Effect of Automatic Lane Changing on Driver’s Behaviour Decision Process*

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Abstract: This paper analyses the driver’s behavioural change about which the usage of automated driving system brings, focusing on the behaviours at changing lanes. Especially the relation between drivers’ sensitivity to risk factors in surrounding environment and their gaze behaviour were analysed. We assumed, in this research, an automated driving of level 2 in the definition provided by NHTSA. At this level of automation, the drivers are required to monitor the driving situation and, when necessary, interrupt the system’s automatic control and thereby recover the safety of the driving. We have conducted a simulation experiment with fifteen drivers, and compared their behaviours in two conditions; the conventional manual driving and the driving where automated driving system automatically changes lanes. By analysing collectively the risk factors at changing lanes, shift of each driver’s sensitivity to risk at changing lanes were estimated. The experimental data shows the correlation between risk sensitivity and gaze behaviour.

Keywords: Driver Behavior Modeling, Cooperation Between Drivers and Assistance Systems, Driver Overdependence and Distrust on Assistance Systems

1. INTRODUCTION

Much research is currently being done on automated driving technologies, and vehicles with partially automated driving systems, capable of operating in limited environments, are already being marketed by automakers. Governments have also begun to modify traffic laws to accommodate automated driving on public roads [Smith (2014)].

Automated driving promises to improve driving safety, reduce driver stress and fatigue, and lower fuel consumption, but automation may have negative effects on driver performance which should also be evaluated. Studies have shown that drivers using advanced driver assistance systems (ADAS), such as adaptive cruise control (ACC), lane-keeping assist systems (LKAS), or automated driving systems, sometimes become overly dependent on these systems [Inagaki (2010); Abbink and Mulder (2008); NHTSA (July 2014)]. As National Highway Traffic Safety Administration (NHTSA) of the United States described in its policy statement concerning automated vehicles [NHTSA (May, 2013)], there are several levels of automation in driving from level 0 (No-Automation) to level 4 (Full Self-Driving Automation). The problem of over-reliance matters especially in lower levels of automation, such as levels 1 (Function-specific Automation) and 2 (Combined Function Automation), the drivers are required to monitor the roadway and vehicle behaviour, and “to be available for control at all times and on short notice”. Driver over-reliance on such automated systems may reduce driver awareness and decreased sensitivity, and may result in drivers being unable to respond quickly enough in the event of system failures. Negative adaptation on the part of drivers to automation needs to be further investigated in order to improve human-machine interfaces and avoid problems such as over-reliance, disuse and misuse. Therefore, the driver’s behavioural change including the negative adaptation, about which the usage of automated driving system brings, needs to be understood, in order to avoid discordance among human, system, and the driving environment. Especially it needs to be analysed in relation to risk in driving situation.

The purpose of this study is the development of a possible method of detecting negative adaptation to an automated driving system. Most driver behaviour studies rely on the monitoring of vehicle operation signals by the driver to collect data for analysis, but since drivers are usually disengaged from vehicle operation during automated driving,
other methods of driver evaluation must be developed. When an automated system operating at a lower level of vehicle automation is engaged, drivers still need to keep their eyes on the road, even if they are not actively controlling the vehicle. Therefore, in this study we focus on driver gaze behaviour while driving as a means of measuring driver attentiveness in relation to risk in driving situation. Our analysis focuses on the driver’s sensitivity to risks at changing lanes, such as the vehicle approaching from behind in the neighbouring lane, and its variation brought by the introduction of automatic lane changing system, assuming the automation of level 2 in definition provided by NHTSA.

We conducted a simulation experiment to collect drivers’ behaviours under two conditions; conventional manual driving condition and automated driving condition. In the manual driving the driver manually operates the vehicle, and in the automated driving the simulated automated driving system autonomously operates the vehicle and changes lanes frequently. Also, the drivers are required, in automated driving, to monitor driving situation and to avoid risky situation by interrupting the system’s driving operation when necessary. Based on the situations where the vehicle changed lanes and where it did not, decision boundaries on risk factors for lane-changing are estimated as the boundary of these situations using logistic regression. By comparing these boundaries between the two driving conditions, variation of decision boundary are estimated as the variation in sensitivity to risks brought about by the automated system. Furthermore the driver’s gaze behaviour was recorded and modelled using Gaussian Mixture Model (GMM) and Hidden Markov Model (HMM). The variation of the gaze behaviour brought about by the automated system is evaluated using HMM built on the learnt GMM. It is shown that the quantified variation of gaze behaviour has high correlation to the variation to risk factors in the driving environment.

