

Takeover performance of Highly Automated Vehicles in Complex Traffic Scenarios

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Abstract:

This study aims to explore the impacts of physiological characteristics and driving behavior of drivers on the takeover speed and quality. One-way ANOVA was used to verify the difference of Correct Control Time and Mean Lateral Offset between different age and gender in complex traffic scenarios including Main-line, On-ramp, Fog-cluster and Accident driving scenarios. The adaptability of the Accelerator, the Wheel and the Brake to the drivers in different age groups was analyzed. The results showed the gender has slightly effect on takeover behavior, the stability of young drivers was significantly higher and takeover speed was faster than old drivers; the speed of takeover using the wheel was faster than other inputs for young drivers, the stability of using accelerator for middle aged drivers was highest while the performance of using the accelerator for old drivers was worse than the wheel and the brake. According the results of this study, the usage of the wheel was recommended for young drivers, the accelerator was recommended for the middle aged drivers and old drivers should avoid using the accelerator.

Keywords: takeover performance; automated vehicles; traffic scenarios; age group.

I. INTRODUCTION

The levels of automated vehicles, which ranged from 0 to 4, had been defined by The National Highway Traffic Safety Administration (NHTSA). The higher level represented the higher possibility to operate the automated vehicle without considering characteristics of the drivers. Level 2 had been already available and have been put into production by several car manufacturers, where the drivers to monitor the vehicles and the road environment for unexpected situations. While the Level 3 allowed the drivers to engage in non-driving activities, the control of the vehicle had to be takeover by the driver unless the automation system malfunctioned or reached its functional limits. How drivers behave after takeover and what factors determine takeover behavior are essential for both scientific researchers and automobile manufacturers.

Abundant studies have analyzed the driving behavior after takeover, including takeover time, minimum time to collision, maximum lateral, maximum longitudinal acceleration and etc [1-4]. Körber (2016) proposed that older drivers reacted as fast as younger drivers, however, they differed in their modus

operandi as they braked more often and more strongly and maintained a higher time-to-collision [5]. Zhang (2019) summarized that alae, not performing a visual non-driving task, having experienced another takeover scenario before in the experiment, and receiving an auditory takeover request as compared to a visual-only or no takeover request, where the mean and standard deviation of the take-over time were highly correlated, indicating that the mean is predictive of variability [6]. On the aspect of the factors that influence the takeover behavior, age, driving task, traffic density, weather and timing threshold were analyzed by the researchers [7-8]. The presence of traffic in takeover situations led to longer takeover times and worse takeover quality in the form of shorter time to collision and more collisions [9-11]. Kim (2017) indicated that the reaction times were significantly different between events, which implies that no single TOR timing is suitable for all TOR situations [12]. The drivers would achieve faster takeovers and demonstrated better takeover performance if given directional rather than non-directional information [13]. A safety compensation in which the system conducts automatic deceleration to prolong the time budget for drivers to response had a significant effect on the longitudinal driving performance [14].

The current studies mainly focused on the influence of takeover time on automated vehicle monitor behavior, where few studies discussed the input application of the drivers after takeover. At the same time, the influence factors were analyzed separately instead of considering the complex driving scenarios. In order to fill these important research gaps, this study specially designed four driving scenario, including Main-line, On-ramp, Fog-cluster and Accident driving scenarios. Correct control time (CCT) and mean lateral offset (MLO) were recorded and collected to examine the relationship between the takeover performance, age and the driving scenarios.

II. MATERIALS AND METHODS

2.1 Data source

2.1.1 Participants

Totally 42 participants took part in this experiment, including 10 females and 32 males. The participants were recruited from three different group by age, the young group ($n = 15$, the mean age was 25.4 years old) ranges from 18 to 30 years, the middle group ($n = 14$, the mean age was 43.3 years old) ranges from 30 to 60 years and the old group ($n = 13$, the mean age was 64.7 years old) ranges from 61 to 82 years. All drivers participating in the test had possessed a valid driver's license for more than one year and had driving behavior in the last month.

2.1.2 Apparatus

A large dataset including different influencing factors was used to model the takeover performance in Level 3 conditional automation. The experiments focused on taking over vehicle control from the automation on four-lane highways with the 26m width of road cross section at speed of 100km/h (the speed of free-flow was 120km/h) in 4 different takeover scenarios. The whole experimental section covered 1000m length. In order to create the smooth driving environment, the traffic flow of each lane was set as 1200 pcu/h including 10% of vehicle lane change behavior. Experiments were conducted in rather

highly authentic driving simulators with 3 kinds of input including accelerator, brake and wheel.

