.6 Visual feedback

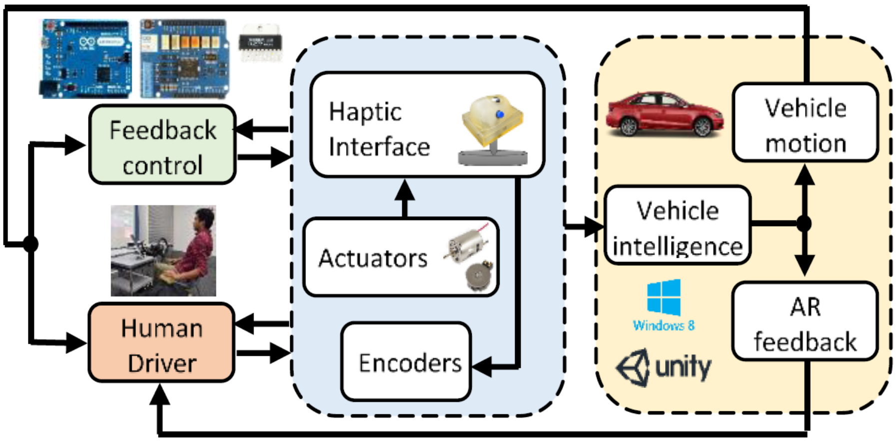


Figure 4.7 Haptic interface - system overview

Compared to physical/tactile interfaces, gestural interfaces lack the ability to provide direct physical feedback to the user. Controlling a vehicle's movements is a critical task and it is important to give feedback to the driver on the success or failure of recognizing gestural input. Therefore, to enhance the driver experience, I created an augmented-reality (AR) system in the driving simulator, that gives the driver visual feedback if a command is recognized and accepted. For lateral input commands, I displayed an AR arrow on the simulator screen, that appeared to be projected on to the road ahead (for changing lanes, merging), or above the road (for turning), showing the intended motion of the vehicle, as shown in Fig. 4.10 (a). For parking, I displayed an AR rectangle surrounding the parking spot, as shown in Fig. 4.10 (b). This AR system can be

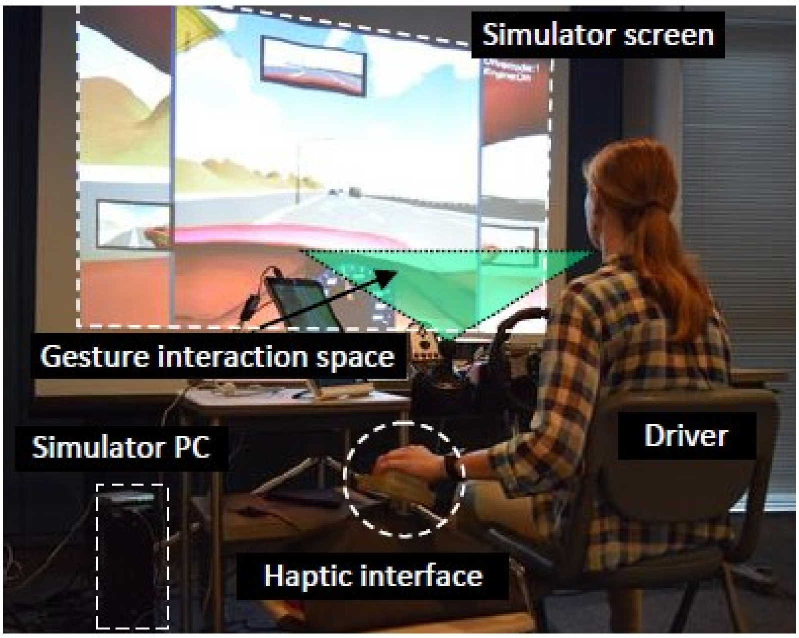


Figure 4.8 HMI setup in the simulator

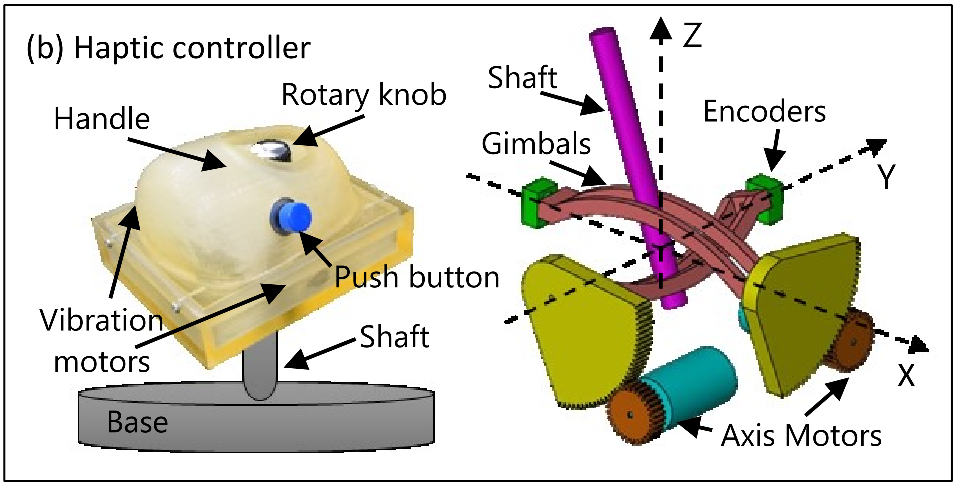


Figure 4.9 Haptic interface- design overview

implemented in an actual vehicle by using heads-up-displays, and transparent displays with OLEDs.

4.5 Haptic Interface

Haptic interfaces are capable of providing the driver with active as well as passive feedback on input acknowledgement, and vehicle/system status. Drivers are familiar with using tangible, physical interfaces inside vehicles, such as the steering wheel, pedals, and shift lever. Such interfaces can enhance the bidirectional interaction between the driver and vehicle, which is an important factor that contributes in increasing driver perception and performance. By using haptic systems, driver's cognitive load could also be reduced, by supplementing other sensory channels such as visual and auditory [70]. In addition, haptic feedback is a better solution for environments that are noisy and distracting, compared to voice feedback. Several automotive manufacturers have demonstrated vehicles that have joystick-type haptic DVIs instead of conventional steering wheel and pedals [60], [61]. Also there are

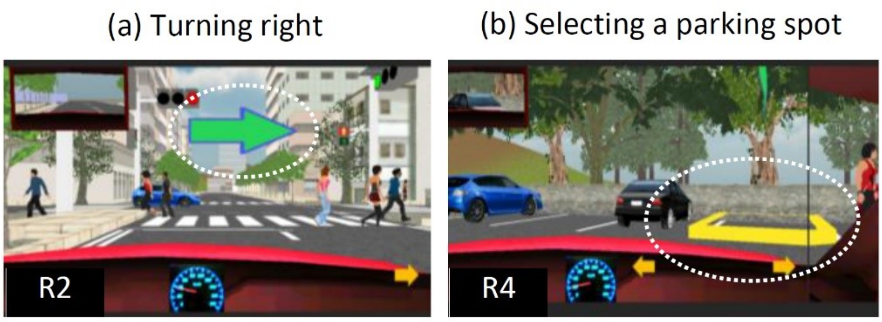


Figure 4.10 Driver support - augmented reality visual feedback

vehicles equipped with such interfaces designed for the use of drivers with various physical disabilities [71]. In addition, many studies investigated the use of tactile feedback for advanced driver assistance systems, and in-vehicle infotainment systems [62], [70], [72].

4.5.1 Design Considerations

In this section, I describe the design considerations and components of the haptic interface.

4.5.1.1 Mechanical configuration

The haptic control interface, as shown in Fig. 4.9, consists of a handle mounted on the top of a shaft and a base that contains the joystick mechanism, actuators, transducers, and microcontrollers. The handle was designed to have a smooth curvy surface, so that when operating for long hours, the fatigue of hand would be minimum. I made the handle using a 3D printer. The handle has a push button and a rotary knob to invoke different functions, combined with the movement of the handle, and two vibration motors of eccentric rotating mass (ERM) type, to provide vibrotactile feedback. I used the base part of displacement type joystick as the platform for our control interface, which has two degrees of freedom; sideways (X-axis) and back-and-forth (Y-axis).

4.5.1.2 Situation awareness assistance

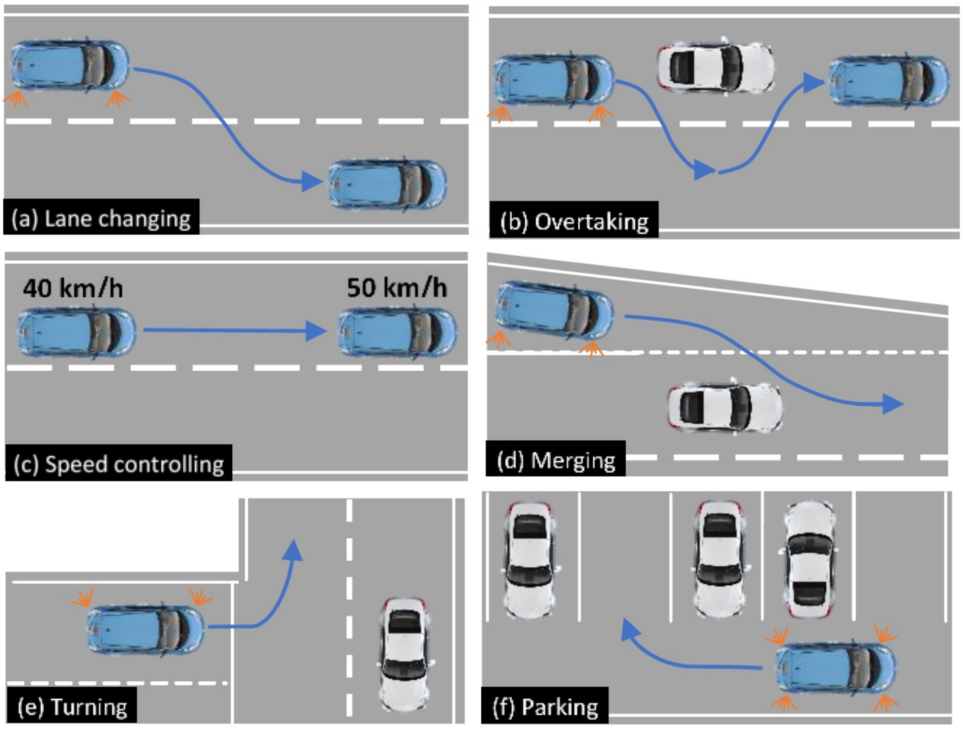


Figure 4.11 Tactical-level control functions

The drivers in autonomous vehicles need not to pay constant attention to the road environment while driven in fully-autonomous mode. Thus, when they want to take control of the vehicle, it is important to increase the situation awareness for ensuring safety. Haptic feedback can efficiently make the driver aware of the surrounding vehicles, applicable traffic rules, as well as the status of the vehicle. This control interface provides haptic feedback in the forms of *kinesthetic*: by controlling torques on relevant axis motors, and *tactile:* by inducing vibrations on the handle using the two vibration motors (Fig 4.9).

4.5.1.3 Control System

I used an Arduino microcontroller board (ATmega32u4) to control motor and communicate with the driving simulator (Fig. 4.7). Arduino motor shield controlled the axis motors and Toshiba's TA7291P IC controlled the vibration motors. The DVI communicates with the simulator PC using serial communication via USB, to validate the user input and execute vehicle control functions in the driving simulator, as shown in Fig. 4.7.

4.5.2 Classification of input commands

Figure 4.12 shows the required movements of the handle in order to input each control command. The handle stays at the neutral position when not operated, as shown in Fig. 4.12 (a). To input a lateral control command, the driver moves the handle to left or right direction (Fig. 4.12 (b_1, b_2)). The simulator will then map the input to a vehicle control function based on the situation, i.e., lane changing, merging, or turning. The vehicle's speed can be controlled within the legal speed limits by moving the handle forward (to accelerate) as shown in Fig. 4.12 (d_1), or backward (to decelerate) (Fig. 4.12 (d_2)). For overtaking a vehicle, driver is required to press the button while moving the handle forward (Fig. 4.12 (d_3)). If the handle is moved backward while pressing the button, as shown in Fig. 4.12 (e), the vehicle will cancel the execution of last input command. In addition, driver can use the rotary dial to change the vehicle orientation when parking.

4.5.3 Kinesthetic and tactile feedback

The haptic DVI is capable of providing two types of feedbacks; kinesthetic (force) and tactile (vibration). Force-feedback is given in instances like when the driver tries to input a command that violates the traffic rules (e.g., speeding up beyond the speed limit or turning in to a one-way road) or imposes a threat to road safety (e.g., changing lanes or overtaking in dangerous situations). When such situations are detected by the vehicle, the haptic controller opposes the motion from the driver. The microcontroller will use

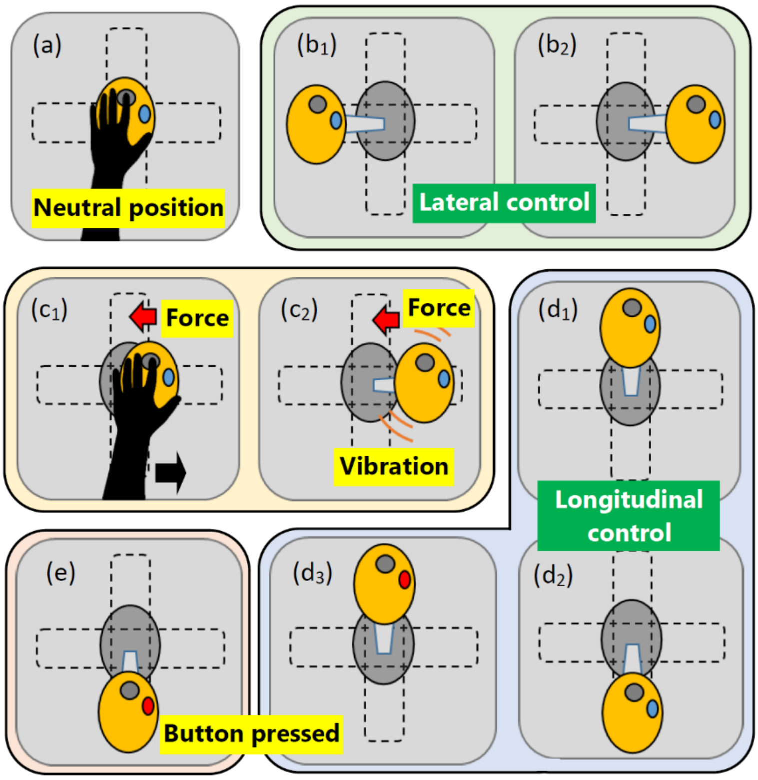


Figure 4.12 Haptic interface - input functions and feedback

pulse-width modulation (PWM) to control the axis motors to apply a force on the shaft (Fig. 4.12 (c_1)). If the driver continues to input (forcefully) ignoring the force-feedback, the vibration motors are activated and the handle will vibrate in a strong and steady manner until the driver corrects or cancels the input command (Fig. 4.12 (c_2)).