2. MODEL ASSUMPTION AND ANALYSIS TARGET

2.1 Decision model of the driver

We set the analysis target under following assumption on driver’s behaviour model. It is reasonably assumed that the driver operates the vehicle keeping the risk of driving situation under certain risk level where he/she can handle the situation in safe. The risk of driving situation depends on the state of the vehicle. For example, when host vehicle is following its leading vehicle, the inter-vehicle distance to the leading vehicle, their velocities and accelerations are the dominant variables for representing the risk, and other variables such as those of vehicles in neighbouring lane are of little relevance. When host vehicle is changing lanes, in addition to the leading vehicle, such variables of vehicles in neighbouring lane are also substantial to the risk of driving situation. Those values contributes to each driver’s subjective risk recognition via Time-To-Collision for instance, and the drivers’ decision boundaries at which the driver’s behaviour switches (e.g. whether to apply deceleration or not, whether to start changing lanes or not) are dependent on drivers [Mima et al. (2009)]. Each driver operates the vehicle keeping the risk of driving situation under subjective threshold.

![Fig. 1. Hypothetical model of driver’s behaviour decision based on risk of driving environment, in manual driving and in automated driving. A & B indicates driver’s decision transition area on risk level.](image1)

![Fig. 2. The presumed risk factors in the surrounding situation at changing lanes.](image2)

Figure 1 shows our hypothetical model of driver’s decision in relation to risk level of driving environment. In conventional manual driving where the driver him/herself operates the vehicle, the driver keeps the risk lower than certain level and avoid driving in riskier situation (Drivable area and Evasion area). In automated driving, the vehicle is operated by the automated driving system and the driver monitors the roadway and the vehicle system behaviour. If the driver is comfortable with the system behaviour, the driver tolerates the system’s operation, and if the driver is uncomfortable with the system behaviour, the driver intervenes the operation of the system to reject the automated behaviour of the system (Tolerating area and Rejection area). In the case of lane changing, the driver changes lanes normally in Drivable area and intervenes in Rejection area.

![Fig.](image3)

2.2 Analysis target

In our experiment, the negative adaptation to the automated system of the driver is represented by the variation of the driver’s decision boundary on the risks in the driving environment, for changing lanes. By estimating and comparing the decision boundaries in manual driving and automated driving, the variation in sensitivity to risk factors are evaluated as the shift of the decision boundaries, as the effect of introduction of automated driving system.

The presumed risk factors in our analysis in the surrounding situation at changing lanes are depicted in the Fig.2: the velocities of leading and following vehicles in current lane \(v_l, v_f\), the velocities of leading and following vehicles in neighbouring lane \(v_{nl}, v_{nf}\), and inter-vehicle distance of the destination of lane changing \(d_n\). For a reason in implementation in our experiment, we further simplified and analysed the velocity difference between lanes \(\Delta v = (v_{nl} + v_{nf})/2 - (v_l + v_f)/2\) and \(d_n\). The drivers’ decision boundaries for changing lanes are estimated on those variables.
Fig. 3. A screenshot of a scenery projected in DS.

Fig. 4. Snapshot of the driving simulator equipments. Three eye-tracking device, Tobii X2-30 are placed on around the driving seat.

Fig. 5. The transition of situations in driving simulation; Faster lane and slower lane flips according to the host vehicle’s driving lane.

Additionally, we investigated the proactive sign of variation of sensitivity to risk, into driver’s appearance. A gaze behavioural feature which correlates to change in sensitivity to risk can be expected to be useful cue to detect the behavioural change.