Four driving scenarios were applied in this test.

Main-line driving: The automated vehicle moved on the highway smoothly with no other external factors affecting the driver's takeover behavior in the whole takeover.

On-ramp driving: The drivers had to take over the vehicle and drive into the ramp on the right side of the highway which needed a lane change behavior.

Fog-cluster driving: The drivers had to completed the takeover behavior in fog area whose visibility was 725m.

Accident driving: There was an accident in front of the automated car and the takeover signal was given 500m away from the accident location. When drivers accept the takeover signal, they had to control the vehicle and drive into the emergency lane steady.

2.1.3 Procedure

The experiment was held in Beijing in 2020. Before the experiment, participants first completed a questionnaire on personal information, then entered the simulated driver to get familiar with the equipment. When participants ensured that they are familiar with the operation of the equipment, the confirmation signal was sent to the control center and the test will start. The data were collected during the experiment.

2.1.4 Data collection

The data of the participants' personal information were collected before the test including the gender and the age. During the driving test, data were recorded at a frequency of 20Hz according to the automation and transferred to the central control room.

Gender. Gender is considered as one of the factors affecting takeover behavior. Gender will affect the driver's reaction ability, which is reflected in the difference of takeover behavior

Age. The age of drivers is considered an influencing factor on take-over performance, as age affects reaction time, judgement skills and cognitive abilities.

First Input. When taking over the automation, the first input will affect the speed and quality of takeover behavior. Therefore, the first inputs (the Accelerator, the Wheel and the Brake) were included as a considered variable.

Correct Control Time (CCT). The time between the warning point and the stability of the automation. This metric is helpful in understanding a driver's reflection speed.

Mean Lateral Offset (MLO). While modeling, the stability of the automation can be inferred from the mean lateral offset. The lower lateral offset represented the more stable takeover process.

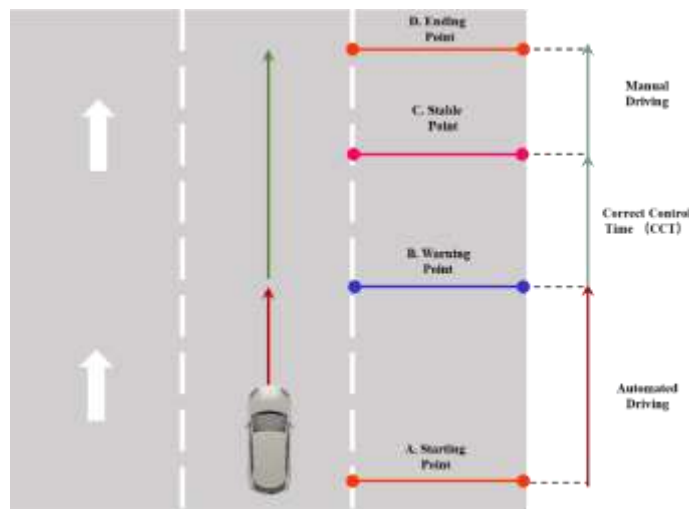


Figure 1. Take-Over situation in Level 3 Conditional Automation

2.2 Methodology

2.2.1 Clustering method

The experiment clusters according to four different driving scenarios (totally 4 groups) to study whether the drivers' physiological attributes (Gender and Age) will have a significant impact on the takeover behavior. The old group was considered as control group, the young group and the middle group was considered as the experiment groups when analyzing the age variable.

In order to analyze whether driving behavior will affect the takeover speed and quality, we cluster the group according to driving scenarios and age (totally 4x3 groups) to avoid the influence of drivers' physiological attributes. The first input was controlled as independent variable.

The clustering method was shown in Figure 2.

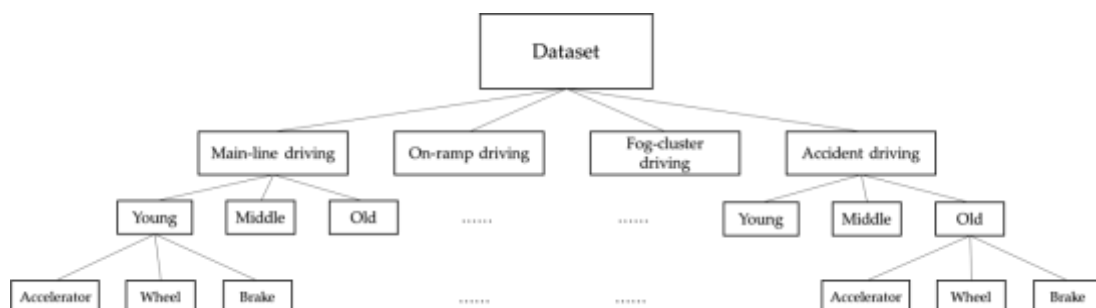


Figure 2. T Clustering method of the dataset

2.2.2 Analysis of differences between groups

One way ANOVA was used to test whether the differences between groups were significant. Assuming the independent variable A_i in the experiment has m different values, n tests are carried out for each case.

