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Analyzing Driver Gaze Behavior and Consistency of Decision Making During Automated Driving*

Chiyomi Miyajima[1], Suguru Yamazaki[1], Takashi Bando[2], Kentarou Hitomi[2], Hitoshi Terai[1], Hiroyuki Okuda[1], Takatsugu Hirayama[1], Masumi Egawa[2], Tatsuya Suzuki[1], Kazuya Takeda[1]

Abstract— **We investigate a possible method for detecting a driver's negative adaptation to an automated driving system by analyzing consistency of driver decision making and driver gaze behavior during automated driving. We focus on an automated driving system equivalent to Level 2 automation per the NHTSA's definition. At this level of automation, drivers must be ready to take control of the vehicle in critical situations by monitoring the driving environment and vehicle behavior. Since drivers are not required to operate the pedals or steering wheel during automated driving, a driver's negative adaptation to an automated system needs to be detected from behavior other than vehicle operation. In this study, we focus on driver gaze behavior. We conduct a simulator study to compare the gaze behavior of fifteen drivers during conventional and automated driving. We also analyze the consistency of driver decision making when changing lanes during conventional and automated driving. Experimental results show that drivers who pay less attention to the road ahead during automated driving tend to be less sensitive to risk factors in the surrounding environment and also tend to make inconsistent lane change decisions during automated driving.**

I. INTRODUCTION

Automated driving has been attracting a great deal of attention in recent years. Many researchers are actively working on automated driving technologies, and some automakers have already commercialized partially automated driving systems capable of operating in limited environments. Traffic laws are also being modified to accommodate automated driving on public roads [1].

There are different levels of automated driving, based on the degree of vehicle assistance [2-4], e.g., the U.S. National Highway Traffic Safety Administration (NHTSA) has defined five levels of automation from Level 0 (no automation) to Level 4 (full automation). Although automated driving increases safety and reduces human error, it can also result in over-reliance or dependency when drivers adapt negatively to such systems [5-7]. Especially at lower levels of automation, such as Levels 1 and 2, where drivers need to monitor the environment themselves, a driver's over-reliance on the vehicle might decrease driver awareness and sensitivity to risks in the environment, and lead to a situation in which drivers are not able to respond in a timely and appropriate manner to critical situations such as system failures. These negative aspects of human interaction with automation need to be further investigated in order to develop more effective human-machine interfaces in automated systems.

In this study, we investigate a possible method of detecting a driver's negative adaptation to an automated driving system. Since drivers are basically disengaged from operating the vehicle during automated driving, a driver's negative adaptation to the automated system needs to be detected from driver behavior other than vehicle operation. At lower levels of vehicle automation, drivers need to monitor the surrounding environment, i.e., drivers need to "keep their eyes on the road", even if their feet are off the gas and brake pedals and their hands are off the steering wheel. Therefore, we focus on driver gaze behavior while driving. A simulator study is conducted using fifteen drivers to investigate the relationship between driver gaze behavior and negative adaptation to an automated driving system. Vehicle operation and gaze behavior during conventional and automated driving on a highway are recorded using a simulator and eye trackers. We use logistic regression [8] to analyze how the drivers make lane change decisions (or allow the automated vehicle to make lane changes) in response to the risk level of the surrounding environment. We then compare the results of the logistic regression with driver gaze behavior during the lane changes.

II. NEGATIVE DRIVER ADAPTATION TO AUTOMATED DRIVING SYSTEM

Automated driving will likely improve driving safety and energy efficiency, as well as relieve drivers of stress and fatigue while driving. However, negative effects of automation on driver performance and behavior should also be addressed [5-7]. When a driver is assisted by an advanced driver assistance system (ADAS) such as Adaptive Cruise Control (ACC), lane-keeping assist system (LKAS), or an automated driving system, the driver tends to become dependent on the assisting system.

Although there may be several kinds of negative adaptation to an automated system, we focus on inconsistency in decision making in relation to the risk level of the driving environment. Figure 1 shows our hypothetical model of negative driver adaptation to an automated driving system. We assume that a driver is more negatively adapted to the automated system if he/she is less sensitive to the risk level of the surrounding environment when making decisions during automated driving than during conventional driving. Negative adaptation can be represented by a decrease in the consistency of a decision threshold during automated driving when compared to conventional driving.

