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An Evaluation Method for Visual Search Stability in Urban Tunnel Entrance and Exit Sections Based on Markov Chain

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ABSTRACT Tunnel section is the throat of transportation and attracts lots of attentions. This paper proposed a method to evaluate the driver's visual search stability based on the Markov Chain properties of eye movements. Firstly, visual and physiological data about 16 participants driving through 13 urban tunnels were collected. Then, the view area was divided into six AOIs (Area of Interest) by fast clustering of the drivers' fixation points. The one-step fixation transition probability and the stable distribution of different lane changing behavior were obtained based on the division of the view area. The probability of transition from the forward windscreen to the left rearview mirror and other 6 visual parameters were selected as indexes by correlation tests. And the first four principal components which covered 96.1% of all information were extracted. Then an evaluation method for visual search stability was implemented by principal component analysis. In order to validate the method, average lane change times, average speed and SDNN (Standard Deviation of NN Intervals) of the drivers' heart rate were clustered into two categories. According to the consistency between the evaluation results and the clustering results, the evaluation method proposed in this paper has been proven to be reliable. Finally, the score threshold for judging the driver's stability was obtained as $E = 0.313$. The method could be applied to adjustment of tunnel facilities, assistance in driving training and development of auto driving system by assessing whether a driver can take over the control of the vehicle or not.

INDEX TERMS Fixation transition, Markov chain, tunnel traffic safety, visual search stability.

I. INTRODUCTION

Driving on public roads is a highly complex and responsible action, with mistakes or risks-taking possibly having fatal consequences. As reported in [1], approximately 1.35 million people in a year lost their lives and 50 million people were injured in road accidents. As for public area, tunnels are considered as scary spaces with severe accidents which are difficult to handle. It has been proven that tunnel entrance and exit sections are accident-prone positions [2], [3] for its sharp changes of the driving environment. Because drivers' psychological factors are directly impacted by mutual interference of vehicles and the sudden change of environment. Specifically, driving behavior is seriously affected by the bad feelings, such as fear, hesitations and anxiety, while approaching

tunnels [4]. Although great efforts have been made to improve the traffic safety, such as ADAS (Advanced Driving Assistant System) of ITS (Intelligent Transport System), the influence of bad driving behavior is still seriously underrated. It is essential to be able to assess whether a driver can take over the control of the vehicle or not. Visual attention has been considered as the foremost factor to traffic activities. Successful driving requires the correct detection, identification, and assessment of the visual stimuli [5].

This paper mainly studied short urban tunnels, and a method based on Markov chain was proposed to evaluate drivers' visual search stability which reflects the ability to observe and process information in urban tunnel entrance and exit sections. Section 2 reviews the findings about drivers' visual characteristic and the application of theory in tunnel sections. Section 3 describes the application of Markov chain in visual theory. Then, a theoretical framework is derived

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to explain the relationship between visual search stability and driver's visual fixation transition. Section 4 contains the experiment procedures in acquiring visual data, so that the method is used in Section 5. Section 6 discusses the results and validates the method. The last section summarizes the results of this paper and puts forward the prospect of the future research.

II. LITERATURE REVIEW

In the early, visual occlusion can be used to assess the visual demands in different traffic environments [6]. Expert knowledge and think-aloud verbal protocol have also been used to assess the driver's attention from the view of subjective perception [7-9]. Scientists were unable to accurately give a good estimate of where the driver's attention is directed until eye-movement technology was developed [10]. Researchers can find both where the person is looking at a given time and the fixation transition from one fixation point to another with eye-tracking technology.

Early work on fixation allocation using pictures has indicated that viewers do not look randomly at the scene but gaze predominantly to informative areas of the picture [11]. In a traffic environment, informative areas are those where hazards can arise from as well as objects in the visual field relevant to the performed task (e.g., a vehicle having priority). Eye-tracking studies conducted among car drivers have shown that hazardous events reduce saccadic activity (i.e., reduced spread of search) and increase fixation durations on the hazardous object, which may reflect in-depth information processing [12]–[15]. Perceptual narrowing in traffic may be similar to the 'weapon focus' phenomenon whereby observers fixate more often and for a longer duration on a threatening object than on a neutral object [16], [17]. It can be expected that road users shift their attention between potentially hazardous objects while allocating most visual attention to high-value information sources [18]. The difference of visual search patterns between the experienced and novice drivers can be evaluated with the drivers' movements [19], [20]. However, the wearing of eye-tracking devices still has an impact on natural experiments. But the developers have been working hard to reduce the device's weight to 45g just like plain glasses.

Literature of tunnel traffic safety has involved with the visual characteristics of drivers. Several studies have explored how the driver's visual characteristics be influenced in tunnel sections. The drivers' fixation point movement characteristics in urban tunnel have been took as research object to obtain the universal pattern of fixation point distribution [21], [22]. In order to study driver's visual characteristics under different curvatures and turning conditions in extra-long urban underwater tunnels, fixation and saccade were regarded as the main research objectives in [23]. The visual cognition probabilistic model was applied to evaluate the safety of the urban tunnel sign with driver's eye-movement characteristics [24]. It has been investigated that how vehicle speed influences the driver's visual characteristics at tunnel sections [25], [26].

