Improving Driver Takeover Performance in Conditionally Automated Driving: Understanding System Limitations, Safety Compensation and Takeover Behaviors

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SUMMARY

Automated driving is getting attractive to us and expected to benefit many aspects of our life, including traffic safety, transportation efficiency, driver comfort, environmental protection, and energy saving. The completely automated driving which requires no input from drivers is perfect but difficult to penetrate into our daily life in the near future. Fortunately, conditionally automated driving (level 3 automated driving) which allows drivers to do non-driving related tasks (NDRT) can be expected easier to get into the market. However, drivers need to take over control of the vehicle when the system encounters situations that the automation system cannot deal with. Sometimes, it becomes difficult for drivers to get back into the control loop from the engagement of NDRT when the system issues a request to intervene (RTI). Therefore, it is a challenge for drivers to achieve good takeover performance. The objective of this dissertation is to investigate the driver takeover performance in conditionally automated driving from the three aspects. 1) How can driver takeover performance be worsened in a sudden system failure situation compared with an operational design domain (ODD) exit situation); 2) How will driver takeover performance be improved if a safety compensation which prolongs the time budget is available; 3) How will driver takeover performance be affected by a driver takeover behavior training.

The issue of driver takeover performance has become one of the significant topics in the research field of automated driving. Chapter 1 introduces the background of conditionally automated driving and driver takeover performance, the literature review and the motivation of the current research. There are two typical limitations in which the system issues an RTI to the driver in a conditionally automated driving according to SAE-J3016 (i.e., the sudden system failure situation and the ODD exit situation). Chapter 2 focuses on the differences of driver takeover performance in the two typical limitations. In the sudden system failure

situation, the time budget for drivers to take over control is extremely short as the system needs to be deactivated immediately with issuing an RTI. However, in the ODD exit situation the time budget is relatively longer as the system could keep active for a while after the issue of RTI. Could the longer time budget help drivers to regain situation awareness and achieve better takeover performance? A driving simulator experiment was conducted to examine how the takeover performance differed in the two types of limitations. The experimental results revealed that drivers responded significantly faster in the system failure situation. There was no significant difference of longitudinal takeover performance between the two types of limitations. However, the drivers generally performed better lateral takeover performance in the ODD exit situation whose time budget was longer.

Based on the results of Chapter 2, Chapter 3 proposes a safety compensation which prolongs the time budget to improve the driver takeover performance in conditionally automated driving. In the safety compensation situation, the system conducts automatic deceleration to prolong the time budget for drivers to respond. We implemented a driving simulator experiment to investigate how the safety compensation affected the driver takeover performance. The results showed no significant effect of safety compensation on the takeover time, but a significant effect on the longitudinal driving performance. Moreover, it indicated a significant effect of safety compensation on the lateral acceleration in a specific scenario (i.e., the lane closing scenario). This finding is useful for the automotive manufacturers to supply users a safer transition scheme from automated driving to manual maneuver.

The longer time budget of RTI can help drivers to regain situation awareness which is potential to benefit driver takeover performance. Additionally, behavior training is another way that can be expected to benefit driver takeover performance. A behavior training is put forward in Chapter 4. Specifically, the participants were reminded to calm down when they hear the RTI message, then check around carefully for the traffic situation, last take over

control safely and smoothly. A driving simulator experiment was implemented to examine how the behavior training influence the takeover performance. The results revealed both the distributed training and massed training improved the lateral takeover performance (i.e., the maximum steering wheel angle and the standard deviation of lane position), but the benefit on standard deviation of lane position was slight.

The current study investigated the driver takeover performance by considering the three aspects: understanding system limitations, safety compensation and takeover behaviors. The experimental results indicated: 1) Understanding system limitations is critical for improving takeover performance as the lateral takeover was significantly worse in the system failure situation than that in the ODD exit situation; 2) The safety compensation significantly benefited the longitudinal takeover performance (i.e., driver brake input and time to event) and the lateral acceleration of lane closing scenario; 3) The behavior training improved the maximum steering wheel angle significantly and the standard deviation of lane position slightly, the drivers could generally maintain the takeover performance in one week.

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Chapter 1. Introduction

1.1 Background

In contemporary society, automotive transportation has been penetrating into our life and benefitting us tremendously. However, automobiles are also leading to a great deal of problems, such as traffic accidents, congestion and energy consumption. For instance, in the United States, there were 34,080 fatalities caused by automobile crashes in 2012 [1], the traffic congestion makes the commuters get delayed 38 hours per year [2], and the road transportation spent around 60% of the total petroleum consumption [3]. Nowadays, automated driving is getting increasing attention from us and has the potential to solve these problems through mitigating traffic accidents, congestion, and fuel consumption [4]. Moreover, automated driving can also be expected to extend elderly people’s driving life, as well as the driving comfort [5].

Driving automation is defined as automation in which some aspects of the dynamic driving tasks are administered by systems instead of drivers. The comprehensive and exact definitions of automated driving have been given by a couple of institutes, such as the National Highway Traffic Safety Administration (NHTSA) [6], the German Federal Highway Institute (BASt) [7], and the Society for Automotive Engineers (SAE) [8]. The definition from SAE seems to be the most widely used one. There are totally six levels of driving automation according to SAE [8]. Specifically, level-zero driving automation (the lowest automation) stands for the fully manual driving. At level-one driving automation, the system can automatically execute either longitudinal or lateral control of the vehicle, such as Adaptive Cruise Control (ACC) and Lane Keeping Assist System (LKAS). In level-two driving automation, the automation system implements both the longitudinal and lateral control of the vehicle, but drivers have to monitor the traffic environment and intervene if necessary. The level-three automated driving allows drivers to do Non-Driving Related Tasks (NDRT) without monitoring the driving environment in the Operational Design Domain (ODD). However, drivers have to take over control if the vehicle encountered situations that the system cannot deal with (i.e., exit ODD or system failure). In level-four driving automation, vehicles can drive automatically in ODD without drivers' intervention. The level-five driving automation is a completely automated driving without any limitation.

The fully automated driving cannot be achieved in the feasible future as there are still some limitations on technologies, laws and ethics. In contemporary society, some automated driving systems have been introduced into our life. For level-one automated driving system, Lane Keeping System (LKS) and Adaptive Cruise Control (ACC) have been put into practical application for many years. For level-two automated driving, Advanced Driver Assistance System (ADAS) is also available in several series of cars. At level-three automated driving, it has been announced that Honda launched the world's first level-three self-driving car [9]. Some other automotive companies have not released any products of level-three, but plan to release them in the near future [10][11].

Level 3 automated driving, also known as conditionally automated driving, has become a hot topic before realizing levels 4 and/or 5 automated driving. Conditionally automated driving has been expected to penetrate the market within the next decade [12][13]. In conditionally automated driving, drivers are allowed to engage in non-driving related tasks (NDRT) instead of concentrating on the driving tasks continuously. Furthermore, a request to intervene (RTI) should be issued and drivers are expected to take over control manually when the automated system encounters some situations that it cannot deal with. However, it is a great challenge for drivers to resume control timely and perform well after being engaged in NDRT [14]. This challenge is also described as the “out-of-the-loop performance problem” [15][16][17][18]. The performance problem can be mainly attributed to a loss of situation awareness [19]. It is inevitable for drivers to loss situation awareness as they have been engaged in NDRT. Hence, in conditionally automated driving, takeover performance which is firmly related to the “out-of-the-loop performance problem” has become an attractive topic to researchers.

1.2 Literature Review

Takeover performance consists of takeover time (i.e., the time interval measured between the moment that the RTI is issued and the moment that the drivers resume control) and takeover quality (e.g., drivers’ steering wheel angle, deviation of lane position, acceleration etc.) [20]. There are a couple of factors which affect the takeover performance. Du et al. [21] examined the effects of emotional valence and arousal on takeover performance in conditionally automated driving. They presented that positive valence led to better takeover quality, but high arousal did not yield any advantage in takeover time. Körber et al. [22] studied the effects of age on takeover performance, found that older drivers braked more often and more strongly and maintained a higher Time to Collision (TTC), but there was no difference in takeover time between younger and older drivers. Wörle et al. [23] investigated how sleep affected the takeover performance in conditionally automated driving. The influence of traffic density on takeover performance has also been investigated by some researchers. Gold et al. [24] presented that high traffic density could lead to higher takeover time and worse take-over quality. Du et al. [25] reported worse takeover performance in heavy traffic density, but no significant difference of traffic density on takeover time. Furthermore, the takeover performance was affected by some driver factors, such as driver fatigue [26] and driver training [27]. It was reported that takeover performance assessed with the takeover-controllability-rating was clearly worse after sleep than after wakefulness. There are so many factors which are potential to affect the takeover performance has been discussed in the previous studies. We are not able to discuss all the factors in this thesis, but we can highlight some of them. Based on the topic of this dissertation, the time budget, NRDT, the system limitations, the safety compensation (or approach) and driver training (or learning) are specifically introduced in the following sections.

1.2.1 Time Budget

In conditionally automated driving, the time budget can be explained as the time provided to drivers to take over control before getting to the system limit (e.g., the obstacle) [15][28][29]. Drivers usually need sufficient time budget to regain the state of system and the traffic environment. Zhang et al. [30] conducted a meta-analysis and found that a longer time budget led to higher driver's takeover time. Besides, the shorter time budget was claimed to significantly induce the driver to take more braking responses, as well as worsened both the longitudinal and lateral takeover performance [31]. Drivers usually prefer to take NDRT in conditionally automated driving [32]. Some researchers presented that the drivers could generally resume control in a relatively short time of 3-5 s [12][33] (the time budget was 7 s in [12], 10 s in [33]). Mok et al. [34] conducted an experiment to examine the takeover performance, proved that the minimum amount of time budget should be 5-8 s in conditionally automated driving. Drivers' takeover performance has been proved to become worse when the time budget was shorter [35]. Therefore, sufficient time budget should be provided to drivers in conditionally automated driving. It was claimed to be appropriate to design the time budget as 7-10 s in conditionally automated driving [36][37].

1.2.2 Non-Driving Related Tasks (NDRT)

We can easily imagine the situation that drivers' attention gets diverted away from the driving task when they are engaged in NDRT. NDRT makes drivers lose situation awareness during automated driving, during which it becomes difficult for drivers to achieve good takeover performance when RTI issues. Although drivers have the freedom to engage in NDRT or not, Winter et al. [38][39] concluded that drivers were more willing to be engaged in NDRT in conditionally automated driving. It is difficult for us to make a conclusion that whether NDRT has significant influence on the takeover time or not based on some previous studies [40][41][42]. However, it is quite clear that NDRT can deteriorate takeover quality [42][43]. Thereby, the effects of NDRT on takeover performance cannot be ignored. The investigation of Wandtner et al. [44] indicated that a visual-manual texting task degraded takeover performance a lot, particularly when performed handheld. Takeover performance might deteriorate when NDRT has overlapping resource demands with the driving tasks [15]. For instance, drivers have to engage in a visual NDRT without gazing on the roadway, which leads to loss of situation awareness and worse takeover performance [45]. Eriksson et al. [40] claimed that manufacturers must adapt to the circumstances, providing longer time budget to drivers who are engaged in NDRT.

1.2.3 System Limitations

In conditionally automated driving, drivers are expected to take over control manually when the automated system encounters system limitations which are divided into two types: the sudden system failure and ODD exit [8]. The system failure might occur suddenly with issuing an RTI. In this case, the automation could deactivate simultaneously (see **Fig. 1.1**). **Fig. 1.1** shows that drivers have to respond instantly to take over control from the system, otherwise the vehicle will be out of control. It is an extremely critical situation that should be discussed in conditional driving automation. Zhou et al. [46] investigated the effect of a sudden system failure on the intervening behaviour of drivers in partially automated driving. Strand et al. [47] showed that drivers were worse at handling complete than partial automation failure. Some other researchers also conducted investigation on the influence of automation failure on driver behaviour in Adaptive Cruise Control (ACC) [48][49]. In an ODD exit situation, the automation will be deactivated once the driver resumes control or be disengaged automatically after T seconds (see **Fig. 2.2**). Hence, drivers have T seconds to regain situation awareness and take control from the system when the RTI issues. However, it is still a challenge for drivers to perform well after taking over control in the ODD exit situation. Vogelpohl et al. [50] showed that distracted drivers required additional time to acquire enough situation awareness comparing with manual drivers. It highlighted the challenge for getting the drivers back into the loop and maintain takeover performance even several seconds was provided to the drivers to do response. An integrated model approach of driver behaviour in emergency takeover situations was presented by Zeeb et al. [51]. It was reported that the takeover time was determined by the driver cognitive processes instead of the motor processes. Although previous studies have highlighted the takeover performance in the system failure situation or in the ODD exit situation, the comparative investigations of the two types of limitations have not been carried out. Therefore, it is necessary to highlight the difference of takeover performance in the two kinds of limitations. The drivers might improve their takeover performance if they can further understand the system limitations.