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[1]C. Miyajima, H. Terai, H. Okuda, T. Hirayama, T. Suzuki, and K. Takeda are with Nagoya University, Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan (corresponding author: miyajima@nagoya-u.jp).

[2]T. Bando, K. Hitomi, and M. Egawa are with DENSO CORPORATION, Showa-cho, 1-1, Kariya, Aichi, 448-8661, Japan.

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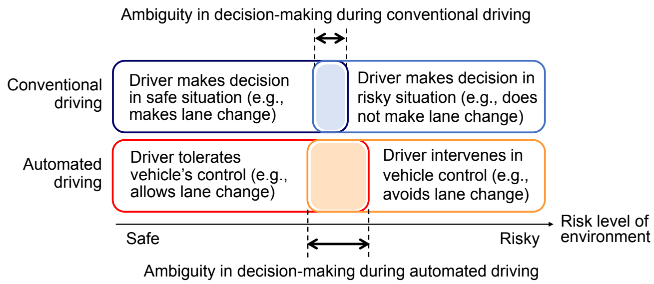


Figure 1. Negative driver adaptation to automated system represented as increased ambiguity in decision making

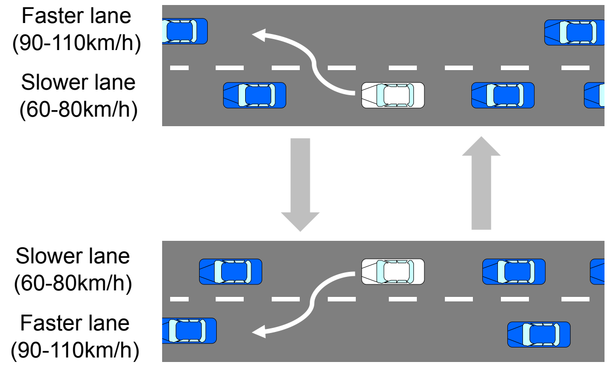


Figure 2. Traffic scenario used in the driving simulator: Drivers under time pressure make lane changes into the faster moving lane, then the faster moving lane gradually becomes congested and turns into a slower moving lane, so drivers move back into their original lane. Traffic flow alternates iteratively.

III. Recording Driver Behavior During Conventional and Automated Driving Using Simulator

We conduct a simulator study to compare driver behavior during conventional and automated driving. We focus on driver behavior during lane changes because drivers need to make appropriate vehicle control decisions in order to make safe lane changes, and these decisions are based on their perception of the surrounding environment.

A. Experimental Conditions

We recruited fifteen subjects (twelve male and three female university students) with driver's licenses. They drove on a simulated highway in the driving simulator under two driving conditions, conventional and automated driving, twice each, resulting in four trials for each subject. Each trial lasted about 20 minutes, i.e., each subject drove 80 minutes in total. Subjects also used the simulator for five minutes before their first trial to become accustomed to the vehicle. In order to counter-balance the order of driving conditions, eight subjects started with conventional driving and seven subjects started with automated driving. They made lane changes approximately 20 times for each direction in each trial.

B. Simulated Scenario

Each subject drove on a straight highway with two lanes in one direction under both the conventional and automated driving conditions. Subjects were instructed as follows:

"Imagine that you are going to take an important exam at your university this morning, but you woke up late. You have to rush to your university by car or you will be late for the exam and fail the class. The speed limit on the highway is 100 km/h. Please drive safely, but try to arrive at the university as quickly as possible by traveling at around the speed limit and by passing other vehicles in front of you by making lane changes if possible. During automated driving, you can take your feet off the gas and brake pedals and hands off the steering wheel, but keep monitoring the roadway so that you can take control of the vehicle at any time, such as when the automated control of the vehicle is risky. Please intervene in control of the vehicle by operating the pedals and steering wheel yourself when you feel there is any danger."

As shown in Fig. 2, one of the two lanes is relatively congested and the traffic flow is slower than in the other lane. Surrounding vehicles in the same lane travel at the same speed and never collide with each other. The velocity of surrounding vehicles in the faster lane is adjusted to a range of between 90–110 km/h, and vehicles in the slower lane travel in a range between 60–80 km/h. Distances between surrounding vehicles are randomly selected from a range between 10–50 m.