The indexes of the drivers' eye movements can be also used to evaluate the driving safety. In [27], the influence of sun glare on individual drivers in urban tunnels is quantitatively illustrated by the change rate of driver's pupillary area. The random choice model of deceleration behavior in response to sun glare (DBSG) is established to study the influence of DBSG on traffic safety. The drivers' heart rate (HR) and eye movement, together with the pupillary diameter at the entrance and exit of urban tunnel were collected to measure the safety of urban tunnel entrance and exit. The validation by comparing with tunnel environmental shows that the measure proposed in [28] is acceptable and more accurate in evaluating the safety of tunnel gateway zones. A driving risk system consisting of visual indexes for urban tunnels was proposed in [29] to assess driving safety in tunnels constructed or in design.

Several studies combined both the drivers' psychological and physiological characteristics to identify the dynamic visual characteristics [30], [31]. The mechanisms of visual adaptability and information perception of drivers in urban tunnel were studied to consider the effect of visual information at different luminance levels [32]. Feng *et al.* studied changes in physiological and behavioral characteristics in longitudinal segments of urban tunnels [33]. When it comes to complex tunnel scenarios where field experiments are difficult to carry out, the driving simulator is a good choice for researchers. Cao *et al.* have compared the real car experiment with driving simulator test and confirmed that the driving simulator is a reliable tool for the analysis of driver behavior in urban tunnels [34]. A driving simulator experiment has been carried out based on a box truck module, with the purpose of investigating the safety of the truck under crosswind at the bridge-tunnel section [35]. Qin *et al.* have explored the impacts of color decoration of interior tunnel walls on improving driving behavior with the driving simulator [36]. In order to improve legibility of traffic signs, the tunnel sign's siting, layout and visual cognition probabilistic model based on driver's eye movement characteristics was established by simulation tests in [37].

Most of the literature is focused on highway tunnels, not urban tunnels. And the use of more specific measures, such as gaze transitions, in drivers' search strategies has been less common. A fixation transition is the movement of the eyes between one fixation and the following fixation, providing information on the positional relationship of fixations. There is a tight link between fixation location and allocation of attention in natural tasks, and fixation patterns have been shown to indicate how drivers select the information [38]. Burling *et al.* compared the eye movement patterns of drivers with different experience when identifying potential dangers [39]. Underwood *et al.* analyzed the difference in horizontal search breadth between the experienced and novice drivers through experiments [40], [41]. Scott studied the drivers' search strategies from the aspect of fixation transition in a simulated right turn junction scenario [42]. Hu *et al.* investigate the fixation transition characteristics of drivers

with different driving experience in extra-long tunnel on expressway [43]. There is little literature on drivers' fixation transition in urban tunnel sections. In this paper, each fixation point is regarded as a continuous point on the time axis, which reflects the characteristics of the movement change of fixation behavior in urban tunnel entrance and exit sections.

III. METHODOLOGY

Fixations are the foremost eye-movement events [44]. Position of fixation points indicates the focal point of a person's attention, which reflects cognitive strategies and prior knowledge or experience. The division of AOI (area of interest) is the premise of studying fixation transition. The measurement of fixations between these areas of interest (AOI) is a standard in interaction studies [45]. As a cluster analysis method, k-means clustering is used for grouping data based upon the distance between the individual data points [46]–[48]. Each data point is assigned to the cluster based on how close the data point is to the centroid. New positions of the cluster center points are computed as the mean value of each data point in the cluster. Data points are then reassigned to the new closest cluster center points. By doing this iteratively, eventually the equilibrium is achieved and the cluster center points become stable, at which point each data point could be correctly grouped. The fixation points of each participant are selected and k-means clustering is utilized to group close fixation points together. Then, the research on fixation transition can be carried out next.

It is assumed that the discrete state space M of the random sequence $\{X(n), n = 0, 1, 2, \dots\}$ is $\{1, 2, \dots\}$. If for any m non-negative integers $n_1, n_2, \dots, n_m (0 \leq n_1 \leq n_2 \leq \dots \leq n_m)$, any natural number k , any i_1, i_2, \dots, i_m , and $j \in M$, satisfy Equation (1).

$$P\{X(n_m + k) = j | X(n_1) = i_1, X(n_2) = i_2, X(n_m) = i_m\} \\ = P\{X(n_m + k) = j | X(n_m) = i_m\} \quad (1)$$

$\{X(n), n = 0, 1, 2, \dots\}$ is called the k step transition probability of Markov chain at time n . The state of Markov model at time $n + k$ is only related to the state of n at the previous moment, independent of the state before n . It is a typical random process without an aftereffect. The drivers' fixation points falling in different visual interest areas are in different states. The area of visual interest where the next fixation point falls is only related to the area where the current fixation point is located [49, 50]. Therefore, this is a typical Markov chain, with discrete time and state. The above transition probability can be expressed as $P_{ij}(n, n+k)$ and denoted as $P_{ij}(k)$. When $k = 1$, $P_{ij}(1)$ is called the one-step transition probability. If \mathbf{P} is the matrix formed by step transition probability $P_{ij}(1)$, according to Equation (2)

$$P = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1n} & \dots \\ P_{21} & P_{22} & \dots & P_{2n} & \dots \\ \dots & \dots & \dots & \dots & \dots \end{bmatrix} \quad (2)$$

