Atlas Analysis of the Impact of the Interval Changes in Yellow Light Signals on Driving Behavior

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ABSTRACT The interval changes in yellow light signals significantly impact driving behaviors that affect traffic safety. This study aims to compare the applicability of different interval changes in yellow light signals from the perspectives of drivers. Data acquisition was conducted in a naturalistic driving experiment with equipment including V-BOX, Ergo LAB, and I-View HED4 to acquire vehicle running index data, driver physiological and psychological index data, and eye movement index data, respectively. Twenty experienced drivers were recruited as subjects and were categorized as safe, average, or dangerous drivers. Based on the data obtained, driving behaviors for different interval changes in yellow light signals were studied using an Atlas. Observations of the driving behavior Atlas reveal that there are notable differences in driving behaviors for different interval changes in yellow light signals. Also, it was found that dangerous drivers are more likely to be affected by the interval changes in yellow light signals. It is necessary to choose reasonable signal transition modes to improve the safety of intersections based on actual road conditions and types of drivers. The results can guide traffic management departments when choosing a reasonable transition method for yellow light signals and help formulate customized training programs for different types of drivers. In particular, the results help in providing training on driving speed and deceleration control for dangerous drivers, which will help improve traffic safety.

INDEX TERMS Driver behavior, Atlas, interval changes in yellow light signals, physiological and psychological reactions of drivers, types of drivers.

I. INTRODUCTION

Traffic problems of urban roads are mainly concentrated on intersections of the spatial dimension, and in the time dimension during the signal transition period. Inappropriate settings of interval changes in yellow light signals at intersections often result in an increase in signal loss time and a decrease in effective green light time. Furthermore, traffic efficiency at urban road intersections is reduced and the problem of urban road traffic congestion is aggravated as a result. Ensuring traffic safety during the yellow light signal transition period at intersections is key to improving the overall operational efficiency of urban traffic [1]. Drivers are the least stable factor of the traffic system, and almost 90% of traffic accidents are related to drivers [2]. A driver’s behavior is closely related to traffic control measures [3]. Current traffic laws do not have clear restrictions on the behavior of “running the yellow light”, which leads to an uncertainty of driver behavior during the yellow light signal, and further increases the probability of traffic conflicts at an intersection [4].

The impact of driver behavior on traffic safety during yellow lights has attracted the attention of researchers. Juan et al. [5] used the enhanced Gaussian Mixture Model and the Kalman Filter algorithm to determine the trajectory of motion of a target vehicle during a yellow light and predicted driving behavior using the Logit Model. Hoehner et al. [6] constructed a stochastic Hybrid System Model for driver behavior in a yellow light dilemma area and calculated the probability of running a yellow light by combining a Gaussian process estimation and a Monte Carlo simulation. Bar-Gera et al. [7] quantified driver behavior during a yellow light signal using an exponential logistic regression and a four-parameter logistic regression. Ding [8] used Line Regression Technology and a Decision Tree Model to analyze the relationship between a driver’s stop/go decision during a yellow light signal and the traffic parameters of...
each vehicle arriving at the intersection. Papaioannou [9] developed a logistic regression model to describe the behavior of Greece drivers and found that a large percentage of vehicles facing the yellow signal was caught in dilemma zone due to their high approaching speeds. Yang et al. [10] developed logistic regression models and found that the probability of stopping was greater for intersections without the countdown timer than that of with countdown timer. Chang et al. [11] have developed an ordered Probit model to describe driver behavior and reported that drivers with more than average stream speed tend to behave aggressively at the yellow phase. Gates et al. [12] used logistic regression to predict the probability of first-to-stop versus last-to-go events. Lavrenz et al. [13] explored the effect of cell phone technology, calling behavior, and driver characteristics on drivers’ decisions to stop or go on yellow time. Although these studies have made some progress in the recognition and prediction of driving behavior, challenges remain in visually depicting change processes of driving behavior. Therefore, it is necessary to explore novel methods to describe the characteristics of different driving behaviors.