3. EXPERIMENT SETUP

3.1 Simulator setting

In the experiment, we used a driving simulator to collect driving behaviour data. Figure 3 shows a scene in simulated driving, which is projected over the screens around the driver seat of the simulator. The simulation system is built on CarSim [Virtual Mechanics Corp. (2014)], a high-fidelity vehicle dynamics simulator. Figure 4 shows the used driving simulator with three eye trackers Tobii X2-30 (Tobii Technology (2014)) mounted on it. It has three screens which provide 180 degrees of front field of view, and the interior equipments around driver seat is the same as a real car. The steering wheel has torque feedback system which reflects the physical status of the vehicle in the simulation in real-time.

The simulated driving environment was implemented with straight two-lane highway in one direction and surrounding other cars (Fig.3 and 5). In each lane, surrounding vehicles travel at the same speed and never collide with each other. The lane in which host vehicle is driving is set to the “slower lane”. The slower lane is relatively congested and surrounding vehicles in this lane travel at the speed selected randomly between 50 km/h and 70 km/h. The other lane is set to the “faster lane”. The faster lane is relatively sparse and vehicles in this lane travel at the randomly-selected speed between 90 km/h and 110 km/h. In both lanes, inter-vehicle distances are randomly set at the distances between 30 m and 100 m. During 10 to 20 seconds after host vehicle’s lane changing, the host vehicle can drive in the fast lane from the slow lane to the fast lane. After this period of time, the setting of both lanes are flipped; the velocity of vehicles in the fast lane gradually shifts into the velocity range of the slower lane, and vice versa. Therefore, the simulator forces the host vehicle to drive in the slower lane most of the time.

The simulation has two conditions; the manual driving and the automated driving. In the manual driving condition, the driver operates the steering wheel and gas and braking pedals as normally as usual driving. In the automated driving condition, the simulated automated driving system, which was implemented in our experiment, autonomously generates the operational input to the host vehicle and it follows leading vehicles and changes lanes when the system considers the appropriate situation for them. The simulator is equipped with a speaker to simulate the sound of turning signal so that the driver can notice the initiation of automatic lane change. Also, the steering wheel rotates automatically according to the operational input from the automated driving system. During the simulation of driving (in both conditions), the driving simulator records the status of each vehicle (e.g. position, velocity, acceleration, orientation), the driver’s operational signals (e.g. steering wheel, gas pedal and braking pedal), and the driver’s gaze direction. The sampling rate of recording is 100 Hz. In analysis, they are down-sampled to 10 Hz in the analysis.
3.2 Simulation scenario

The drivers were instructed in manual condition as follows, to keep the velocity of the vehicle at 100 km/h as possible as he/she can.

“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 travelling 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.”

Therefore the drivers were pushed to change lanes frequently. In the automated driving, the background story in the instruction is the same. Concerning the automated driving system, the drivers were told as follows:

“Use the automated driving system whose preferred velocity is set to 100 km/h. However, the automated system is not perfect for any possible situation. If you notice any risk of collision, use the steering wheel, gas pedal and braking pedal in order to recover safety. After the risk diminishes enough, please take you hands and foot off from the steering wheel and pedals to let the automated driving system operate the vehicle again.”

3.3 Analysis of negative adaptation

Through the manual driving trials, we collected the samples of situation at initiation of lane changing and situation before the host vehicle was passed on by the neighbouring vehicle. The former situation indicates that the driver was comfortable to change lanes in that situation, i.e. the situation is in his/her drivable area for changing lanes. The latter situation indicates that the driver was uncomfortable to change lanes in that situation, i.e. the situation was in his/her evasion area. Hence, the decision boundary for lane change is estimated as the boundary between those two situations. In the upper panel in Fig.6, the situation where the driver made lane changes and the situation where the driver did not make lane changes are depicted as circles at \( Y = 1 \) and \( Y = 0 \) on the vertical axis against the corresponding risk level on the horizontal axis. Risk level in our experiment consists of velocity difference between lanes \( \delta v \) and the inter-vehicle distance of the destination of lane changing \( d_n \), as described in the section 2.2.