Taking each fixation area as a state of Markov chain, the probability of one-step transition between the interest

areas is calculated. This paper assumes that $\{X(n), n > 0\}$ is a homogeneous Markov chain, the state space is I , and the transition probability is P_{ij} . If there is a probability distribution $\{\pi_j, j \in I\}$ satisfying Equation (3), then the probability distribution $\{\pi_j, j \in I\}$ is the stationary distribution of Markov chain. If Markov chain is standard, there is a probability vector $\pi = [\pi_1, \pi_2, \dots, \pi_j]$ and its transition probability matrix \mathbf{P} satisfies $\mathbf{P}^t \pi = \pi$. π_j is the stationary probability of the state, and π is the stationary probability matrix. According to this chain, the probability of the fixation point falling in each area tends to be stable after driving for a long time.

$$\begin{cases} \pi_j = \sum_{i \in I} \pi_j p_{ji} \\ \sum_{j \in I} \pi_j = 1, \pi_j \geq 0 \end{cases} \quad (3)$$

IV. EXPERIMENT DESIGN

A. PARTICIPANTS AND APPARATUS

A total of 16 participants had a mean age of 29.4 years (SD = 8.3) with an age range of 23-45 years, including 11 male and 5 female. They had a mean driving experience of 7 years (SD = 9.4) with an experience range of 4-21 years. Participants' occupations include college students, teachers and employees. All participants satisfy the minimum Chinese drivers licensing criteria. And they were familiar with the experimental route. The participant were given a full explanation regarding the nature of the study, experimental protocols and possible consequences of the study, and written informed consent was obtained with the option to withdraw at any time. All of the participants did not drink alcohol or take drugs on the day and day before the test.

The eye tracking device was the Tobii Pro Glasses 2 portable eye-tracker which has a wearable eye tracker with wireless real-time observation function. The non-invasive headwear tracking module ensures comfort and freedom of movement. Fixation attributes data (e.g., duration, gaze direction, background, and the object) captured from the eye tracking video frames and vehicle positions with lane changing were linked by the driver's ID and the time fields. This is the core of the visual-motor coordination data model. Since each fixation point is a period of eye movement, the gaze behavior during this period, e.g., Fixation $i+1$ can be inspected from the vehicle dynamic between the start time at Vehicle j to the end time at Vehicle $j+1$. The Dji Phantom 4 drone was used to shoot video above to calculate traffic flow density. The drivers' heart rate data was collected by the physiological module device and the vehicle speed was recorded by the driving recorder. The test vehicle was a well-maintained Volkswagen Magotan with a maximum power of 118kw, a maximum torque of 250N·m and a wheelbase of 2709mm.

B. EXPERIMENT LOCATIONS AND PROCEDURES

All experiments were conducted in November 2019 when weather is clear. The 13 urban tunnels in Nanjing are selected as the test sections as shown in the Figure 1. The length of

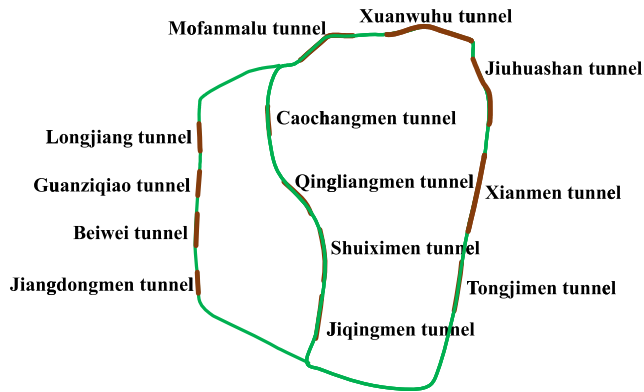


FIGURE 1. Test sections.

the tunnels varied between 275 and 1643m. The speed limit inside the tunnels is 60km/h. To compare the drivers' visual characteristics under different traffic flow density, the participants were asked to drive along the experiment route, passing through 13 urban tunnels from 7:00 a.m. to 9:00 a.m. and 10:00 a.m. to 12:00 a.m. respectively. Helbing *et al.* found that the traffic flow density is about 45 veh/km with the average velocity being 30 km/h on the highway [51]. However, due to the low traffic speed limit and the dense ramp distribution, drivers drive at a speed on urban expressway much lower than that on the highway under the same traffic flow density. Wei *et al.* found that the traffic flow density is about 60 veh/km with the average velocity being 30 km/h on the urban expressway [52]. Therefore, the high and low traffic flow density was divided by 60 veh/km in this paper. The participants were provided with information and the requirement about the test when arriving at the starting point. The headlights should be turned on to provide additional lighting inside the tunnel. Prior to the start of the experiment, the participants were assisted to wear the eye tracker and the physiological module device, all of which have been calibrated and verified to minimize test errors. The participants drove along the test route freely according to their driving experience and habits, so that the data under different traffic circumstances could be accessible. During the test, the relevant parameters were recorded by the eye tracker and the physiological module device automatically. At the end of the test, the data would be examined. If the sampling rate was less than 50%, the participant would be asked to repeat the test after a break.