Atlas greatly improves the visualization of multi-dimensional complex data with data mining, information extraction, graphics rendering, and other processes. Atlas has been widely used in informatics, cartography, astronomy, biology, and other fields such as knowledge Atlas, geographic information Atlas, social Atlas, etc. Atlas can show complex knowledge intuitively and reveal the relationship between the process and structure of knowledge development. In recent years, some researchers have started exploring the application of Atlases for driving behavior research. Yipeng [14] studied the description and estimation of eco-driving behavior using data-driven methods of Atlas theory and machine-learning-based microscopic driver behavior big data. Chen et al. [15] adopted a graphical method to describe driving behavior in real-time. By constructing time and spatial elements, and ordering their combination, driver performance Atlases were established. Chang et al. [16] proposed a risk assessment method of driving behavior based on information entropy, and the creation of a driving behavior Atlas, and thereby provided a solution for driving behavior risk prediction. This study uses the form of Atlas to analyze driving behavior, realizes the accurate description of driving behavior data characteristics and their relationships, and intuitively expresses the changing process of driving behavior.

As mentioned above, previous studies on driving behavior are mostly based on mathematical models, and the accurate description and visual representation of driving behavior characteristics need to be further improved. A small number of researchers have tried to apply Atlas theory to driving behavior research. However, current research is in its initial stages. From the perspective of driver factors, this paper discusses the impact of different interval changes in yellow light signals on driver physiology and psychology, analyzes the applicability of different interval changes in yellow light signals, introduces a human-oriented concept in traffic management, expands the theory of driving behavior Atlas, and describes fluctuations in driving behavior more vividly, thus providing a novel approach in the study of driving behavior.

II. METHODS

A. DRIVING BEHAVIOR CHARACTERISTIC INDEX

A comprehensive analysis was conducted in three aspects: physiology and psychology, eye movement behavior, and vehicle operation characteristics of drivers. The characteristic indicators of driving behavior considered for this study are as follows:

1) The physiological and psychological indicators of drivers: EMG (monitor the fatigue of driver’s arm muscles), EDA (evaluate driver’s emotional tension), ECG (indicates the degree of mental fatigue of drivers), and PPG (indicate the driver’s physiological and emotional arousal level) [17]–[20];

2) Eye movement behavior indicators of drivers: fixation, blinking, and saccade;

3) Vehicle operation indicators: velocity and acceleration.

B. EQUIPMENT

The purpose of this paper is to study driver responses to different interval changes in yellow light signals in real traffic situations. Data acquisition was carried out using naturalistic driving experiments. The equipment including V-BOX, Ergo LAB, and I-View HED4 were used to acquire vehicle running index data, driver physiological and psychological index data, and eye movement behavior index data, respectively (Fig.1).

C. PARTICIPANTS

The participants in the data collection process of this study included researchers and subjects. Researchers were responsible for debugging equipment and recording data, and drivers were the subjects of the experiments. The location of a researcher relative to a subject in the test vehicle is shown in Fig.2. Among them, researcher No.1 was the primary data collector and was responsible for debugging I-View HED4 and recording the driver’s eye movement data; researcher No. 2 was responsible for recording the physiological and psychological data of the driver which were monitored by Ergo LAB and assisted researcher No. 1 in
TABLE 1. Subject demographic information.

| Number of Subjects | Age       | Driving Age |
|--------------------|-----------|-------------|
| 20                 | 22 ~ 35 years old | 3 ~ 14 years |
| 7 women            | 13 men    |             |
|                    | M - 29.1  | S.D. - 3.08 |
|                    | M - 6.9   | S.D. - 2.13 |

The number of male and female subjects was determined according to the sex ratio of Chinese drivers.

data collected in this study, the driver’s driving styles were classified by analyzing the jerk profile of the driver, and the subjects were divided into safe, average, or dangerous drivers. (Table 2).

E. EXPERIMENTAL PROCEDURES

Based on data obtained from the experiments, this study analyzed driving behavior for different interval changes in yellow light signals and compared the applicability of different interval changes in yellow light signals from the driver’s perspective. Therefore, the reliability of the test data is the primary condition for ensuring the validity of the conclusions of this study. To obtain the most authentic driving response of drivers during the transition periods of different interval changes in yellow light signals, this research adopts naturalistic driving experiments for data collection. The subjects completed their driving tasks under actual traffic control conditions; the signal states were not deliberately adjusted for the tests to obtain the subject’s natural driving responses, without disturbing normal traffic flow. The staff recorded the tests from which driving behavior data during transition periods of yellow light signals were obtained. The experimental process included two parts: a preparatory stage before the experiment and a formal experimental stage.

The preparatory stages included investigations of signal controls at intersections, selection of experimental routes, and recruitment and screening of subjects. Five typical interval changes in yellow light signals widely using in China were selected for the study (Table 3).