4.6 Summary

In this chapter, I introduced the component interfaces of the multimodal HMI system for collaborative control; touchscreen, hand-gesture, and haptic. Presenting the design requirements for each interface type, I described the development of the interfaces. Set of input functions were defined for each interface and associated them with vehicle control functions in tactical-level. In order to evaluate the effectiveness of the multimodal interface system and the usability of each interface modality, experimental evaluation is necessary. The evaluation of multimodal HMI system will be presented in chapter 5.

5 HMI ASSESSMENT

To determine the effectiveness of any human-machine interface system, carefully designed user experience evaluations are necessary. This chapter presents a detailed experimental evaluation of the multimodal HMI system using the driving simulator. Twenty participants involved with the driving experiments. Their driving experience was compared when using the multimodal HMI and each unimodal components. Data related to HMI operation including input error, choice of modality, reaction times, and vehicle telemetry were recorded. Moreover, a subjective evaluation was done using a questionnaire and NASA task-load index. The results highlighted the effectiveness of the multimodal interface in terms of perceived workload, efficiency, error avoidance, and situation adaptability.

5.1 Experimental Design

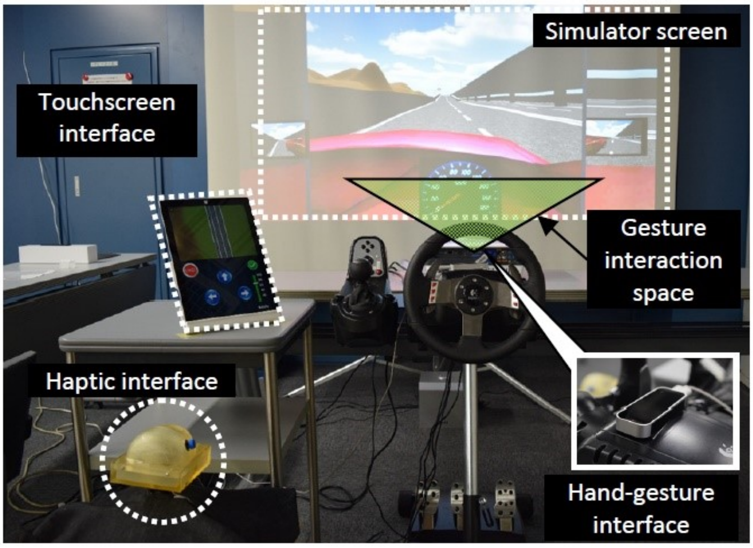


Figure 5.1 Multimodal interface system

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.

5.1.1 Scenarios and events

To evaluate the proposed HMI system, the virtual environment of the driving simulator requires to simulate different scenarios and events to represent many traffic situations that drivers encounter in the real world. Thus, I created driving route having a length of 2 km, including areas such as: expressway area (R_1), urban area (R_2), rural and residential area (R_3), and parking (R_4). In addition, I designed and triggered several events (E) that drivers experience in each area. Below I describe the characteristics of traffic scenarios and events implemented in each area.

Table 5.1 Input-output relationship

Lateral commands	Merge/exit	Right/left buttons	Right/left swipe	Right/left movement
	Lane change	Right/left buttons	Right/left swipe	Right/left movement
	Overtake	Right button	Right swipe	Right movement
	Turn	Right/left button	Right/left swipe	Right/left movement
Longitudinal commands	Acceleration	Slider - up	Vertical swipe –upward	Forward
	Deceleration	Slider -down	Vert. swipe – downward	Backward
Parking commands	Selecting	Tap	Left/right/up/down swipes	Left/right/up/down movements
	Confirming	Double tap, Confirm button	Poke/point	Button + forward
Other	Cancel	Cancel button	Left-right swipe (shake)	Button + backward

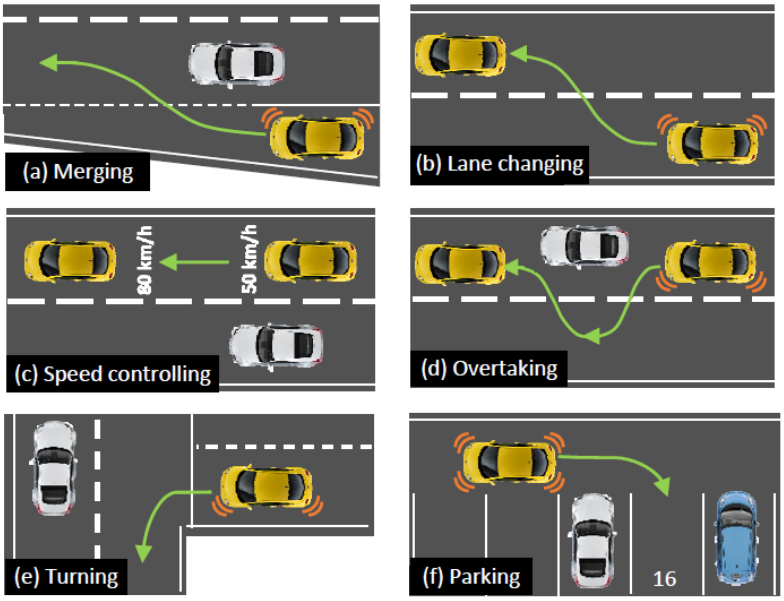


Figure 5.2 Tactical level input functions

5.1.1.1 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, and vehicles moving in that lane were required to merge into the lane to the right.

5.1.1.2 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.

5.1.1.3 Sub-urban 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 vehicle had pulled over due to a mechanical problem, and it was blocking half of the lane. The driver had to wait for oncoming traffic to pass before going around the parked vehicle. There was a sudden detour in the rural area. Drivers had to take a bypass road as indicated by road signs. I also triggered an unexpected incursion of a pedestrian into the path of the subject vehicle. The driver had to brake immediately to avoid hitting the pedestrian.

5.1.1.4 Parking area

The parking lot consisted of parked vehicles and people. There was a dedicated parking spot for the subject vehicle. As the event, there was a person standing close to the dedicated parking spot, requiring the driver to be much more cautious to avoid hitting her.

5.1.2 Experimental procedure

Drivers first drove on a training course to get used to the simulator and the HMIs. I observed the training and guided the drivers until they gained enough competence in using each of the input devices. For the experiments, I asked them to control the autonomous vehicle in four trials, using each interface alone (unimodal) and using the multimodal HMI system. When using the MMI system, drivers could choose any modality to input tactical-level control commands.

5.1.3 Participants and evaluation

Twenty participants (n=20; 13 males, 7 females, mean=26.5 years, SD=4.3, age range 21–36 years) involved in the experiments. Their years of driving experience ranged from 0 to 16, (mean=7.1, SD=4.9). All of them possessed a driving license, and 30% of them had experience in a driving simulator. For objective evaluation, I measured the number of input errors, time taken to make an input, information carried by different input modes, and the use of each input modality based on situations and road segments. As for subjective evaluation, after completing each trial, I asked the participants to respond to the NASA-TLX which is a tool to assess subjective workload. I also gave them a questionnaire to evaluate subjective driving experience.

5.2 Experimental results

In this section I present the quantitative and qualitative results obtained from driving simulator experiments.

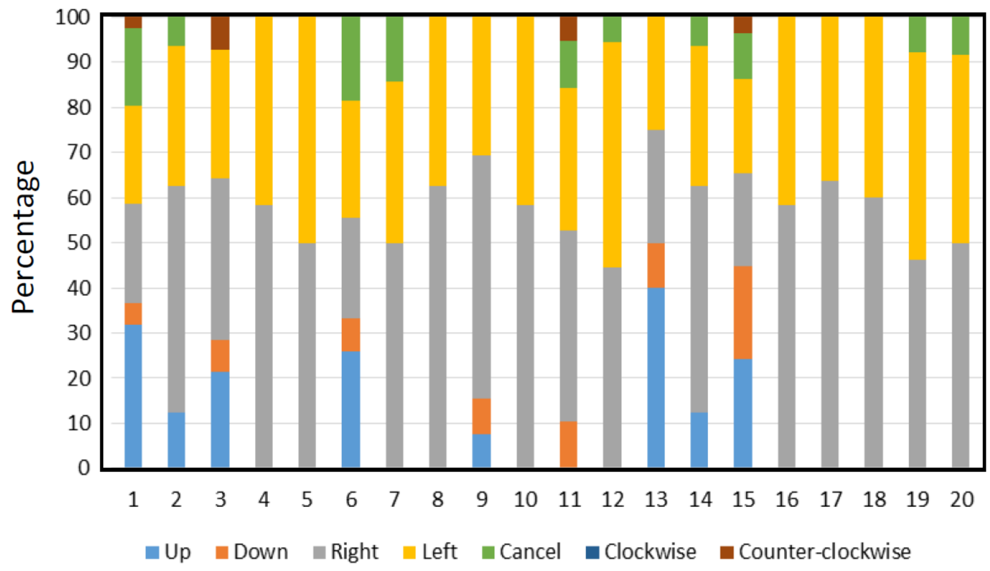


Figure 5.3 Usage of hand-gestures by each driver

5.2.1 Usage patterns and information

To determine the context of use of MMI system's component modalities, I analysed the input patterns of each driver (Fig. 5.7). I found that when using the MMI system, 90% of drivers have used 2 or more input modalities, and 45% of drivers have used all three modalities to input tactical level control commands. This indicates that if available, drivers tend to use different input modalities in different traffic conditions.

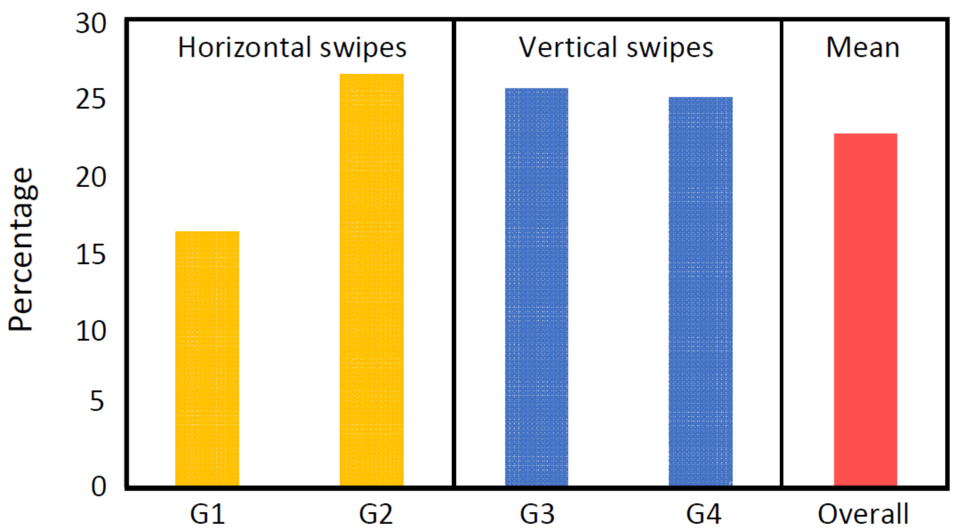


Figure 5.4 Average input error - gesture interface

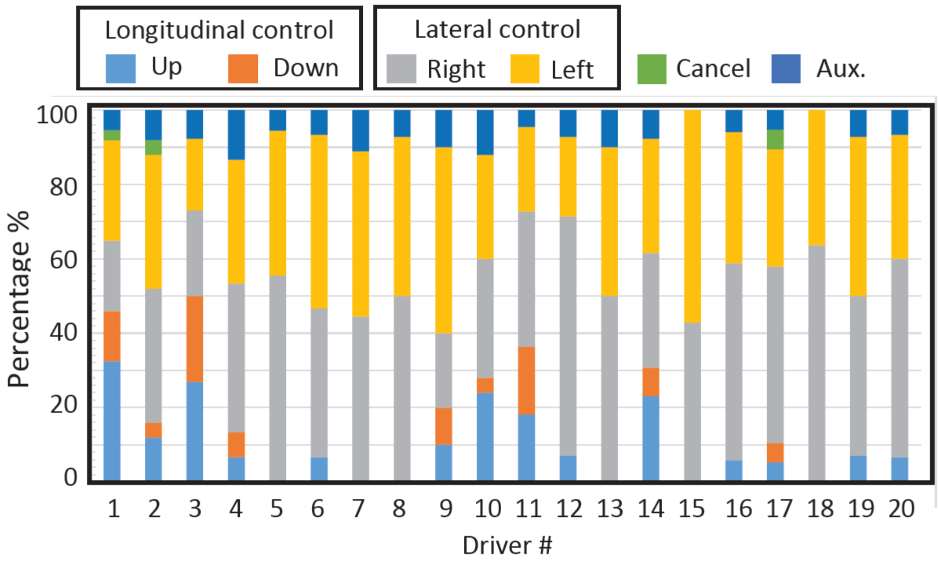


Figure 5.5 Usage of input patterns - haptic interface

In order to realize a relationship between different tactical-level control functions (i.e., lane changing, turning, and parking) and driver's choice of input modalities, I analyzed the input patterns further, as shown in Fig. 5.7. The use of touchscreen interface to input location-based commands (i.e., parking) is notable. Drivers used the touchscreen interface to input 77.5% of parking commands followed by gesture (12.5%) and haptic (10%) modalities (Fig. 5.7 (g)). Furthermore, 50% of merging commands were input using the touchscreen. On the other hand, for longitudinal control commands, the use of haptic modality is notable, as 86% of speed control commands were given through haptic inter-face, followed by gesture (12%) and touchscreen (2%) (Fig. 5.7 (f)). In addition, 60% of exit commands, 51% lane changing commands, and 50% of overtaking commands were given using haptic interface. For lateral control commands, again, haptic interface was the most used modality (48%), but I can see an increase of use in touch and gesture modalities to input lateral commands as opposed to longitudinal commands (Fig. 5.9). The use of touchscreen got remarkably increased to 33%, while hand gestures have also been used to input 18% of the lateral control commands.