In this scenario, drivers should try to make lane changes from the slower lane to the faster lane. About 10–20 seconds after a driver makes a lane change to the faster lane, the faster lane gradually becomes congested and turns into a slower lane. Hence, the driver has to make a lane change back into the other lane again so that they can get to the university in time, i.e., drivers have to make lane changes iteratively from left to right and from right to left while driving.

Our simulated automated driving system automatically makes lane changes according to the risk level of the surrounding environment. However, it sometimes try to make relatively risky lane changes. Drivers can hear the sound of a turn signal in advance when the automated vehicle is going to make a lane change, so drivers can intervene and take control of the vehicle to avoid making a risky automatic lane change if they want to by over-riding the automated system. For example, drivers can avoid a risky automated lane change by operating the steering wheel or the pedals when the vehicle behind them in the passing lane is moving too fast or is too close to the driver's vehicle.

C. Equipment for Experiment

Each driver's vehicle operation behavior is recorded by the driving simulator shown in Figs. 3 and 4. Conventional and automatic vehicle control is simulated in the same driving simulator. The simulator does not provide vehicle acceleration motion feedback but it does provide torque feedback in the steering wheel, which is directly coupled with the vehicle dynamics.

Three eye trackers (Tobii X2-30) [9] were used to record driver gaze from the front, left, and right of the driver, to cover a wide range of gaze directions while driving. Calibration of the eye trackers was conducted for each driver before recording gaze data. Driver gaze direction was recorded at 30 Hz sampling rate and was resampled at 10 Hz for analysis. Other driving signals were also sampled at 10Hz.

Figure 3. Driving simulator view of the road ahead

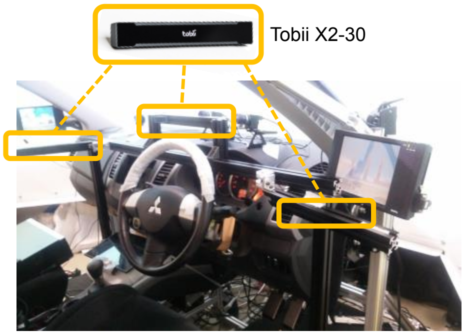


Figure 4. Three eye trackers mounted on simulator for measuring driver gaze direction

IV. Comparison of Driver Gaze During Conventional and Automated Driving

We first analyzed how driver gaze behavior during automated driving differs from that during conventional driving.

A. Gaze Direction during Lane Changes

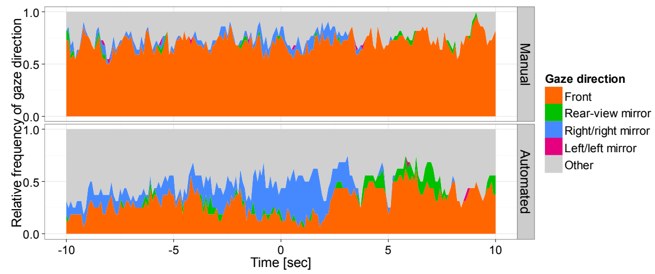
The gaze direction of each driver is categorized into the following five directions:

1. Front (road ahead)
2. Rear-view mirror
3. Right (including right rear-view mirror)
4. Left (including left rear-view mirror)
5. Other (Out of range or lost eye tracking)

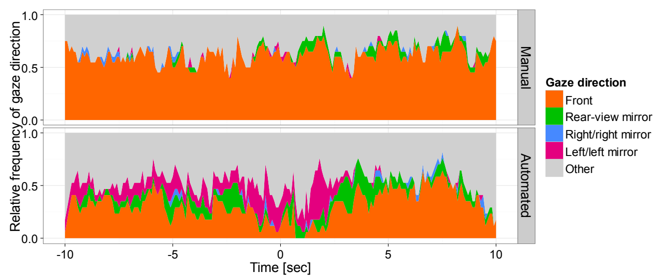
Driver gaze direction is classified into one of the five directions above using the driver's gaze coordinates on the screen of the simulator.

Figures 5 and 6 show examples of the gaze behavior of two drivers, Subjects 8 and 12, respectively. The figures show the relative frequencies of the five gaze directions accumulated at each point in time during right lane changes (a) and left lane changes (b). The top and bottom graphs correspond to conventional and automated driving, respectively. We analyzed gaze direction for 20 seconds, ten seconds before and ten seconds after the beginning of each lane change. 0 seconds on the horizontal axes corresponds to the beginning of the lane changes, and negative values (less than 0 seconds) correspond to seconds preceding lane changes.