C. DATA COLLECTION

The field experiments data were simultaneously recorded as illustrated in Figure 2, including vehicle movements, traffic conditions, driver's psychological data and eye movements.

All the driving samples were divided into the entering tunnel part and the exiting tunnel part. The manoeuvres executed by the participant were manually annotated as lane changing from left to right, lane changing from right to left, and drive without lane changing. The lane changing usually starts a few seconds before an actual vehicle movement, because it



FIGURE 2. Example of the experimental set up.

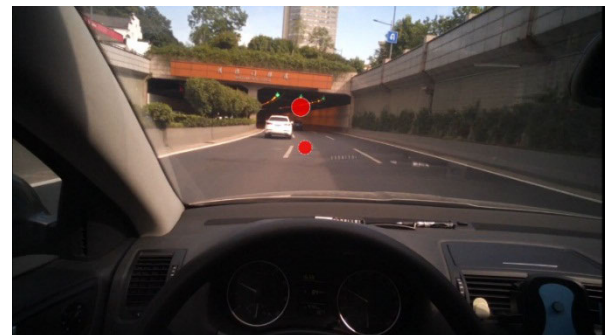


FIGURE 3. Screenshot of scenario. The red spots indicate the fixation positions of the driver.

is assumed that the participant has already prepared for the manoeuvre during this time [53].

The traffic conditions were observed from the video shoot by the drone. The heart rate data were sorted out by the physiological module device. The eye movements were recorded using several infrared cameras as shown in Figure 3. At the same time, the scene from the participant's perspective was recorded by another wide-angle camera. The eye movements and scene images were superimposed to acquire real-time information about when and where the fixation was located. Eye tracking data was denoised by a moving average filter with the inherent structure of fixations preserved. The filter was implemented to facilitate non-causal interpolation of short segments of missing data by ignoring missing values in the sliding median calculation [54].

V. RESULTS

A total of 416 pieces of data in entrance sections and 416 pieces of data in exit sections were collected. Because some gaze data could not be correctly identified by

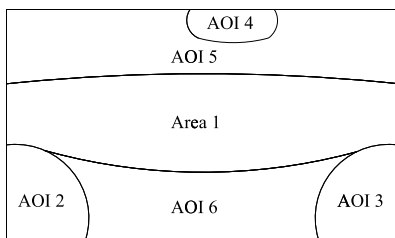


FIGURE 4. Division of view area.

the system, the 375 pieces of valid data in entrance sections and 382 pieces of valid data in exit sections were preserved after statistical processing. There were 98 times of lane changing to the left and 81 times of lane changing to the right in entrance sections, 84 times of lane changing to the left and 107 times of lane changing to the right in exit sections.

A. DISTRIBUTION OF VIEW AREA

By comparison, it is concluded that the clustering boundary is relatively clear when $k = 6$, providing six AOIs as shown in Figure 4: forward windscreen (AOI 1), left rearview mirror (AOI 2), right rearview mirror (AOI 3), central rearview mirror (AOI 4), upward windscreen (AOI 5), and dashboard (AOI 6).

B. ONE-STEP FIXATION TRANSITION AND STATIONARY DISTRIBUTION

The probability of the repeat fixation in 6 AOIs with 3 manoeuvres (lane changing from left to right, lane changing from right to left, and drive without lane changing) under high and low traffic flow density in tunnel entrance and exit sections were obtained respectively. The probability of the repeat fixation in tunnel entrance and exit sections are shown in Figure 5 and 6. The average probability of fixation transitioned from all AOIs in tunnel entrance and exit sections are shown in Figure 7 and 8.

According to the stationary distribution of Markov chain, the distribution of drivers' fixation points tends to be stable after a long period of driving. As shown in Table 1 and 2, the stationary distribution of transition probability in 6 AOIs in 6 cases in tunnel entrance and exit sections were obtained respectively.

C. EVALUATION INDEXES

In order to evaluate visual search stability in terms of fixation transition characteristics, it is crucial to select reasonable indexes based on one-step transition matrix and stationary distribution. The indexes determine the reliability of the model. The variation coefficient test is conducted to

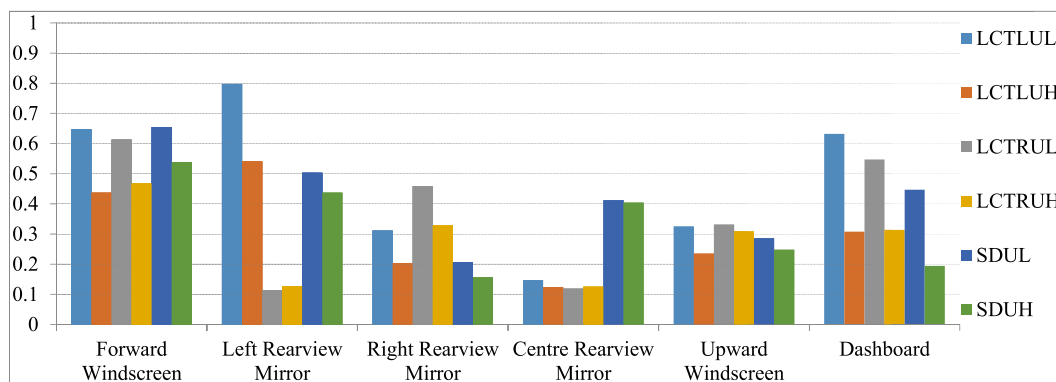


FIGURE 5. The probability of the repeat fixation in tunnel entrance sections.