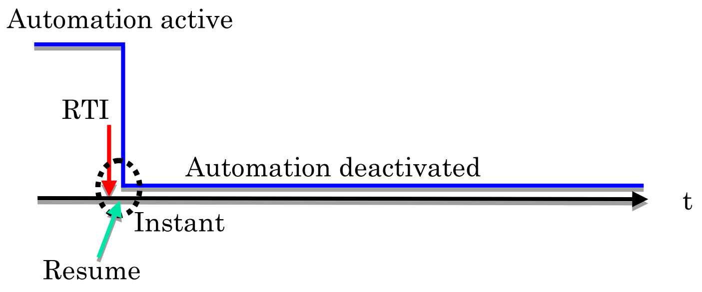


Fig. 1.1. Transition in system failure

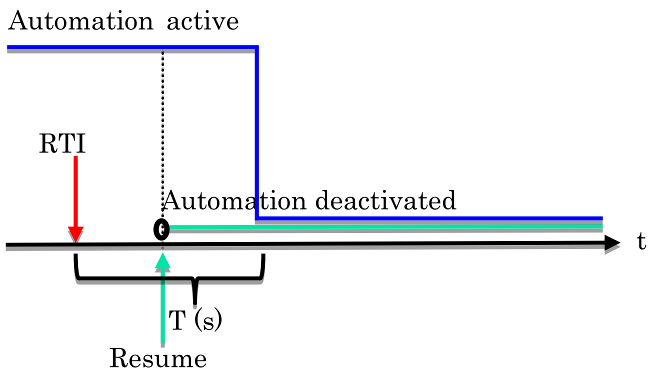


Fig. 1.2. Transition in ODD exit

1.2.4 Safety Compensation

In conditionally automated driving, drivers have to face the challenges of limited time budget, distraction from NDRT and sudden system failure situation. Accordingly, it is significant to provide drivers a safety compensation which can be expected to improve takeover performance. Many recent studies have investigated safety approaches to realize safe control transition or improve takeover performance. Nilsson et al. [52] used a vehicle model and reachability analysis to evaluate whether the states of the vehicle start and remain within the driving controllability set (DCS) during the transition to manual driving. They also demonstrated that only if the states are within the DCS is the transition to manual driving classified as safe. Gold et al. [53] proved that with shorter takeover time, decision makings and reactions are faster but generally worse in takeover quality. In case of not enough situation awareness for drivers to make a proper decision, partial brake may be used as a safety compensation to reduce speed and to gain more time for decision making or for the lane change maneuver. Moreover, a novel system was proposed to keep the driver in-the-loop or supporting the driver in takeover situations with supplementary features such as gaze guidance or increased decelerations [54]. In addition, Inagaki and Sheridan [55] clarified that some automatic safety control action (e.g., partial braking) can be expected to extend the time to the critical point and improve the driver's performance by reducing her sense of panic when an RTI issues. The previous research put forward the safety compensation, but how does this approach affect the driver takeover performance has not been investigated. Hence, it is meaningful to explore the effects of safety compensation on driver takeover performance in varying scenarios.

1.2.5 Prior Training

Prior training is another potential factor that might affect the takeover performance in conditionally automated driving. It seems a great challenge for users to respond to the RTI and achieve good takeover performance when they firstly experience the conditionally automated driving. The drivers without prior training are not familiar with the system functions and limitations of conditionally automated driving. These drivers cannot build the mental model of the system. The lay drivers might take an immediate maneuver without getting enough situation awareness when the RTI issues. It is also possible for the lay drivers to become nervous when they receive the RTI messages suddenly, which makes the drivers unable to make appropriate decisions. It is necessary to provide the new users of conditional driving automation with basic training which helps them to regain situation awareness, build mental model and achieve better takeover performance. Some researchers have made progress on driver training in conditionally automated driving. Forster et al. [56] conducted a driving simulator study on effects of different user education approaches, found that the mental models evolve more accurately if users are educated. Hergeth et al. [57] investigated the effects of prior familiarization with the RTI on drivers' initial takeover performance. Their results indicated that the prior familiarization had a more positive effect on takeover performance in the first than in a subsequent takeover situation. Ebnali et al. [58] evaluated the effects of Simulator Training and Video Training on driver's attitudes and takeover performance in conditionally automated driving. The results revealed that both training methods improved takeover time, speed variance, and standard deviation of lane position. Ebnali et al. [59] also utilized virtual reality (VR) to investigate the effect of pre-trip familiarization tours on automation trust and driving performance in conditionally automated driving. The results suggested takeover quality only improved when practice was presented in high-fidelity VR. Zhou et al. [60] examined the effects of explanation-based knowledge regarding system functions and driver's roles on takeover performance, found that explanations of HMI and RTI-related situations are effective for helping drivers safely and successfully negotiate the events. These prior studies focused on the training which mainly transfers the basic knowledge or familiarization to benefit the takeover performance. Thereby, the prior training is significant, further investigation can be expected to improve the driver takeover performance.

1.3 Research Motivation and Objectives

The numerous prior studies have proved that sufficient time budget should be provided to drivers to achieve good takeover performance. In some takeover situations, the automation system can estimate the limitation far in advance and provide drivers enough time budget (e.g., exiting the highway), but in some other takeover situations, the automation system cannot predict the limitation far in advance and can only provide drivers limited time budget (e.g., front car cut in suddenly) [15]. Even in the system failure situation, the time budget is extremely limited, and the automation system requires drivers to take over control immediately. In these takeover situations, there are several issues related to takeover performance should be investigated.

Firstly, the takeover performance in the system failure situation is still not clear. We need to uncover how takeover performance worsen when the time budget is extremely limited. The findings would help drivers to understand system limitations, which can be expected to improve drivers' takeover performance. Secondly, if an approach is available to prolong the time budget which is not far sufficient, how would the takeover performance be improved? Thirdly, if a takeover behavior training process is taken for drivers, how would the takeover performance be affected?

Therefore, the objectives of this study are: 1) discovering the difference of takeover performance in the two types of limitations (i.e., the system failure and the ODD exit); 2) Exploring the takeover performance when a safety compensation is provided; 3) Investigating the influence of behavior training on takeover performance.

1.4 Dissertation Outline

This dissertation consists of five chapters which focuses on the takeover performance of conditionally automated driving. The chapter one is about introduction. The chapter 2, 3, 4 are three experimental studies on takeover performance. The chapter five is about the conclusions.

Chapter one is the introduction section. It includes the background of automated driving, the previous work on takeover performance and the motivation of the current research.

Chapter 2 reveals how takeover performance worsen in a system failure situation. We conducted expected utility analysis to predict the takeover performance both in system failure situation and ODD exit situation. Then, driving simulator experiment was conducted to verify the prediction of the takeover performance. The results revealed that drivers responded significantly faster in the system failure situation. Besides, drivers generally performed better lateral takeover performance in the ODD exit situation.

Chapter 3 investigates how a safety compensation which prolong the time budget affect the takeover performance. An experiment was carried out by using a driving simulator. The results indicated that the safety compensation benefited the longitudinal takeover performance of driver brake input and the time to event. It also improved the lateral acceleration after driver's takeover.

Chapter 4 focuses the effects of driver takeover behavior training on takeover performance. We put forward a driver behavior training process. Then the effects of the training and space of training were investigated through a driving simulator experiment. The training process was verified to benefit the maximum steering wheel angle, but no significant improvement for other dependent variables.

Last, chapter 5 summaries the main findings and limitations for these studies.

Chapter 2. Driver Takeover Performance in Conditionally Automated Driving: Sudden System Failure Situation versus ODD Exit Situation

2.1 Introduction

Based on the introduction of conditionally automated driving in **chapter 1**, we can claim that the driver is expected to take over control manually when the automated system encounters some limitations which generally include two types: the sudden system failure and ODD exit [8]. No matter what kind of limitation the system encounters, the drivers are expected to regain situation awareness, make decision and take over control timely when the RTI is issued from the system. These two kinds of limitations are so crucial that should be discussed explicitly in conditionally automated driving. The **section 1.2** has highlighted the importance of takeover performance in conditionally automated driving. In this chapter, we will conduct investigation on how driver takeover performance worsen in a system failure situation. Nevertheless, takeover performance is derived from the drivers' decision which is usually made based on their expected utility [61][62][63]. Inagaki & Sheridan [55] established mathematical model of expected utility to evaluate the design of RTI messages. The mathematical analysis of driver's expected utility should be developed here as it helps to further explain the differences of takeover performance in the two types of limitations. Therefore, we conducted expected utility analysis in **section 2.2.1** and put forward hypotheses in **section 2.2.2**. Then a driving simulator experiment was implemented to realise the first objective in **section 1.3**.

2.2 Methodology

2.2.1 Expected Utility Analysis

In a sudden system failure situation, the time budget for drivers to resume control could be extremely limited. There would be two possible actions taken by the drivers. One is taking over control immediately, the other one is doing response calmly but with delay. Let *P*(IR|System-failure) denote the probability of driver's immediate resuming (IR) after the RTI is issued, and *P*(CR|System-failure) be the probability of driver's calm resuming (CR) after the RTI. Since the driver's response to the RTI is either IR or CR in the system failure situation, we have:

$$P(IR|System\text{-}failure) + P(CR|System\text{-}failure) = 1 \tag{2.1}$$

Let *a* be the utility of driver's immediate resuming (e.g., the driver resumes control immediately in the short time budget, he/she is satisfied. Utility is a variable to evaluate how satisfied he/she is), and *b* denote the utility of driver's calm resuming. The expected utility $U_{\text{-}system\text{-}failure}$ can be given by:

$$U_{\text{-}system\text{-}failure} = aP\,(IR|System\text{-}failure) + bP(CR|System\text{-}failure) \tag{2.2}$$

In an ODD exit situation, drivers are given long enough time to do response. There are also two possible actions that would be taken by drivers (i.e., immediate resuming and calm resuming). Similarly, let P(IR|ODD-exit) denote the probability of driver's immediate resuming (IR) in the ODD exit situation, and P(CR|ODD-exit) be the probability of driver's calm resuming (CR). Since the driver's response to the RTI is either IR or CR in the ODD exit situation, we have:

$$P(IR|ODD\text{-}exit) + P(CR|ODD\text{-}exit) = 1 \tag{2.3}$$

Here, let a^* be the utility of driver's immediate resuming in the ODD exit situation, and b^* denote the utility of driver's calm resuming. The expected utility $U_{\text{-}ODD\text{-}exit}$ can be given by:

$$U_{\text{-}ODD\text{-}exit} = a^* \, P\,(IR|ODD\text{-}exit) + b^* P(CR|ODD\text{-}exit) \tag{2.4}$$

Substitute (2.1) into (2.2), substitute (2.3) into (2.4), and calculate the difference between (2.2) and (2.4), we can get:

$$\begin{aligned} &U_{\text{-}ODD\text{-}exit} - U_{\text{-}system\text{-}failure} \\ &= (a^* - a) + (b^* - a^*)P(CR|ODD\text{-}exit) + (a - b)P(CR|System\text{-}failure) \end{aligned} \tag{2.5}$$

In the system failure situation, the automation disengages simultaneously when the RTI issues. In this case, the takeover time given to the driver is extremely short. the driver would have lower satisfaction on CR because the response is too late as the automation has got disengaged for a period. Therefore, $a > b$. In the ODD exit situation, the automation does not disengage immediately when the RTI issues. In this case, the takeover time given to the driver is relatively longer. The driver would have higher satisfaction on CR, because he/she has better preparation (e.g., more situation awareness) for resuming control. Hence, $b^* > a^*$. The automation has just been disengaged for an extremely short time when the driver takes immediate resuming in the system failure situation. Therefore, the driver's satisfaction on IR in the system failure situation could be the same with that in the ODD exit situation. Thereby, $a = a^*$.

Accordingly, we can assume: $b^* > a\ (a^*) > b$

Thus, $U_{\text{-}ODD\text{-}exit} > U_{\text{-}system\text{-}failure}$

2.2.2 Hypotheses

Here, it has been shown that the expected utility of ODD exit situation is higher than that of the system failure situation. The expected utility would affect their decision making which suggested by their takeover performance. For instance, the driver's higher expected utility on ODD exit situation makes them more satisfied with the RTI system of ODD exit situation. Then, they would take soft braking or smooth steering after taking over control. Hence, we put forward the two following hypotheses:

H1: the drivers respond faster to the RTI in the system failure situation as they have lower expected utility then are eager to resume control immediately.

H2: the drivers perform more smoothly (both longitudinal behaviour and lateral behaviour) in the ODD exit situation as their expected utility is higher.

2.3 Experiment

A driving simulator experiment was carried out to validate the hypotheses. This study was conducted under the approvement of the ethics committee of University of Tsukuba.

2.3.1 Apparatus

The experiment was conducted with a Mitsubishi Driving Simulator (Fig. 2.3). The simulator was designed to accommodate a simple cab, which was static but provided the driver with immersive driving environment. Realistic road and engine sounds were played over a sound system. The visual environment was displayed on a 180-degree visual field which composed of five flat screens. The steering wheel and pedals mounted with the Moog Control Loading System could provide drivers with force feedback. The experimental data were recorded at the frequency of 120Hz.

Fig. 2.1. The driving simulator

2.3.2 Participants

In order to conduct the driving simulation experiment, a total of 32 participants (17 males + 15 females) were recruited with the support of a professional human resource corporation. The range of their age was from 21 to 35 years old (M=25.3 years, SD=4.6 years). They all held a valid Japanese driving license for at least 1 year, drove at least several times a month.