5.2.2 Mean input times

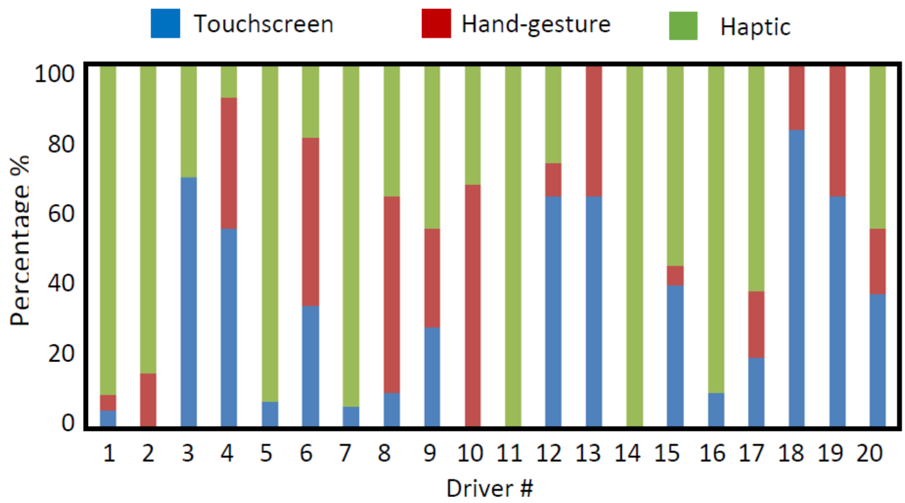


Figure 5.6 Input patterns

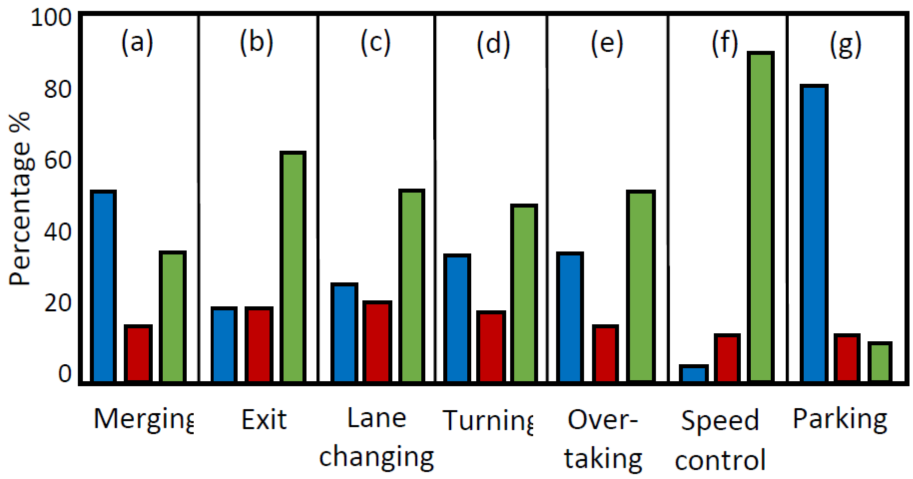


Figure 5.7 Choice of input modality

Since some tactical-level control commands can be time-critical, it is important to determine which modalities have faster input times. I considered the time period from when the driver starts moving his/her hand to make an input to the point of time the system accept that input, as the in-put time. I measured the input times of drivers in each trial, and Fig. 5.8 (b) shows the mean input time for each interface. The lowest average input time, 0.96 s (standard deviation (SD)=0.64) was observed when drivers used the hap-tic interface alone, and it was significantly lower than that of the hand-gesture interface (t-test: t (20)=2.03, $p<0.05$). However, when they used the MMI system, the average input time (mean (M)=1.23 s, SD=0.33) was lower than that of touchscreen (M=1.38 s, SD=0.49) and gesture (M=1.35 s, SD=0.72) alone.

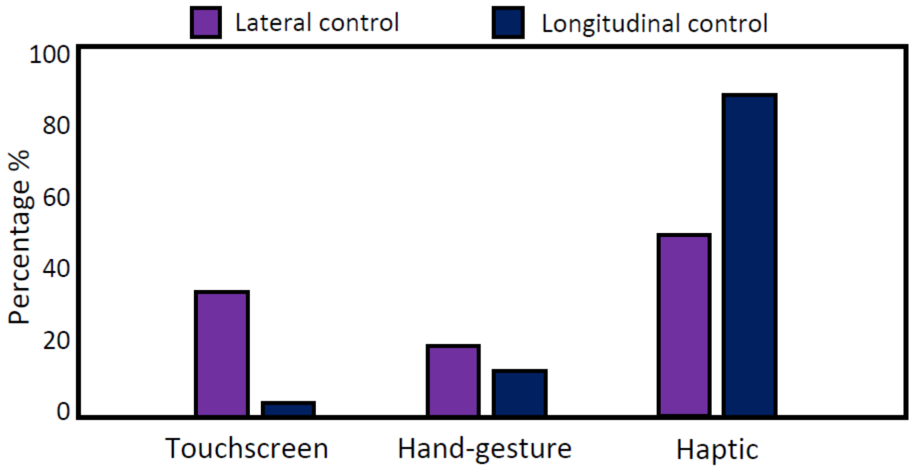


Figure 5.8 Lateral and longitudinal control

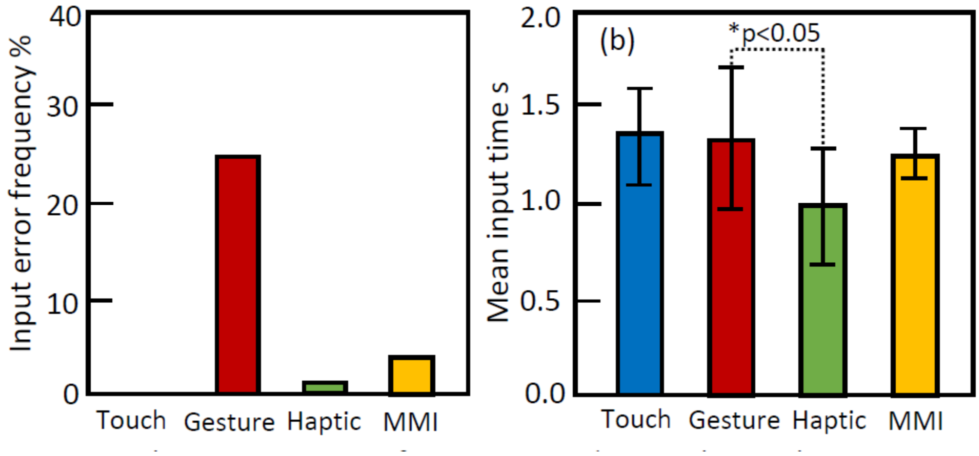


Figure 5.9 Input error and input time

5.2.3 Mean input error frequency

Error avoidance is an inherent characteristic of MMI systems. In each trial, an input error was recorded when a driver made an attempt, but failed to give an input that the system can recognize. When drivers used each unimodal interface alone, the hand-gesture interface recorded a high input error frequency of 24.8%, as opposed to haptic (0.8%) and touchscreen (0.0%) interfaces (Fig. 5.8 (a)). The error frequency was 4.4% for the MMI system. All the input errors occurred in MMI were associated with the hand gesture interface. This result indicates that MMI system has collectively mitigated the input errors of its component modalities.

5.2.4 Perceived workload

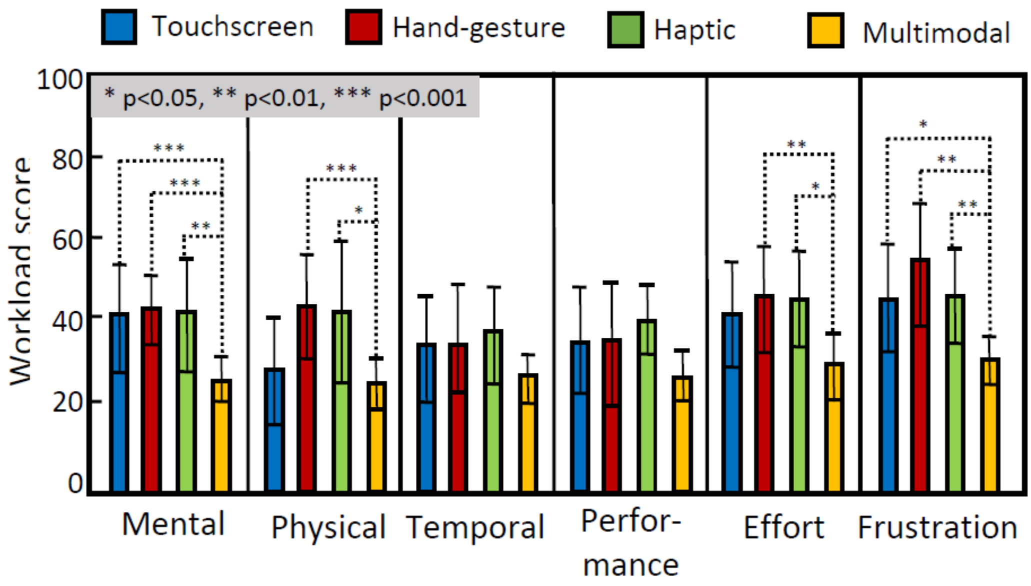


Figure 5.10 Perceived workload

To evaluate the effectiveness of the MMI system I analyzed the perceived driver workload under the categories of mental, physical, temporal, performance, effort, and frustration using NASA-TLX. The overall workload is significantly lower in MMI (mean=28.67, SD 8.9) compared to touch (t=2.89, p<0.01), gesture (t=4.71, p<0.001), and haptic (t=3.98, p<0.001). As shown in Fig. 10, mental workload and frustration are also significantly lower in MMI compared to each unimodal interface system (*mental*–touch: t=3.40, p<0.001, gesture: t=4.19, p<0.001, haptic: t=3.48, p<0.01. *frustration*–touch: t=2.09, p<0.05, gesture: t=4.26, p<0.001, haptic: t=2.79, p<0.01). In addition, physical workload and effort are significantly lower in MMI compared with gesture and haptic interfaces (Fig. 5.10).

5.3 Discussion

The evaluation of driver workload has a vital impact on the design of new HMI systems. Here, I have shown that perceived workload associated with the new MMI system is significantly lower than its component modalities (Fig. 10). Hence the MMI system is proved to be an effective inter-face that further minimizes the driver workload. Our MMI system has lower input times than two of its component modalities (Fig. 9 (b)). Even though the unimodal haptic interface has lower input time, there is a trade-off between efficiency and flexibility. The MMI system minimized the error rates associated with component modalities. Therefore, I have proved that MMI system has functional advantage over each unimodal system, in terms of efficiency and error avoidance.

Furthermore, our MMI system provides drivers the ability and flexibility to adapt to different driving tasks and traffic scenarios. Usage patterns analysis showed that drivers adaptively chose different modalities based on the input type (i.e., location-based, function-based, time-critical) as well as the context (i.e., driving environment, traffic conditions). I found that touchscreen interface is best suited for location-based inputs such as parking, as touchscreens are inherently suitable for discreet and pointing tasks. For speed controlling as well as time-critical inputs, the use of haptic interface is dominant. This is due to the direct physical feedback, lowest mean input time. However, for function-based commands that are not time-critical, all three modalities have been increasingly used (Figs. 7 (c)–(e)). This indicates the difference in preference for each modality among drivers.

5.4 Summary

In this chapter, I presented the evaluation of a multimodal human-machine interface for tactical level controlling of intelligent vehicles. I integrated three modalities: touchscreen, hand gesture, and haptic and created tactical level vehicle control input functions to conduct lateral and longitudinal control tasks. Twenty drivers participated in a simulator-based experiment for evaluation. The results highlighted the effectiveness of the multimodal interface in terms of perceived workload, efficiency, error avoidance, and situation adaptability.

6 CONTROL TRANSITIONS IN AUTOMATED VEHICLES

Even though automated vehicle technologies have made significant progress in the last decade, the current systems are still far away from achieving full autonomy. Such AD systems require the human driver to make control decisions, or take back control from time to time. This chapter presents the state-of-the-art of control transitions from AD to human driver. It describes planned and unplanned control transitions including the driving scenarios that require the human driver to intervene. It also highlights the safety and performance challenges associated with the lack of situational awareness of the disengaged driver. This chapter propose the use of collaborative control in takeover scenarios to overcome driver performance limitations and improve overall traffic safety.

6.1 Introduction

Figure 6.1 Examples of unscheduled takeover situations

Automated driving (AD) will make the future transportation safer, efficient, and more comfortable. SAE has defined 6 levels of automation. Level 0 is pure manual driving without lateral or longitudinal control automation. Whereas a vehicle operating in level 4 or 5 can drive itself from point A (start) to point B (destination) without any human intervention in between. Thus level 4 and 5 can be considered as full autonomy. On the other hand, level 1, 2, require human driver to monitor the environment and/or conduct the dynamic driving task, while level 3 require the human to intervene (takeover) in situations given a prior request, usually before 10 seconds. Consequently,

Figure 6.2 Road worker using hand-gestures

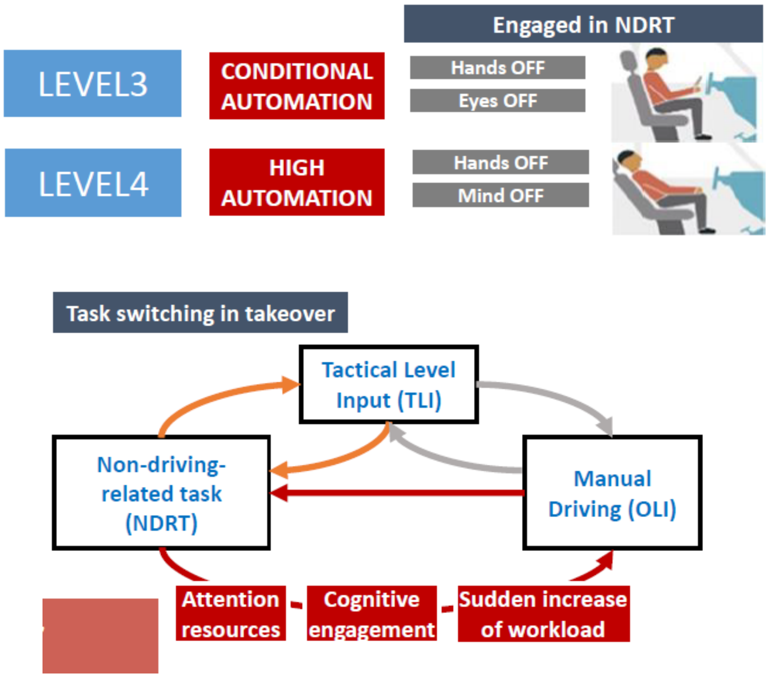


Figure 6.3 Task switching in takeover

levels 1, 2 and 3 can be considered as human-centered autonomy. I thus considered research questions of driver-vehicle interaction in human-centered automated vehicles from a human-robot interaction perspective.