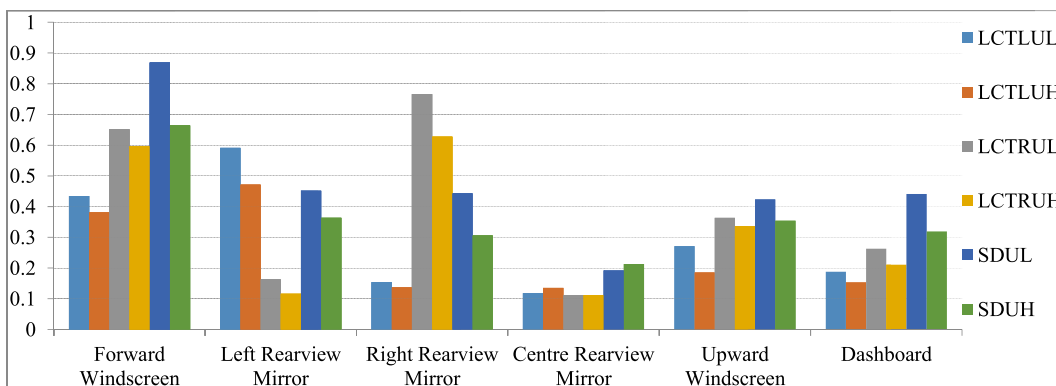


FIGURE 6. The probability of the repeat fixation in tunnel exit sections.

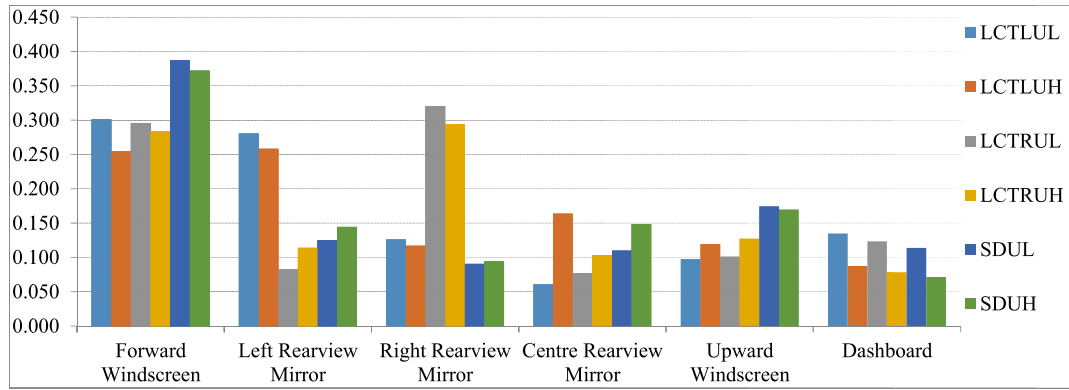


FIGURE 7. The average probability of fixation transitioned from all AOIs in tunnel entrance sections.

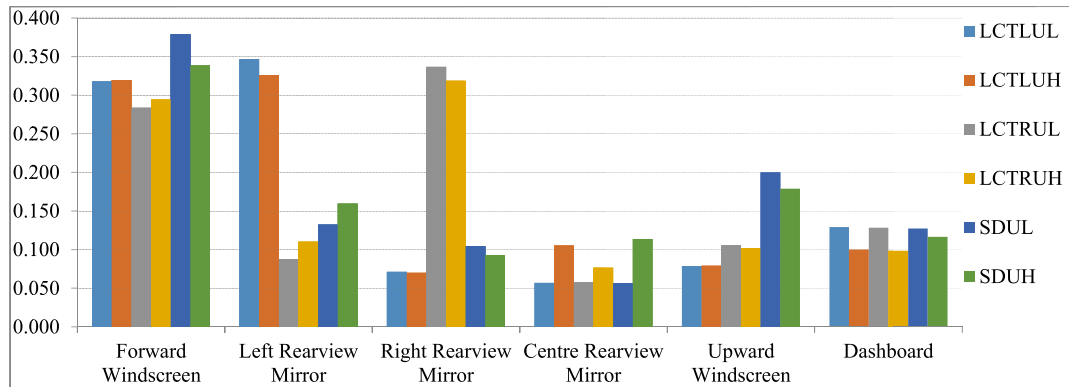


FIGURE 8. The average probability of fixation transitioned from all AOIs in tunnel exit sections.

TABLE 1. Stationary distribution of transition probability in entrance section.

Starting Area	LCTLUL	LCTLUH	LCTRUL	LCTRUH	SDUL	SDUH
Forward Windscreen	0.351	0.273	0.436	0.347	0.491	0.405
Left Rearview Mirror	0.568	0.324	0.053	0.097	0.092	0.147
Right Rearview Mirror	0.019	0.094	0.357	0.304	0.059	0.068
Central Rearview Mirror	0.011	0.148	0.058	0.092	0.063	0.141
Upward Windscreen	0.015	0.118	0.042	0.124	0.214	0.183
Dashboard	0.036	0.043	0.054	0.036	0.081	0.056

TABLE 2. Stationary distribution of transition probability in exit section.