The result variable matrix is as follows:

$$X = [A_1 \quad \dots \quad A_m] = \begin{bmatrix} x_{11} & \dots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \dots & x_{nm} \end{bmatrix} \#(1.)$$

$$A_i = [x_{i1} \quad \dots \quad x_{im}] \#(2.)$$

A_i conforms to the normal distribution. In this test, the statistical data of each group are considered as conforming to the normal distribution.

$$x_{ij} \sim N(\alpha_j, \sigma^2) \quad i = 1, 2, \dots, m \#(3.)$$

In this experiment, when analyzing the age variable, $m=3$ (young, middle, old) and the ANOVA test will be repeated for 4 times because of the different driving scenarios. When analyzing the first input variable, $m=3$ (Accelerator, the Wheel and the Brake) and the ANOVA test will be repeated for 12 times because of the different driving scenarios and group age. The significance of the difference between groups was marked by the F value

$$F = \frac{MSB}{MSE} \#(4.)$$

MSB= Mean Squared Between, MSE= Mean squared error.

Compared the F value with F_α at the degree of freedom of the dataset according to significance level α to judge whether the effect of variables were significant. In this test, the significance level α was taken as 0.1.

III. CONCLUSION

3.1 Results

The results of the takeover performance of different groups by participants' gender and age were showed in Table I. Gender had no significant impact on takeover speed and quality in all driving scenarios, the difference of CCT was kept within 1s and the difference of MLO was in 0.05m.

In terms of the age variable, the difference between groups were significant. The CCT of the old group was lager in most cases although the difference was not significant. The middle group was most cautious in the accident scenario because the CCT of middle group was 14.99s and was significantly longer than other 2 groups. The driving performance of the young group was more aggressive which can be implied from the CCT of the young group was 13.38s and was significantly shorter than other groups. It may because the lack of driving experience.

The MLO of the old group in main-line driving was 0.49m which was significantly higher than other age groups which means the takeover quality will reduce with drivers get older. Middle aged drivers have strong driving stability on ramps which can be detected from the MLO of the middle group in on-ramp driving was significantly shorter than other age groups.

TABLE I. Results obtained from ANOVA test of gender and age

Scenario	Variables	Male	Female	Young	Middle	Old
Main-line	CCT(s)	10.10	10.14	9.97	9.75	10.59
	MLO (m)	0.40	0.42	0.39	0.35	0.49^{***}
On-ramp	CCT(s)	14.62	14.41	13.38[*]	14.89	15.66
	MLO (m)	0.47	0.48	0.48	0.45[*]	0.49
Fog-cluster	CCT(s)	10.67	10.36	10.31	10.49	11.06
	MLO (m)	0.57	0.62	0.57	0.57	0.61
Accident	CCT(s)	12.42	12.51	11.80	14.99^{***}	10.52
	MLO (m)	0.48	0.43	0.44	0.46	0.50

Note: ^{***}, ^{**}, ^{*} = significance at 1%, 5%, and 10%.

From the last stage, we concluded that the age will significantly affect the takeover behavior. In order to analyze the affect of first input, we considered the age as a clustering criterion to further refine the clustering groups. Totally 12 complex driving scenes (4 driving scenarios x 3 age groups) were built to analyze whether the first input played a different role in different situations.

Table II showed the results of the first input, where the takeover driving behavior varied significantly from age and scenarios. Under Main-line scenario, the middle group reached the lowest lateral offset of 0.28m by accelerating the vehicles after takeover. The MLO of braking was 0.48m, while the MLO of Accelerating in young and old group were 0.43m and 0.51m separately. By evaluating the On-ramp scenario, the CCT of young group was 12.88s by wheel, where the old group used 18.18s by accelerating. The MLO of accelerating in young group was significantly higher than the first input of wheel and braking. A significant difference between the MLO was found in the middle group under the Fog-cluster scenario, where the MLO of wheel was nearly 0.13m higher than the behavior of accelerating and braking. On the aspect of the Accident scenario, the CCT by wheel was 4.7s and 7.42s shorter than accelerating and braking in middle group, while the CCT by accelerating was 1.86s and 1.02s longer than wheel and braking in old group.