The formal stage included obtaining basic personal information of subjects, installation of V-BOX for the test vehicle, subjects wearing Ergo LAB and I-View HED4, adaptation of
subjects to the operation of experimental vehicles, operation of experimental vehicles to complete driving tasks, and the extraction of driving behavior data, as shown in Fig. 3.

**F. SCOPE OF ANALYSIS AT AN INTERSECTION**

Driving behavior is affected by various factors such as the speed limit of the road, driver’s personality, driver’s reaction time, operating conditions of other vehicles, and weather conditions. Therefore, the scope of dilemma zones differs for different traffic conditions. In this study, driving behavior data within 200m before stop lines were collected [24]. From experimental observations and preliminary analysis of the data obtained, it was found that the method of yellow light transition has a more significant impact on driver behavior within 30 meters from the stop line. Thus, experimental data obtained within this range is more suitable for the analysis of driving behavior in the dilemma zone for the conditions investigated in this study.

During the interval changes in yellow light signals, drivers have two kinds of decision-making outcomes i.e., stopping or continuing driving. The driving behavior data for these two decision-making results were analyzed. LS and LD indicate that the subjects chose to stop or drive, respectively, as shown schematically in Fig. 4.

**G. CONSTRUCTION STANDARD OF AN ATLAS NODE**

Based on the calculation of driving behavior nodes with the experimental data, a driving behavior Atlas is constructed to describe and analyze the driving behavior data, and the change law of driving behavior is presented more intuitively.

For an Atlas analysis, an index node was constructed to represent a significant change in the index [25]. In the process of constructing a driving behavior Atlas, nodes were constructed to indicate driving behaviors that were significantly different from other types of driving behaviors for a certain interval change in yellow light signals. The steps of node construction were as follows:

1) The original data was smoothed to eliminate the effect of isolated noise on the results, as shown in Eq. (1):

\[
d_s^k = \frac{(d_{k-1} + d_k + d_{k+1})}{3} \quad (1)
\]

where \(d_s^k\) represents the smoothing result; \(d_{k-1}\), \(d_k\), and \(d_{k+1}\) represent the input data for \(k-1\), \(k\), and \(k+1\), respectively.

2) Based on the smoothed driving behavior data, the mean and standard deviation of each index variable were calculated, as shown in Eqs. (2-3):

\[
m = \frac{\sum_{i=1}^{N} f(x_i)}{N} \quad (2)
\]

\[
s = \left\{ \frac{\sum_{i=1}^{N} (f(x_i) - \bar{m})^2}{(N - 1)} \right\}^{1/2} \quad (3)
\]

where \(f(x_i)\) represents Eq. (1); \(N\) represents the number of data points in a driving behavior index; \(\bar{m}\) and \(s\) respectively represent the mean and standard deviation of the smoothed index data.

3) Based on the smoothed driving behavior data, the maximum difference \(D_{\text{max}}\) of each index variable was calculated, as shown in Eq. (4):

\[
D_{\text{max}} = d_{\text{max}} - d_{\text{min}} \quad (4)
\]

where \(d_{\text{max}}\) and \(d_{\text{min}}\) represent the maximum and minimum values of the smoothed data, respectively.

4) The dynamic thresholds \(T_u\) and \(T_d\) were then calculated, as shown in Eqs. (5-7):

\[
T_{10} = D_{\text{max}} \times 10\% \quad (5)
\]

\[
T_u = \bar{m} + \text{max} (s, T_{10}) \quad (6)
\]

\[
T_d = \bar{m} - \text{max} (s, T_{10}) \quad (7)
\]

5) Based on a comparison of each index data with \(T_u\) and \(T_d\), a decision was made regarding whether corresponding
TABLE 4. Expressions of driving behavior node.

| Subject | Acceleration | Speed | Fixation Pupil Size | EMG |
|---------|--------------|-------|---------------------|-----|
| safe    | AV           | V     | FX                  | MG  |
| average | AV           | V     | FX                  | MG  |
| dangerous| AV          | V     | FX                  | MG  |

H. NODE EXPRESSIONS OF DRIVING BEHAVIOR

The driving behavior nodes of each indicator are shown in Table 4. AV is the symbol of vehicle acceleration, V is the symbol of vehicle speed, MG and DA stand for EMG and EDA respectively. Similarly, other terms are also the representative symbols of indicators in the Atlas. In this study, abbreviations are used to make the driving behavior Atlas more concise. Also, the symbols of the same indicators of different types of drivers are distinguished by color. Green, yellow, and red represent the corresponding driving behavior nodes for safe, average, and dangerous drivers, respectively.