In the automated driving, we collected the samples of situation at the initiation of automatic lane changes which the driver tolerated and those which the driver did not. The lower panel in Fig.6 depicts the driver’s decision boundary for lane changes in the same manner.

Our focus in negative adaptation is the variation of decision boundary on risk of the situation, i.e. the variation of the sensitivities to the risk factors in the driving situation. They are estimated by applying logistic regression to the collected data. Let \( p = P(Y = 1|\delta v, d_n) \), which is, in the manual driving, the probability that the driver changes lanes given the risk of driving situation \((\delta v, d_n)\), i.e. \( 1 - p \) is the probability that the driver does not change lanes. Logistic regression is the probabilistic plane expressed as

\[
\log \frac{p}{1-p} = \beta_0 + \beta_{\delta v} \cdot \delta v + \beta_{d_n} \cdot d_n,
\]

where \( \beta_{\delta v} \) and \( \beta_{d_n} \) represent the driver’s sensitivity to risk factors \( \delta v \) and \( d_n \), respectively. The coefficients \( \beta_0 \), \( \beta_{\delta v} \), and \( \beta_{d_n} \) are estimated from the collected behaviour data of \((Y, \delta v, d_n)\). In the automated driving, \( p \) is the probability that the driver tolerates the automated lane change by the system, and \( 1 - p \) is the probability that the driver will interrupt and refuse the automated lane change. Our analysis investigate the driver’s negative adaptation by comparing the sensitivities to the risk factors obtained using logistic regression.

Additionally the gaze behaviour of the driver was investigated as the indicator of negative adaptation on the driver’s appearance. This also includes the comparison of the gaze behaviours in the two conditions of driving. The difference of the gaze behaviours in two conditions were evaluated in relation to the negative adaptation represented as the insensitivity to risk factors. The gaze direction is recorded at 30 Hz and down-sampled to 10 Hz in the analysis.

4. EXPERIMENT RESULTS

Fifteen subjects with driving license participated in our experiment as the drivers in the driving simulator. Each driver is required to drive the simulator for four trials in total; two trials for each driving conditions and each trial continues about twenty minutes. They made about twenty lane changes in one trial. Each driver is given five minutes of practice to get used to the simulator itself, and another five minutes to get used to the simulated automated driving system.

4.1 Variation of decision boundaries

Examples of the probability surfaces estimated using logistic regression for Subjects 05 and 08 are shown in Figs. 7 and 8. Lane change decisions made by these drivers in manual and automated driving are shown in the graphs on the left and on right, respectively. Samples of left and right lane changes have been combined into one data set and are included 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, based on their assessment of the risk level of the surrounding environment, (i.e. based on \( \delta v \) and \( d_n \) as described in the section 2.2). A red dot indicates the driver decided to make a lane change, either manually or by allowing the vehicle to automatically change lanes in the case of automated driving. A blue dot indicates the driver decided not to make a lane change during conventional driving, or intervened to prevent an automated lane change during automated driving. These red and blue dots correspond to the samples of \( Y = 1 \) and of \( Y = 0 \) in the Fig.6, explained in the section 3.3. The more the red and blue dot distributions overlap, the more inconsistent
a driver was when making lane change decisions (i.e. the more randomly the subject made or avoided lane changes in relation to the subjective risk level). Figure 7 shows that Subject 05 displayed relatively consistent behaviour regarding lane change decisions during both manual and automated driving, but seemed somewhat more conservative during automated driving than during manual driving. Although he tended to avoided making lane changes when it was risky, and tended to make lane changes when it was safe, he also tended to make a greater number of risky lane changes during conventional driving. Accordingly, his decision plane obtained by logistic regression has relatively more sharp slope in manual driving. In contrast, Subject 08 exhibited more random risk taking behaviour during automated driving. Although he tended to avoided making lane changes when it was risky, and tended to make lane changes when it was safe, he also tended to make a greater number of risky lane changes during conventional driving. Accordingly, his decision plane obtained by logistic regression has relatively more uniform during automated driving as her decision threshold became more ambiguous.

Table 1. Regression coefficients estimated for each driver using logistic regression. “M” and “A” in the “Condition” column indicate manual and automated driving, respectively.