2.3.3 Experimental Design

In this experiment, a 2×3 mixed design was utilized. One was a between-subjects factor which was the type of limitations (system failure, ODD exit), and the other was within-subjects factor which was the takeover scenarios. Three takeover scenarios: fog, route choosing, and lane closing were designed in this experiment as previous work claimed that road works, freeway exit ramps and fogs were complicated driving situations in which an RTI should be issued [40][64][65]. The three experimental takeover scenarios were shown in Fig. 2.4. Each participant had to experience three trials (one for each fog, route choosing, lane closing) in the ODD exit condition. In the system failure condition, the participants also experienced the three events (one for each fog, route choosing, lane closing). It was used to ensure the same road environment after resuming control under the ODD exit condition.

Every participant experienced each scenario once. The events occurred at different time points of the trials. It aimed at preventing the participants' prediction to the event appearing. The RTI issued 7 seconds ahead of the events as the time budget was appropriate according to the previous research [65]. A beep emitted as an auditory signal when the RTI issued in both the system failure and ODD exit conditions. Each experimental trial lasted for varying duration (fog 230s, route choosing 50s, lane closing 160s). The sequence of the driving trials was randomized for every participant to counteract order effects. The speed was 80 km/h during automated driving.

Fog Route choosing Lane closing

Fig. 2.2. Three takeover scenarios

2.3.4 Non-driving Related Task (NDRT) and Human-machine Interface (HMI)

In the current study, Tetris was administered on an iPad to help the participants get distracted from driving task. The iPad was mounted near the steering wheel (see **Fig. 2.1**). All the participants were immersed in the Tetris during the automated driving mode. Additionally, a display which showed the state of driving model (i.e., automated driving or manual driving) was located on the left of the steering wheel (see **Fig. 2.1**). Participants could acquire the RTI messages auditorily and visually. A beep emitted as an auditory waning when an RTI was issued. The icon of driving model changed from green to amber when the automation was disengaged (see **Fig. 2.3**).

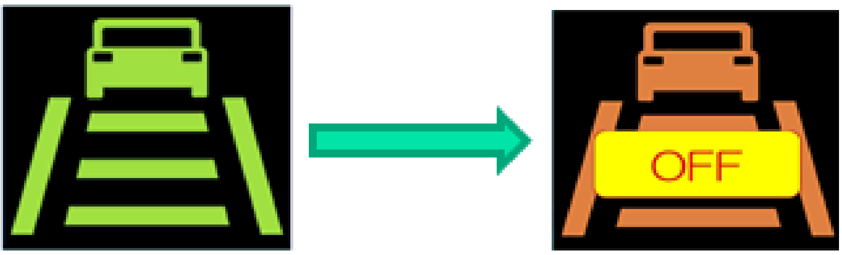


Fig. 2.3. HMI: the icon changes when automation disengages

2.3.5 Procedure

Each participant was firstly welcomed into the room to complete the demographic survey, a questionnaire measuring their driving experience and frequency, and the experimental consent. Afterwards, participants were given general instructions of the conditionally automated driving system and the experimental motivation through slides. After that, a three-steps-practice was administered for each participant from step one to step three. (1) step one: participants were provided with a manual driving practice, during which basic maneuver of the driving simulator were instructed; (2) step two: participants experienced conditionally automated driving and NDRT, during which some explanations were given to them; (3) step three: each participant was asked to experience the RTI and the resuming maneuver. During the three-steps-practice, it was possible for the participants to take practice of any step for more than once if they required. The three-steps-practice was taken to ensure that the participants were familiar enough with the maneuver of conditionally automated driving. The main experiment initiated after the driving practice. The participants received their rewards after completion of the experiment.

2.3.6 Dependent Variables

In the current study, the following metrics were measured to assess the takeover performance of system failure and ODD exit conditions. All the measurements were recorded by the simulation system, then extracted from the data after the experiment.

● Reaction time: elapsed time from the time point of RTI issuing to the time point of driver resuming control. The reaction time to the RTI is a metric to assess how quickly the participants respond in system failure and ODD exit situations. If the reaction time is shorter in the system failure situation, the first hypothesis can be proved to be reasonable.

● Maximum driver brake input: brake pedal position (%) implemented by the driver. The driver brake input is a metric that indicated by the brake pedal position implemented by the driver. According to the second hypothesis, less driver brake input can be expected as a smoother maneuver in the ODD exit situation.

● Maximum longitudinal acceleration: Longitudinal acceleration was widely utilized to evaluate the longitudinal driving performance in a couple of prior investigations [66][67][68]. A smaller longitudinal acceleration is expected in the ODD exit situation based on the second hypothesis.

● Maximum steering wheel angle: The maximum steering wheel angle was measured in this experiment. It was a metric that used to show the lateral takeover performance after the transition from system to manual control. A greater maximum steering wheel angle can be observed in the system failure situation if the second hypothesis is reasonable.

● Maximum lateral acceleration: The maximum lateral acceleration was also a widely used metric to assess the lateral driving performance in previous research [66][67][68]. A greater maximum lateral acceleration will also be observed in the system failure situation based on the second hypothesis.

2.4 Results

Data of the dependent variables were analyzed through a two-way mixed ANOVA (analysis of variance) as the mixed-subject design. Data of one participant in the system failure were missed. SPSS was used to administer the data analysis.

2.4.1 Reaction Time

A two-way mixed ANOVA revealed significant main effect of the type of limitations on the reaction time (see **Table 2.1**). No significant main effect of scenarios and the interaction were shown. **Fig. 2.4** depicted the data.

Table 2.1. Result of Two-way Mixed ANOVA for Reaction Time

Factors	df	F	η^2	p
Scenarios	2	.972	.032	.385
Limitations	1	80.650	.736	<.001**
Interaction	2	2.382	.076	.101

**p<.001

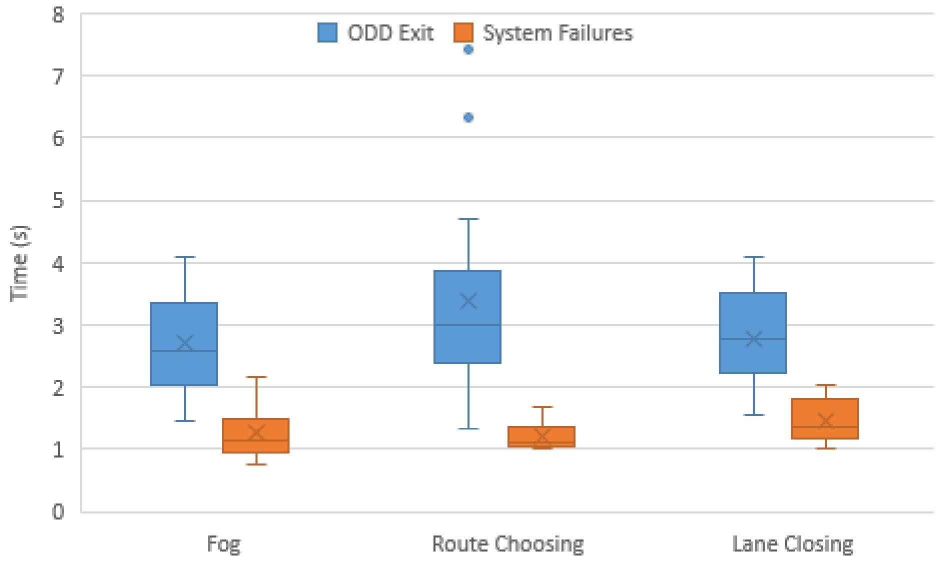


Fig. 2.4. Reaction time in system failure and ODD exit condition

2.4.2 Maximum Driver Brake Input

Although we hypothesized that drivers take more brake input in the system failure situation, the result showed no significant main effect of the limitation type on the maximum driver brake input. The main effect of scenarios and interactions were also not significant (see **Table 2.2**). The data were shown in **Fig. 2.5**.

Table 2.2. Result of Two-way Mixed ANOVA for Maximum Driver Brake Input

Factors	**df**	**F**	**η^2**	**p**
Scenarios	2	1.933	.063	.154
Limitations	1	.232	.008	.634
Interaction	2	.971	.032	.385

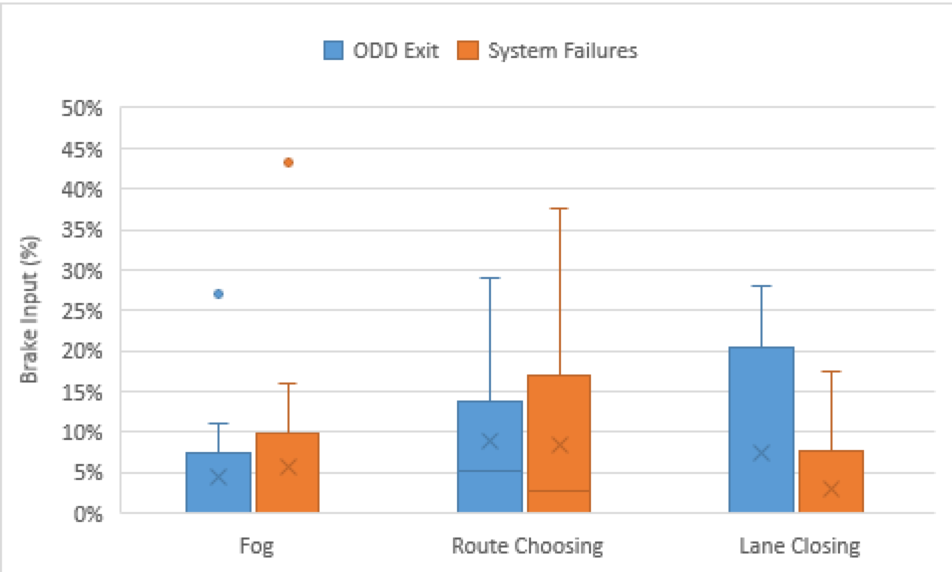


Fig. 2.5. Maximum driver brake input in system failure and ODD exit condition

2.4.3 Maximum Longitudinal Acceleration

The result of ANOVA analysis revealed no significant main effect of the type of limitations on the maximum longitudinal acceleration. The main effect of scenarios and interactions were also not significant (see **Table 2.3** and **Fig. 2.6**).

Table 2.3. Result of Two-way Mixed ANOVA for Maximum Longitudinal Acceleration

Factors	**df**	**F**	η^2	**p**
Scenarios	2	2.640	.083	.080
Limitations	1	.013	<.001	.908
Interaction	2	.528	.018	.592

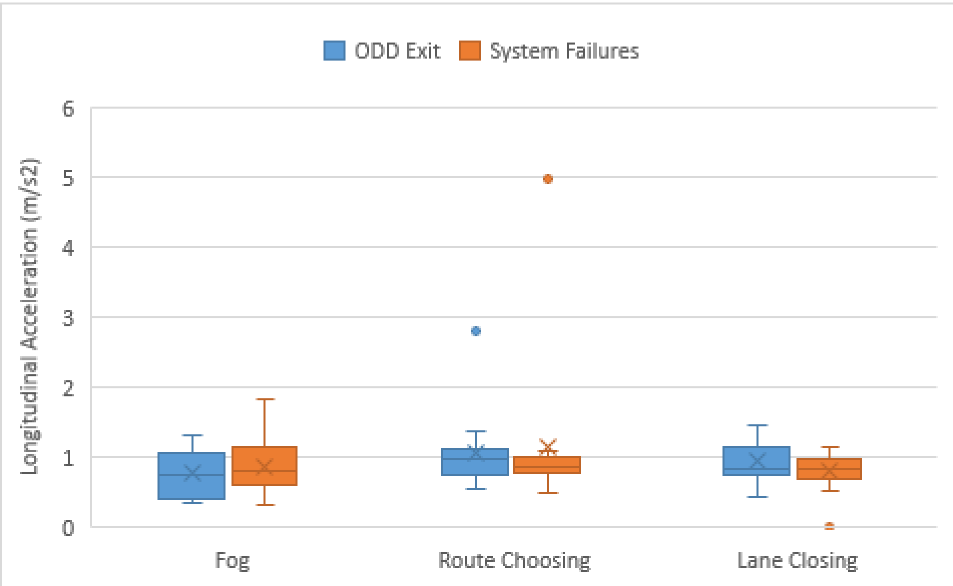


Fig. 2.6. Maximum longitudinal acceleration in system failure and ODD exit condition

2.4.4 Maximum Steering Wheel Angle

The result of a two-way mixed ANOVA was reported in **Table 2.4**. It showed significant main effect of the type of limitations on the maximum steering wheel angle. The main effect of scenarios on this metric was also significant. Post hoc tests with the Bonferroni corrected method revealed that the route choosing scenario had much higher maximum steering wheel angle than the fog scenario and lane closing scenario ($p<.001$). Besides, the lane closing scenario had higher maximum steering wheel angle than the fog scenario ($p=.022$). No significant interaction effect of these two factors was shown. The data were also illustrated in **Fig. 2.7**.