Level 3 systems allow the driver to engage in non-driving related tasks (NDRTs) while AD is engaged (no need to monitor), but he/she is still responsible to takeover in case of a system limitation. Takeover scenarios can be divided into two; scheduled, and unscheduled, based on the predictability of such situation. Scenarios that require driver intervention (takeover) due to the AD system knows in advance, thus have high predictability. On the other hand, system limitations detected by onboard sensors have low predictability [31]. Figure 6.1 and 6.2 shows some examples of unscheduled takeover scenarios. When level 3 vehicles travel in urban environments unscheduled roadwork situations with manual traffic control will pose a major challenge for them (fig. 6.1 (a), (b)). In such situations drivers have limited time period (usually 10 seconds) to intervene. Unscheduled takeovers involve task-switching from NDRT to manual driving (fig. 6.3). Drivers engaged in NDRTs are often distracted and may have low or zero situation awareness. It requires considerable time to physically and cognitively engage in the driving task, and requires driver attentional resources. This could result in sudden increase of workload to meet demands of driving scenario, and

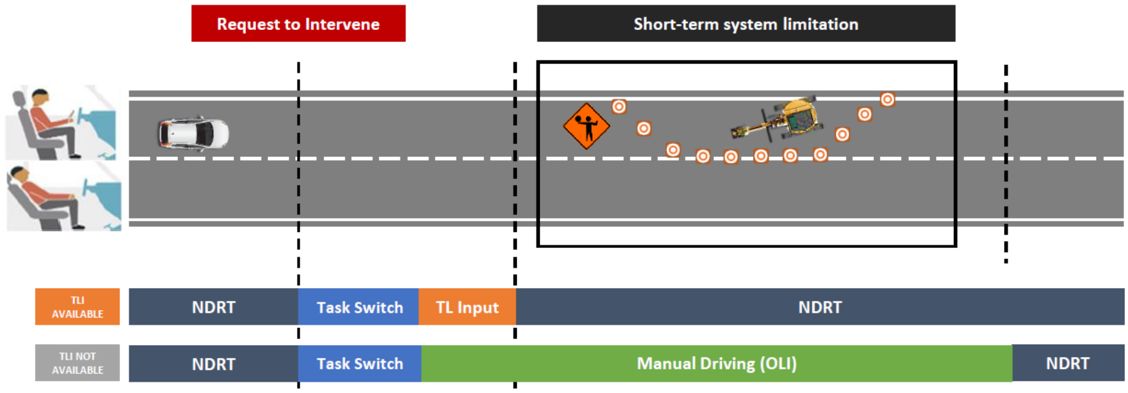


Figure 6.4 Experiment scenario

may decrease the quality of driver input. Thus, manual takeover in Level 3 involves a considerable risk.

6.1.1 Unscheduled takeover

Unscheduled takeover scenarios in urban areas can often result from unplanned roadworks. They may involve secondary lane markings, signs, and especially, persons using hand gestures and signs to control traffic. Although AD system can detect obstacles, traffic signals, and recognize some hand gestures, it requires the human judgment to select one from a set of candidate trajectories, or to decide when to proceed forward when the system confidence level is low [73]. When a level 3 vehicle encounter such scenario, drivers can use tactical level control rather than using operational level control, as the AD system is capable of controlling the lateral and longitudinal motions. In this study, I show that tactical level input will enable safe, seamless and effective vehicle control and result in lower driver workload in unscheduled takeovers. I conducted driving experiments comparing takeovers in manual and TLI.

In a previous chapter, I proposed and evaluated a tactical-level input (TLI) method to control lateral and longitudinal motions of automated vehicles (level 4 and 5). I further developed a multimodal HMI system for TLI.

In order to use TLI in certain takeover situations effectively, the AD HMI should fulfill the information needs of the driver to increase the situation awareness. The status of the AD system (e.g. availability of TLI, takeover request, etc.), information about the AD car’s environment are important for the driver to make a control input/decision. Looking from a human-robot interaction (HRI) perspective, [37] provides a set of guidelines to improve situation awareness in human-robot systems. In designing the HMI and HRI in our study, thus, I adopted the following guidelines; providing a map to show robot’s

Figure 6.5 HMI system for automated driving

path, providing fused sensor information to lower the cognitive workload, and providing spatial information to make operator aware of robot's immediate surroundings.

The aim of this section is to evaluate tactical level input for unscheduled takeover situations in an urban environment. I utilize the HMI and control framework introduced in chapter 4 for TLI and integrated a new HMI consisting audio and ambient light interfaces (fig. 6.5) for conveying AD system intentions in control transitions for this study. I will present and discuss driver reaction times, physiological responses, and subjective workloads in manual and TLI takeovers.

6.2 Tactical Level Input for takeover

Four types of transition of control categories can be identified in human-centred automated vehicles: driver-initiated driver control (DIDC), driver-initiated automation control (DIAC), automation-initiated driver control (AIDC), and automation-initiated automation control (AIAC) [29]. AIDC type of transfer can occur due to automation limitation, and requires the human driver to takeover lateral and/or longitudinal control either fully or partially, within a set transition time period. From an information processing perspective, the takeover process from AD to manual driving can be assumed to contain the following four phases: attention shift from a non-driving related task to the driving scenery, interpretation of the current driving situation, choice of action based on the existing situation awareness, and control actions carried out by the driver. Previous research in has shown that increasing degree of automation generally reduce situation awareness and mental workload [35], [74], [75]. Moreover, it has been found that with decrease of time to takeover the gazes in mirrors and shoulder checks decrease [76]. The lack of driver situation awareness in the takeover process thus creates safety issues.

Driving tasks can be categorized into three levels of driver control; strategical, tactical, and operational [36]. In strategical level, the driver determines the long-term planning such as the destination, route, travel time, driving mode. In tactical level driver can input medium-term control commands such as overtaking, lane-changing, speed controlling, merging, turning, and parking. In operational level (manual driving), driver controls the steering angle and speed in real-time. In certain takeover situations arising from short-term system limitations, drivers may input tactical level commands rather than reverting to manual driving. Such TLI commands may include 'go', 'overtake', 'turn', 'lane-change', and others. Using TLI for short-term takeovers will thus reduce/eliminate the traffic safety risks compared to manual takeover.

6.3 Automated Driving HMI

This section describes the design characteristics/aspects of the HMI and multimodal feedback system. Essentially, the autonomous driving system needs to be capable of informing the human driver regarding current system status. Such information may include; current driving mode, availability/unavailability of automated driving, takeover requests, and system failure. I integrated a visual and audio HMIs to convey these information in our driving simulator.

6.3.1 Visual HMI

Figure 6.6 Experimental conditions

The LED HMI consists of 120 RGB LEDs controlled by an Arduino microcontroller (Fig. 6.5). I created a set of icons to indicate different system statuses as part of visual HMI. When an AD capable vehicle, currently driven by human driver enters a geographical area where AD is available, the LED will be illuminated in a pulsing pattern in blue for 3 seconds. In the same time a corresponding icon (Fig. 6.5 (a)) will appear on touchscreen and stay on. If the driver turns on AD, the LED will illuminate in light blue (with reduced brightness) and stay on. The corresponding icon (Fig. 6.5 (b)) will appear and stay on. In a takeover situation, where tactical-level input is available, LEDs will start blinking in orange at 2 Hz. If only manual takeover is available, LED will blink in red in 3 Hz. With the difference in blinking frequency, drivers having color vision deficiency will also be able to distinguish the two notifications. Along with the LEDs, the corresponding icons (Fig. ## (c), (d)) will appear and blink on the touchscreen interface until driver makes a control input. When in manual driving, the LEDs will turn off, but the corresponding icon will be shown on the touchscreen.

6.3.2 Audio HMI

Since drivers can engage in NDRTs while in AD mode, audio interfaces play an important role in notifying the drivers whose visual attention is away from the road and visual HMIs. The audio HMI in our simulator consists of three speakers (Fig. ##) mounted in front of the driver. It provides notification in takeover requests by playing distinctive beep sounds for takeover when TLI is available, and manual takeover is available.

6.3.3 Steering-wheel HMI

I designated two push-buttons on the steering wheel to change the automation level. The AD button engages automated driving when available, and by pressing the MD button drivers can engage manual driving.

6.4 Experimental Design

This section describes the simulated short-term system limitation scenario, data acquisition, participants, and experimental procedure.

6.4.1 Takeover scenario

The takeover scenario implemented in the simulator is a roadwork situation in urban environment. Part of the lane is obstructed as shown on Fig. 6.4 and 6.6, and vehicles travelling on that lane require to move to the next lane (with traffic in opposite direction), and move back to the original lane after passing the work zone.

6.4.2 Data acquisition

Vehicle telemetry data and HMI control data provide insight to driver behavior. We recorded vehicle telemetry including position, speed, lane position, steering angle, pedal position, and multimodal HMI input data from the simulator at 100 Hz. The human autonomic nervous system responses physiologically to mental stress by accelerating heart rate, and increasing electrodermal activity among others [77]. We obtained driver skin conductance at 4 Hz and mean heart rate at 1 Hz using E4 wristband.

6.4.3 Questionnaires

Figure 6.7 Driving simulator setup

I used NASA task load index to evaluate subjective workloads for each trial. After completing the experiment, participants responded to a questionnaire to evaluate the driving experience focusing on takeover situation.

6.4.4 Participants

Eleven participants (6 males and 5 females, age *M*: 28.6 years, *SD*: 4.2) took part in this study. They had 0 to 16 years of driving experience (*M*: 5.3, *SD*: 5.5), and 6 (54.5%) of them had previous experience in a driving simulator. All had normal or corrected-to-normal vision.

6.4.5 Procedure

After receiving informed consent, we explained the participants about the takeover process, and how to takeover using manual driving and using TLI. Participants practiced driving in the simulator until they were confident. The experiment consisted of three trials: manual driving from start to end (with no automation), takeover using TLI, and takeover using manual driving. The two trials involving takeover starts in AD mode, and drivers engage in NDRT. We used a 2-back cognitive task implemented in an Android tablet as the NDRT (Fig. 2), and participants engaged in the task until they receive a request to intervene. After the short-term takeover, we instructed them to switch back to AD and to revert to the NDRT. The trials were presented to participants in a pseudo random order, and the location of work zone was randomly set in each trial. After each trial they responded to task load questionnaire, and after completing all three trials, they responded to the driving experience questionnaire. Participants were compensated for their contribution.

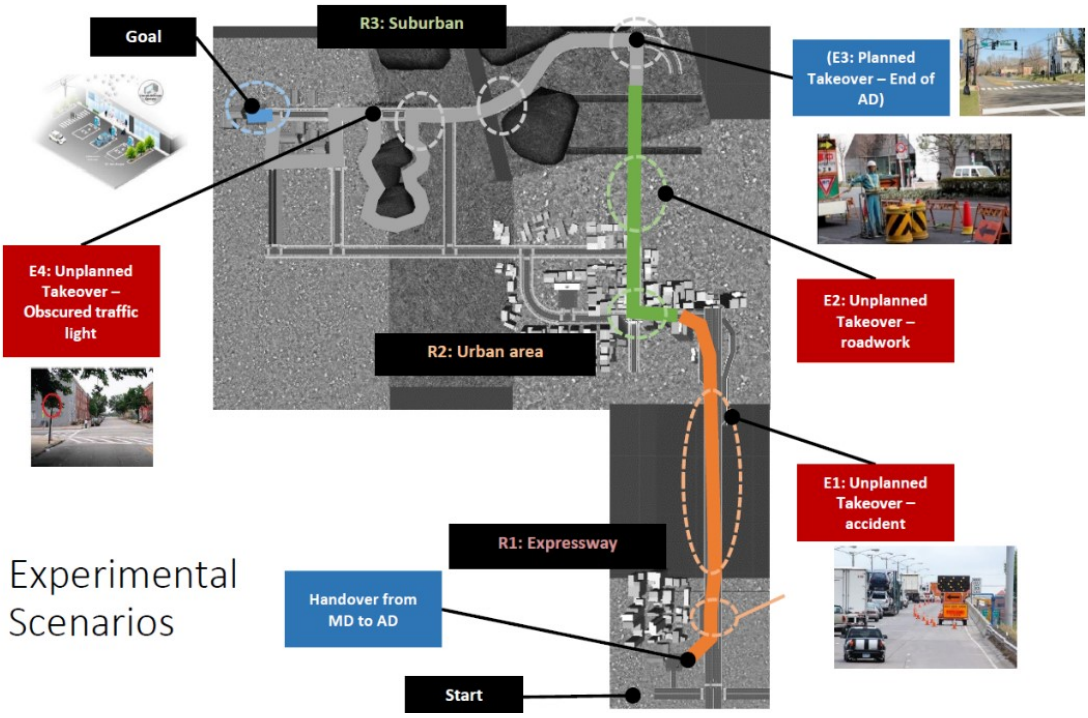


Figure 6.8 Experimental scenarios

6.5 Results and analysis

In this section I present the results of the driving experiment conducted to evaluate TLI for short-term takeover scenarios. Driver workload, response times, HMI operation data, vehicle telemetry data, and driver physiological data are presented and analysed.

6.5.1 Driver reaction time

I defined the driver reaction time for manual takeover as the time between RTI and first steering control input (with a threshold of 5 degrees). For takeover using TLI, the reaction time is the time from RTI until driver input a TLI command using the multimodal HMI. Fig. 5 (a) and (b) show the individual reaction times and mean reaction time, respectively. Driver reaction time in TLI (M = 4.27, SD = 1.19) was significantly lower ($p<0.05$) than in manual takeover (M = 6.27, SD = 1.90). Thus, it shows that TLI enables efficient interaction.

6.5.2 Physiological response

Note that we had to omit the data from participants 2, 3, and 10 from the analysis due to a technical issue.

6.5.2.1 Electrodermal activity

We recorded skin conductance as a measure of driver electrodermal activity. Fig. 6 shows the maximum values of skin conductance for all drivers in both TLI and manual takeover. Higher skin conductance corresponds to higher cognitive load. The average of the maximum skin conductance values in TLI (*M* = 0.5215, *SD* = 0.139) was lower than in manual takeover (*M* = 0.7082, *SD* = 0.3433). Fig. 8 shows the skin conductance variation of participant no. 7.

6.5.2.2 Heart rate

Fig. 7 shows the maximum heart rate values for all drivers. It can be seen that TLI contributes to lower the maximum heart rate in some drivers. Heart rate is an indication of high workload (cognitive, physical), and our results indicate that TLI impose lower workload on some drivers. However, the average of the maximum heart rate values in TLI (*M* = 79.78, *SD* = 7.919) was similar to that in manual takeover (*M* = 79.26, *SD* = 8.81).

6.5.3 Driver workload

Drivers responded to NASA task load index after completing each trial. Fig. 9 shows the average task load scores for each category: mental, physical, temporal, performance, effort, and frustration. TLI resulted in lower subjective workload than manual takeover in all the categories. Moreover, scores corresponding to *physical* and *effort* were significantly lower ($p<0.05$) in TLI (*Physical*: *M* = 17.72, *SD* = 19.79; *Effort: M* = 28.63, *SD* = 21.45) compared to manual takeover (*Physical*: *M* = 42.72, *SD* = 29.01; *Effort: M* = 58.63, *SD* = 24.80). This result indicates that by adopting a tactical-level input method, driver perceived workload attributed to control transitions can be reduced significantly.

