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Takeover Quality Assessment and Eye Movement Behavior Analysis for Limited Autonomous Vehicle

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Abstract: With the continuous development of automation research, automatic driving has become the trend of The Times. In practice, the driver can relax during driving and enter the state of breaking out of the control loop. However, due to the technical limitations of autonomous driving, the driver is required to take over the vehicle to deal with sudden dangerous situations. Therefore, we conducted a driving simulator experiment to analyze the eye movement behavior and take-over performance of the driver before and after taking over the vehicle in the state of off-loop. The operational response of drivers to emergencies after the release of take-over request (TOR) was used to measure take-over performance. Eye-movement behavior parameters of drivers in take-over process were obtained by tracking eye-movement behavior with eye tracker. At the same time, uc-WinRoad, a virtual reality software, was used to obtain the driver's reaction time and evaluate the quality of the control.

1. Introduction

Studies show that autonomous driving technology [1] has benefits for society, drivers, and pedestrians. Automatic driving can realize automatic emergency braking to avoid obstacles, recognize traffic signs, plan ahead routes, assist parking, and other functions [2].Autonomous vehicles can reasonably plan their respective routes through information interaction between vehicles, save traffic congestion costs and ensure the safety of drivers and pedestrians [3]. Second, autonomous driving provides drivers with a new in-car experience. Kim et al. recently described in their research on autonomous vehicles that drivers can participate in social interaction, entertainment, or office activities while driving vehicles [4, 5]. However, the application of automatic driving in real life will also cause many harms: Lucifora et al. [6] investigated the dual contributions of moral judgment and risk analysis in subjects facing dangerous situations when automatic driving vehicles are faced with inevitable conflicts. Monkhouse et al. [7] defined an enhanced vehicle control model (VCM), extending the concept of controllability and joint cognition to highly automated tasks.

The American Society of Automotive engineers (SAE), according to the development of the automatic driving process, vehicle automated driving grading standards for six grades [8].In the future, conditional automatic driving will occupy the automated vehicle market for a long time, which requires the driver to take over the car again in the case of automatic driving system failure or system limit, which is called automatic driving takeover [9]. As automation dominates vehicle control in advanced intelligent driving, the measurement standards of actual operation in the vehicle running state are no longer applicable.

Many scholars have studied the quality of automatic driving takeover in different aspects. Korber et al. [10] study influence of age on driver take-over quality. Zeeb et al. [11] Analyzed the influence of driver's gaze on the road in take-over request mode on the occurrence of accidents. In the study of Feldhutter et al. [12], after more than 20 minutes of continuous automatic driving time, the driver's sight began to deviate from the driving screen.

2. Experimental Design and Process

2.1. Experimental Equipment

Simulation and data acquisition module: This study was conducted in Forum8's driving simulator (Fig1), which consists of three LED screens and a cockpit to produce realistic vehicle operation effects (e.g. steering, braking) and provide a view of about 180 °. To create a more visually realistic autonomous driving environment and takeover scenes, three-dimensional real-time virtual reality software UC-WinRoad was used to realize the panoramic simulations of the driving environment and trigger events. The subjects wore Tobii Pro Glasses2 eye tracker (Fig2) throughout the experiment to track eye movement behavior and record eye movement data. The portable recording equipment connected with THE HDMI cable ensured the behavioral freedom of the participants while driving. At the same time, through the eye movement instrument is ultra wide angle camera output, participants view direction video scenes, using pupil corneal reflection and eye dark pupil position tracking, eye movement trajectory through the eyes of four eye cameras, a gyroscope and an acceleration sensor were the real horizon of eye movement data, guaranteeing the stability of eye movement data collection and data of high quality, as shown in Figure 1 and 2.

Figure 1: Driving simulator

Figure 2: Eye tracker

Data extraction module: Approved by the ErgoLAB human-machine interactive platform for data preprocessing, linear interpolation, packet loss compensation, by moving average filtering method for signal de-noising, using I - VT (incremental visual tracking) algorithm extraction and scanning data, finally obtain each simulation driving and look at all subjects, scanning, and the pupil related eye movement parameters.