Table 2.4. Result of Two-way Mixed ANOVA for Maximum Steering Wheel Angle

Factors	**df**	**F**	η^2	**p**
Scenarios	2	41.584	.589	<.001**
Limitations	1	7.899	.214	.009*
Interaction	2	1.119	.037	.334

**p<.001 *p<.05

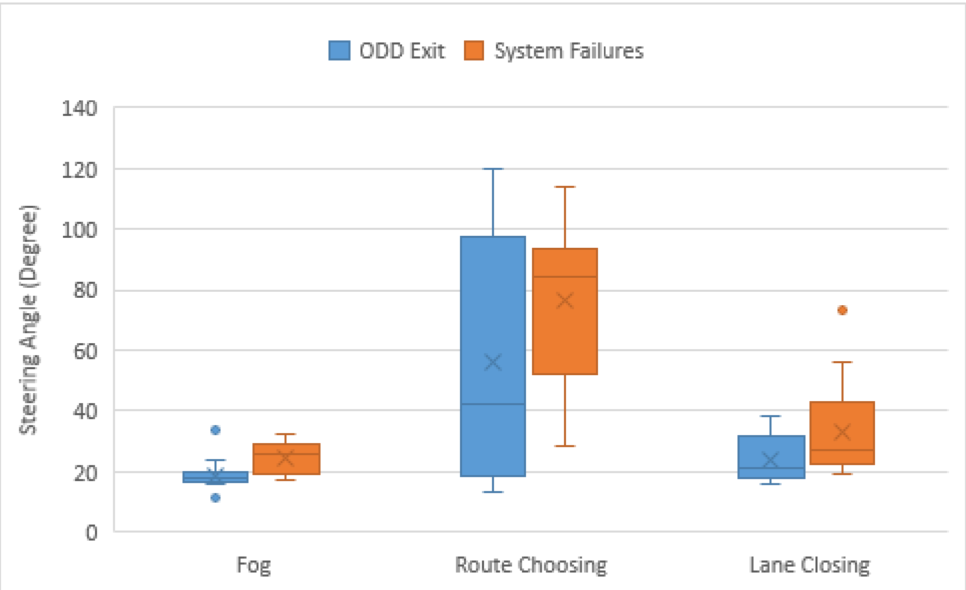


Fig. 2.7. Maximum steering wheel angle in system failure and ODD exit condition

2.4.5 Maximum Lateral Acceleration

The result in **Table 2.5** revealed significant main effect of the type of limitations on the maximum lateral acceleration. The main effect of the three scenarios was highly significant. Post hoc tests with Bonferroni adjustment revealed that the route choosing scenario had much higher maximum lateral acceleration than the fog scenario and lane closing scenario (post hoc: all p values <.001). However, it showed no significant difference between the fog scenario and lane closing scenario (p=.072). The result comparison between system failure and ODD exit conditions was also shown in **Fig. 2.8**.

Table 2.5. Result of Two-way Mixed ANOVA for Maximum Lateral Acceleration

Factors	**df**	**F**	**η^2**	**p**
Scenarios	2	36.452	.557	<.001**
Limitations	1	4.383	.131	.045*
Interaction	2	1.063	.035	.352

**P<.001 *p<.05

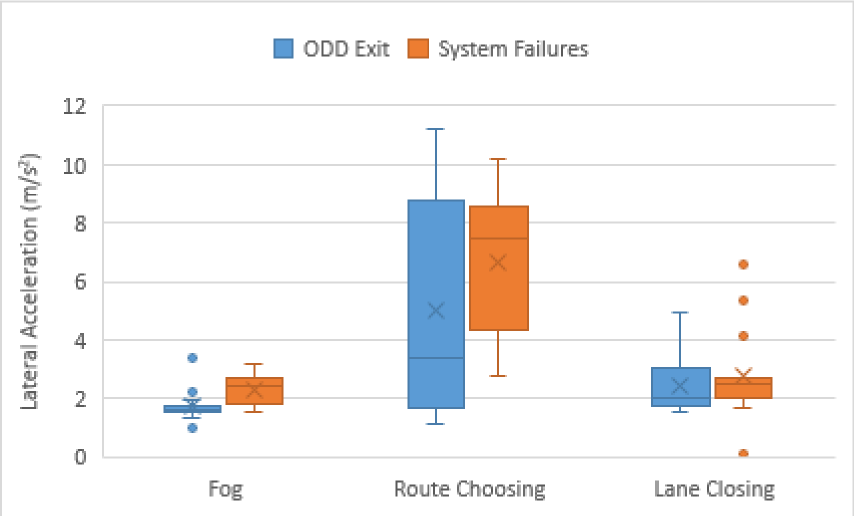


Fig. 2.8. Maximum lateral acceleration in system failure and ODD exit condition

2.5 Discussions

Based on the results of driving behavior, the difference of takeover performance in system failure and ODD exit conditions was analyzed. In this section, we mainly discussed how the experimental result support the hypotheses. We discussed the maximum driver brake input and maximum longitudinal acceleration together as these two metrics belonged to longitudinal takeover performance. Similarly, we discussed the maximum steering wheel angle and maximum lateral acceleration together as they belonged to lateral takeover performance.

2.5.1 Reaction Time

In the system failure situation, we observed participants performed significantly faster than the ODD exit situation. It appeared in **Table 2.1** and **Fig. 2.4**. This result supported our first hypothesis (drivers respond faster in the sudden system failure situation). However, we could not say that all the drivers responded faster in the system failure situation, as the slowest participant in system failure situation responded slower than the fastest one in the ODD exit situation (see **Fig. 2.4**). Generally, we can further claim that drivers are inclined to resume control faster as they have less satisfaction on the system in the system failure situation. The satisfaction represents the expected utility in decision making. Thereby, the faster response also demonstrated the driver's lower expected utility in the system failure situation. It supported our expected utility analysis ($U_{\text{-}ODD\text{-}exit} > U_{\text{-}system\text{-}failure}$). The assumption ($b^* > a\ (a^*) > b$) was also proved to be reasonable. Besides, the time budget of system failure situation was much shorter than that of ODD exit situation based on the definition of system failure and ODD exit situation. Radlmayr & Bengler [36] claimed that longer time budget usually led to longer takeover time. Hence, the participants in system failure situation responded much faster. Nevertheless, the ANOVA presented no significant effect of scenario on the reaction time. Radlmayr et al. [45] suggested that the complexity of takeover situation and the NDRT were two critical factors that influenced the reaction time significantly. Thereby, one possible explanation is that the complexity of the three scenarios in this experiment is generally the same.

2.5.2 Longitudinal Takeover Performance

The analysis of maximum driver brake input and maximum longitudinal acceleration suggested no significant difference between the system failure and ODD exit situations. It further indicated that the drivers did not take worse longitudinal takeover performance significantly in the system failure condition. Hence, the second hypothesis (drivers take smoother actions in the ODD exit situation) was not supported by the longitudinal takeover performance significantly. It was also hard to say that the expected utility in the ODD exit situation was higher than that in the system failure situation. Thereby, the mathematical relationship ($U_{\text{-}ODD\text{-}exit} > U_{\text{-}system\text{-}failure}$), as well as the assumption ($b^{*} > a\ (a^{*}) > b$), was not supported by the experimental results of longitudinal takeover performance.

However, **Figs. 2.5**, **2.6** revealed drivers' slightly less brake input and longitudinal acceleration in the system failure situation of lane closing scenario. It further indicated that drivers were slightly inclined to take smoother longitudinal actions in the system failure situation of lane closing scenario, which was beyond our expectation. This result might be explained by the driver maneuver preference, on which Drivers preferred to firstly hold the steering wheel to stabilize the vehicle in the lane. Furthermore, Blommer et al. [69] claimed that drivers usually tended to use evasive steering rather than braking to avoid forward collision in manual control in a lane closing scenario. Hence, the longitudinal metrics were not sensitive to reflex the difference of the takeover performance in the two types of limitations.

2.5.3 Lateral Takeover Performance

For the lateral takeover performance, there were significant difference between the two types of limitations, as well as the varying scenarios. No factor interaction was revealed from the results. **Figs. 2.7, 2.8** suggested these results graphically. These two figures indicated that the drivers performed smoother lateral takeover performance in the ODD exit situation of all the scenarios, which supported our second hypothesis (i.e., drivers perform smoothly in the ODD exit situation). Namely, $U_{\text{-}ODD\text{-}exit} > U_{\text{-}system\text{-}failure}$. The assumption ($b^* > a\ (a^*) > b$) was also reasonable. The drivers had higher expected utility, which led to higher satisfaction on the system in the ODD exit situation. They would not maneuver too much or take actions excessively as they are more satisfied with the system in the ODD exit situation. Moreover, it was quite difficult for drivers to acquire enough situation awareness before resuming control in the system failure situation as the shorter time budget. Situation awareness contributes to the perception of elements, the comprehension of meaning, and the prediction of the status in the environment [70]. Thereby, the drivers could not take exact maneuver as the situation awareness was too limited. In the varying scenarios, the curve and lateral gradient of roads were quite different. Hence, the effect of scenario on lateral driving performance was significant. There were three different scenarios in the current study. Post hoc tests had to be conducted to exactly check the differences between any two scenarios. For the lateral acceleration, Post hoc tests showed no significant difference between the fog scenario and lane closing scenario ($p=.072$). The p value was not low. It could be illustrated by the relatively small sample size of the experiment.

2.5.4 Limitations

In the current study, all the driving scenarios were designed with the same driving speed (80 km/h). Nevertheless, the driving speed is always changing during driving in the real world. Additionally, there were no other vehicles around the ego-vehicle during the control transition from system to human in this experiment. This design is a bit far from the real world in which the traffic environment is usually complicated. The driver might perform a little worse in the real world than that in the driving experiment. Furthermore, all the participants of this experiment are youngers. How aged driver takeover worsen in a sudden system failure of conditionally automated driving is still not clear.

2.5.5 Conclusion

The present investigation offered insights into the issue: how does driver takeover worsen in a sudden system failure of conditionally automated driving. The experimental results revealed drivers' faster reaction to the RTI under the system failure condition, which supported the first hypothesis. For the second hypothesis, there were no significant difference of longitudinal takeover performance between the two types of limitations. However, drivers generally performed smoother lateral takeover performance in the ODD exit situation. This would contribute to the conditionally automated driving system design with considering the characteristics of takeover performance in the two types of limitations (sudden system failure and ODD exit). Moreover, drivers are able to get a better understanding of the system limitations, which can be expected to improve driver takeover performance.

Chapter 3. Effects of a Safety Compensation on Driver Takeover Performance in Conditionally Automated Driving

3.1 Introduction

In conditionally automated driving, the necessity of proving drivers a safety compensation has been specifically introduced in **section 1.2.4**. Safety compensation has been discussed in many previous studies, there are several approaches to realize safety compensation (see **section 1.2.4**). In this chapter, we implement the safety compensation through a system automatic deceleration which can prolong the time budget for drivers to respond. Gold et al. [53] and Inagaki et al. [55] have proposed the system automatic deceleration as a safety compensation previously. However, how does this approach affect the driver takeover performance is still unclear.

As described in **section 1.3**, the objective of this investigation is to explore the effect of safety compensation on driver takeover performance in varying scenarios. Here, we put forward the following two hypotheses:

H1: the safety compensation might be a trigger that stimulate the driver to respond to the RTI more quickly.

H2: the safety compensation would be generally effective to improve the takeover quality, but the influence might be different in various scenarios.

3.2 Methodology

In the current study, totally 16 participants were recruited to conduct a driving simulation experiment by using a driving simulator (**Fig. 3.1**) which located in Laboratory for cognitive systems science, University of Tsukuba. This experiment was carried out under the approvement of the ethics committee of University of Tsukuba.

3.2.1 Participants

In this study, totally 16 participants were recruited through a professional human resource company. The participants consist of 8 males and 8 females who held a valid driver's license in Japan. Their ages range from 21 to 34 years old (M= 25.1 years, SD= 4.2 years).

3.2.2 Apparatus

A Mitsubishi Driving Simulator (**Fig. 3.1**) that consisting of a simple driving cab and a visual display system was utilized to conduct the experiment. The cab, including a Moog Control Loading System, provided participants with a realistic haptic feeling for the driving simulation. Both the steering wheel and pedals use motors and pneumatics simulation to give realistic feedback to the participants. A 180-degree visual field which composed of 5 flat screens is located around the driving cab. In this experiment, the D3SIM software supplied by MITSUBISHI PRECISION CO.LTD was provided to develop scenarios. The software recorded the data at 120 Hz.

Fig. 3.1. The driving simulator

3.2.3 Experimental Design

According to the prior works, road works, freeway exit ramps and fogs were complicated driving situations in which an RTI would be issued [40][64][65]. These three scenarios exceeded the ODD as the system limited to conduct the lane change maneuver, still not permitted on secondary way, and become inefficient in fog. In this experiment, three takeover scenarios (i.e., fog, route choosing and lane closing) were designed (see **Fig. 3.2**).

Fog Route choosing Lane closing

Fig. 3.2. The takeover scenarios

The two factors (SC approach and scenario) were designed as within-subjects in this experiment. *Note here, SC is the abbreviate of safety compensation and will used in the following context.* The within-subjects design requires fewer participants and minimizes the random noise. Accordingly, one participant had to experience six driving trials (three trials with SC and the other three trials without SC). The six driving trials were counterbalanced to counteract order effects.

The experimental trials lasted for different duration (fog 230s, route choosing 50s, lane closing 160) starting with the automated driving, during which participants were engaged in NDRT. The different duration of trials was aimed at eliminating participants' prediction for the RTI. An RTI was presented at the end of each trial. For all the automated driving conditions, the speed was 80 km/h. It was found that a time budget of 7 s is appropriate for taking over control according to previous research [40][53]. Therefore, the time budget from

TOR issuing to a critical event was designed as 7 s in the current study. A brake stroke was taken automatically as a safety compensation when an RTI issued during the SC driving trial. The acceleration derived from the brake stroke was designed as -1.11m/s^2 when the SC executed.