6.5.4 Driving experience questionnaire

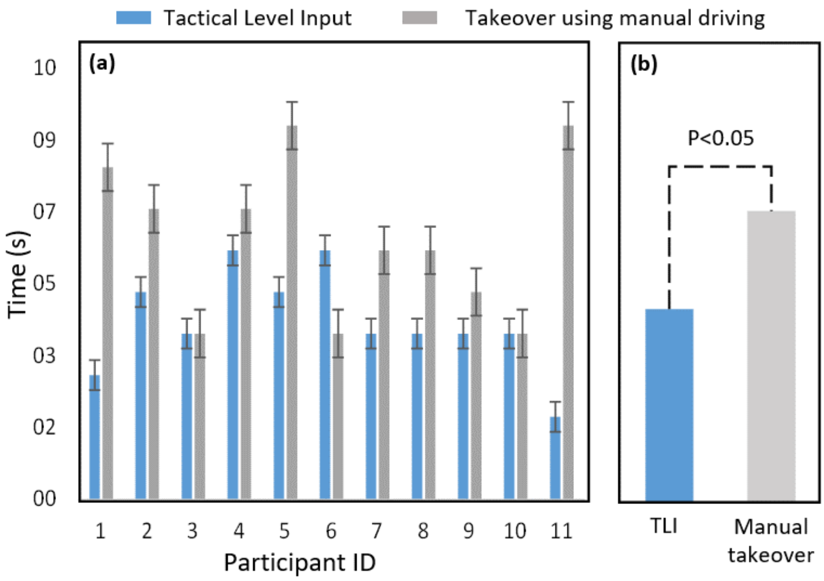


Figure 6.9 Driver reaction times

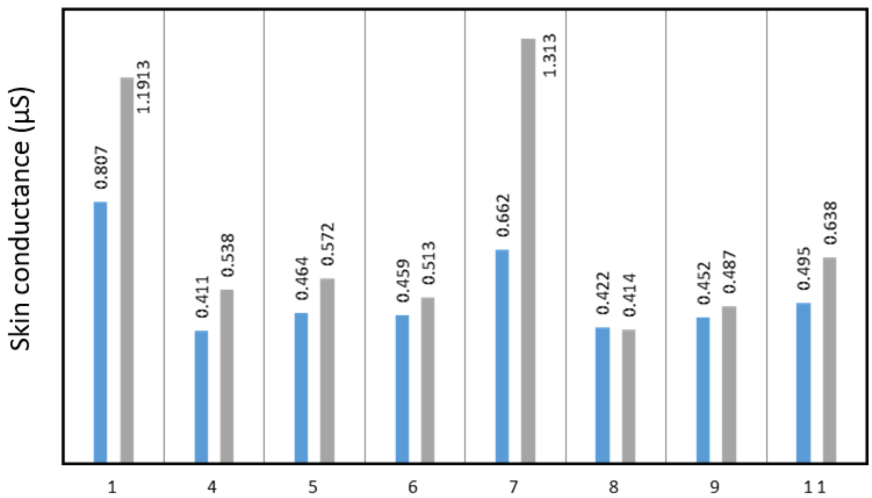


Figure 6.10 Maximum skin conductance

We asked the drivers if TLI is available, would they prefer to use TLI or manual driving to intervene in a short-term takeover situation. 90.9% of the drivers mentioned they would use TLI if available. Among the reasons were: TLI require less physical engagement and cognitive attention, convenient, efficient input method, and less effort needed. The reasons provided by drivers are also reflected in their subjective workload scores.

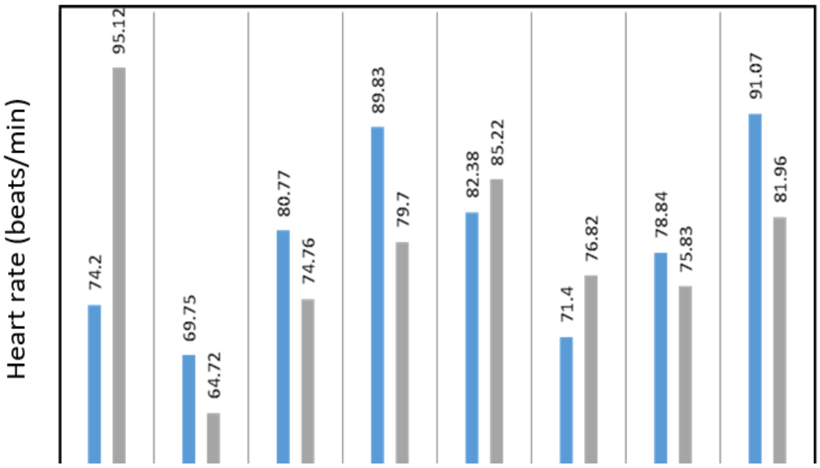


Figure 6.11 Maximum heart rate

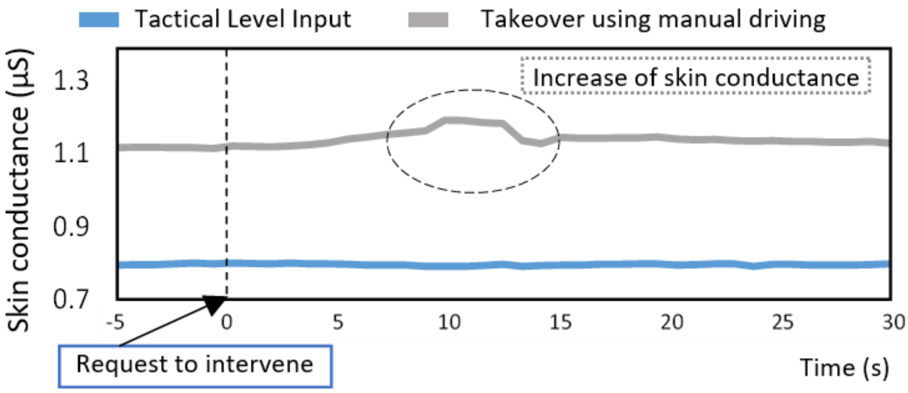


Figure 6.12 Skin conductance (Subject #7)

6.6 Discussion

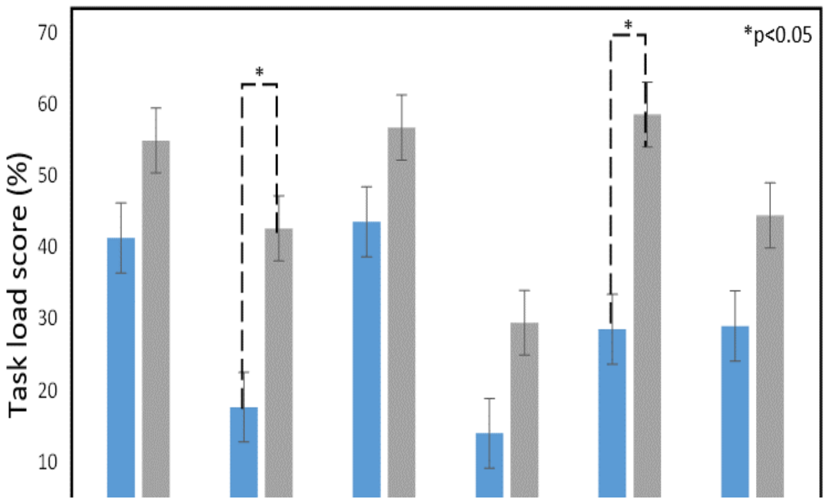


Figure 6.13 Subjective task load score

In order to investigate the safety issues in manual takeover, we analyzed driver performance data. For comparison we used data from the trial of manual driving with no automation as baseline. Steering angle and speed variation provide information on smoothness of lateral and longitudinal vehicle control. Smoothness of vehicle control has found to be related with driver workload, and smoothness decreases when drivers tend to interject more error corrective maneuvers, as illustrated in Fig. 10. Steering angle and speed variation for subject 1 in both manual driving and takeover using

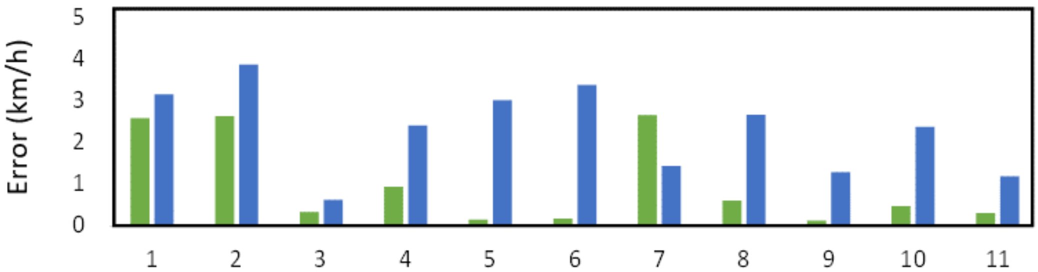


Figure 6.14 Maximum absolute error - speed

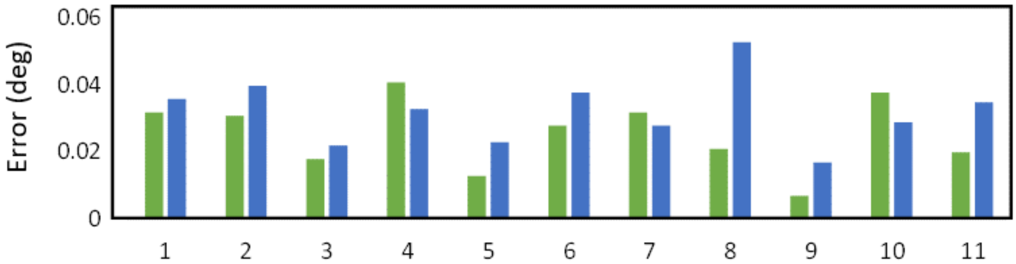


Figure 6.15 Maximum absolute error - steering angle

manual driving are shown in Figs. 11 and 12. It can be seen in takeover situation using manual driving, lateral and longitudinal controlling is less smooth. By adopting the method of steering entropy presented in [78], we calculated the predicted steering angle, and speed by performing a second-order Taylor expansion. The predicted value is expected to obtain if the controlling is executed in a very smooth manner. We then calculated the prediction error as the difference between the predicted value and real value. Fig. 13 and 14 show the maximum absolute prediction error of steering angle and speed in both manual driving and takeover using manual driving. The average

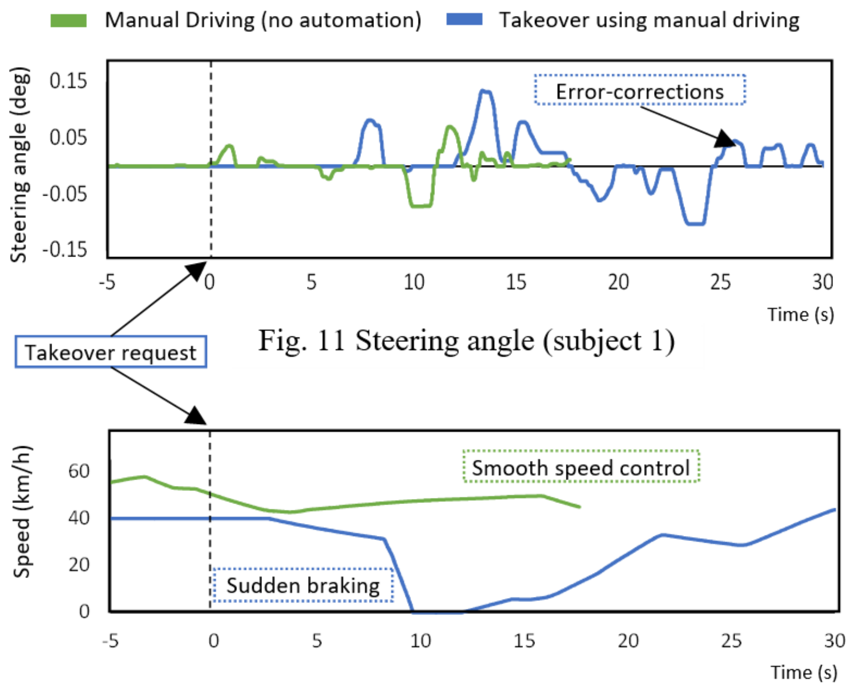


Figure 6.16 Steering angle and speed variation (Subject #1)

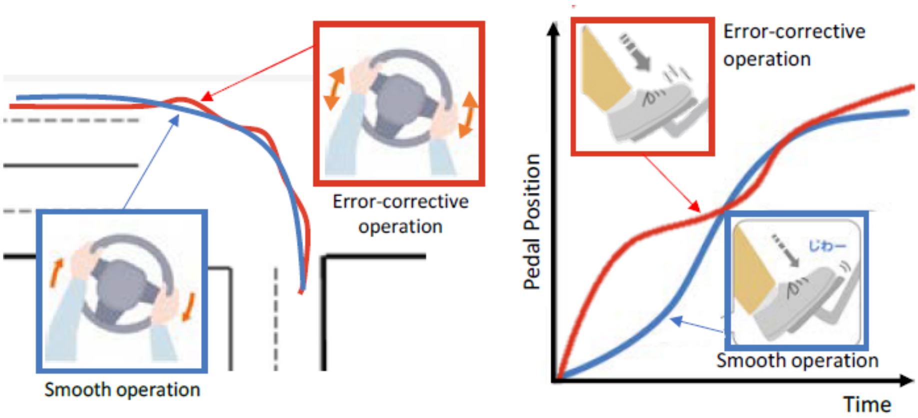


Figure 6.17 Performance measures: steering angle and pedal position

prediction error for speed was significantly higher ($p<0.05$) when in takeover using manual driving (M = 2.324, SD = 1.04), compared to no automation (M = 1.00, SD = 1.07), as shown in Fig. 15 (b). Fig. 16 shows that steering entropy increase in manual takeover. This indicates sudden increment of driver workload due to manual takeover.

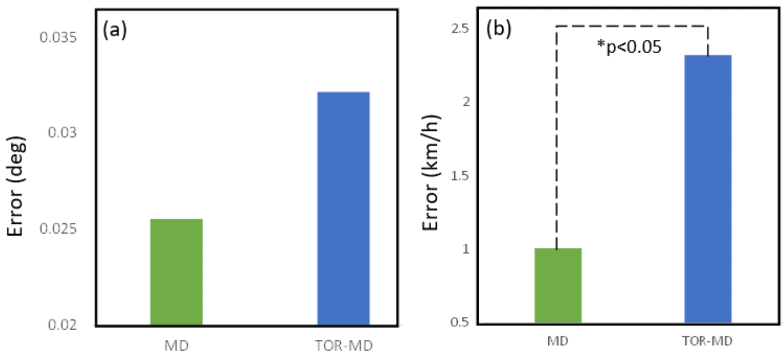


Figure 6.18 Average prediction error

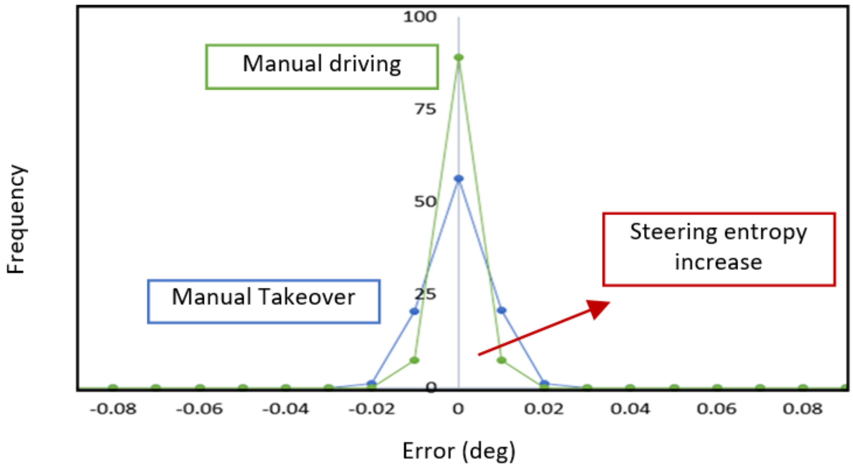


Figure 6.19 Steering entropy

6.7 Summary

Takeover using manual driving creates safety issues due to lack of situation awareness and sudden increase of workload of human drivers. As a solution, in this study we investigated application of tactical level input (TLI) as a driver intervention method in automated vehicles. We designed a short term system limitation scenario in a simulated urban environment and conducted driving experiments using 11 participants. Results show that driver reaction time and perceived workloads were significantly lower when using TLI. Drivers preferred the TLI method over manual takeover due to its efficiency of interaction, less effort needed, and convenience. On the other hand, erroneous driver behavior was observed in manual takeover. Driver performance significantly decreases in unscheduled takeover situations where drivers are distracted due to non-driving related tasks. Future works include integrating driver monitoring to quantify driver situation awareness for effective and safe control transition.