We can see from Fig. 5 that the proportion of Subject 8's gaze directed in front of the vehicle decreased significantly during automated driving. The proportion of Subject 8's gaze to the front was about 70% during conventional driving, but only about 30% during automated driving. Subject 8 also looked to the right or into the right rear-view mirror more often when the vehicle was making automatic right lane changes than when he made manual right lane changes, and also looked more to the left or into the left rear-view mirror when the vehicle was making automatic left lane changes than when he made manual left lane changes. Subject 12, shown in Fig. 6, also looked more often to the right and left when the automated vehicle was making lane changes than when she made manual lane changes. However, she did not show a significant decrease in her attention level to the front during automated driving. We can also observe other differences in gaze behavior, e.g., Subject 12 looks in the rear-view mirror more often than Subject 8 during lane changes.

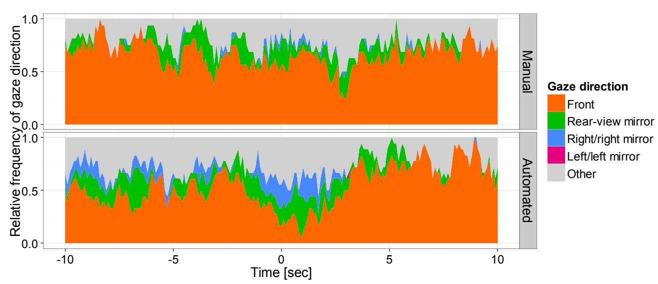


(a) Right lane change (top: conventional driving, bottom: automated driving)

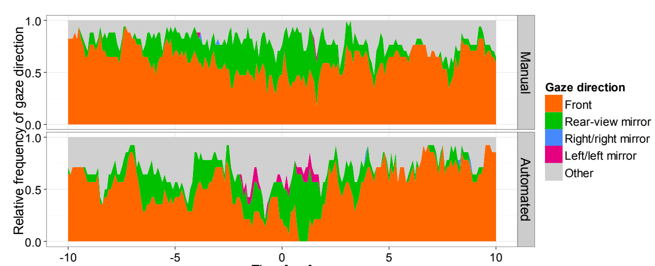


(b) Left lane change (top: conventional driving, bottom: automated driving)

Figure 5. Gaze direction during lane changes (Subject 8)



(a) Right lane change (top: conventional driving, bottom: automated driving)



(b) Left lane change (top: conventional driving, bottom: automated driving)

Figure 6. Gaze direction during lane changes (Subject 12)

B. Measuring Differences in Gaze Behavior between Conventional and Automated Driving

Figure 7 compares proportions of gaze to the front during conventional and automated driving. This proportion is similar to the percent road center (PRC) used for detecting driver distraction [10]. Figure 8 compares proportions of gaze to the other three directions (rear-view mirror, right, and left). We can see all drivers decreased their proportions of gaze to the front during automated driving. On the other hand, they increased the proportion to the other three directions during automated driving.

We quantified these differences in gaze behavior between conventional and automated driving. To represent how driver attention to the road ahead of the vehicle decreased during automated driving, we calculated the following proportion of gaze direction:

$$R_{A/M} = \frac{\sum_{-N}^{N} G_A[n]}{\sum_{-N}^{N} F_A[n]} \Big/ \frac{\sum_{-N}^{N} G_M[n]}{\sum_{-N}^{N} F_M[n]}, \quad (1)$$

where $F_M[n]$ and $F_A[n]$ are the relative frequencies of gaze direction towards the front at the n-th point in time during manual and automatic lane changes, respectively. $G_M[n]$ and $G_A[n]$ represent the sum of relative frequencies of gaze directions in the other three directions (rear-view mirror, right, and left) during manual and automatic lane changes, respectively. The proportion of gaze directions is accumulated in the range $[-N, N]$. We chose N=100, which corresponds to 10 seconds.