3.2.4 Non-driving Related Task (NDRT) and Human-machine Interface (HMI)

In the current study, each experimental trial started with automated driving mode. Participants were asked to play Tetris as NDRT from the beginning of trials. An iPad used for Tetris task was mounted on the right side of the steering wheel (see **Fig. 3.1**). When RTI was issued, participants should stop playing Tetris and engage into driving task. Participants could acquire the RTI messages auditorily (a beep). The icon changes from green to amber when the automation is disengaged (see **Fig. 2.3**).

3.2.5 Procedure

The participants were initially instructed with the overall motivation of current study, the schedule and the general points (e.g., the whole driving experience would be recorded by video) that should be known previously. Then they signed an experimental consent sheet and video utilization permission sheet. Afterwards, they were asked to fill out a demographic questionnaire on their age and driving experience.

After that, the participants were given a manual driving practice, during which detailed explanations were provided on how to use the simulator manually. Besides, the participants were provided instructions on driver’s general maneuver, automation dis/engage, HMI (human machine interface) and Tetris in conditionally automated driving. At last, maneuver practice for intervention (i.e., resume by braking, resume by steering, when the TOR issues) was conducted several times to make sure the participants can take actions completely on their decision without maneuver mistakes. The main experiment initiated with the baseline group session after confirming that the participants understood the automated driving system enough. The participants were permitted to have a 10-minutes break after the prior three experimental sessions. The whole experiment took around 90 minutes.

3.2.6 Dependent Variables

A couple of measures were administered to evaluate the takeover performance in this investigation.

● Takeover time: the time interval measured between the moment that the TOR was issued and the moment that the drivers resumed control. This metric was applied to evaluate how quickly the participants responded to the RTI. The takeover time would be smaller if the first hypothesis is reasonable.

● Maximum steering wheel angle: a metric that used to show the lateral takeover performance after the transition from system to manual control. A greater maximum steering wheel angle can be observed when SC is provided if the second hypothesis is rational.

● Maximum lateral acceleration: another metric utilized to assess the lateral driving performance after driver takeover. A greater maximum lateral acceleration will also be observed when SC is provided based on the second hypothesis.

● Maximum driver brake input: a metric that indicated by the brake pedal position (%) implemented by the driver. According to the second hypothesis, less driver brake input would be expected if SC is implemented.

● Time to event (TTE): the time remaining for the ego vehicle getting imminent to the critical event point at an assumed constant speed. This metric is used to evaluate the longitudinal driving performance after the transition from automated system to human. A greater TTE indicates a safer takeover behavior. Thus, drivers will perform a greater TTE when SC is conducted if the second hypothesis is reasonable.

3.3 Results

A two-way repeated measures ANOVA was carried out to explore the influence of safety compensation on takeover performance as there were two within-subject factors in the experiment.

3.3.1 Takeover Time

A two-way repeated measures ANOVA revealed neither significant main effect of SC, nor takeover scenario on the takeover time, and no significant effect of interaction (See **Table 3.1**). Therefore, it was concluded that the takeover time was not influenced significantly by the SC approach in all the three scenarios. The graphical results were shown in **Fig. 3.3**. We could see from this figure that the average takeover time of SC situation was slightly lower than that of without SC situation in fog scenario and route choosing scenario.

Additionally, the cumulative frequency curves revealed the characteristics of takeover time in different scenarios (see **Fig. 3.4**). It showed a lightly slower takeover for the route choosing scenario as its curve was less steep than that in the two other scenarios. This result was also available in **Fig. 3.3**. According to the figure, participants could response a slightly faster in the fog scenario with SC, but the effect was not significant. Besides, the maximum takeover time was generally shorter in the lane closing scenario than that in the two other scenarios.

Table 3.1. Report of Two-way Repeated Measures ANOVA for Takeover Time

Factors	F	**df**	**Partial η^2**	**p**
SC	.001	1, 15	<.001	.981
Scenario	2.431	2, 30	.139	.118
SC × Scenario	.208	2, 30	.014	.785

*p<.05

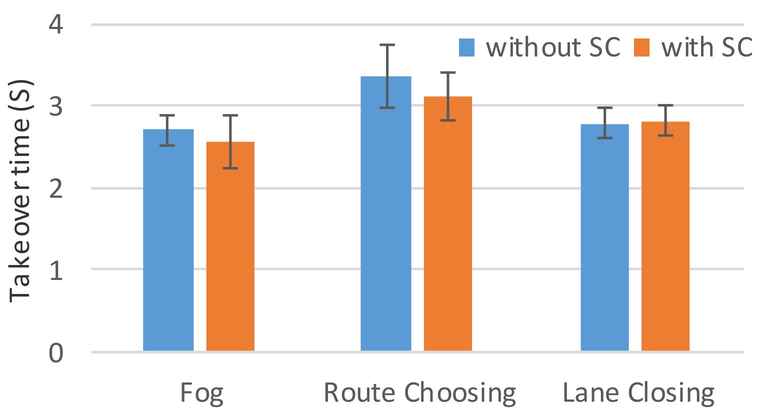


Fig. 3.3. The takeover scenarios

3.3.2 Maximum Driver Brake Input

A two-way repeated measures ANOVA was administered to analyze the data of maximum driver brake input (see **Table 3.2**). The report from **Table 3.2** revealed a significant main effect of SC on the maximum driver brake input ($p = .012$), but no main effect of scenarios ($p = .192$) or an effect of interaction ($p = .369$). **Fig. 3.5** showed these results graphically. Thus, drivers took less braking action in the "with SC" condition compared with the "without SC" condition, regardless of the different scenarios during conditionally automated driving.

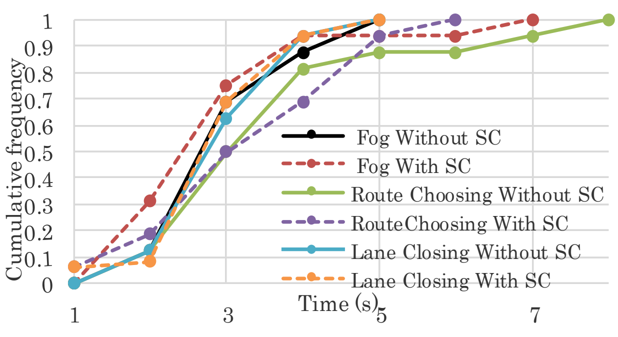


Fig. 3.4. Cumulative frequency of takeover time in different scenarios

Table 3.2. Report of Two-way Repeated Measures ANOVA for Maximum Driver Brake

Factors	F	df	Partial η^2	p
SC	8.116	1, 15	.351	.012*
Scenario	1.769	2, 30	.105	.192
SC × Scenario	.996	2, 30	.062	.369

*p<.05

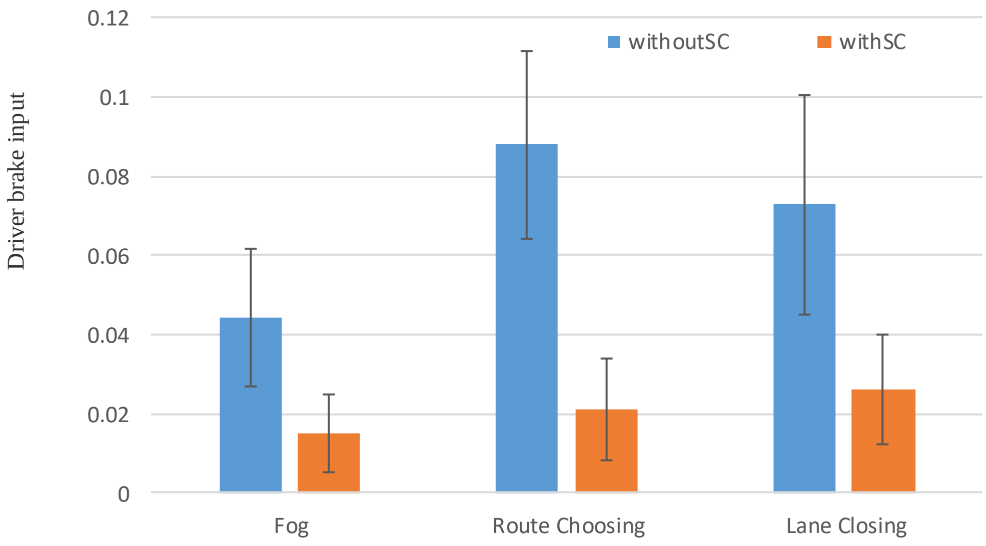


Fig. 3.5. Maximum driver brake input after takeover

3.3.3 Time to Event (TTE)

Similarly, a two-way repeated measures ANOVA was conducted to analyze the data of TTE (see **Table 3.3**). The report from **Table 3.3** revealed a significant main effect of SC on the TTE ($p < .001$), but no effect of scenarios ($p = .186$) or an effect of interaction ($p = .855$). These results were shown graphically in **Fig. 3.6**. Hereby, the SC can provide the drivers with a safer TTE during the transition, regardless of the various scenarios in conditionally automated driving.

In this study, the TTE is a new definition with the same principle of TTC (i.e., time to collision). As we know, the TTC is used as an efficient variable to evaluate the safety of the ego- vehicle's collision with the obstacle or other vehicles. However, there are no collisions in the fog scenario and route choosing scenario, which means the TTC versus the TTE is not an appropriate term in current investigation.

Table 3.3. Report of Two-way Repeated Measures ANOVA for TTE

Factors	**F**	**df**	**Partial η^2**	**p**
SC	55.837	1, 14	.800	<.001**
Scenario	1.870	2, 28	.118	.186
SC × Scenario	.084	2, 28	.006	.855

**p<.001

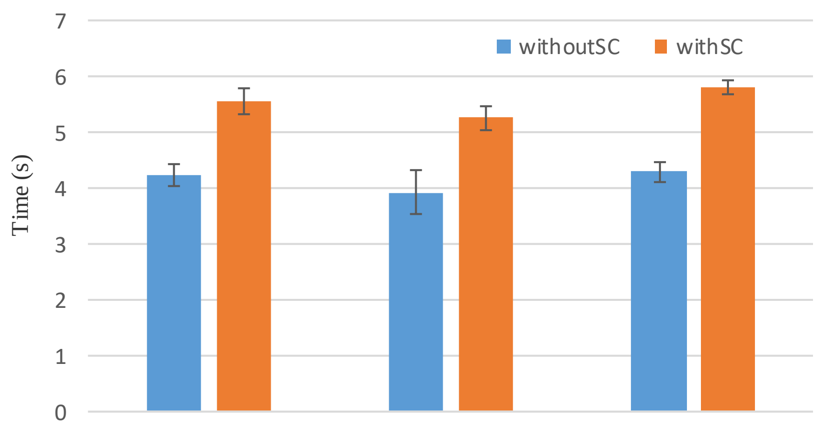


Fig. 3.6. Time to event at the takeover time point

3.3.4 Maximum Steering Wheel Angle

We investigated the effect of SC on the maximum steering wheel angle. The result revealed no effect of SC or any effect of interaction on the maximum steering wheel angle, but significant main effect of scenarios (see **Table 3.4**). The graphical results were shown in **Fig. 3.7**. Thus, the participants' steering behavior was influenced by the scenarios significantly, but not influenced by the SC. The significant effect of scenarios on the maximum steering wheel angle is reasonable as the drivers had to conduct the steering maneuver depending on the route curves which were designed quite different in different scenarios.

Table 3.4. Report of Two-way Repeated Measures ANOVA for Maximum Steering Wheel Angle

Factors	**F**	**df**	**Partial η^2**	**p**
SC	.299	1, 15	.020	.592
Scenario	19.150	2, 30	.561	<.001**
SC × Scenario	.145	2, 30	.010	.269

**p<.001

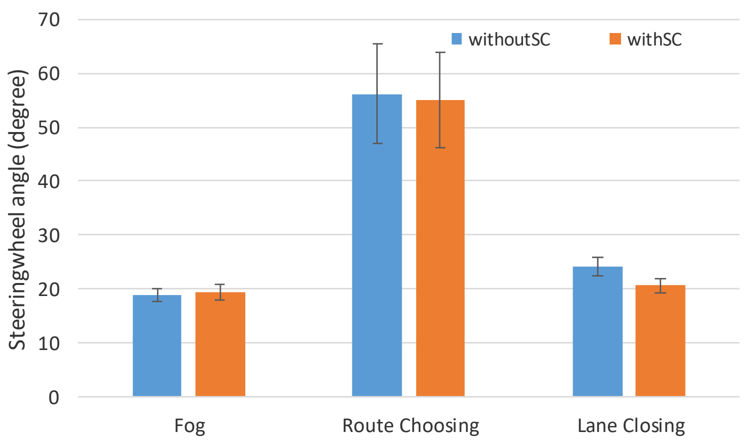


Fig. 3.7. Maximum steering wheel angle after takeover

3.3.5 Maximum Lateral Acceleration

Firstly, we conducted a two-way repeated measures ANOVA for the lateral acceleration, found that a significant main effect of scenarios ($p<.001$) on the maximum lateral acceleration and significant effect of interaction ($p=.035$) between the two factors, but no significant effect of SC ($p=.206$) (see **Table 3.5**). Therefore, we had to further explore the effect of SC by carrying out a Paired-Samples T Test.

The Paired-Samples T Test showed a significant main effect of SC approach on lateral acceleration in the lane closing scenario, but no significant effect in the two other scenarios (see **Table 3.6**). **Fig. 3.8** showed these results graphically.