<table>
<thead>
<tr>
<th>Subject #</th>
<th>Condition</th>
<th>(\exp(\beta_0))</th>
<th>(\exp(\beta_{nv}))</th>
<th>(\exp(d_n))</th>
</tr>
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<tbody>
<tr>
<td>01</td>
<td>M</td>
<td>0.032</td>
<td>0.838</td>
<td>1.094</td>
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<tr>
<td></td>
<td>A</td>
<td>0.193</td>
<td>0.972</td>
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<td>02</td>
<td>M</td>
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<td>1.034</td>
<td>1.062</td>
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<tr>
<td></td>
<td>A</td>
<td>0.064</td>
<td>0.937</td>
<td>1.077</td>
</tr>
<tr>
<td>03</td>
<td>M</td>
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<td>0.954</td>
<td>1.066</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>0.043</td>
<td>0.927</td>
<td>1.066</td>
</tr>
<tr>
<td>04</td>
<td>M</td>
<td>0.377</td>
<td>0.763</td>
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</tr>
<tr>
<td></td>
<td>A</td>
<td>0.340</td>
<td>0.819</td>
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</tr>
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<td>05</td>
<td>M</td>
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</tr>
<tr>
<td></td>
<td>A</td>
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<td>0.876</td>
<td>1.128</td>
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<tr>
<td>06</td>
<td>M</td>
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<td>0.993</td>
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<td></td>
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<td></td>
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<td>09</td>
<td>M</td>
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<tr>
<td></td>
<td>A</td>
<td>0.057</td>
<td>0.980</td>
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<td>10</td>
<td>M</td>
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<td>0.158</td>
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<td>11</td>
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<td>M</td>
<td>0.009</td>
<td>0.980</td>
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<td>13</td>
<td>M</td>
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<td>0.875</td>
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<td></td>
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<td>0.083</td>
<td>0.963</td>
<td>1.028</td>
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<tr>
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<td>M</td>
<td>0.044</td>
<td>0.991</td>
<td>1.067</td>
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<td>M</td>
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<td>A</td>
<td>0.124</td>
<td>1.117</td>
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</table>

Regression coefficients (odds ratios \(\exp(\beta_i)\) where \(i \in \{0, \delta v, d_n\}\)) estimated for each driver are listed in Table 1. Regression coefficients for manual driving (\(\exp(\beta_i^{(M)})\)) and automated driving (\(\exp(\beta_i^{(A)})\)) are compared. Odds ratio \(\exp(\beta_{nv})\) represents inconsistency in a driver’s lane change decision making for given differences in relative velocity between the two lanes \(\delta v\), while \(\exp(d_n)\) represent inconsistencies in decision making based on distance between vehicles in the faster lane \((d_n)\). Risk level of the surrounding environment increases as relative velocity \(\delta v\) increases and distance \(d_n\) decreases, thus we can infer that drivers with larger odds ratios \(\exp(\beta_{nv})\) and small odds ratios \(\exp(d_n)\) are more inconsistent in their decision making in relation to these risk factors (i.e. they are less sensitive to the relative velocity of vehicles and to the distance between vehicles when making lane changes).

4.2 Variation of gaze behaviour

The data of gaze direction is recorded as the sequence of positions on the simulator’s screen. It is converted and categorized into one of the following five categories, according to the positions of equipments on the simulator.

1. To the front (the road ahead)
2. Into the rear-view mirror
3. To the right (including right rear-view mirror)
4. To the left (including left rear-view mirror)
5. Other (out of range or unknown)