Figure 9 shows proportion $R_{A/M}$ calculated as in (1) for the fifteen subjects. If the proportion is close to $R_{A/M}$ =1, the driver's gaze behavior during automated driving does not differ much from that during conventional driving. The greater the proportion is than 1, the more a driver's gaze behavior varied. Since the proportions for all fifteen subjects were more than 1, we can say that, in general, drivers decrease their attention ahead of the vehicle during automated driving. Subjects 2, 8, 10, and 15 showed significant decreases in their attention to the road ahead during automatic driving compared with conventional driving.

V. Analysis of Driver Decision Making

We then analyze how driver sensitivity to risk factors in the surrounding environment affected their decision making during conventional and automated driving.

A. Logistic Regression

As discussed in Section II, we assume that a driver's negative adaptation to automated systems (such as over-reliance on the automated vehicle) can be represented by inconsistency (ambiguity) in decision making. Figure 10 shows a diagram of decision making related to lane changes. Each circle represents a decision whether or not to make a lane change, i.e., "Y=1" or "Y=0." If a driver is overly dependent on the automated system, their decision threshold for making (or not making) a lane change in response to the risk level of the surrounding environment will be inconsistent, i.e., their decisions will not correlate well with the objective risk level.

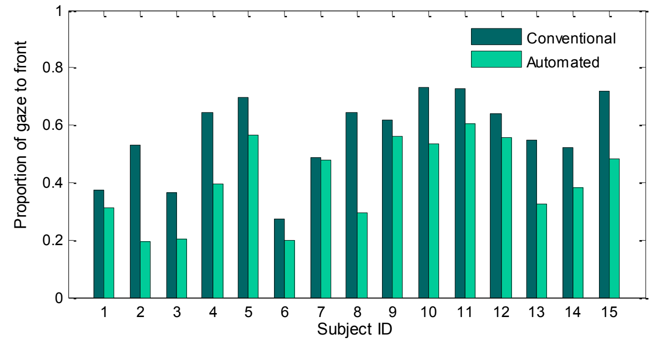


Figure 7. Proportions of gaze to the front during conventional and automated driving

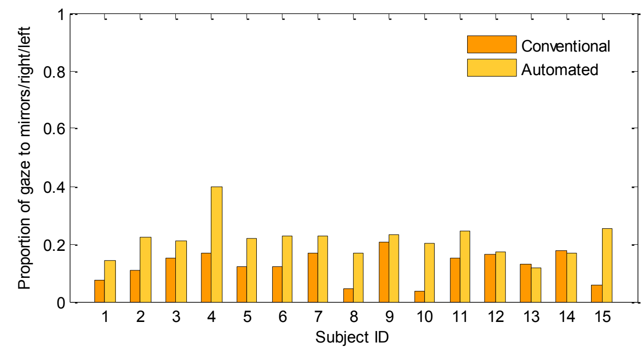


Figure 8. Proportions of gaze to the other three directions (rear-view mirror, right, and left) during conventional and automated driving

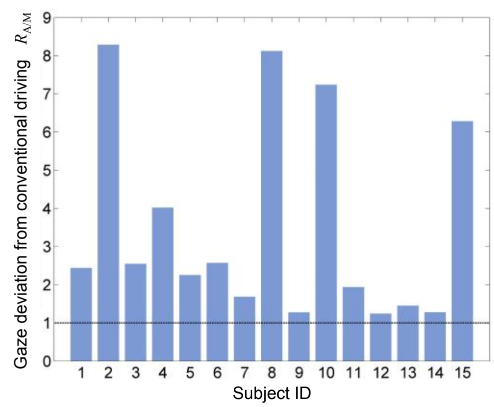


Figure 9. Gaze behavior deviation between automated driving and conventional driving for fifteen subjects (per $R_{A/M}$ in (1))

We used logistic regression to quantify ambiguity in lane change decisions as regression coefficients. Although there are many risk factors in the surrounding environment which should be taken in account to when making a lane change decision, we focused on the following two factors in this study:

x_1: Difference between vehicle speeds in the two lanes
x_2: Distance between two vehicles in the faster lane when driver is cutting in