Table 3.5. Report of Two-way Repeated Measures ANOVA for the Lateral Acceleration Among Various Scenarios

Factors	F	df	Partial η^2	p
SC	1.747	1, 15	.104	.206
Scenario	14.091	2, 30	.668	<.001**
SC × Scenario	4.305	2, 30	.381	.035*

**p<.001

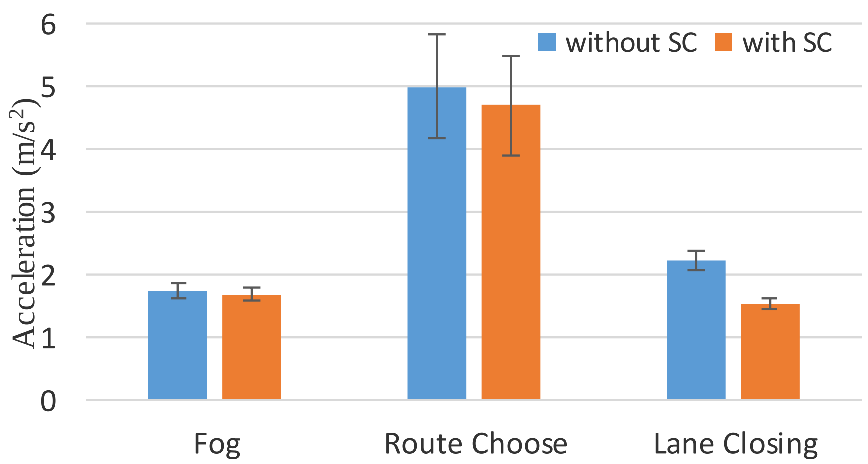


Fig. 3.8. Maximum lateral acceleration after takeover

Table3.6. Report of Paired Samples T Test for the Lateral Acceleration Among Various Scenarios

		Mean	Std. Deviation	Std.Error Mean	95% CI Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	**Fog(withoutSC-withSC)**	.051	.356	.089	-.138	.241	.577	15	.573
Pair 2	**Route choosing(withoutSC-withSC)**	.311	3.390	.847	-1.495	2.117	.367	15	.791
Pair 3	**Lane closing (withoutSC-withSC)**	.694	.726	.181	.307	1.081	3.823	15	.002*

*p<.05

3.4 Discussions

In the current study, the main objective was to examine the influence of safety compensation on driver takeover performance in different scenarios in conditionally automated driving on a highway. The takeover performance includes the takeover time, longitudinal driving performance and lateral driving performance. The experimental results with respect to the influence of the SC approach indicated no significant difference on the takeover time. In addition, no significant difference was found on the takeover time among different scenarios although the emergency of the events was quite different. Some participants reported that they instinctively put their hands on the steering wheel or their feet on the brake pedal when the TOR issued. It means that the drivers may take actions even without enough situation awareness during the transition in conditionally automated driving. This can help to explain some outliers of the data.

Furthermore, the two hypotheses can be discussed based on the results. The results were found to be not in line with the first hypothesis due to many participants claimed that they did not feel the action of brake pedal when TOR issued. However, the effects of SC on longitudinal driving performance were significant and equal in different takeover scenarios. Although both the steering behavior and the lateral acceleration can be mainly influenced by the route curves, a significant effect on the lateral acceleration was revealed in the lane closing scenario. The high emergency of the lane closing scenarios may help to explain this phenomenon. Accordingly, the second hypothesis was found to be in line with the results.

However, the effect of SC on longitudinal acceleration of vehicle cannot be discussed in this research as both the drivers' longitudinal action and the SC stroke can contribute to the longitudinal acceleration of vehicle. Effects of these two factors on the longitudinal acceleration were integrated. Hence, we cannot use the longitudinal acceleration to evaluate the effect of the SC on drivers' takeover performance in the current study.

3.5 Conclusions

A crucial finding of current investigation is that driver takeover performance revealed no significant difference of SC on takeover times, but significant difference on longitudinal driving performance in all the three scenarios. Furthermore, SC was proved to benefit the lateral acceleration in the lane closing scenario.

This study also has a limitation as the SC action is not able to provide participants with feeling interface of speed deceleration. It would mitigate the positive influence of SC on driver takeover performance.

Chapter 4. Effects of Behavior Training on Driver Takeover Performance in Conditionally Automated Driving

4.1 Introduction

The **chapter 1** has explained clearly that drivers need to take over control of the vehicle in conditionally automated driving when the system encounters situations that it cannot deal with. Moreover, it is a challenge for drivers to achieve good takeover performance, as well as driving safety after intervention. In **section 1.2.5**, the significance of prior training has been highlighted. A couple of previous studies mainly focused on the training of basic manual knowledge in conditionally automated driving, but rare research related to takeover behavior training. Without takeover behavior training, drivers may be unaware of the system limitations and surrounding environment in their mental model, and subsequently fail to behave or act appropriately. Hence, appropriate takeover behavior training process should be developed in conditionally automated driving. Moreover, the spacing of training (i.e., distributed or massed training) usually affects performance of training and retention [71]. Therefore, we should also examine which space of training benefits more for the takeover skill acquisition and retention. The conclusion can be used for arranging the schedule of training courses in driving schools or car dealerships.

The research objective of this chapter has been proposed abstractly in **section 1.3**. The specific contents of the objective: 1) to develop a driver behavior training approach which is expected to benefit the driver takeover behavior and improve the takeover performance; 2) to validate whether the proposed training procedure is effective or not by a driving simulator experiment; 3) to reveal how the space of training affects the takeover skill acquisition; 4) to examine how the space of training affects the takeover skill retention. Furthermore, we put forward the following hypotheses:

H1: the behavior training can significantly improve the takeover performance.

H2: the distributed training will benefit takeover performance more than the massed training or vice versa.

H3: the behavior training can help drivers to maintain the takeover performance in one week.

H4: the distributed training will benefit the retention of takeover performance more than the massed training or vice versa.

4.2 Methodology

This study was conducted under the approvement of the ethics committee of University of Tsukuba.

4.2.1 Apparatus

In this investigation, the behavior training, Pre- and Post-training assessments were carried out on a Mitsubishi driving simulator (see **Fig. 4.1**), located in Laboratory for Cognitive Systems Science, University of Tsukuba. This driving simulator has a static cabin with a realistic steering wheel, brake and accelerator pedals. The steering wheel and pedals can provide drivers with force feedback which produced by the Moog Control Loading System. The traffic scenarios are displayed on 5 monitors subtending an approximate 180-degree visual field. Realistic noises of road and engine are modelled through the simulator. The experimental data can be recorded by the system at the frequency of 120 Hz.

4.2.2 Participants

A total of 45 participants (31 Male + 14 Female) were recruited from the campus of University of Tsukuba for this investigation. Their ages ranged from 19 to 58 years old (M=29.07 years, SD=8.93 years). All the participants had a valid Japanese driving license.

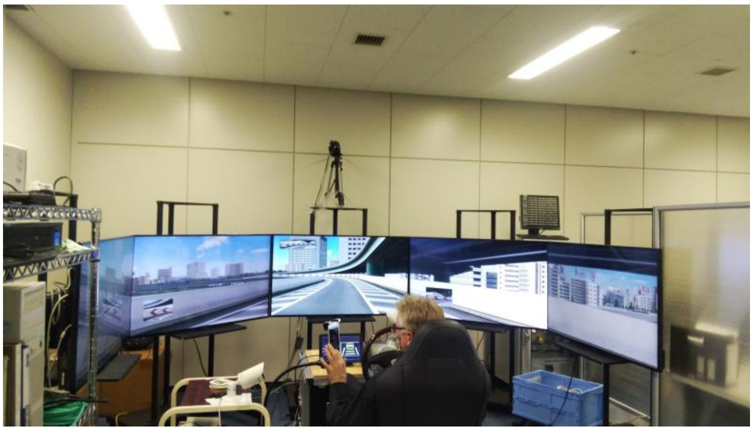


Fig. 4.1. The driving simulator

4.2.3 Takeover Behavior Training Process

Training has specific goals of improving one's capability, capacity, productivity and performance. In conditionally automated driving, drivers might resume control without enough situation awareness when they receive the RTI message. The careless of driver takeover behavior would lead to awful accidents when the traffic is complex or critical. We put forward a takeover behavior training process, aiming at improving driver takeover performance. There are totally three steps for the training process (see **Fig. 4.2**).

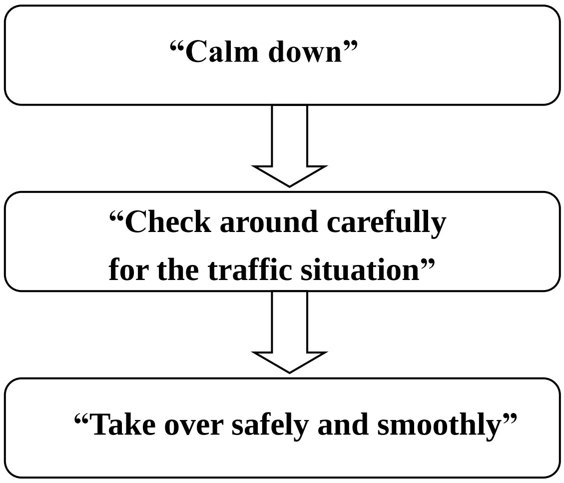


Fig. 4.2. Takeover behavior training process

4.2.4 Experimental Design

The participants were evenly divided into three groups (Massed training group, Distributed training group and Control group) as we planned to examine the effects of training and how the schedule of training affected the takeover performance. All the participants had to experience "assessment scenarios" for three times (Assessment I was conducted at the first day for testing the takeover performance before training, Assessment II was carried out at the fourth day for examining the takeover performance after training, Assessment III was implemented at the eleventh day for evaluating the retention of takeover performance after one week). The experimental framework was shown in **Fig. 4.3**. The participants of Training groups were provided with takeover behavior training for three times. Specifically, the participants of the Distributed training group obtained a training each day from the second day to the fourth day. However, the participants of the Massed training group got all the trainings together at the fourth day. The participants of the Control group did not acquire any training. We designed three takeover scenarios for the training (see **Fig. 4.4**) and another three takeover scenarios for the assessment (see **Fig. 4.5**). Hence, a 3×3×3 mixed-factor experiment was designed, with the between-factor (massed training & distributed training & control group), within-factor (timeline: pre-training & post-training & one-week-later retention), within-factor (scenario: road construction & car broken & front car cut in).

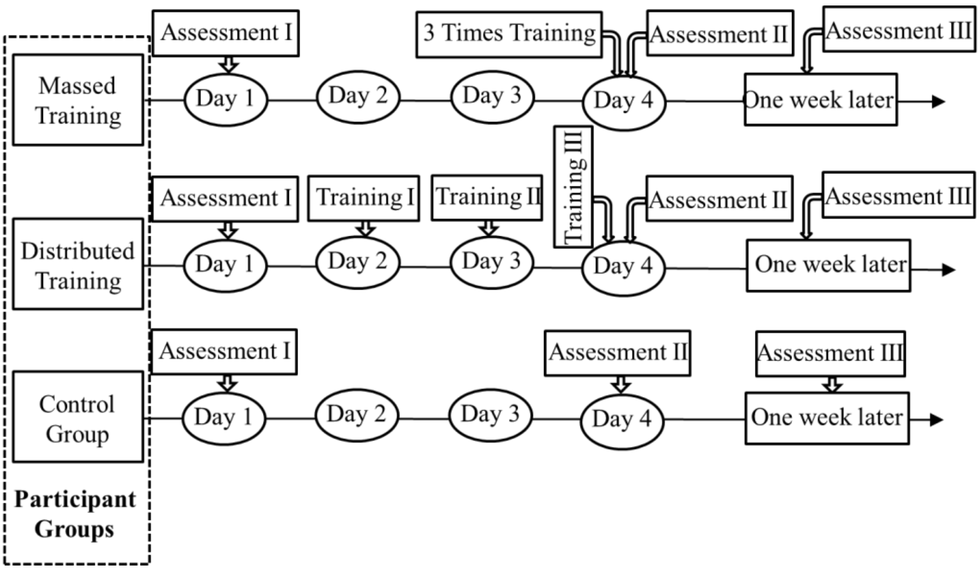


Fig. 4.3. Experimental framework

Lane merging (60km/h)

High traffic density (70km/h)

Broken car in front of the tunnel (80km/h)

Fig. 4.4. Training scenarios

Front car insert in tunnel (60km/h)

Car broken (70km/h)

Road construction(80km/h)

Fig. 4.5. Assessment scenarios

4.2.5 Non-driving Related Task (NDRT) and Human-machine Interface (HMI)

The experiment started from automated driving model, in which participants were engaged in playing Tetris as NDRT (see **Fig. 4.1**). Participants were instructed that they did not have to monitor the traffic environment during automated driving. Once RTI was issued, participants should get back into loop and take over control of the vehicle. A beep was emitted as an RTI message. The icon changes from green to amber when the automation is disengaged (see **Fig. 2.3**).