2.2. Participants and Experimental Design

We recruited a total of 11 subjects, all of whom held driving licenses, had normal visual function, strong awareness of traffic safety, had no traffic accident experience, and had no automatic driving experience.

Uc-winroad design event type factors include dynamic (D) and static (S) events . The time budget factor is 4S and 6s, and all events appear before the takeover request (TOR) 5s. There are ten key takeovers, which occur every 120s. The adjacent events include DD, SS, DS and SD in four possible sequences. The traffic volume in the opposite direction is moderate. In the same direction, to avoid the driver always perceiving dynamic events in advance, the driver will occasionally be overtaken by a faster vehicle. The simulation scenario was carried out on a three-lane expressway, with a total length of about 19km and a duration of about 25min. When the vehicle is not under takeover, it drives automatically at a speed of 60km/h and runs in the right-most lane. TOR is represented by visual plus auditory warning signals. The automated system is deactivated along with TOR's cues, and the vehicle slows down slightly without driver intervention.

2.3. Experimental Process

After understanding the simulation experiment process, participants sat in a driving simulator wearing a good eye tracker, adjusted their driving position, and calibrated the eye-tracking system. The experiment started with about 5min of training, which was similar to the formal experiment. During the training, no key events were set and only a takeover alarm was demonstrated. The purpose was to help participants get familiar with the simulator and the autonomous driving vehicle and adapt to the presentation of the takeover requests.

The official experiment started in manual driving mode, and the driver switched to automatic driving mode after driving about 500 meters. The driver is asked to take his hands off the steering wheel, feet off the pedals and remain free to observe the driving environment when the automatic system is activated. After driving for a period of time, a critical takeover scenario will appear. 4s or 6s (the set time budget) will give an alarm before the system limits, and the driver will take over the vehicle control and perform the corresponding operations, then return to the right-most lane, and then the system will automatically switch back to the automatic driving mode. Each participant experienced 10 key takeover scenarios, which lasted about 40 minutes.

3. Data analysis

To process vehicle data using MATLAB, the driver's UC data should be read first: Time, distance Along Road, speed Limit, speed In Km Per Hour),throttle, break and steering Velocity, offset From Lane Center and offset From Road Center.

With position as the independent variable and speed In Km Per Hour, throttle break, steering velocity, offset From Lane Center, and offset From Road Center as the dependent variables, the scatter chart of one driver is shown in figure 3:

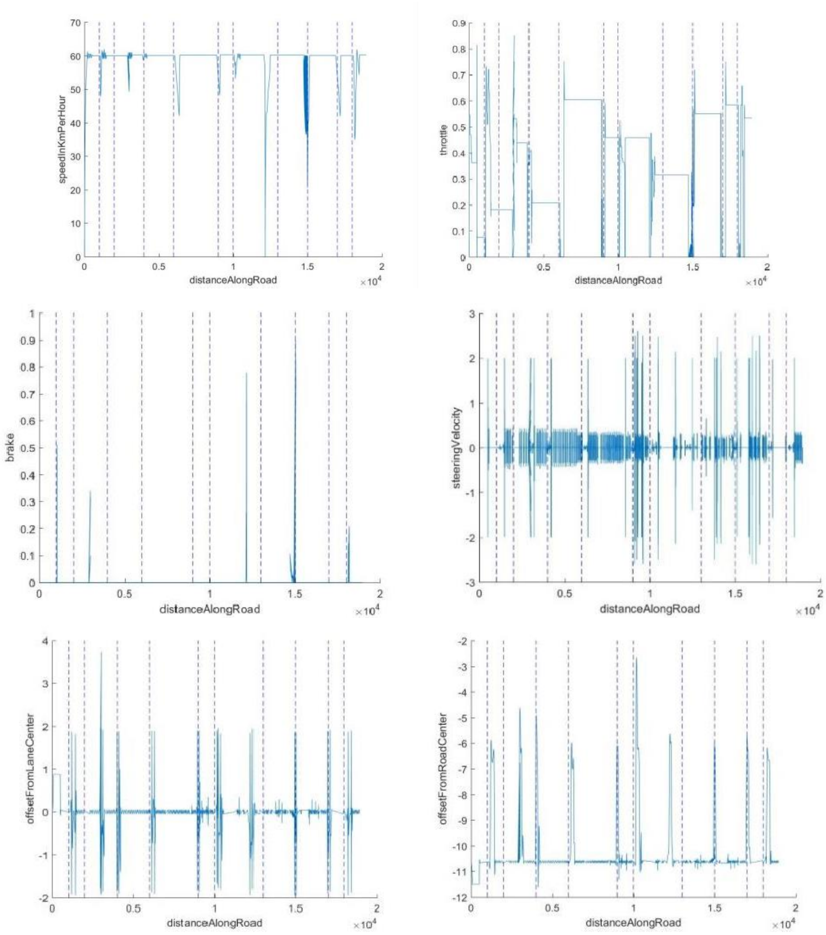

Figure 3: Scatter diagram of driver's UC data

3.1. Eye Movement Behavior of Drivers in Takeover Process

3.1.1. Visual Attention Allocation of Drivers before TOR

We first explore the allocation of visual attention of drivers in the process of conditional automatic driving. Due to different ways of presenting events, drivers may have different stimuli, so it is expected that drivers will show different visual attention responses when perceiving different event types before the alarm.

According to the corresponding relationship between the start and end locations and the time of each subject's UC data event location, the start and end times of 10 events were divided into time units to screen visual data in the event occurrence process. Take time as independent variable, blink(Blink), gaze(Fixation), sundering(Saccades), and left eye pupil diameter(leftPupil) as the dependent variable, respectively, to draw the scatter diagram and histogram of the driver. The maximum and minimum value, mean value, variance, and standard deviation of visual data from the beginning to the end of each subject were calculated. Taking one of the drivers as an example, the histogram and scatter diagram of the blink data are drawn, as shown in Figure 4. Histogram and scatter plot of fixation data, as shown in Figure 5. Scan histogram and scatter plots of the data, as shown in Figure 6.