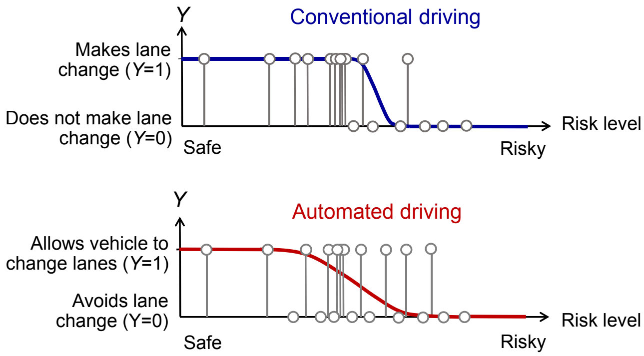


Figure 10. Driver's decision to make lane changes during conventional and automated driving based on risk level of surrounding environment

Let $p = \{Y{=}1 \mid x_1, x_2\}$ be the probability that a driver makes a lane change (Y=1), given surrounding environment (x_1, x_2), i.e., $1{-}p$ is the probability that the driver does not make a lane change (Y=0). In the case of automated driving, p represents a probability that the driver will allow the vehicle to make an automated lane change, and $1-p$ represents the probability that the driver will intervene to avoid an automated lane change. Logistic regression was used to estimate coefficient β_i in the following equation:

$$\log\frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_2, \qquad (2)$$

where β_1 and β_2 represent the driver's sensitivity to risk factors x_1 and x_2, respectively.

B. Result of Logistic Regression.

Figure 11 shows examples of the probability surfaces estimated using logistic regression for two drivers (Subjects 5 and 8). Drivers' lane change decisions during conventional and automated driving are shown in the left and right graphs, respectively. Data from left and right lane changes are analyzed together and shown in the same graph.

Each dot in the graph shows the result of a driver's decision whether or not to make a lane change according to the risk level of the surrounding environment, based on x_1 and x_2. A red dot indicates the driver made a lane change, either conventionally or by allowing the vehicle to automatically change lanes during automated driving (Y=1). A blue dot indicates the driver did not make a lane change during conventional driving or intervened to avoid an automated lane change by operating the steering wheel and/or the pedals (Y=0). The more the red and blue dot distributions overlap, the more inconsistent the driver's decision making (i.e., the more randomly the subject makes or avoids lane changes in relation to the risk level).

We can see from Fig. 11 that Subject 5 showed relatively consistent decision making regarding lane changes during both conventional and automated driving, and seemed more conservative when making lane changes during automated driving than during manual driving. He tended to avoided making lane changes when it was risky and tended to make lane changes when it was safe, but he also tended to make more risky lane changes during conventional driving. On the other hand, the red and blue dots on Subject 8's graphs overlapped more widely during automated driving than during conventional driving, and the decision surface became more uniform during automated driving, i.e., the decision threshold became more ambiguous.

Table 1 shows regression coefficients (odds ratios $\exp\beta_i$) estimated for each driver. We focus on the difference in regression coefficients between conventional driving $\beta_i^{(M)}$ and automated driving $\beta_i^{(A)}$. Odds ratios $\exp\beta_1$ and $\exp\beta_2$ represent inconsistencies in a driver's decision to make a lane change for given relative velocity between two lanes x_1 and distance between vehicles in the faster lane x_2, respectively. We can say drivers with larger $\exp\beta_1$ and smaller $\exp\beta_2$ are more inconsistent in decision making for given risk factors, because the risk level of surrounding environment increases as relative velocity x_1 increases and distance x_2 decreases. These inconsistencies in decision making could also be described as driver's insensitivities to the relative velocity of vehicles and the vehicle distance when making lane changes.

C. Relation between Inconsistency of Driver Decision Making and Driver Gaze Behavior.

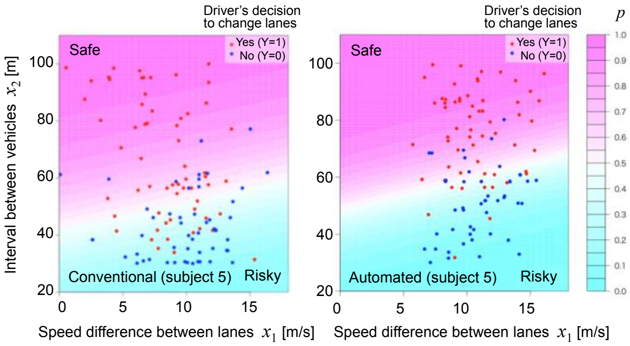
Figure 12 shows the relation between $R_{A/M}$ shown in Fig. 9 and $\exp(\beta_1^{(A)}-\beta_1^{(M)})$, which represents how inconsistency in a driver's decision to make a lane change during automated driving increased as compared with inconsistency during conventional driving for given relative velocities between two lanes. We see some correlations between these parameters. Note that Subject 2, an outlier in the graph, fell asleep during last half of the automated driving session, and the subject's gaze direction during drowsy driving could not be properly recorded.