4.2.6 Procedure

Each participant was individually welcomed in the room where the driving simulator located. Firstly, all the participants were instructed to sign for the experimental agreement based on the experimental tasks, then complete the demographic survey and a questionnaire which measured their driving experience and frequency. Secondly, they were introduced the functions and limitations of conditionally automated driving system, the motivation of the current experiment and the specific tasks for the participants. Thirdly, a three-steps-practice was implemented for each participant of all the groups. (1) step one: the participant took part in a manual driving practice, which helped the drivers get familiar with the basic maneuver of the driving simulator; (2) step two: each participant experienced the conditionally automated driving and NDRT, during which the commentary explanations were conducted; (3) step three: all the participants were asked to experience the RTI and the resuming maneuver. The participants could require for further practice at any step. We confirmed that all the participants got familiar with the maneuver of conditionally automated driving completely. Last, each participant took part in the main experiment according to the experimental schedule (see **Fig. 4.3**). They all received rewards after the experiment.

4.2.7 Dependent Variables

In this research, a couple of dependent variables were measured to evaluate the effects of behavior training on driver takeover performance. The measurements will become better after training if **H1** is reasonable, the drivers from training groups can keep the measurements after one week if **H3** is rational. The varying of the measurements in distributed training group will be significantly different with that in massed training group if **H2** is reasonable. According to **H4** the retention of measurements after one week will also become significantly different between distributed training group and massed training group. All the measurements were extracted from the data recorded by the driving simulator.

- Takeover Time: the duration from the time point of RTI issuing to the time point of driver resuming control. It can be used to evaluate how fast drivers respond to the RTI.
- Standard Deviation of Lane Position (SDLP): It is a measurement of lateral takeover performance. A smaller SDLP suggests a better lateral takeover performance.
- Maximum Steering Wheel Angle (MSWA): MSWA is another metric to assess the lateral takeover performance. A higher value of MSWA indicates a worse lateral takeover performance in the same scenario.
- Standard Deviation of Speed (SDS): This metric can be used to reveal the fluctuation of speed after takeover. It has been used to evaluate the longitudinal takeover performance in prior studies [58]. The smaller the SDS is, the smoother the takeover performance is.

4.3 Results

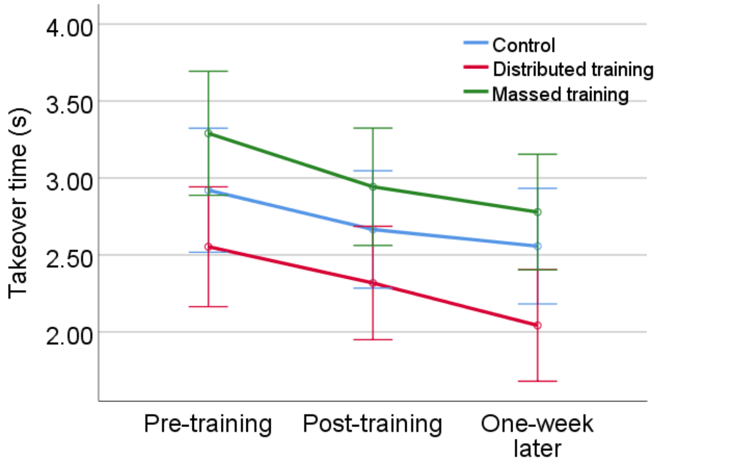
We administered a three-way mixed ANOVA (analysis of variance) to examine the effects of takeover training on the driver takeover performance as the mixed-subject experimental design. Driving data of two participants were missing (one from Control group, one from Massed training group), resulting in 43 participants' data were used for the analysis of takeover performance.

4.3.1 Takeover Time

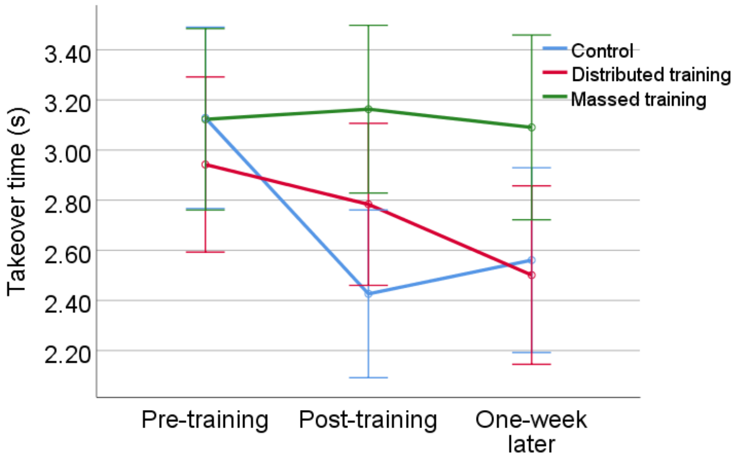
The three-way mixed ANOVA revealed no significant effect of training group, $F(2, 383) = 1.097$, $p=.344$; scenario, $F(2, 383) = 2.509$, $p=.121$; or time, $F(2, 383) = 3.558$, $p=.067$, on takeover time. None of the interaction effects were significant (see **Table 4.1**). **Fig. 4.6** depicted the data. It was shown in the figures that participants had a slight tendency to respond_faster as the repeated experience increase in all the three training groups. The participants from Control group and Massed training group in the "Broken car in front" scenario, could not maintain the acquired takeover skills well, which led to a bit slower takeover reaction after one week.

Table 4.1. Results of effect of training on takeover time

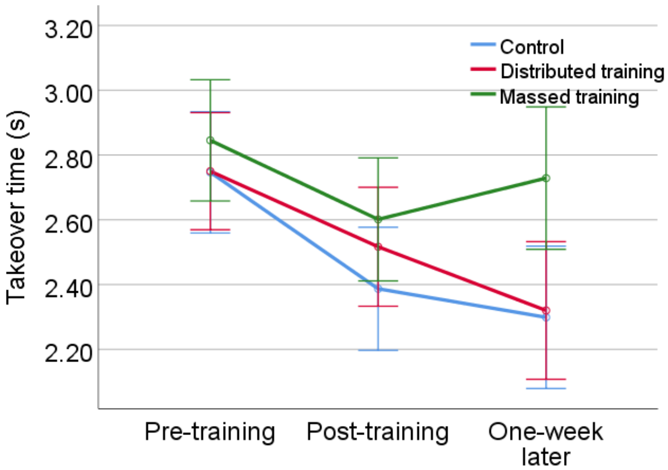
Factors	**df**	**F**	**η^2**	**p**
Group	2	1.097	.052	.344
Time	2	3.558	.082	.067
Scenario	2	2.509	.059	.121
Scenario*Group	4	.992	.047	.380
Time*Group	4	.283	.014	.755
Scenario*Time	4	.110	.003	.742
Scenario*Time*Group	8	.338	.017	.715



(a) Road construction



(b) Broken car in front



(c) Front car cut in

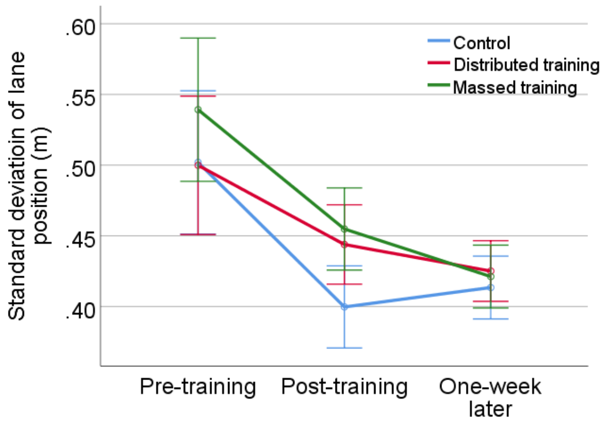
Fig. 4.6. Takeover time in varying scenarios *(error bar is standard error)*

4.3.2 Standard Deviation of Lane Position (SDLP)

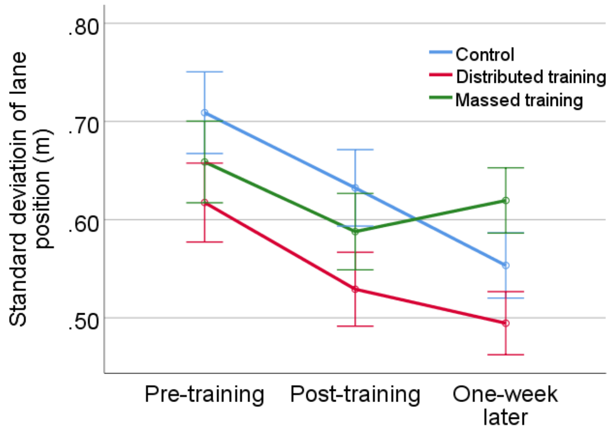
A three-way mixed ANOVA was administered for examining the effects of takeover behavior training on the Standard Deviation of Lane Position (SDLP). The results were shown in **Table 4.2** and **Fig. 4.7**. There were significant main effects of scenario $F(2, 383) = 50.203$, $p<.001$, and time $F(2, 383) = 25.583$, $p<.001$, on SDLP. No other significant effects were found. The pairwise comparisons suggested that there is significant difference between "Road construction" scenario and "Broken car in front" scenario ($p<.001$), between "broken car in front" scenario and "Front car cut in" scenario ($p<.001$), but no significant difference between "Road construction" scenario and "Front car cut in" scenario ($p=.502$). The pairwise comparisons also revealed that the effect of training on SDLP is significant ($p<.001$), the effect of one-week interval on SDLP is not significant ($p=.645$). Furthermore, the main effect of the space of training schedule on SDLP tended to significant ($p=.084$). **Fig. 4.7** (c) showed a tendency that the distributed training benefited more to reduce the SDLP, otherwise made the participants more difficult to keep the performance.

Table 4.2. Results of effect of training on Standard deviation of lane position

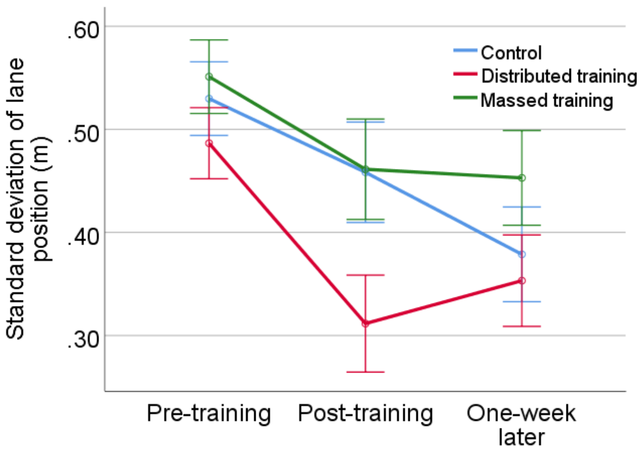
Factors	**df**	**F**	**η^2**	**p**
Group	2	2.633	.116	.084
Scenario	2	50.203	.557	<.001*
Time	2	25.583	.390	<.001*
Scenario*Group	4	2.142	.097	.131
Time*Group	4	.577	.028	.566
Scenario*Time	4	.302	.007	.586
Scenario*Time*Group	8	.571	.040	.440



(a) Road construction



(b) Broken car in front



(c) Front car cut in

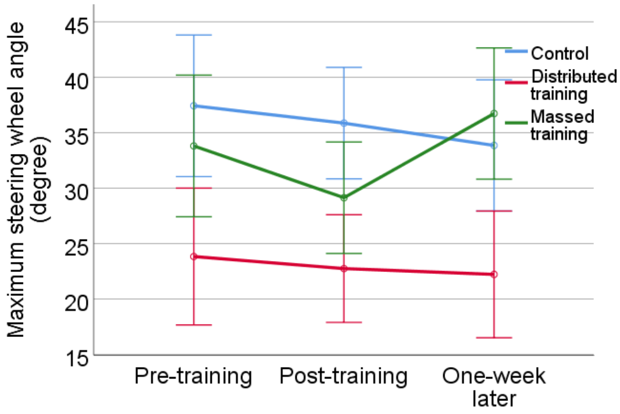
Fig. 4.7. Standard deviation of lane position in varying scenarios *(error bar is standard error)*

4.3.3 Maximum Steering Wheel Angle (MSWA)

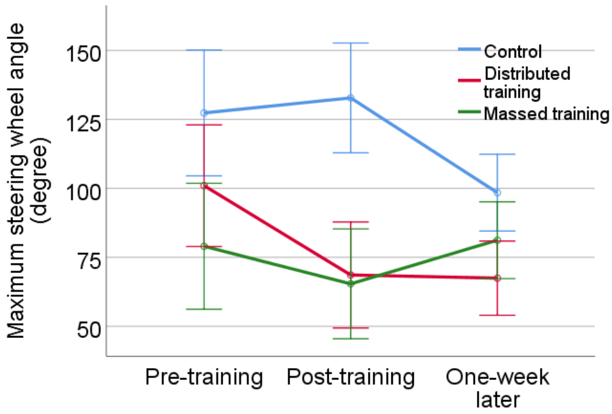
We carried out a three-way mixed ANOVA to investigate the effects of training on the maximum steering wheel angle (see the results in **Table 4.3** and **Fig. 4.8**). There were significant main effects of group $F(2, 383) = 4.715$, $p=.014$; scenario $F(2, 383) = 74.344$, $p<.001$; time $F(2, 383) = 3.766$, $p=.027$, and interaction effect of group and scenario, $p=.006$, on MSWA. No other significant effects were found. Furthermore, The Post Hoc Tests suggested that there was significant difference between control group and distributed training ($p=.019$), between control group and massed training ($p=.048$), no significant difference between distributed training and massed training ($p= .935$). Besides, the pairwise comparisons suggested that there was significant difference between “Road construction” scenario and “Broken car in front” scenario ($p<.001$), between “Broken car in front” scenario and “Front car cut in” scenario ($p<.001$), no significant difference between “Road construction” scenario and “Front car cut in” scenario ($p= .476$). Additionally, the pairwise comparisons also revealed that there is slight significant difference of MSWA between pre-training test and one-week test ($p=.086$), but no significant difference between pre-training test and post-training($p=.124$).