III. RESULTS

In statistics, Pearson correlation analysis is widely used to measure the correlation between two variables [26]. The data obtained in this study meet the applicable conditions of Pearson correlation analysis. Pearson correlation analysis can be used to test whether the interval changes in yellow light signals have a significant impact on the vehicle operation, eye movement behavior, driver’s physiology, and psychology. The statistical software SPSS has nested the calculation module of Pearson correlation analysis, which can be used to accurately analyze the correlation between variables.

A. ANALYSIS OF VEHICLE OPERATION CHARACTERISTICS

Vehicle operation indicators include speed and acceleration. A Pearson correlation analysis of vehicle operation indices for different interval changes in yellow light signals was conducted. The results are shown in Table 5. It is seen that:

(1) In LS, the interval changes in yellow light signals are not significantly correlated with speed but are significantly correlated with acceleration.

(2) In LD, both velocity and acceleration are significantly correlated with the interval changes in yellow light signals.

In LS, the correlation between speed and the interval changes in yellow light signals is not significant. This may be because the driver had taken braking measures before the vehicle entered the section of the road being studied. When a vehicle was within 30 meters of the stop line, its speed gradually approached zero for different interval changes in yellow light signals, and the correlation between speed and the interval changes in yellow light signals decreased.

B. ANALYSIS OF PHYSIOLOGICAL AND PSYCHOLOGICAL CHARACTERISTICS

ECG, EMG, EDA, and PPG data were used as key indicators to evaluate the physiological and psychological characteristics of drivers. ECG data indicates the degree of mental fatigue of drivers. EMG data can be used to monitor driver arm muscle fatigue. EDA data is an important indicator to evaluate a driver’s alertness which, in turn, can be used to evaluate the driver’s emotional state. PPG data is used to indicate a driver’s physiological and emotional arousal level.

The Pearson correlation method was used to analyze the correlation between the interval changes in yellow light signals and the physiological and psychological indicators of drivers. The results are shown in Table 6. It is seen that:

(1) The EMG and EDA data were significantly correlated with the interval changes in yellow light signals.

(2) Both ECG and PPG data have no significant correlation with the interval changes in yellow light signals. This may be due to the time of the day (i.e., morning or afternoon) when participants were monitored for the experiment, resulting in different levels of fatigue and emotional arousal which reduced the correlation between the ECG and PPG data and the interval changes in yellow light signals.

C. ANALYSIS OF EYE MOVEMENT BEHAVIORS

Fixation, blink, and saccade were used as the key indicators to evaluate a driver’s eye movement behavior. The correlation between the interval changes in yellow light signals and eye
TABLE 6. Relevance analysis of physiological and psychological indicators.

| Interval Change | ECG | EMG | EDA | PPG |
|-----------------|-----|-----|-----|-----|
| Pearson Relevance | .002 | .003* | .057** | .001 |
| Significance (bilateral) | .183 | .022 | .000 | .840 |
| N | 33876 | 64182 | 44719 | 4252 |
| L Signal transition method | | | | |

TABLE 7. Relevance analysis of eye movement indicators.

| LS | LD |
|----|----|
| Interval Change | Interval Change |
| Pearson Relevance | Significance (bilateral) | Pearson Relevance | Significance (bilateral) |
| Duration | .035 | .244 | -.035 | .130 |
| Fixation | -.132** | .000 | -.064** | .005 |
| Pupil Size Y | .000 | -.057* | .012 |
| Blink | | | | |
| Duration | -.024 | .580 | .039 | .328 |
| Start Position X | -.030 | .417 | -.039 | .168 |
| Start Position Y | .041 | .268 | -.001 | .984 |
| Saccade | | | | |
| End Position X | -.030 | .423 | -.041 | .145 |
| End Position Y | .056 | .134 | .006 | .824 |
| Amplitude | .059 | .111 | -.018 | .530 |
| Acceleration | .075* | .045 | -.020 | .468 |
| Average | | | | |
| Acceleration Peak | .097** | .009 | -.008 | .775 |
| Velocity | .083* | .026 | -.015 | .591 |
| Average | | | | |
| Velocity Peak | .084* | .024 | -.017 | .532 |

| *, significant correlation at 0.05 level (bilateral). |
| **, significant correlation at 0.01 level (bilateral). |

movement behavior was analyzed. The results are shown in Table 7. It is seen that:

1) There is a significant correlation between fixation and the interval changes in yellow light signals.
2) The correlation between blinking and the interval changes in yellow light signals is not significant. This may be due to blinking being closely related to fatigue. The duration of this experiment is relatively short, and the fatigue level of the subjects does not affect the results.
3) In LS, the correlation between saccade and the interval changes in yellow light signals is significant, but the correlation is not significant in LD. This may be because the subjects aim to drive forward and pay little attention to traffic on either side of the road which reduces the differences between a driver’s saccade for different interval changes of yellow light signals in LD.

IV. DISCUSSION

By observing and analyzing the Atlas, it was found that when the driver’s type was dangerous and the interval change in yellow light signals was C9B9, the difference in a driver’s behavior was very pronounced. Therefore, the behavior Atlas of dangerous drivers at C9B9 was further enhanced and compared with the behavior Atlas of safe drivers.

A. CONSTRUCTION OF DRIVING BEHAVIOR ATLAS FOR DIFFERENT INTERVAL CHANGES IN YELLOW LIGHT SIGNALS

A Pearson analysis of driving behavior indicators and the interval changes in yellow light signals was conducted. The interval changes in yellow light signals were designated as the horizontal axis index, and variables significantly related to the interval changes in yellow light signals were designated as the longitudinal index. The driving behavior Atlas of different types of drivers for different interval changes in yellow light signals was constructed. Vehicle operation data and a driver’s physiological and psychological data are continuous, while eye movement behavior data are discrete. Since there were differences in data types, the Atlas form was improved, and connection lines were eliminated.

1) LS DRIVING BEHAVIOR ATLAS FOR DIFFERENT INTERVAL CHANGES IN YELLOW LIGHT SIGNALS

In the Atlas analysis, an index node was constructed to represent a significant difference in the index. In LS, the following conclusions can be drawn from Fig.5:

(1) Compared with safe and average drivers, dangerous drivers are associated with substantial differences in vehicle speed, psychological tension, pupil size, and the mean and peak values of scanning velocity.
(2) When the interval change in yellow light signals is C9B9, the EMG data of the three types of drivers show obvious differences.
For safe drivers, the EMG data changes substantially only when the signal type is C9B9, while other indicators do not fluctuate significantly for the five interval changes in yellow light signals.

2) LD DRIVING BEHAVIOR ATLAS FOR DIFFERENT INTERVAL CHANGES IN YELLOW LIGHT SIGNALS

In the Atlas analysis, an index node was constructed to represent a significant difference in the index. In LD, the following conclusions can be drawn from Fig.6:

(1) Compared with other indicators, a driver’s EMG is more affected by the interval changes in yellow light signals.

(2) When the interval change in yellow light signals is C9B9, substantial fluctuations are seen for the EMG indicators of all three types of drivers, the vehicle speed and acceleration indicators of dangerous drivers, and the speed indicators of safe drivers.

(3) Compared with the other two types of drivers, the driving behavior of dangerous drivers is more affected by the interval changes in yellow light signals.

B. CONSTRUCTION OF DRIVING BEHAVIOR ATLAS WHEN THE INTERVAL CHANGE IN SIGNALS IS C9B9

From an analysis of the driving behavior Atlas for different interval changes in yellow light signals, it can be seen that when the interval change in yellow light signals was C9B9, the stability of driving behavior was the worst, which shows that a driver’s physiological and psychological state fluctuated the most for this method. Moreover, compared with other indicators, the stability of vehicle speed, acceleration, and driver EMG data were worse, which shows that these indicators were more seriously affected by the interval changes in yellow light signals. Therefore, the data for vehicle speed, acceleration, and EMG of a dangerous and a safe subject were extracted, when the interval change in yellow light signals was C9B9.

Designating the driving time as the horizontal axis and driving behavior indicators as the vertical axis, driving behavior Atlases of LS and LD were constructed. The driving behavior characteristics of LS and LD were analyzed when the interval change in yellow light signals was C9B9. (The eye movement index is discrete data that cannot be matched with the time axis, so no further analysis was conducted.)