TABLE II. Results obtained from ANOVA test of first input

Scenario	First input	Variables	Young	Middle	Old
Main-line	Accelerator	CCT (s)	10.51	9.55	10.83
		MLO (m)	0.43	0.28**	0.51
	Wheel	CCT (s)	10.05	10.27	10.26
		MLO (m)	0.40	0.38	0.48
	Brake	CCT (s)	9.20	9.23	11.03
		MLO (m)	0.32	0.48	0.43
On-ramp	Accelerator	CCT (s)	13.63	14.41	18.18***
		MLO (m)	0.51**	0.45	0.52
	Wheel	CCT (s)	12.88**	15.10	13.66
		MLO (m)	0.44	0.46	0.47
	Brake	CCT (s)	17.90	19.17	13.22
		MLO (m)	0.43	0.37	0.51
Fog-cluster	Accelerator	CCT (s)	10.70	10.74	10.86
		MLO (m)	0.61	0.52	0.51
	Wheel	CCT (s)	10.49	10.04	11.10
		MLO (m)	0.57	0.64**	0.66
	Brake	CCT (s)	9.18	11.30	11.33
		MLO (m)	0.55	0.51	0.64
Accident	Accelerator	CCT (s)	11.19	18.71	11.62**
		MLO (m)	0.43	0.47	0.53
	Wheel	CCT (s)	12.29	11.29***	9.76
		MLO (m)	0.46	0.43	0.47
	Brake	CCT (s)	10.99	16.99	10.60
		MLO (m)	0.41	0.51	0.51

Note: ***, **, * = significance at 1%, 5%, and 10%.

Considering the impact of age, driving scenario and the first input on takeover performance, CCT and MLO were analyzed and evaluated. The young drivers performed strongly difference in On-ramp scenario, where the first input of accelerating resulted the longest MLO and the wheel resulted the shortest CCT. It is indicated that the young drivers were better at using the steering wheel to control the vehicles instead of changing the speed. While the outcome of the middle group verified the takeover performance under different scenario could be different, the first input of wheel could result significantly high MLO under Fog-cluster scenario but low CCT under Accident scenario. This was the further exploration of the previous research that the traffic density strongly influenced the takeover performance. [6,9,10] Additionally, accelerating would keep the automated vehicles in stability under Main-line scenario by middle group, which indicates that the middle aged drivers were accustomed to control the vehicles by accelerator. On the aspect of the old group, it is significant that the performance of accelerator was worse than the wheel and brake. Because of the conservative driving psychological characteristics, the older drivers braked more often and maintained a higher CCT, which was consistent with the conclusion of previous research [12].

3.2 Conclusion

This study focused on the differences of takeover performance in complex traffic scenarios and age group. Four automated driving scenarios have been specially designed, including Main-line, On-ramp, Fog-cluster and Accident driving scenarios. The significance of the driving behavior among three age group and driving scenarios had been examined by ANOVA test. The results verified that the age and driving scenarios affected the takeover performance, where the young group were better at using the steering wheel to control the vehicles. Simultaneously, the middle aged drivers were accustomed to control the vehicles by accelerator. Additionally, the takeover performance of accelerator was worse than the wheel and brake in old group.

The results of this study showed essential references for scientific researchers and automobile manufacturers. The assisted driving tips and systems could be specially design for different aged drivers to avoid unsafe takeover performance, where the older drivers should reduce the use of the accelerator after takeover, and the wheel should be more suggested to younger drivers. What's more, the usage of the wheel was recommended in Accident scenarios instead of Fog-cluster scenarios for the middle aged drivers.

There are, nevertheless, two potentially important limitations in the present study. On the one hand, more dependent variable should be analyzed to identify the takeover performance between three age group and driving scenarios. On the other hand, the driving scenarios are designed for the automated vehicles on the highway, where the results of this study may not provide implication for the automated driving system in urban.

This study is an initial research in exploring the takeover performance of highly automated vehicles in complex traffic scenarios. For further research, scenario in city should be taken consideration, where the impact of the traffic signal, pedestrian and non-motor vehicle are necessary to evaluated. Finally, the specific implications should be tested to verify whether the appropriate takeover suggestions and limitations would help the stability for the different aged drivers.

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