7 CONCLUSION AND FUTURE WORKS

Automated driving (AD) will make the future transportation safer, efficient, and more comfortable. Intelligent vehicles that can operate in different levels of driving automation are being increasingly developed and tested in many countries including Japan. The advent of such vehicles, however, is changing the driver-vehicle relationship that has been the norm throughout the last 100 years. The Society of Automotive Engineers (SAE) has documented six levels of driving automation distinctively defining the boundaries of automation, where level 0 means no automation and level 5 being fully autonomous in all situations. A vehicle capable of full autonomy with no human intervention (lv. 5) is still far away. In the intermediate levels, the automated driving (AD) system will be able to conduct the dynamic driving task (DDT) in its operational design domains (ODD) and will occasionally require the driver to take part in the dynamic driving task when it reaches system boundaries or limitations. Thus, the intermediate levels which essentially require a human-machine collaboration can be considered as human-centered autonomy levels. I contend that a collaborative, human-in-the-loop approach will maximize the utility of automated driving. However, such kind of novel and complex human-machine interaction is creating new research questions and it highlights the need to expand boundaries of human-robot interaction research into the mobility domain.

Increasing driving automation will transform the role of human from an active driver into a passive passenger. Recent prototypes of automated vehicles often have no driver controllers such as steering wheel or pedals. Previous studies have shown that removing drivers from the control loop will result in drawbacks, for instance, lack of driving pleasure and reduced flexibility in controlling. Driving pleasure and flexibility are inherently characteristics of manual driving, thus, losing them would be a downside in conventional AD systems. It would, in turn, affect the acceptance of automated vehicles. On the other hand, intermediate levels of automation require a vehicle control interface for the human driver/operator to take back control of the DDT either fully or partially at system boundaries. Such situations include scheduled takeovers i.e., driver taking back control at the end of AD system operational design domain, or unscheduled takeovers such as roadwork, manual traffic diversions, severe weather conditions, and system failure. Since in level 3 and 4, drivers do not need to constantly monitor the driving environment, taking back control within several seconds could be safety critical. Previous research has shown that being out of the control loop reduce operator situation awareness (SA) and result in decreased performance and reduced safety. To summarize, I identified two research questions with the intermediate levels of driving automation: (1) lack of driving pleasure and reduced flexibility in controlling in AD mode, and (2) decrement of driver performance and safety due to low SA in takeover situations.

As a solution to both the above research questions, I proposed a collaborative control method between human driver and AD system based on tactical level controlling of DDT. Driving tasks can be categorized under three levels of driver control; strategical, tactical, and operational. This hierarchy is adapted to differentiate the levels of driving automation for the present study. In strategical level (lv. 4, 5), the driver inputs long-term commands such as the destination and route, and the vehicle conducts entire DDT. In tactical level driver can input medium-term control commands such as overtaking, lane-changing, speed controlling, merging, turning, and parking. In this level, the vehicle conducts the DDT with in accordance with driver intention. In operational level (lv. 0, 1), driver controls the steering angle and speed in real-time. By adopting tactical level input (TLI) method for controlling in AD can provide the driver with flexibility and driving pleasure associated with manual driving, while ensuring safety and comfort of automated driving.

Since conventional human-machine interfaces (HMIs) such as steering wheel and pedals are not pragmatic to input tactical and strategical level control commands, it is important to investigate other types of HMIs such as visual, haptic, gestural, voice, augmented reality (AR), and even direct-neural interfaces. Multimodal interface (MMI) systems have the ability to process two or more combined user input modes, (i.e., touch, speech, gestures, and body movements) in a coordinated manner with multimedia output. Such systems entail many advantages such as improved recognition and understanding, faster and intuitive interaction, and ability to adapt to different environment and users. Since vehicles traverse through highly dynamic environments, and their user groups are diverse, use of a multimodal interface system for tactical-level controlling will bring remarkable merits to drivers by allowing them to accomplish vehicle control tasks using the modality most appropriate to the driving situation, or a modality they are comfortable with. There have been many studies in the automotive domain investigating user interfaces with multimodal feedback, but relatively smaller number of studies on multimodal input. Most of such studies focus on reducing driver distraction when performing secondary and tertiary tasks while engaged in manual driving. There is a lack of studies investigating the use of HMIs with multimodal input *and* feedback for tactical-level controlling of vehicles in AD mode. Therefore, I developed a prototype HMI with multimodal input and feedback to realize collaborative control using tactical level input in highly automated vehicles. Key objectives of the multimodal HMI for tactical level input are to (1) facilitate highly efficient interaction (shorter input time, lower input error), and to (2) reduce driver workload.

The multimodal interface system for collaborative control provides the medium for seamless interaction between the two agents (driver and AD system) at any time during a drive. From a technical point of view, collaborative control could overcome the system limitations in perception and motion planning by integrating human driver in the loop. Purpose of HMI: facilitate intent communication between driver and AD system in real-time, support shared situation awareness, enhance bi-lateral understanding of intents and actions between AD system and driver. The proposed multimodal HMI system consists of a touchscreen, haptic, and hand-gesture based interfaces. Each interface, coupled with the AD system facilitate context-adaptive interaction by providing dynamic visual, audio, force and tactile feedback to the driver. The touchscreen interface, developed using Unity, displays a high-definition map with fused sensor information on the top left, showing the position and orientation of ego-vehicle and other surrounding traffic in real-time. On top right, from top to bottom, displays an icon corresponding to current driving mode, a sign indicating the next tactical-level maneuver, and the current speed limit, respectively. Drivers can use the directional and speed control buttons on the lower half of the touchscreen to input tactical level commands. The haptic interface has two degrees of freedom, and drivers can input tactical level commands by moving the haptic device along lateral and longitudinal axes. It is capable of providing spatial information to the driver through tactile and force-feedback to improve situation awareness. Lastly, I adopted a hand-gesture interface to enable natural interaction using the Leap Motion sensor as the platform. This interface uses sound feedback and visual feedback to indicate acknowledgement or rejection of driver input, accordingly. The multimodal HMI system can adapt to different traffic situations by changing its feedback parameters.

In order to evaluate the proposed HMI system, I conducted driving experiments in a simulator with 20 participants. The driving route designed for this experiment is 2 km long and consists of a section of an expressway (R1), urban area (R2), sub-urban area (R3), and a parking lot (R4). Each of the traffic regions has unique traffic conditions and triggered-events to recreate the situations that drivers encounter in real-world. For experiment results, I obtained usage patterns, reaction times, gaze transitions, perceived workload and driver preference. The usage pattern analysis showed that drivers increasingly tend to use different input modalities for TLI. Further analysis showed that drivers used certain interface types for certain control inputs: i.e., haptic interface for longitudinal, and time-critical control commands, while touchscreen interface for location-based input commands such as parking. Moreover, multimodal interface minimized the overall input errors compared with unimodal components, and the driver perceived workload associated with multimodal interface was significantly lower. The results proved that multimodal interface has functional advantages and is an effective and efficient HMI for TLI in human-centered automated vehicles. In addition, results showed the need for tactical input method in automated vehicles, as 70% of drivers used the HMI to override automated driving during the experiments. TLI was preferred more in less traffic situations such as in expressway and in sub-urban area. Thus, the results substantiate the effectiveness of both tactical level input method and the multimodal interface system.

Reduced performance and decreased safety in takeover situations is another human-factor issue associated with automated vehicles. Unplanned takeover situations, in essential, will leave the human driver only few seconds to engage in the manual driving task both physically and cognitively. In such situations, the inadequate situational awareness and sudden increase of driver workload could lead to accidents. I conducted another experiment to evaluate tactical-level input method for short-term takeover situations using the multimodal HMI system. TLI commands applicable for short-term takeover situations include turning, overtaking, and lane-changing. TLI along with an HMI capable of multimodal feedback can provide situation-adaptive spatial information which enhance the driver situational awareness in a short time. To evaluate the proposed system, we conducted driving experiments involving unscheduled takeover situations in urban environment using eleven participants in the driving simulator. I analyzed driver reaction times, physiological responses including heart rate, skin conductance and subjective workload as well as qualitative feedback. The results show that 90% of drivers tend to choose TLI for takeover. Moreover, TLI resulted in significantly lower driver workload, significantly lower reaction times, and improved driver response compared with manual takeover.

In conclusion, I developed and evaluated a multimodal human-machine interface for tactical level controlling of human-centered automated vehicles by integrating three modalities: touchscreen, hand gesture, and haptic. As a key contribution, this study introduced tactical level input functions to control lateral and longitudinal motion of automated vehicles. Two experiments were conducted; (1) to evaluate the usability of HMI system and TLI method, (2) to evaluate the application of TLI in short-term takeover situations. The results highlighted the effectiveness of the multimodal interface in terms of perceived workload, efficiency, error avoidance, and situation adaptability. Further, TLI proved to be an effective input method for certain takeover situations in human-centered automated vehicles. For short-term system limitation scenarios, 90% of drivers preferred to use TLI for intervention, rather than using manual takeover.

The collaborative control method and HMI can be further applied for tactical-level teleoperation of driverless automated vehicles such as robot-taxis and delivery vehicles, especially when they come across system boundaries. Future works include integrating an intelligent driver monitoring system that will quantify driver situation awareness and dynamically adapt the HMI support and automated driving parameters to enhance seamless and safe interaction between humans and automated vehicles

APPENDICES

Appendix 1: Classification of Driver Workload Using Recurrent Neural Networks

Human sensing enables intelligent vehicles to provide driver-adaptive support by classifying perceived workload into multiple levels. Objective of this study is to classify driver workload associated with traffic complexity into five levels. We conducted driving experiments in systematically varied traffic complexity levels in a simulator. We recorded driver physiological signals including electrocardiography, electrodermal activity, and electroencephalography. In addition, we integrated driver performance and subjective workload measures. Deep learning based models outperform statistical machine learning methods when dealing with dynamic time-series data with variable sequence lengths. We show that our long short-term memory based recurrent neural network model can classify driver perceived-workload into five classes with an accuracy of 74.5%. Since perceived workload differ between individual drivers for the same traffic situation, our results further highlight the significance of including driver characteristics such as driving style and workload sensitivity to achieve higher classification accuracy.

Introduction

Driving is a dynamic and complicated activity that impose varying amounts of demand on the driver. It involves monitoring the traffic environment, controlling vehicle speed, steering angle, while, in sometimes, operating in-vehicle information systems (IVIS) or engaging in a conversation simultaneously. Driver workload can be identified as the impact on the individual driver resulting from engaging in the driving task in a specific context (i.e., subtask, traffic). Although fully automated vehicles operating in SAE level 5 [8] could eliminate human driver from the control loop, humans will still need to conduct driving tasks until full autonomy is realized. Highly automated intelligent vehicles (operating in levels 2, 3, and 4) with advanced driver monitoring systems that can detect and classify driver workload could provide workload-adaptive support to reduce/optimize driver workload. Such support may include engaging automated driving [79], adapting IVIS parameters, as well as communicating safety-critical information to the driver through human-machine interfaces (HMIs) [80]. Intelligent driver monitoring systems will thus make the roads safer, and driving more enjoyable.

With more and more people moving into urban areas, traffic complexity in cities and highways will tend to increase. Driver workload is found to be sensitive to

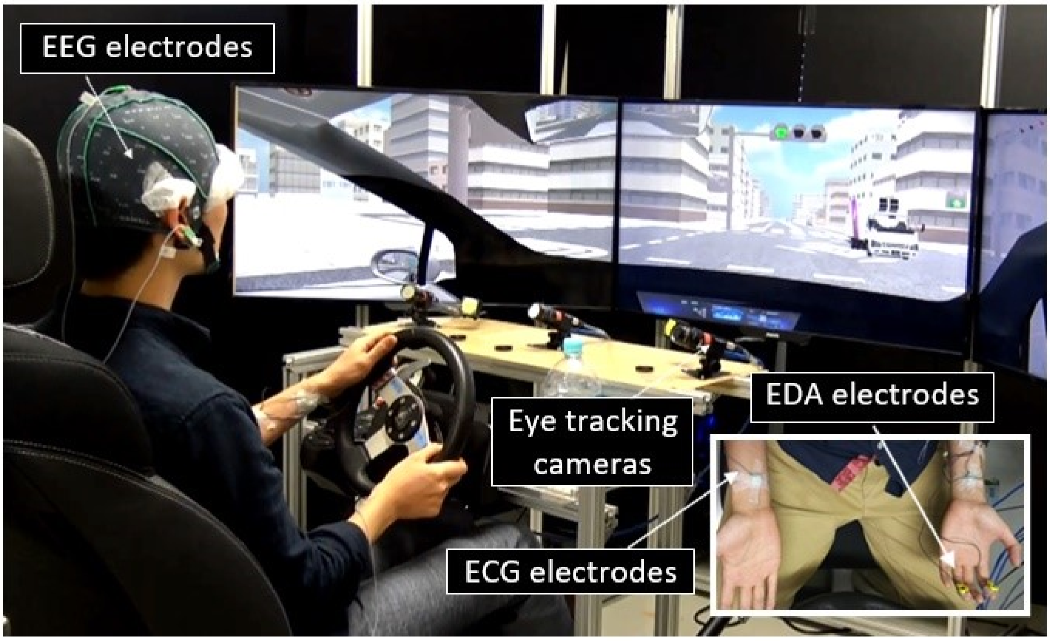


Figure 0.1 Experimental setup

traffic complexity. In [81], authors reported that subjective driver workload rating has a linear upward trend with increasing traffic flow. Traffic situation data from onboard database was used in [82] for estimating current driver workload. There are studies on detecting only segments of high workload/stress associated with driving [83]–[85]. However, the number of studies on detecting multiple levels of driver workload is limited. It is important to note that advanced driver assistance systems (ADAS) could adapt their functions according to the level of driver workload. Most of the existing work have focused on detecting driver workload or distraction associated with secondary tasks [86]–[88]. There is a lack of studies focusing on quantifying driver workload attributed to systematically varied traffic complexity levels.