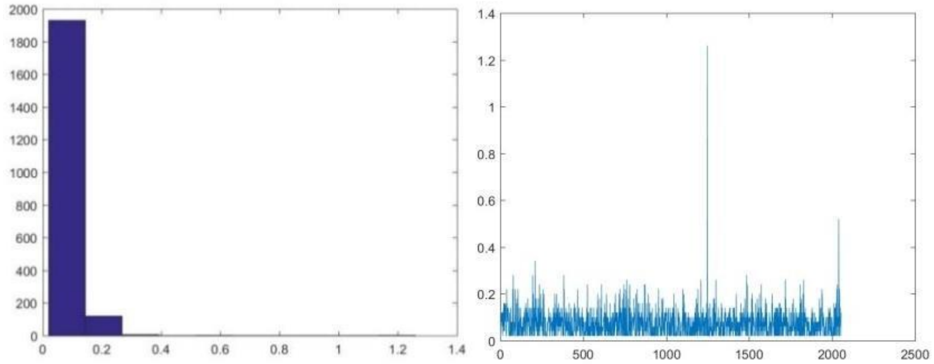

Figure 4: Histogram and scatter diagram of blink data

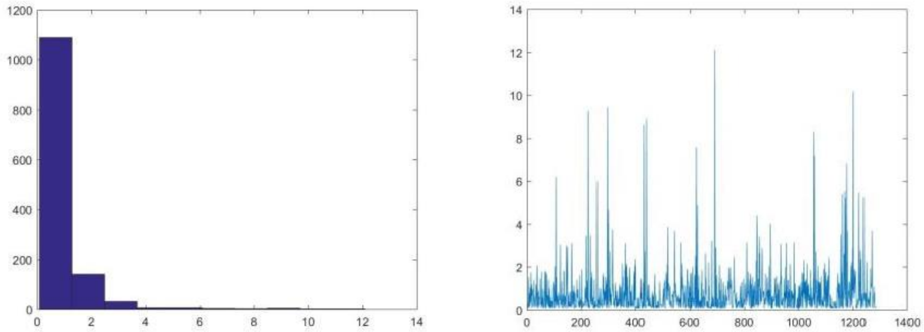

Figure 5: Histogram and scatter plot of fixation data

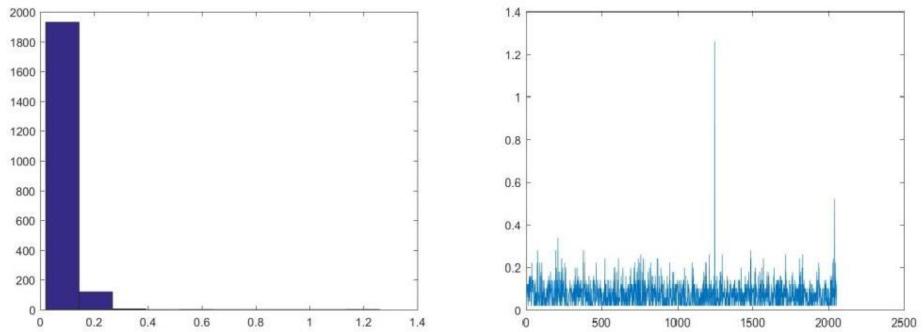

Figure 6: Histogram and scatter plot of scan data

The obtained data show that in the first 5s of the take-over request, the average sundering duration of the driver is 0.64s (SD=0.33) and 0.40s (SD=0.25) respectively in the face of the events induced by dynamic and static scenes. The fixation duration was 2.73s (SD=1.18) and 3.47s (SD=0.92).

Analysis shows that in dynamic scenes, drivers search for potential danger information except for moving targets through frequent saccades and short-term gaze.In static scenes, the driver will spend longer focusing on a few specific fixation targets without fully scanning other elements on the road due to the progressively wider field of view of the target that induces takeover.

3.1.2. Analysis of Eye Movement Indicators before and after TOR

In comparison, the saccades of drivers after TOR were significantly reduced compared with those before TOR, but the release of TOR did not significantly affect the saccade duration of drivers, and drivers' fixation behavior increased, which was manifested by a significant increase in fixation duration and average fixation time. Meanwhile, the pupil diameter of the driver TOR was significantly enlarged.

The analysis shows that the decrease of saccades and the increase of gaze behavior indicate that the drivers have strengthened their attention to potential dangerous events after taking over the request.

In addition, the tension and urgency brought by the sudden alarm lead to a sudden increase in the psychological load of the driver, which is shown by a sudden increase in the diameter of the driver's pupil, reflecting the driver's eager to control the psychology when facing the sudden change.Therefore, saccade duration and pupil diameter can predict the driver's behavior after control transfer to some extent.

3.2. Take-over Response of the Driver

3.2.1. Reaction Time

However, there were significant differences in braking response time and steering response time between different event types, which triggered our thinking.

The braking response of dynamic events is 0.48s faster than that of static event, which has shorter braking response time. At the same time, the steering response of static events is 1.12s faster than that of dynamic events, and the steering response time is shorter. In addition, there is a significant difference in the steering response time between 4S and 6s, so it can be seen that the shorter the time budget given to the driver, the faster the steering response will be.

The analysis shows that, due to the uncertainty of dynamic events, more drivers subconsciously choose to reduce the speed first to ensure driving safety. However, as the sense of crisis brought by static events is far less than that of dynamic events, many drivers will first think of changing lanes or going around to avoid obstacles.

3.2.2. Operation Mode and First Reaction Behavior

3.2.1 is the stress behavior after the emergency, so in the few seconds of preparing to take over, how will the driver choose to avoid risk?