Starting Area	LCTLUL	LCTLUH	LCTRUL	LCTRUH	SDUL	SDUH
Forward Windscreen	0.361	0.328	0.366	0.333	0.652	0.439
Left Rearview Mirror	0.441	0.383	0.053	0.111	0.101	0.175
Right Rearview Mirror	0.029	0.048	0.417	0.369	0.048	0.065
Central Rearview Mirror	0.025	0.105	0.028	0.059	0.014	0.102
Upward Windscreen	0.042	0.059	0.054	0.059	0.103	0.137
Dashboard	0.102	0.077	0.082	0.069	0.082	0.082

determine the key indexes among the one-step transition probability matrix, and the Spearman correlation test is utilized to analyze the interaction between stationary distribution, environment, and driving behavior, as shown in Table 3 and 4.

Under different driving environment and lane changing conditions, the variation coefficients of five indexes are

relatively large: the probability of transition from the forward windscreen to the left rearview mirror (n_{12}), the probability of transition from the left rearview mirror to the forward windscreen (n_{21}), the probability of transition from the left rearview mirror to the right rearview mirror (n_{23}), the probability of repeating on the forward windscreen (n_{11}) and the probability of repeating on the right rearview mirror (n_{33}).

TABLE 3. Variation coefficient of transition probability matrix.

Starting Area	Forward Windscreen	Left Rearview Mirror	Right Rearview Mirror	Central Rearview Mirror	Upward Windscreen	Dashboard
Forward Windscreen	1.235	1.231	0.818	0.897	0.524	0.696
Left Rearview Mirror	1.068	0.562	1.127	0.651	0.683	0.865
Right Rearview Mirror	0.333	0.738	1.183	0.494	0.755	0.886
Central Rearview Mirror	0.445	0.683	0.606	0.592	0.284	0.540
Upward Windscreen	0.189	0.318	0.567	0.615	0.211	0.633
Dashboard	0.387	0.792	0.893	0.815	0.781	0.453

TABLE 4. Spearman correlation test of stationary distribution, environment and driving behaviour.

Starting Area	Forward Windscreen	Left Rearview Mirror	Right Rearview Mirror	Central Rearview Mirror	Upward Windscreen	Dashboard
Traffic Flow	-0.531	0.242	0.266	0.821	0.485	-0.317
Density	p=0.046	p=0.449	p=0.403	p=0.081	p=0.110	p=0.316
Entrance and Exit Section	0.048	0.121	-0.048	-0.241	-0.218	0.779
Lane Changing	p=0.882	p=0.708	p=0.881	p=0.450	p=0.496	p=0.203
	0.789	-0.563	0.207	0.089	0.682	0.283
	p=0.132	p=0.027	p=0.518	p=0.784	p=0.114	p=0.372

There is a significant correlation between the traffic flow density and the stationary distribution probability of the fixation points falling on the forward windscreen (n_1). The lane changing behavior shows a significant correlation with the stationary distribution probability of fixation points falling on the left rearview mirrors (n_2). Therefore, the above seven indexes are selected to subjected to principal component analysis to avoid multicollinearity.

D. EVALUATION MODEL

The data of 16 participants are sorted into the original matrix. Due to the large level difference between the indexes, the original data are standardized to ensure the validity of the original data. The mean value of each index is 0 and the variance is 1. $F_1 \sim F_7$ are the seven principal components which are expressed as some linear combination of the original variables in order that the information contained in these principal components does not overlap. It is assumed that the eigenvalue of the i principal component is λ_i which determines the contribution rate. The larger the cumulative contribution rate of the principal component, the higher the degree of interpretation of the extracted principal component to the original problem. Therefore, the cumulative contribution rate of principal component is taken as the main basis for extracting principal component, as illustrated in Table 5. The cumulative contribution rate of the first four principal components is 0.961 which meant the first four principal components cover 96.1% of all information.

The seven corresponding indexes of the first four principal components are calculated, as shown in Table 6. The expressions of each principal component are obtained as Equation (4) – (7).

$$F_1 = -0.391n'_{11} + 0.403n'_{12} + 0.280n'_{21} - 0.331n'_{23} - 0.092n'_{33} + 0.499n'_1 - 0.490n'_2 \quad (4)$$

TABLE 5. Cumulative contribution rate of principal componets.

Principal component	Eigenvalue	Contribution rate	Cumulative contribution rate
F_1	3.186	0.455	0.455
F_2	1.995	0.285	0.740
F_3	1.093	0.156	0.896
F_4	0.453	0.065	0.961
F_5	0.173	0.025	0.986
F_6	0.071	0.010	0.996
F_7	0.029	0.004	1.000

TABLE 6. Index transition probability.