Data collection in real world naturalistic driving, also known as passive data collection, may lead to many problems when creating a computational model [89]. Due to the simultaneous changes in multiple factors, the observed changes in a dependent variable may not be caused by, but still correlated with independent variables. This will result in interactions that are difficult to classify into individual effects. On the other hand, designed experiments can overcome these problems. In a designed experiment, the experimental environment and independent variables are actively manipulated to improve the quality of information and to eliminate redundant data. In addition, data collection is usually done with great care and attention. Driving simulators provide the safety, consistency, repeatability, and ease of a controlled environment. Therefore, in this study, we designed and conducted driving experiments in a simulator.

In order to determine the driver workload corresponding with different levels of traffic complexity, experimental scenarios need to be carefully designed to systematically vary the traffic complexity. In this study, we created a fundamental driving scenario in the simulator based on turning right at an intersection (left-hand traffic) with varying degrees of situational complexity. We recorded physiological, performance, and subjective measures to classify the driver workload in each situation. Nonparametric, nonlinear machine learning models use past data to learn stochastic dependency between past and the future of an observable variable. Artificial neural networks (ANNs) can outperform classical statistical methods, and can be successfully used for modeling and forecasting nonlinear time series data [90]. Conventional Recurrent Neural Networks (RNNs) fail to perform well with long-range time series data due to the vanishing and/or exploding gradient problems. The method we used is Long Short Term Memory (LSTM) based RNN that can overcome above problems [91]. We evaluated the models based on classification accuracy.

Related works

A. Physiological measures and workload

The human autonomic nervous (ANS) works with the central nervous system to maintain homeostatic conditions and regulates body functions. ANS consists of two divisions that provide physiological responses to stress, fear, relaxation, panic etc. They are: *sympathetic* division which responds to mental stress or physical danger, and the *parasympathetic* system that allows the body to function in a 'rest and digest' state. The ANS responses physiologically to mental stress by accelerating heart rate, dilating pupils, and increasing eccrine sweat gland activity among others [77]. Therefore, by measuring the changes in such physiological indicators, it is possible to quantify driver workload.

Table 0.1 Workload Levels

Level	Description
5 (max)	Workload extremely high: At or beyond the driver's capacity for safe control of the vehicle. No capacity for any additional tasks
4	Workload high: little spare capacity. Level of effort allows little capacity for additional task without compromising the driving task
3	Workload moderate: enough spare capacity for some tasks that have been optimized for the driving situation. Unlimited additional tasks cannot be accommodated.
2	Workload low: sufficient spare capacity for attentional tasks that do not demand continual concentration
1 (min)	Workload insignificant: zero or almost zero driving workload with enough spare capacity for all desirable additional tasks

1) Cardiovascular measures: Heart rate metrics are frequently used in evaluating operator workload in human-machine systems as they reflect the activities of ANS. Sensitivity of heart rate and heart rate variability (HRV) measures were examined in [92] to distinguish single task driving from periods of secondary workload. It has been found that stress measurements provided by low frequency (LF: 0.04–0.15 Hz) range of HRV correlate well with the mental workload component of NASA-TLX subjective workload assessment tool [93].

2) Electro-Dermal activity (EDA): EDA is also a commonly used indicator for measuring ANS activity. EDA measures include skin conductance level (SCL) and skin conductance response (SCR). Their sensitivity to mental workload in driving has been studied in [83], [94], [95].

3) Pupil size and gaze information: Pupil diameter is used in driving studies as a reliable and sensible indicator of cognitive activity. It is found to have a positive correlation with mental workload. In addition to pupil size, horizontal eye movement is also considered as a good indicator of visual and mental workload [96].

B. Performance measures

Table 0.2 Experimental conditions

		Pedestrian density (ped./hour)		
		120	240	360
Oncoming traffic flow (vehicles/hour)	120	A	B	C
	360	D	E	F
	720	G	H	I

Driving performance measures such as steering angle, pedal position, and lane position can provide means to quantify driver workload. Smoothness of steering control is found to have a direct link with perceived driver workload. In the steering entropy method described in [78], the authors showed that steering predictability decreases as drivers make more error-corrective maneuvers, and the frequency and magnitude of the steering corrections increase with the task difficulty. Figure 2 illustrates smooth operation and error-corrective operation of steering angle and pedal position.

C. Subjective measures

A range of subjective assessment tools are available to evaluate perceived workloads in human-machine systems. The NASA task load index (TLX) is a widely used assessment tool consisting of six subscales: mental demand, physical demand, temporal demand, overall performance, frustration level, and effort. Another driver workload assessment tool used in the IVIS domain consists of five workload levels: workload insignificant, workload low, workload moderate, workload high, workload extremely high, as listed in Table 1. Subjects with similar personal characteristics are found to respond similarly to tasks with same demand. The Driving Style Questionnaire (DSQ) and Workload Sensitivity Questionnaire (WSQ) described in [97] have been used in studies to quantify driver personal characteristics.

Methodology

1. *Driving simulator*

In this study, we used a fixed-base driving simulator, as shown in Fig. 1, described in detail in [49]. Data that reflect the driving behavior and performance were recorded at a sampling rate of 100 Hz. Driver input data consist of steering angle, accelerator and brake pedal position, and turn signals state, while vehicle telemetry data comprise velocity, position and orientation in three-dimensions. Data from vehicle

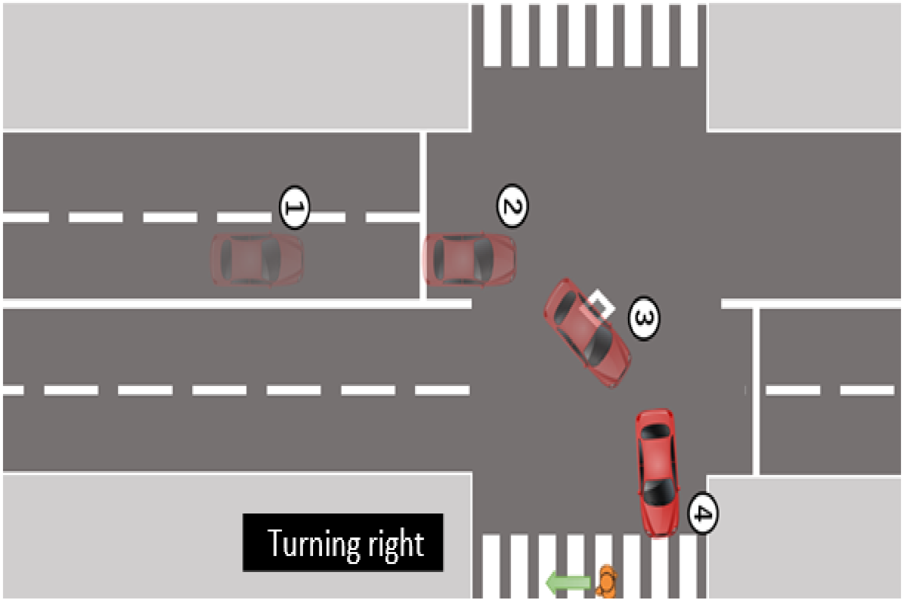


Figure 0.2 Driving scenario (left-hand traffic)

sensors include headway, surrounding obstacle count, types and distances, and lane position.

2. Sensing equipment

We used physiological signal amplifier system PolymateV AP5148 to acquire EEG, ECG and EDA signals. It supports sampling rates up to 8 kHz. In order to acquire gaze information, we used Smart Eye Pro gaze tracking system with a 3-camera configuration. It uses pupil and iris reflection with a head model for eye tracking, and has maximum accuracy of 0.5 degrees. Sampling rate is 60 Hz and pupil diameter, eye opening, and gaze position were logged among other parameters.

2. Data acquisition and feature extraction

In this section, we describe the acquisition and processing of physiological signals. We obtained electrocardiogram (ECG), Electro-Dermal Activity (EDA), electroencephalography (EEG), and gaze behavior as driver physiological data. These signals often contain artefacts and anomalies, and therefore, need to be pre-processed. We employ below signal processing methods to increase the overall signal-to-noise ratio with minimal signal degradation.

1) ECG signal: We use a low-pass Butterworth filter with cutoff frequency of 30Hz for ECG signal. We then calculate frequency-domain and time-domain metrics from the filtered signal. To obtain low frequency (LF: 0.04–0.15 Hz) power and high frequency (HF: 0.15–0.40 Hz) power, we use fast Fourier transform (FFT), and then calculate the LF/HF ratio. To obtain the RR interval from the ECG signal, we use a peak detection algorithm and then measure the distance between prominent (R) peaks.

2) EDA signal: For EDA signal, we again use a Butterworth bandpass filter with lower cutoff frequency of 0.5 Hz and higher cutoff frequency of 30 Hz. Then we use an algorithm to detect and replace outliers in the filtered data using linear interpolation.

3) EEG signal: We use a Butterworth bandpass filter with low cutoff frequency of 0 Hz and higher cutoff frequency of 40 Hz for the EEG signal. We then use FFT to obtain the power spectrums corresponding to alpha (8–14 Hz), beta (14–38 Hz), theta (4–8 Hz) and delta (0.5–4 Hz).

We acquire pupil diameter (in mm), eye-opening (0–1), and gaze position (x, y) from the Smart Eye system. The data is already filtered by the system, therefore, did not require preprocessing.

3. LSTM based recurrent neural network

Recurrent neural networks have recurrent connections between units that allow to exhibit dynamic temporal behavior, and to retain contextual information. However, in practice, conventional RNNs often fail to handle long-term dependencies due to vanishing gradient or exploding gradient problems. LSTM based RNNs can overcome these problems with their capability to retain long-term context. A common LSTM unit, also known as a gated memory cell, consists of an input gate, output gate, and a forget gate. The input gate controls the flow of new values into the cell while forget gate controls the extent to which a value remains in the cell. Finally the output gate determines the extent to which the value in the cell is used in the output of the LSTM cell. In this study we used a deep stacked unidirectional LSTM neural network architectures that specifically use contextual information of the past data. For all architectures we used one dropout layer after the input layer and one fully connected layer before the output layer.

Experimental Design

4. Driving scenarios

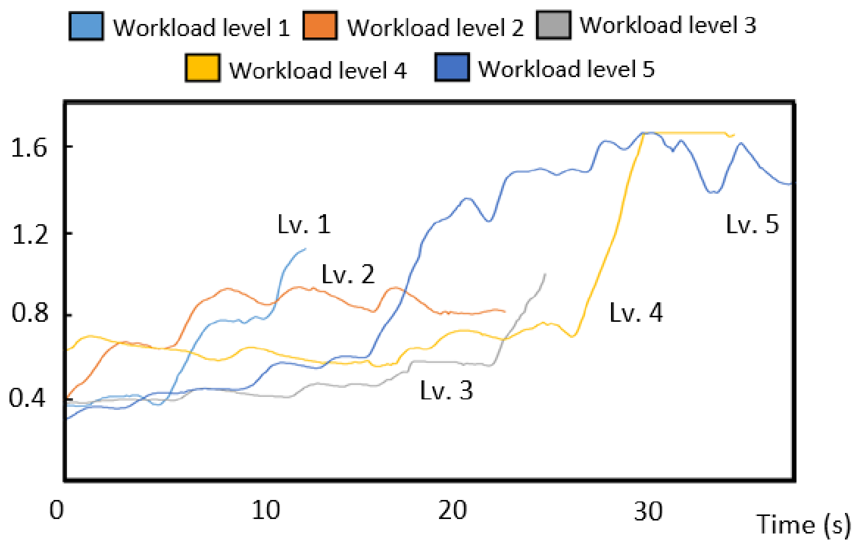


Figure 0.3 Normalized skin conductance level

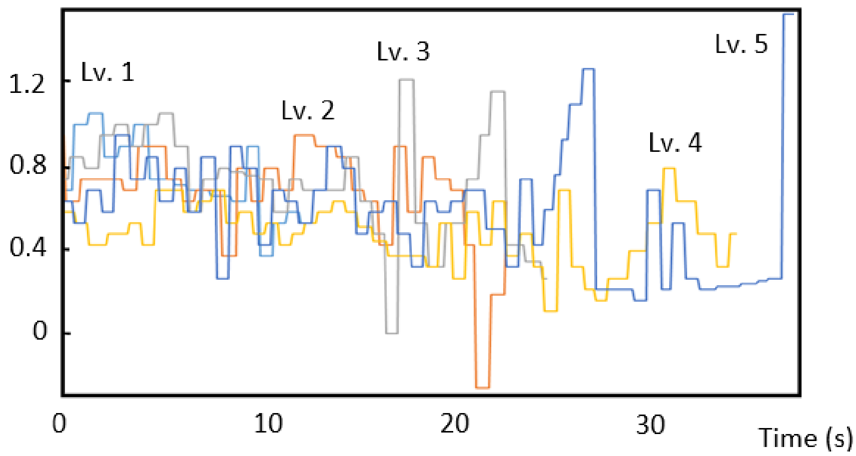


Figure 0.4 Normalized R-R interval

In Japan, vehicular traffic moves on the left and turning right at a traffic controlled intersection involves following steps, as shown in Fig. 2. First, turn on the turn signal indicator, drive along the center line of the road and approach the intersection. Secondly, keep the vehicle straight, without turning the wheels, and wait to turn right. In the meantime, check for oncoming vehicles, and also the pedestrians, cyclists on the crossing. Thirdly, when there are no oncoming vehicles, proceed cautiously to turn right while paying attention to the opposite lane. Finally, approach the pedestrian crossing slowly, pay attention to pedestrians and cyclists coming from right as well, and proceed cautiously. In order to vary the traffic complexity in each scenario, we defined two variables: oncoming traffic volume, which is the no. of vehicles crossing the intersection in a unit time period, and pedestrian and cyclist density. The

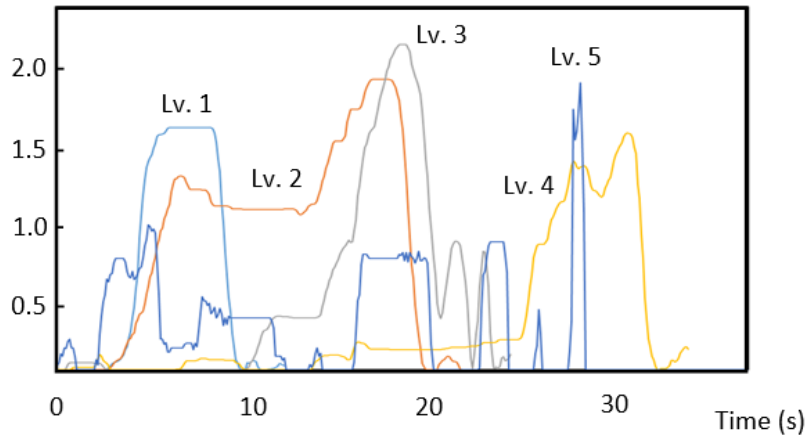


Figure 0.3 Steering angle prediction error

experiment consists of the nine (A-I) traffic situations shown in Table 2. We use a pseudo-random order in presenting the traffic situations for each participant.