For further research, Pearson correlation analysis (Table 1) was conducted on four response time indicators (takeover response time, braking response time, steering response time, and throttle response time), and it was found that there was a strong positive correlation between takeover response time and braking response time ($r=0.907$, $P<0.001$). This indicates that after the take-over request is issued, the driver will consciously brake to make the first reaction to the take-over control.

Table 1: Correlation analysis of response indicators

Pearson’s r	Takeover response time	Brake reaction time	Turn reaction time	Throttle response time
Takeover response time	—	0.907 ($p < .001$)	0.154	0.431($p < .001$)
Brake reaction time		—	0.011	0.211
Turn reaction time			—	0.106
Throttle response time				—

3.3. Driver Take-over Quality

By analyzing the descriptive statistics of the four indicators measuring the quality of the nozzles (Table 2), it can be concluded that the driver shows greater steering wheel rotation in the face of static events and more brake control in the face of dynamic events. And the 6s's time budget shows a safer control takeover than the 4S. Therefore giving more time to budget when issuing TOR can improve the takeover quality.

There are several related dependent variables.

Max_lateral_offset is the maximum lateral displacement of the driver-controlled vehicle at the TOR moment after issuing TOR, which can represent the stability of lane change after the driver takes over control in obstacle avoidance scenarios.

Standard deviation of steering velocity(Steering Velocity_std) is used as an evaluation index of driver's lateral control stability, in which the steering wheel rotation rate refers to the rate of change of steering wheel Angle, and its dispersion degree is measured by the standard deviation of the steering wheel rotation rate. A smaller standard deviation indicates a more stable steering wheel control.

Percentage change in average speed(Per_Speed Change) provides a cumulative reading of the driver's speed change over the course of the takeover, providing a comprehensive assessment of the driver's longitudinal control operation. The formula is as follows, with a higher percentage indicating a sharp change in speed (severe braking or acceleration).

$$\text{Per\_SpeedChange}=\frac{100}{n-1}\sum_{k=1}^{n-1}\frac{|x_{k+1}-x_k|}{x_k} \tag{1}$$

(x is the speed input value, k is the number of frames, and n is the window size)

Minimum Collision Time(Min_CT) is an alternative measure of safety and controllability. It refers to the shortest time before a vehicle collides with a vehicle or an obstacle in front of it. If a collision occurs, Min_CT is zero. In this study, Min_CT was measured before the driver had performed sufficient steering to make a lane change through the obstacle.

Table 2: Analysis of data of four indicators to measure takeover quality

	The event type		Time budget	
	dynamic	static	4s	6s
Max_lateral_offset	4.52 (0.83)	4.89 (0.95)	4.84 (1.42)	4.61 (0.90)
Steering Velocity_std	0.02 (0.01)	0.03 (0.02)	0.03 (0.02)	0.02 (0.02)
Per_Speed Change	0.61 (1.47)	0.19 (0.79)	0.96 (2.10)	0.26 (0.66)
Min_CT	2.04 (1.63)	1.80 (1.86)	1.15 (1.85)	2.52 (1.36)

3.4. Comprehensive Indicators of Takeover Performance

Sections 3.2 and 3.3 of this paper have analyzed the situation of driver take-over control in detail from the time level and quality level, but failed to comprehensively evaluate the advantages and disadvantages of take-over performance.

For the takeover response time, the results show a significant positive correlation with the maximum lateral offset and a significant negative correlation with the minimum collision time. There is a negative correlation between the standard deviation of steering wheel rotation rate and the change percentage of average speed, which reflects the driver's handling stability. The two strongest correlation coefficients in the output results appear in the minimum collision time index, which has a negative correlation with the standard deviation of steering wheel rotation rate and the maximum lateral offset, as shown in Table 3.