Index	F_1	F_2	F_3	F_4
n_{11}	-0.391	0.484	0.080	0.135
n_{12}	0.403	-0.450	-0.136	-0.291
n_{21}	0.280	0.581	0.138	0.031
n_{23}	-0.331	-0.205	-0.602	0.585
n_{33}	-0.092	-0.402	0.710	0.440
n_1	0.499	0.104	0.103	0.544
n_2	-0.490	-0.104	0.280	-0.253

$$F_2 = 0.484n'_{11} - 0.450n'_{12} + 0.581n'_{21} - 0.205n'_{23} - 0.402n'_{33} + 0.104n'_1 - 0.104n'_2 \quad (5)$$

$$F_3 = 0.080n'_{11} - 0.136n'_{12} + 0.138n'_{21} - 0.602n'_{23} + 0.710n'_{33} + 0.103n'_1 + 0.280n'_2 \quad (6)$$

$$F_4 = 0.135n'_{11} - 0.291n'_{12} + 0.031n'_{21} + 0.585n'_{23} + 0.440n'_{33} + 0.544n'_1 - 0.253n'_2 \quad (7)$$

$n'_{11}, n'_{12}, n'_{21}, n'_{23}, n'_{33}, n'_1, n'_2$ are standardized indexes of $n_{11}, n_{12}, n_{21}, n_{23}, n_{33}, n_1, n_2$ respectively. The principal component evaluation score E is obtained by the linear regression method with the contribution rate of each principal

component as the weight.

$$E = 0.455F_1 + 0.285F_2 + 0.156F_3 + 0.065F_4 \quad (8)$$

The influence degree of indexes reflects the positive or negative contributions to the evaluation result, so that the facilities can be adjusted. The influence degree of each index is obtained by multiplying the coefficient matrix by the corresponding variance contribution rate.

VI. DISCUSSION

There are several advantages and disadvantages with each of the evaluation methods for traffic safety in tunnels. The think aloud protocol is appropriate to gain insight about the driver mental representation of the situation other than objective performance [7]. Expert judgement is not reliable for the assessment of driver's attentional distribution because the quality of the method depends on the knowledge of the experts [9]. Evaluation of driving safety by visual characteristics can be objective and reliable. However, most of the literature on tunnel safety with eye tracking system mainly explored the characteristics of driver's eye movement indexes such as fixation time and saccade velocity [21], [22]. In addition, some researchers tried to find out the driver's fixation transition patterns in tunnels [43]. Very little literature evaluated the driving safety from the point of visual search stability. The method proposed in this paper selected objective indexes from characteristics of fixation transition which reflects driver's visual search patterns. And we used these indexes to evaluate visual search stability which is an important factor to traffic safety by principal component analysis.

A. ONE-STEP FIXATION TRANSITION ANALYSIS

Except the central rearview mirror, the drivers are more likely to fixate repeatedly. It is hard for the driver to obtain the required road traffic information through a single fixation. However, the probability of the repeat fixation decreases when the traffic flow density increases, indicating that the transition becomes more frequently. The probability of fixation transition to the target direction side rearview mirror and repeat is higher when changing lanes, which is consistent with the pattern that drivers making greater use of their mirrors under complicated driving conditions found by Crundall and Underwood [20]. It indicates that the driver pays more attentions to the adjacent vehicles on the target side. Contrary to what Kircher and Ahlstrom found that speedometer glances are uncommon before the lane change, but increase during and especially after the lane changing [55], the probability of fixation transition from the left and right rearview mirrors to the dashboard increase without lane changing under low traffic flow density due to the speeding concerns. Drivers pay more attention to the central rearview mirror at high traffic flow density, indicating that the drivers pay more attentions to the traffic situation behind. Yan *et al.* found that the right side fixation of drivers gradually increased in highway tunnel entrance sections [56]. However, no significant difference of

TABLE 7. Influence degree of indexes.

Index	Meaning	Influence degree
n_{11}	Probability of fixation transition from the forward windscreen to the left rearview mirror	-0.019
n_{12}	Probability of fixation repeating at forward windscreen	0.015
n_{21}	Probability of fixation transition from the left rearview mirror to the forward windscreen	0.317
n_{23}	Probability of fixation transition from the left rearview mirror to the right rearview mirror	-0.265
n_{33}	Probability of fixation repeating at the right rearview mirror	-0.017
n_1	Stationary distribution probability of fixation points on the forward windscreen	0.308
n_2	Stationary distribution probability of fixation points on the left rearview mirror	-0.225

the average probability of fixation transitioned from all AOIs has been found between the entrance and exit sections. It is assumed that the side wall effect has less influence on drivers in urban tunnels than that in highway tunnels because of the lower speed limit in urban tunnels. Only at high speeds are drivers more susceptible to the side-wall effect.

B. STATIONARY DISTRIBUTION ANALYSIS

Generally, more than 50% of the drivers' fixation points are distributed in the forward windscreen, which shows that the road condition in front of the vehicle is the main source of traffic information. The increase of driver's attention to the distance without lane changing shows that the driver tends to focus on the traffic situation at a distance to get good foresight and be prepared in advance. This is consistent with research result of another study that large visual distance makes the effective information easier to obtain [23]. In order to obtain the information of adjacent vehicles, drivers' fixation points are mainly distributed on the side of the target direction when changing lanes. This feature is conducive to the judgement whether the surrounding environment meets the condition of changing, but not good for the overall driving strategy, such as the route choice and grasp of distant conditions.