Table 4.3. Results of effect of training on Maximum steering wheel angle

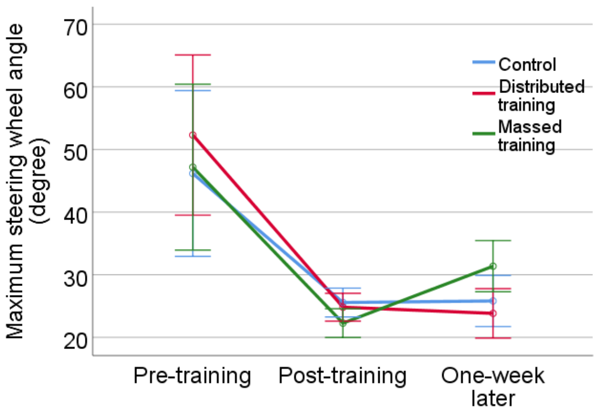
Factors	**df**	**F**	η^2	**p**
Group	2	4.715	.191	.014*
Scenario	2	74.344	.650	<.001**
Scenario*Group	4	3.952	.165	.006**
Time	2	3.766	.086	.027*
Time*Group	4	.892	.043	.473
Scenario*Time	4	.905	.022	.462
Scenario*Time*Group	8	.371	.018	.935



(a) Road construction



(b) Broken car in front



(c) Front car cut in

Fig. 4.8. Maximum steering wheel angle in varying scenarios *(error bar is standard error)*

4.3.4 Standard Deviation of Speed (SDS)

The three-way mixed ANOVA revealed that only the main effects for the training is significant $F(2, 383) = 3.956$, $p=.023$ (see **Table 4.4**). The pairwise comparisons suggested that there was significant difference between “Control group” and “Distributed training group” ($p=.030$), slight significant difference between “Control group” and “Massed training group” ($p=.055$), but no significant difference between “Distributed training group” and “Massed training group” ($p=.879$). **Fig. 4.9** indicated the results graphically. It showed that the participants performed higher SDS after training in “Broken car in front” scenario. Besides, only the participants in the “Distributed training group” performed higher SDS after training in “Road construction” scenario. The drivers tried to adjust the driving speed to realize a safe driving although the motivation led to unstable driving speed. The participants in the three groups could get a good retention of the takeover performance.

Table 4.4. Results of effect of training on SDS

Factors	**df**	**F**	**η^2**	**p**
Group	2	.318	.016	.730
Scenario	2	1.759	.042	.179
Scenario*Group	4	.596	.029	.667
Time	2	3.956	.090	.023*
Time*Group	4	.495	.024	.740
Scenario*Time	4	.989	.024	.415
Scenario*Time*Group	8	.861	.041	.551

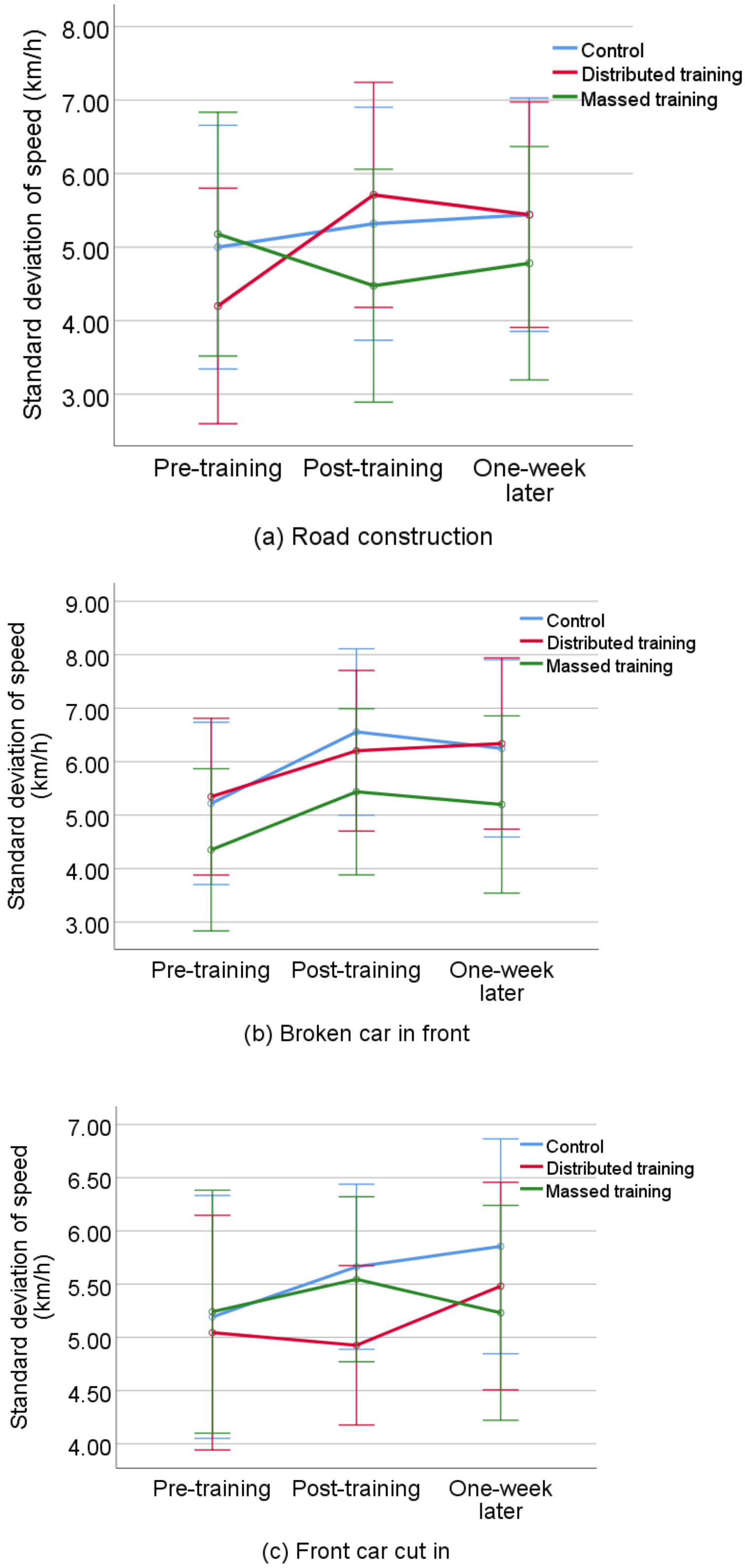


Fig. 4.9. Standard deviation of speed in varying scenarios *(error bar is standard error)*

4.4 Discussions

4.4.1 Takeover Time

The experiment revealed no significant effect of time on takeover time ($p=.067$). It means the developed behavior training process cannot make the driver to respond faster or slower to the RTI. Moreover, there is also no significance of the training group on takeover time. Hence, the space of training (massed training or distributed training) does not affect the takeover time. The prior studies which focused on driver training also revealed no significant effect of training on takeover time or reaction time [58][72]. The result of takeover time in the current study is in line with the previous studies. Actually, the reaction to RTI is somehow an instinct response. Therefore, the driver training cannot change the reaction time.

4.4.2 Takeover Quality

The standard deviation of lane position (SDLP) is a metric for assessing lateral takeover performance. The experimental results revealed great significance of time on the SDLP ($p<.001$). It means the SDLP between pre-training and post-training are significantly different. We can also check this conclusion from **Fig. 4.7**. However, the effect of training group on the SDLP is not significant ($p=.084$). It suggests that in the control group (without training), the SDLP in the second assessment is also better than that in the first assessment. This can be explained by the learning effect which derived from the driver's experience. The prior research [72] also indicated that the takeover performance of the drivers' second experience could be improved a lot. What's more, in the front car cut in scenario, the distributed training benefits more than the two other training schedule (see **Fig. 4.7**).

The maximum steering wheel angle (MSWA) is another measurement of lateral takeover performance. The experimental results revealed significant difference of time on the MSWA.

It means the drivers from the three groups (massed training, distributed training, control group) perform better during the second assessment. They can maintain this performance after one week. Furthermore, there is also significant difference of training group on the MSWA. It means the effects of the training groups on the MSWA are different. We can check this result from Fig. 4.8, the training group benefit MSWA much more than the control group in the broken car in front scenario. It proves that in this scenario, the driver behavior training is efficient to improve the MSWA. However, there is no difference between these two kinds of training (massed training and distributed training). The drivers can maintain the takeover performance of MSWA in one week.

The standard deviation of speed (SDS) is a metric to evaluate the longitudinal takeover performance. The results of ANOVA revealed significant difference of training on the SDS, but no significant difference of the groups on the SDS. Participants generally performed higher SDS when they experience the same scenario again, no matter they acquired the training or not. One possible explanation is that the participants become defensive when they experience the second trial, then decelerate frequently to achieve safe driving. The deceleration maneuver leads to a higher SDS. The results of ANOVA also revealed no significant varying of SDS after one week. It presented that the participants can also maintain the takeover performance of SDS in one week.

4.5 Conclusions

The proposed behavior training improved the maximum steering wheel angle significantly, improved the standard deviation of lane position slightly. It did not affect the other dependent variables significantly in the current study. The drivers can maintain the takeover performance after one week. It is difficult for the experimental results to reveal the effects of driver behavior training. It could be derived from the experimental design. Each participants experienced the same assessment scenarios for three times. Maybe the learning effect is too strong which has covered the training effect.

Chapter 5. Conclusions

5.1 Overall Findings

This dissertation explored improving the takeover performance from the three aspects: understanding system limitations, safety compensation and takeover behavior. Firstly, we found that the lateral takeover performance worsened significantly in the system failure situation compared with the ODD exit situation. This finding helps drivers understand system limitations, which can be expected to improve the takeover performance. Secondly, the safety compensation was observed to improve the longitudinal takeover performance significantly. Thirdly, the behavior training was proved to benefit the maximum steering wheel significantly and the standard deviation of lane position slightly. These findings are further explained in the following paragraphs.

The research focused on exploring the difference of takeover performance between the system failure situation and the ODD exit situation are significant. The experimental results make it clear that there are mainly difference of lateral takeover performance. The difference of longitudinal takeover performance is not significant. The system failure situation is characterized by extremely short time budget. Therefore, it is possible that short time budget usually worsens the lateral takeover performance. This would contribute to the conditionally automated driving system design with considering the characteristics of takeover performance in the two types of limitations. We should also mainly pay attention to the lateral takeover performance if the system failure occurs. The efforts for mitigating the negative influence of system failure should also focus on preventing the lateral injury and destroys. Drivers are also able to get a better understanding of the system limitations, which can benefit the takeover performance.

It is not a surprising result that the safety compensation which prolong the time budget mainly benefit the longitudinal takeover performance. It is quite easy for us to imagine that drivers can take less effort on the brake operation as the system have done it for us. The drivers can get a longer time-to-event if they do not take the accelerator. Furthermore, the safety compensation can improve the lateral acceleration in a lane closing scenario. One potential conclusion is that the safety compensation can benefit only the lateral acceleration in only the lane closing scenario. Another potential conclusion is that the with-in experimental design is too weak to show the effects of safety compensation completely.

The driver takeover behavior training has been highly expected to benefit the takeover performance. In the situation that the time budget is not far sufficient, the time budget is potential to be insufficient if the drivers are too engaged in the NDRT or the traffic situation is too complex. In this situation, drivers would become more difficult to get enough situation awareness. However, the experimental results only suggested the significant influence of training on the maximum steering wheel angle. The learning effect is too strong as the training factor was designed as a with-in effect. Otherwise, the effects of the driver takeover behavior training might benefit the takeover performance more.

5.2 Limitations

In the research of chapter 2 and chapter 3, the automated driving speed was designed as 80 km/h in all the scenarios. However, in the real word, the speed should be varying. Besides, there were no other cars around the ego-car when the RTI issued in the experiments. These designs made the traffic situations too simple, which was a bit far from the real word.

In the investigation of chapter 4, the test scenarios of pre-training and the test scenarios of post-training are the same. Therefore, it is inevitable for the participants to remember the test scenarios, which might mitigate or even cover the effects of behavior training. This limitation might prevent us to get reasonable conclusions.

In the study of chapter 2, chapter 3 and chapter 4, all the participants are young drivers. It is still not clear whether the conclusions are reasonable for the older drivers.

5.3 Future Work

In future work, a more complicated traffic environment (e.g., traffic density, weather) around the ego-vehicle during transition should be considered. This consideration makes the investigation closer to the real world. Older participants should also be recruited to conduct studies on driver takeover performance as older drivers are the potential users of the conditionally automated driving system.

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- Hua Yao, Suyang An, Huiping Zhou, and Makoto Itoh, "Driver Takeover Performance in Conditionally Automated Driving: Sudden System Failure Situation versus ODD Exit Situation" *[J], SICE Journal of Control, Measurement, and System Integration,* Vol.14, No.1, 2021. *(Peer-reviewed)*

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