Table 3: Correlation of indicators

	Maximum lateral offset	Standard deviation of steering Velocity	Per_Speed Change	Min_CT
Takeover response time	0.249*	0.126	-0.042	-0.303**
Maximum lateral offset		0.148	-0.123	-0.398***
Standard deviation of steering Velocity			-0.309**	-0.457***
Per_Speed Change				0.194

In other words, after we understand what happens in the takeover process through specific takeover indicators, we also need a comprehensive indicator of takeover performance to systematically and objectively rate takeovers. In this study, the weight of each indicator was determined through PCA(principal component analysis), and then the multiple indicators reflecting different characteristics of the takeover were weighted and summed up to obtain a comprehensive Takeover_Performance index.

First, the method is used to standardize the data, first determine the positive and negative direction of the index (the smaller or larger the index is, the better the performance), and then calculate the standardized index by the formula. The standardization processing here makes all index data turn into positive, that is, for any standardized data, the higher the value, the better the performance.

For positive indicators:

$$S_i = \frac{X_i - \min X}{\max X - \min X} \tag{2}$$

For negative indicators:

$$S_i = \frac{\max X - X_i}{\max X - \min X} \tag{3}$$

Where S_i is standardized data, X_i is original data.

Principal component analysis reconstructs a group of unrelated principal component variables through linear combination after dimensionality reduction, namely:

$$\begin{cases} F_1 = a_{11}S_1 + a_{21}S_2 + \cdots + a_{n1}S_n \\ F_2 = a_{12}S_1 + a_{22}S_2 + \cdots + a_{n2}S_n \\ \cdots \\ F_m = a_{1m}S_1 + a_{2m}S_2 + \cdots + a_{nm}S_n \end{cases} \tag{4}$$

Where $F_1, F_2, \ldots, F_m$ is m principal components, a_{ij} is the coefficient in linear combination. Among them:

$$a_{ij} = \frac{f_{ij}}{\sqrt{\lambda_j}} \quad j = 1, 2, \cdots, m \tag{5}$$

Where f_{ij} is the number of factor loads, λ_j is the corresponding eigenvalue of the Jth principal component.

Thus, it can be determined that the coefficient of each index in the comprehensive scoring model is:

$$W_i = \frac{\sum_{j=1}^{m} a_{ij} V_j}{\sum_{j=1}^{m} V_j} \quad j = 1, 2, \cdots, m \tag{6}$$

Where, V_j is the variance contribution rate of the Jth principal component.

Finally, the coefficients of each standardized index in the comprehensive scoring model are normalized to obtain the weight coefficient w_i（i=1,2…,n）

The range of the comprehensive index (Takeover_Performance) was [0,1], and the closer the value was to 1, the better the takeover performance was. The final formula is as follows:

Takeover_Performance=0.24* S_Takeover_RT + 0.22* S_Max_lateral_offset +0.07* S_steeringVelocity_std + 0.2 * S_Per_speedChange + 0.27 * S_Min_TTC.

4. Conclusions

The results of this study provide a better evaluation of the driver's driving state and subsequent takeover quality in the process of conditional autonomous driving. When the driver's task changes from operation to surveillance, the eye movement behavior survey can better help expand the understanding of driver takeover behavior. Therefore, this paper has the following implications for the analysis of eye movement parameters: fixation and saccade indicators can be used to reversely infer the event types encountered by vehicles; drivers need to interpret the current scene information and identify event features more deeply through fixation. At the same time, we obtained a more reasonable index to judge the quality of the nozzle through the analysis of various reaction time and vehicle data. However, due to time and other reasons, our data processing is not in-depth enough, and we have not successfully connected the eye movement data and takeover quality reasonably. We expect to integrate the eye movement data and takeover quality in the future to obtain the relationship between the two.

Application Prospect

A series of previous studies have shown that self-driving cars are beneficial to society, drivers and pedestrians, and the accident rate of self-driving cars can be reduced to almost zero. The results provided by this study provide new insights into driver takeover performance and eye movement behavior during conditional autonomous driving. Participants' eye movement behavior before triggering a takeover requests can be used to predict their performance, and it is even hoped to be used to evaluate the safety of the subsequent takeover control loops. In the future, perhaps the analysis of eye-movement behavior data will become a reliable way for efficient cooperation and "mutual understanding" between autonomous vehicles and drivers.

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