This figure shows that drivers who pay less attention to the road ahead during automated driving tend to also be less sensitive to risk factors in the surrounding environment. It also indicates that negative driver adaptation to the automated system could be detecting by monitoring the deviation of driver gaze behavior from their behavior during conventional driving.

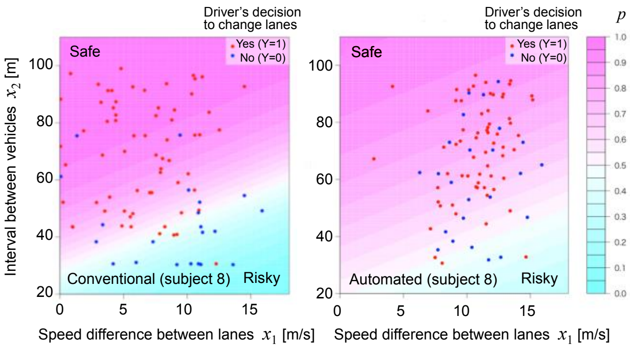
VI. Conclusion

We analyzed driver gaze behavior during conventional and automated driving to investigate a possible method of detecting negative driver adaptation to an automated driving system. We conducted a simulator study to compare driver gaze behavior during lane changes during conventional and automated driving, and our experimental results showed that drivers who paid less attention to the road ahead during automated driving tended to be more dependent on the automated system. These drivers were less consistent when making decisions regarding lane changes and less sensitive to risk factors in the surrounding environment.

Changes in negative driver adaptation over time, and driver adaptation to different levels of automation should be examined in future research.



(a) Subject 5



(b) Subject 8

Figure 11. Drivers' decisions regarding lane changes based on risk level of surrounding environment and probability surface derived using logistic regression (left: conventional driving, right: automated driving)

TABLE I. COEFFICIENTS (ODDS RATIOS) OBTAINED FOR EACH SUBJECT USING LOGISTIC REGRESSION

Subject	Driving condition	$\exp\beta_0$	$\exp\beta_1$	$\exp\beta_2$
Subject 1	***Conventional***	0.032	0.838	1.094
	Automated	0.193	0.972	1.034
Subject 2	***Conventional***	0.019	1.034	1.062
	Automated	0.064	0.937	1.077
Subject 3	***Conventional***	0.033	0.954	1.065
	Automated	0.034	0.927	1.066
Subject 4	***Conventional***	0.377	0.763	1.065
	Automated	0.330	0.819	1.054
Subject 5	***Conventional***	0.040	0.929	1.079
	Automated	0.003	0.876	1.128
Subject 6	***Conventional***	0.024	0.993	1.069
	Automated	0.041	1.002	1.052
Subject 7	***Conventional***	0.010	1.037	1.063
	Automated	0.022	0.783	1.110
Subject 8	***Conventional***	0.090	0.863	1.088
	Automated	0.519	0.941	1.036
Subject 9	***Conventional***	0.051	0.952	1.071
	Automated	0.057	0.980	1.054
Subject 10	***Conventional***	0.171	0.754	1.124
	Automated	0.158	0.893	1.051
Subject 11	***Conventional***	0.047	0.958	1.083
	Automated	0.107	0.836	1.067
Subject 12	***Conventional***	0.009	0.980	1.088
	Automated	0.046	0.854	1.081
Subject 13	***Conventional***	0.153	0.875	1.043
	Automated	0.083	0.963	1.028
Subject 14	***Conventional***	0.044	0.991	1.067
	Automated	0.272	1.010	1.026
Subject 15	***Conventional***	0.145	0.993	1.062
	Automated	0.124	1.117	1.028

Figure 12. Gaze behavior deviation during automated driving compared to conventional driving (defined as $R_{A/M}$ in (1)) in relation to inconsistency in lane change behavior

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