1) LS DRIVING BEHAVIOR ATLAS FOR THE C9B9 INTERVAL CHANGE IN SIGNALS

According to the results of node construction and the time of appearance of a node, the driving behavior Atlases of safe and dangerous drivers in LS were constructed (the time measure on the x-axis refers to the time when a driving behavior node was constructed), as shown in Fig.7:

In the Atlas analysis, an index node was constructed to represent a significant difference in the index. In the process of constructing a driving behavior Atlas, a node was constructed to indicate that a certain type of driving behavior was significantly different from other types of driving behaviors for a certain interval change in yellow light signals.

Comparing the driving behavior Atlases of safe and dangerous drivers in LS, it can be seen that when the interval change in yellow light signals is C9B9:

(1) The frequency of behavior nodes of dangerous drivers is significantly higher than that of safe drivers, implying that...
the driving behavior of dangerous drivers is more unstable when they are near the stop line.

(2) The instability of the behavior of dangerous drivers is manifested in the accelerations of their vehicles.

2) LD DRIVING BEHAVIOR ATLAS FOR THE C9B9 INTERVAL CHANGE IN SIGNALS

According to the results of node construction and the time of appearance of a node, the driving behavior Atlases of safe and dangerous drivers in LD were constructed (the time measure on the x-axis refers to the time when a driving behavior node was constructed), as shown in Fig.8:

In the Atlas analysis, an index node was constructed to represent a significant difference in the index. In the process of constructing a driving behavior Atlas, a node was constructed to indicate that a certain type of driving behavior was significantly different from other types of driving behaviors for a certain interval change in yellow light signals.

Comparing the driving behavior Atlases of safe and dangerous drivers in LD, it can be seen that when the interval change in yellow light signals is C9B9:

(1) The behavioral instability of safe and dangerous drivers is manifested in their vehicle accelerations.

(2) In this study, the value of the speed node obtained for the safe driver was 37.36 km/h, and that for the dangerous driver was 56.48 km/h. It can be seen that the speed of a dangerous driver is significantly higher than that of a safe driver.

V. CONCLUSION

In this paper, the impact of different interval changes in yellow light signals on driver physiology and psychology was studied, and the driving behavior characteristics were described by an Atlas. The results indicate that the selection of signal transitions need to be based more on the characteristics of driver behaviors. Also, by observing the driving behavior Atlas, it can be seen that when the interval change in yellow light signals is C9B9, the stability of driving behavior is the worst, indicating that the signal transition form of C9B9 is not conducive to traffic safety.

In urban traffic management and control, it is recommended to choose C9B3 as the interval changes in yellow light signals, and avoid C9B9 as far as possible. Besides, the instability of the driver’s behavior is mainly manifested in the acceleration of the vehicle, and dangerous drivers tend to drive at a higher speed. Therefore, it is suggested that driving training institutions and urban traffic control departments should cooperate. Urban traffic control departments should focus on improving the detection of speed while driving training institutions should focus on strengthening the training of drivers’ speed control ability.

From the perspective of driver factors, this paper discusses the applicability of different interval changes in yellow light signals under the premise of traffic safety, which is conducive to the implementation of people-oriented concepts in traffic management and control. Moreover, driving behavior is described by Atlases, which reflect the volatility of driving behavior more vividly, further improve the theory of driving behavior research, and provide a novel approach for driving behavior research.

In this study, the demographics of drivers have not been categorized based on age and gender, which need to be addressed in future research. Also, the driving behavior Atlas can be applied to analyze the differences in driving behaviors on urban roads and highways and to study the differences in driving behaviors of different types of vehicles, such as trucks and cars. Moreover, the driving behavior data can be obtained by simulated driving tests, video-based detection, and other methods, which is not limited to the naturalistic driving experiment used in this paper.

REFERENCES

[1] K. Tang, S. Zhu, Y. Xu, and F. Wang, “Modeling drivers’ dynamic decision-making behavior during the phase transition period: An analytical approach based on hidden Markov model theory,” IEEE Trans. Intell. Transp. Syst., vol. 17, no. 1, pp. 206–214, Jan. 2016, doi: 10.1109/TITS.2015.2462738.
[2] T. A. Dingus, F. Guo, S. Lee, J. F. Antin, M. Perez, M. Buchanan-King, and J. Hankey, “Driver crash risk factors and prevalence evaluation using naturalistic driving data,” Proc. Nat. Acad. Sci. USA, vol. 113, no. 10, pp. 2636–2641, Mar. 2016, doi: 10.1073/pnas.1513271113.