5. Participants

Fourteen participants (1 female, 13 males) involved in the experiments. Their mean age was 23.5 years and had average driving experience of 3.1 years. Eight of them had previous experience in a driving simulator, and all of them had normal or corrected to normal vision. All the participants received monetary compensation for their contribution.

6. Procedure

The procedure for experiments is as follows. First, we explained the participants regarding the steps in making a right turn and asked them to practice driving and turning maneuvers in the simulator without other traffic nor pedestrians. Then we attached the sensors and asked them to drive along a straight road with minimal traffic and verified the signals acquisition. This was done also to obtain baseline values of their physiological signals and driving performance. After that, for the experiment, they drove along an urban route consisting of the traffic situations listed in Table 2. Soon after making each maneuver, participants input their perceived workload level on a 1 to 5 scale (see Table 1) using a touchscreen interface. After completing all the trials, participants responded to the questionnaires: DSQ and WSQ.

Results and analysis

In this section we present the results from feature extraction, and the classification accuracies of our LSTM based RNN models.

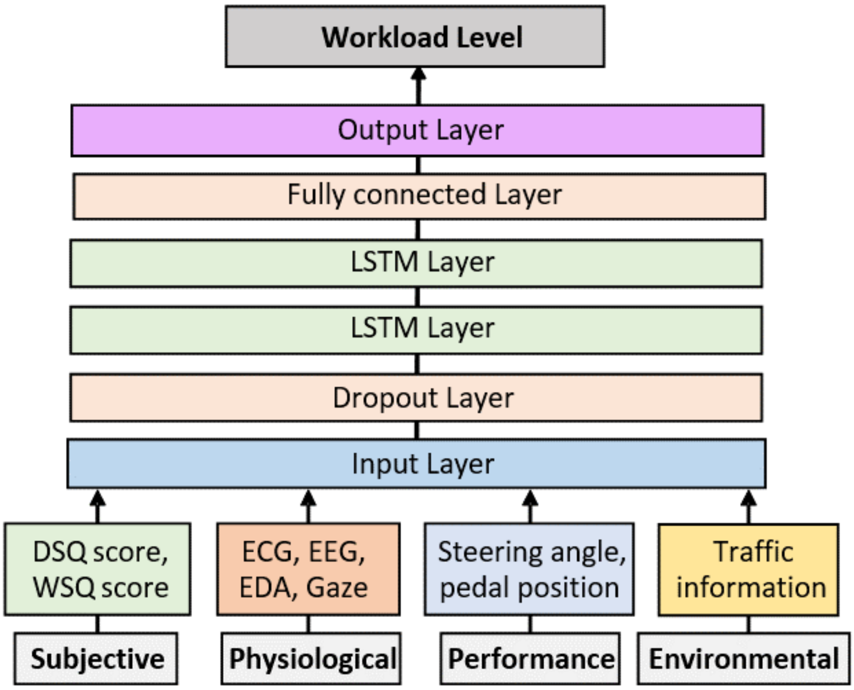


Figure 0.6 Architecture of driver workload classification system

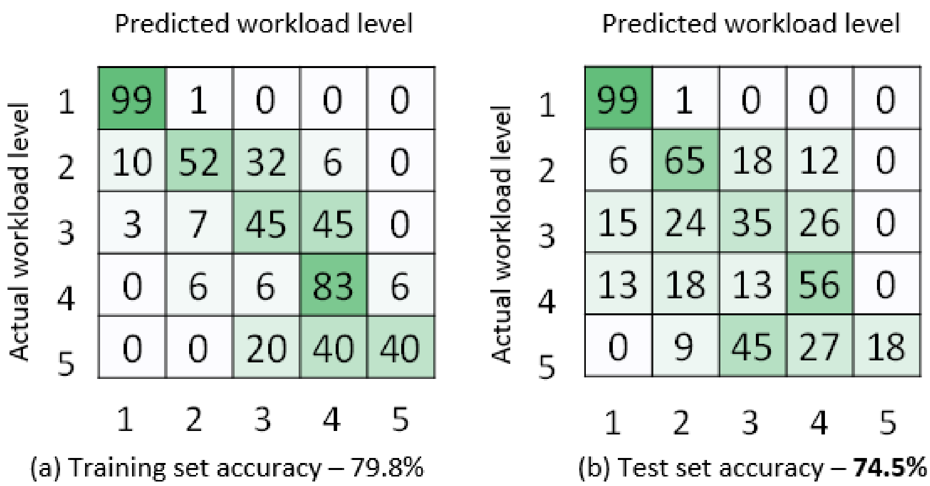
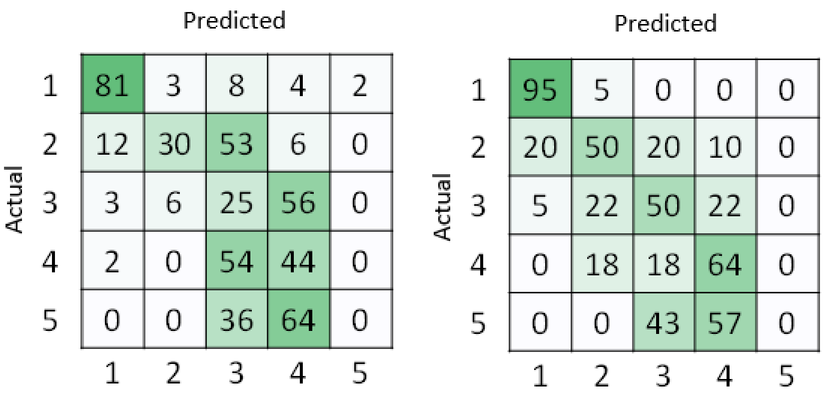


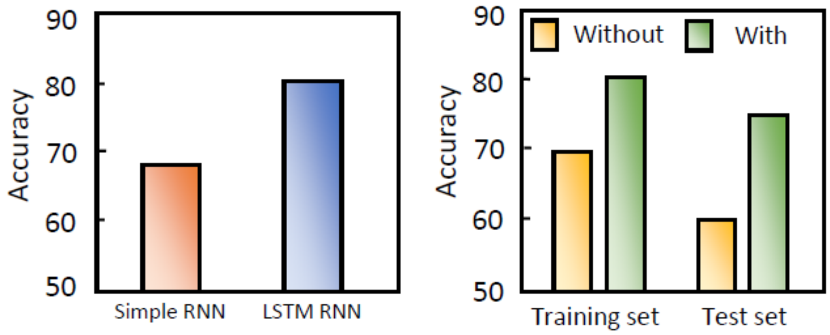
Figure 0.7 Prediction accuracies when using personal characteristics

7. Features



(a) Training set accuracy – 70.0%   (b) Test set accuracy – 59.2%

Figure 0.8 Prediction accuracies when not using personal characteristics



(a) Effect of LSTM units   (b) Effect of personal features

Figure 0.9 Model comparison

Figures 4 to 6 show the normalized SCL, RRI, and prediction error of steering angle for one driver. Note that the sequence lengths are different for individual workload levels due to the difference in times taken by driver to complete the right turn task in each situation. In Fig. 4, we can see a clear difference in the SCL between higher workload levels (4 and 5) and lower levels. Increments in SCL suggest increased sweat gland activity resulting from the arousal of ANS due to high perceived workload. Figure 5 shows higher variability in RRI when perceived workload is high, and vice versa. Acceleration of heart rate indicates the arousal of sympathetic nervous system due to high perceived workload. From Fig. 6 we can see the number of steering angle corrections (peaks), as well as their magnitude increased with the levels of perceived workload. This proves that the smoothness of control input decreases with increasing workload.

8. Classification accuracy

We used 5-fold cross validation approach for model assessment and conducted mini-batch training with batch size of 10. Learning rate was 0.001. We experimented with 50 different model architectures by using different number of LSTM layers and units. The top 5 architectures based on classification accuracy are shown in Table 3. A network with two LSTM layers and 100 units in each outperformed other architectures. Figure 7 shows the system architecture of the driver workload classification system. Confusion matrices showing classification accuracy percentages for each workload level are shown in Figs. 8 (a) and (b). We achieved overall accuracies of 79.8% and 74.5% for training set and test set, respectively.

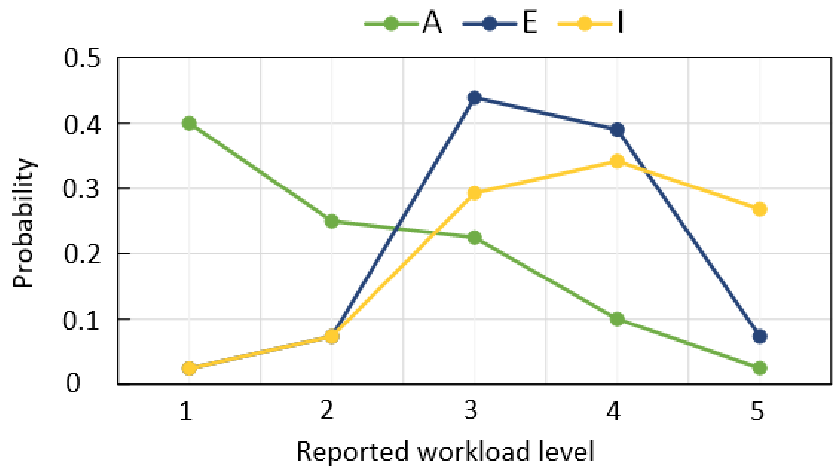


Figure 0.4 Reported workloads for three traffic complexity levels

9. Comparison

In order to show the importance of using driver characteristics such as driving style and workload sensitivity as input features, we compared the classification accuracies. When not using DSQ and WSQ scores, as shown in Figs. 9 (a) and (b), the training set accuracy decreased to 70.0% from 79.8%. The test set accuracy

Table 0.3 Errors in reporting workload levels

Average workload	2.1	2.7	2.9	3.0	3.2	3.4	3.4	3.5	3.8
Standard deviation	1.1	0.93	1.1	1.0	0.98	0.71	0.86	0.86	0.97
Traffic scenario	A	D	B	C	G	E	F	H	I

significantly decreased to 59.2%, a 15.3 point reduction compared with the model contained personal characteristics.

Discussion

RNN based classification models allow to use dynamic time series data sequences of varying lengths, as opposed to statistical machine learning methods that require fixed sequence lengths. We adopted an LSTM-RNN architecture which outperformed simple RNN architectures, as shown in Fig. 10 (a), due to LSTM's ability to retain long-term context. One limitation in our method is the approach of labelling. When reporting perceived workload levels, drivers may have made errors as we observed they change their initial response in some cases. It is possible that in some situations drivers may have experienced a higher workload level but reported a lower level, and vice versa, hence our training set labels contain human error. We assume this has significantly affected the estimation accuracy of our model. Figure 11 shows the distribution of probabilities for reported workload levels in three traffic complexity levels A, E, and I (out of the nine scenarios described in Table 2). Situation 'A' has the lowest traffic complexity and situation 'I' has the highest, while 'E' lies in between. However, from Table 4, it can be seen that for each traffic complexity level, the reported workload has an average standard deviation of 0.95. Thus, we understand the labelling has an error in the range of ±1. Our model's accuracy increased drastically up to 96.5% when we adopt a tolerance of ±1 for the output workload level.

Perceived workload level for the same traffic complexity (which incur same demand on drivers) may differ between drivers due to individual characteristics related to driving. Our results further show the significance of including driver characteristics such as driving style and workload sensitivity to achieve a higher classification accuracy. Quantifying driver characteristics by using driving style questionnaire and workload sensitivity questionnaire helps to significantly increase the prediction accuracy for new drivers, as shown in Fig. 10 (b).

Conclusion

In this study we proposed a Long Short-Term Memory (LSTM) based recurrent neural network (RNN) architecture to classify driver perceived workload into 5 levels. Our model takes driver physiological signals including electroencephalography (EEG), electrocardiogram (ECG) and electrodermal activity (EDA), driver performance data including steering and pedal operation, and driver subjective data including driving style and workload sensitivity as inputs. We conducted driving simulator based experiments to create a dataset. By including driver characteristics such as driving style and workload sensitivity, we achieved an overall classification accuracy of 74.5%. Due to personal characteristics, different drivers perceive different workload levels even in the same traffic situation. Therefore, our results show the importance of including individual driver characteristics in predicting perceived workload. Moreover, we understand the human error in reporting perceived workload levels (labelling) has a significant impact on the classification accuracy. By compensating for human error, our model achieved a remarkable accuracy of 96.5%. Future works include experimenting using bidirectional LSTM RNNs and RNNs with attention to further improve the classification accuracy.

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No.1

早稲田大学　博士（工学）　学位申請　研究業績書

(List of research achievements for application of doctorate (Dr. of Engineering), Waseda University)

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Academic Papers (Journals)	○ 1. Udara E. Manawadu, Masaaki Ishikawa, Mitsuhiro Kamezaki, and Shigeki Sugano, "Analysis of Preference for Autonomous Driving Under Different Traffic Conditions Using a Driving Simulator", Journal of Robotics and Mechatronics, Vol. 27, No. 6, pp. 660-670, 2015
Academic Papers (International conferences)	○ 2. Udara E. Manawadu*, T. Kawano, H. Hayashi, T. Ema, M. Kamezaki, and S. Sugano, "Tactical-Level Input with Multimodal Feedback for Unscheduled Takeover Situations in Human-Centered Automated Vehicles" IEEE Intl. conf. on Advanced Intelligent Mechatronics (AIM), New Zealand, 2018.
	○ 3. Udara E. Manawadu*, T. Kawano, S. Murata, M. Kamezaki, and S. Sugano, "Estimating Driver Workload with Systematically Varying Traffic Complexity Using Machine Learning: Experimental Design" International Conference on Intelligent Human Systems Integration (IHSI-2018), Dubai, UAE, Jan. 2018.
	○ 4. Udara E. Manawadu*, M. Kamezaki, M. Ishikawa, T. Kawano and S. Sugano, "A Multimodal Human-Machine Interface Enabling Situation-Adaptive Control Inputs for Highly Automated Vehicles" 2017 IEEE Intelligent Vehicles Symposium (IV-2017), CA, USA, Jun. 2017
	○ 5. Udara E. Manawadu*, M. Kamezaki, M. Ishikawa, T. Kawano and S. Sugano, "A Driver Preference Analysis for Different Levels of Driving Automation in Heterogeneous Traffic Scenarios" 2017 JSAE Annual Congress, Yokohama, Japan, May 2017
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	○ 8. Udara E. Manawadu*, Masaaki Ishikawa, Mitsuhiro Kamezaki, and Shigeki Sugano, "Analysis of Individual Driving Experience in Autonomous and Human-Driven Vehicles Using a Driving Simulator", proc. IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM-2015), Busan, Korea 2015.