The gaze coordinates of the driver’s focus on the screen of the simulator were used to classify gaze direction into one of these five categories. Figures 9 and 10 show examples of the gaze behaviour data collected from Subjects 8 and 12, respectively. The relative frequencies of driver gaze into each of the five directions was calculated for each point in time during both right lane changes (a) and left lane changes (b), with the top and bottom graphs corresponding to conventional and automated driving.
respectively. We analysed driver gaze direction during the ten seconds before and after the beginning of each lane change. 0 seconds on the horizontal axes represents the beginning of these lane changes, with negative values representing the seconds preceding those lane changes. We can see from Figs. 9 and 10 that the gaze behaviour of both drivers varied between conventional and automated driving. Subject 08’s gaze was directed to the front about 70% of the time during manual driving, but only about 30% of the time during automated driving. This subject also tended to look to the right or into the right rear-view mirror more often when the vehicle was making automated right lane changes than when he made manual right lane changes, and he exhibited parallel behaviour when making automated lane changes to the left. Fig.10, which shows the data for Subject 12, reveals that this driver also looked more often to the right and left during automated lane changes compared to when she made manual lane changes. However, this driver did not exhibit a significant decrease in attention to the front during automated driving. We can also see that Subject 12 looked into the rear-view mirror more often than Subject 08 during both automated and manual lane changes.

4.3 Relation between Decision Making Behaviour and Gaze Behaviour

The gaze behaviour of the drivers are further investigated in relation to the negative adaptation appeared on the decision boundaries. To quantify the difference of gaze behaviours between two driving conditions, they are modelled using Gaussian Mixture Model (GMM) and Hidden Markov Model (HMM). The process for evaluating the difference is as follows.

For each subject,

(1) Relative frequency of five gaze direction during lane changes in automated and manual driving (e.g. Fig.9) are merged into one data set. A GMM with ten Gaussian distributions is trained on the data set (i.e. each component is a distribution on five dimensional space).

(2) Using the obtained ten Gaussian distributions for relative frequencies as the emission probabilities of hidden states in HMM, its transition probabilities are learnt based on the relative frequency of gaze direction in manual driving.

(3) For each state of the learnt HMM, the number of frames where it is visited is counted in manual and automated driving respectively.

(4) The difference of histograms of states visited in the two driving conditions are evaluated using Hellinger distance metric.

The gaze direction time sequences used for learning the transition probabilities are the same sequences used for generating the relative frequency of gaze direction during lane changes (such as shown in Figs. 9 and 10 for the...
Fig. 11. Correlation between driver’s sensitivity to relative speed and driver’s behavioural deviation from his/her gaze model.

Subjects 08 and 12). The Hellinger distance is a metric to measure the distance between two probability distributions, which is expressed as follows when the distributions are discrete,

\[ H(P, Q) = \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{k} (\sqrt{p_i} - \sqrt{q_i})^2}, \]

where \( P \) and \( Q \) are the discrete probability distribution with \( p_i \) and \( q_i \) as their i-th component.

The relationship between the variation of gaze behaviour, evaluated as the Hellinger distance \( H_j \) for the driver \( j \), and the variation of decision boundary, evaluated as the variation of odds ratio \( \exp(\beta_{sv}^{(A)} - \beta_{sv}^{(M)}) \), is shown in Fig. 11.

The value of \( \exp(\beta_{sv}^{(A)} - \beta_{sv}^{(M)}) \) represents the increase in inconsistency in driver decision making regarding lane changes, when inconsistency in decision making during automated and manual driving are compared for given differences in relative velocities between two lanes. Note that Subject 02, 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 measured. The correlation coefficient between these values including the data of Subject 02 is 0.40. Excluding the data of Subject 02, it is 0.72.

Figure 11 reveals that drivers whose gaze behaviour differs more in automated driving from that in manual driving also tend to be less sensitive to risk factors in the surrounding environment. This suggests that negative adaptation to an automated driving system can be detected by measuring the deviation in driver gaze behaviour between automated and manual driving.

5. CONCLUSION

In order to develop a method for detecting negative driver adaptation to an automated driving system, we investigated the driver’s negative adaptation in the decision boundaries for changing lanes and the driver gaze behaviour, using a driving simulator experiment. We found that drivers who paid less attention to the road ahead during automated driving tended to be more dependent on the automated system. Compared to their driving behaviour during conventional manual driving, these drivers were less consistent when making lane change decisions during automated driving, and less sensitive to risk factors in the surrounding environment, such as differences in relative speeds and distances between nearby vehicles. Changes in driver adaptation to automated driving systems over time, as well as adaptation to different levels of automation, should be examined in future research.

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