[3] D. Farooq, S. Moslem, R. F. Tufail, O. Ghobanzadeh, S. Duleba, A. Majooom, and T. Blaschke, “Analyzing the importance of driver behavior criteria related to road for safe driving cultures,” Int. J. Environ. Res. Public Health, vol. 17, no. 6, pp. 1893–1907, Mar. 2020, doi: 10.3390/ijerph17061893.

[4] C. W. Bryant, H. A. Rakha, and I. El-Shawarby, “Study of truck driver behavior for design of traffic signal yellow and clearance timings,” Transp. Res. Rec., J. Transp. Res. Board, vol. 2488, no. 1, pp. 62–70, Jan. 2015, doi: 10.3141/2488-07.

[5] L. Juan, J. Xudong, and S. Chunfu, “Predicting driver behavior during the yellow interval using video surveillance,” Int. J. Environ. Res. Public Health, vol. 13, no. 12, pp. 1213–1228, Dec. 2016, doi: 10.3390/ijerph13121213.

[6] D. Hoehener, P. A. Green, and D. Del Vecchio, “Stochastic hybrid models for predicting the behavior of drivers facing the yellow-light-dilemma,” in Proc. Amer. Control Conf. (ACC), Jul. 2015, pp. 3348–3354, doi: 10.1109/ACC.2015.7171849.

[7] H. Bar-Gera, O. Musicant, E. Schechtman, and T. Ze’evi, “Quantifying the yellow signal driver behavior based on naturalistic data from digital enforcement cameras,” Accident Anal. Prevention, vol. 96, pp. 371–381, Nov. 2016, doi: 10.1016/j.aap.2015.03.040.

[8] Y. X. Ding, “A comparative analysis of stop/go driving behavior during the amber light at city signalized intersections,” Appl. Mech. Mater., vols. 744–746, pp. 2045–2048, Mar. 2015, doi: 10.4028/www.scientific.net/AMM.744.2045.

[9] P. Papaoannou, “Driver behaviour, dilemma zone and safety effects at urban signalised intersections in Greece,” Accident Anal. Prevention, vol. 39, no. 1, pp. 147–158, Jan. 2007, doi: 10.1016/j.aap.2006.06.014.

[10] Z. Yang, X. Tao, W. Wang, X. Zhou, and H. Liang, “Research on driver behavior in yellow interval at signalized intersections,” Math. Problems Eng., vol. 2014, pp. 1–8, Jan. 2014, doi: 10.1155/2014/518782.

[11] G.-L. Chang, M. L. Franz, Y. Liu, Y. Lu, and R. Tao, “Design and evaluation of an intelligent dilemma-zone protection system for a high-speed rural intersection,” Transp. Res. Rec., J. Transp. Res. Board, vol. 2356, no. 1, pp. 1–8, Jan. 2013, doi: 10.3141/13233560101.

[12] T. J. Gates, D. A. Noyce, L. Laracuente, and E. V. Nordheim, “Analysis of driver behavior in dilemma zones at signalized intersections,” Transp. Res. Rec., J. Transp. Res. Board, vol. 2030, no. 1, pp. 29–39, Jan. 2007, doi: 10.3141/2030-05.

[13] S. M. Lavrenz, V. D. Pyralakou, and K. Gkritza, “Modeling driver behavior in dilemma zones: A discrete/continuous formulation with selectivity bias corrections,” Anal. Methods Accident Res., vols. 3–4, pp. 44–55, Oct. 2014, doi: 10.1016/j.amar.2014.10.002.

[14] W. Yiping, “Research on eco-driving behavior characteristics identification and feedback optimization method,” Ph.D. dissertation, College of Transportation, Wuhan University of Technology, Oct. 2014, doi: 10.1016/j.amar.2014.10.002.

[15] S. Lou, L. Ren, J. Xiao, Q. Ding, and W. Zhang, “Expression profiling based graph-clustering approach to determine renal carcinoma related pathway in response to kidney cancer,” Eur. Rev. Med. Pharmacol. Sci., vol. 16, no. 6, pp. 775–780, Jun. 2012, doi: 10.1016/j.ejep.2012.03.007.

[16] P. Ahlgren, B. Jarneving, and R. Rousseau, “Requirements for a cocitation similarity measure, with special reference to Pearson’s correlation coefficient,” J. Amer. Soc. Inf. Sci. Technol., vol. 54, no. 6, pp. 550–560, Apr. 2003, doi: 10.1002/asi.10242.

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