C. EVALUATION MODEL VALIDITY

The indexes from characteristics of fixation transition selected by the method in this paper reflects driver's visual search patterns. The influence degree of indexes can be used to assist the training of drivers. Table 7 shows that both the probability of transition from the left rearview mirror to the forward windscreen and stationary distribution probability of fixation points on the forward windscreen have positive influence on the evaluation result. And the probability of transition from the left rearview mirror to the right rearview mirror has a negative influence on the evaluation result. Contrary to the previous study [41], the influence degree of indexes in Table 7 shows that drivers should reduce the wide horizontal and pay more attention to forward vision in tunnel entrance and exit sections. Because the law against

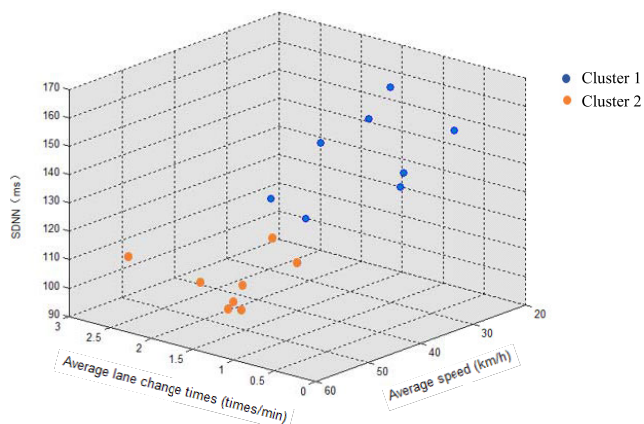


FIGURE 9. Clustering results based on average times of lane changing, average speed and SDNN.

TABLE 8. Evaluation score of visual search stability.

Participant	Clustering Result	<i>E</i> Value	Evaluation Result
1	1	2.544	stable
2	1	2.385	stable
3	1	2.177	stable
4	1	1.678	stable
5	1	1.321	stable
6	1	0.845	stable
7	1	0.313	stable
8	2	0.088	unstable
9	1	-0.362	unstable
10	2	-0.754	unstable
11	2	-0.939	unstable
12	2	-1.013	unstable
13	2	-1.624	unstable
14	2	-1.758	unstable
15	2	-1.918	unstable
16	2	-1.944	unstable

lane changing reduces the threat to driver on both sides so that the driver only needs to focus on the traffic ahead.

Although the evaluation results have been obtained, their reliability still needs to be validated by other objective indexes other than fixation transition characteristics. It has been found that urban tunnels affect both the visual and psychological characteristics of drivers [21], [57]. Psychological workload might decrease drivers’ heart rate variability such as SDNN (standard deviation of NN intervals). Less average lane changing times and low average speed usually represent stable driving behavior according to our experience and observation. Therefore, the k-means division was conducted for the average lane changing times, average speed and SDNN of 16 drivers on the test section, and *k* value was set as 2, as illustrated in Figure 9.

The clustering results were compared with the stability evaluation scores, as illustrated in Table 8. The cluster 1 contains driving samples with less average lane changing times, low average speed and high SDNN, which means the stable driving behavior. The cluster 2 is the exact opposite. There is a significant difference between the scores of drivers in cluster

result 1 and those in cluster result 2. It is considered that $E = 0.313$ is the threshold after ranking the scores, and a value greater than 0.313 is considered as stable driving which means the driver searches visual information calmly, while a value less than 0.313 is regarded as unstable driving which means the driver searches visual information in a flurry. The results are basically consistent with the two clusters obtained by k-means. However, there is no obvious regularity between the *E* value and the driver’s average times of lane changes, average speed and SDNN within each group.

VII. CONCLUSION

Overall, this study attempts to observe the fixation transition of the drivers in the urban tunnel entrance and exit section, so that the evaluation method for visual search stability is proposed to associate the visual variation with traffic safety. Firstly, the probability matrix of fixation transition and the stationary distribution are established by driving data. Then, 7 indexes are selected by statistical tests to propose the method by principal component analysis. Finally, the reliability of the method is verified by clustering results based on the average lane change times, average speed and SDNN of the drivers, during which the score threshold for judging stability is obtained as $E = 0.313$.

The method proposed in this paper can be useful to promote auto driving system by assessing whether a driver can take over the control of the vehicle or not, especially when both the situation and driver assessment is available in real time. On the other hand, the method could be applied to adjust the safety facilities for traffic safety. For existing tunnels, the evaluation object could be real driving tests. For those under construction roads, the evaluation object could be visual scenes obtained from a driving simulation device. In addition, the method can also be used to assist the training of drivers. By evaluating the influence degree of the indexes, the stability of drivers’ visual search behavior can be improved. Currently, little evidence has been found to prove the difference existing in the probability matrix of fixation transition between the entrance and exit sections. The method should be tried in different weather conditions rather than just clear days. Considering and demographic factors of drivers including age and driving experience, more driver samples must augmented to improve the applicability of the model. These issues are within considerations of our future research.

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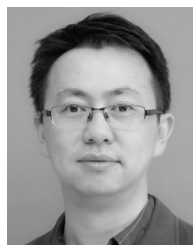
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