Lane changing intent identification based on logistic regression model

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Abstract

To reduce the risk of the lane changing behaviors, based on integrated collection platform, the research group conducts experiments under real road environment for the purpose of studying divers' lane changing intent identification. On the basis of the drivers' fixation characteristics of the rearview mirrors before changing lanes, the length of lane changing intent time window is determined. Based upon differential analysis of visual characteristics between lane keeping and lane changing intent stages, saccade numbers, visual search extent, saccade amplitude, standard deviation of head rotation angles in the horizontal direction are selected as the characteristic indexes of the identification. The logistic model is built according to feature extraction of the leaning samples, then applied to the identification process after the validity test. Results show that the identification success rate may reach 90.42%, thus verifying the feasibility and effectiveness of the logistic model to identify drivers' lane changing intent.

Keywords: lane change, intent identification, logistic model, index system

1 Introduction

Lane change is a common driving behavior, due to the restricts of vehicle condition, road environment, drivers' decision-making level and so on, lane changing behaviors have complexity and uncertainty attributes. Once coupling disorders occur, it may cause a traffic accident, which will bring about huge economic losses and casualties. In order to reduce the possibilities of lane change accidents, various of assistance systems become available, their general working principles are: Monitor the vehicle observed in rear view with radars or cameras, once there exists conflict vehicles within the given distance threshold, warning signals will be sent to the drivers [1]. The default rule of the lane changing assistance system is regarding the turn signals as the main basis to identify drivers' lane changing intent. According to the previous statistical results of the researching group, by the initial time of the lane changes, the opening rate of the turn signals is about 48.4% [2]. During practical applications, due to the irregular operational behaviors of the drivers, high false alarm rate always trouble the lane changing assistance system, requiring more reliable methods to identify drivers' lane changing intent.

Many scholars spent their efforts on lane changing behavior researching, which may provide new ideas to lane changing intent identification. Salvucci D D designed simulated test, results showed that by the initial time of the lane changes, the opening rate of the turn signals was about 50%, and during the lane changing process, drivers' fixation points always shifted from current lane to the target lane [3, 4]. Tijerina L conducted experiments under real road environment, results indicated that before lane change occurred, drivers would pay more attention than lane keeping behaviors [5]. Liu A proposed that visual characteristics were the essential tool to identify drivers' operative intention, and eye movements could provide key information for design and development of the intelligent vehicle [6]. Doshi A affirmed that besides eye movements information, head movements characteristics also could be used to effectively identify drivers' operative intention [7]. Lethaus F insisted that drivers would pay more attention to rearview mirrors than to inside mirrors when executing left lane changes [8]. Henning M J asserted that both turn signals and visual characteristics could identify drivers' operative intention, and the latter had the identification time series advantage [9]. Olsen E C B divided interest regions of drivers' lane changing process, based on analysis of fixation parameters, drew the conclusion that when executing left lane changes, drivers would double their fixation duration at rearview mirrors in lane changing intent stage compared with lane keeping stage [10]. Based upon above researching results, this paper tries to propose a new method to identify drivers' lane changing intent, so as to send warning signals before potential dangers take place, guarantee the safety during lane changing process.

2 Experiments

The research group built an integrated collection platform around driving behavior characteristics (Figure 1), the platform consisted of several data collecting equipment and sensors, such as FaceLAB 5, millimeter wave radar, VBOX inertia sensor, lane identification system and so on.

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The platform could synchronously collect multi-parameter from different sensors, which contained drivers' visual characteristics, vehicles' motion states, driving conditions (distance, relative speed between target vehicle and own vehicle), etc.

FIGURE 1 Driving behaviour collection platform

The researching group conducted experiment under real road environment. 16 professional drivers (2 women and 14 men, between the ages of 28 and 50, Mean = 41.1, standard deviation = 5.85) were recruited to take part in the naturalistic driving test. All the subjects passed the strict physical examination, without visual or hearing disorders, uncorrected visual acuity all over 1.3, and had 5 years or more driving experience.

The research group selected G25 Changxing-Huzhou (Zhejiang, China) expressway as the experimental routes, a total length of 25 km. The routes were bidirectional 4 lanes, separated by green belts, and the speed limit was 110 km/h.

Disposal plans for different emergencies were established before experiment could be run. After a general introduction to the experiment, the drivers had 10 minutes to be familiar with the testing vehicle. Meanwhile, experimenters recorded drivers' name, gender, age, driving experience and so on. Subjects were told to perform the driving missions completely according to his or her driving habits and expectation. Furthermore, experimenter should reduce the interference with the subjects, so as to get the parameters which could characterize subjects' real driving behaviors.

3 Lane changing intent time window

Precious research results have revealed that drivers always show specific visual search law in a time window before changing lanes. Lee S E proposed that drivers may show typical visual characteristics within the 3-second before changing lanes [11]. Guo Y S observed the experiment video with fixation point, drew the conclusion that lane changing intent time window was about 6-second [12]. In order to reduce negative effects of subjective assumption of the time window, this paper proposes a new method to determine the lane changing intent time window according to drivers' fixation characteristics of rear-view mirrors.

Suppose that drivers' fixation times of rearview mirror regions (inside rearview mirror, side mirror) before a lane change is a natural number N (N=1,2,3,…), the interval between drivers' first fixation at rearview mirror and the initial time of the lane change is regarded as the time window length. The initial time of the lane change is determined by changing trends of steering wheel angle during lane changing process. According to the method mentioned above, distribution laws of the lane changing intent time window for the 16 subjects are shown in Figure 2. Time window length difference of the drivers is measured by single factor variance analysis, $F=0.923<F_{0.05}(15, 213)=1.67$, which indicates that there is no significant difference in the time window length of the subjects. This could provide objective basis for determining an agreed time window length. The median reflected overall level of the data, we can see that median time window lengths of the subjects are distributed between 1.5-second and 4-second. The dotted line in Figure 2 represents 5-second time window length, and most of the subjects' third quartiles are below it, so ultimately we determine 5-second as the lane changing time window length.

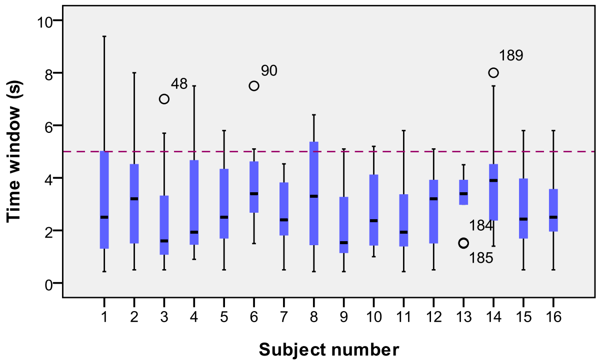

FIGURE 2 Time window length distribution of different subjects

In order to achieve the goal of lane changing intent identification, firstly, the characterization index should be determined. This paper tries to establish index system based on the differential analysis between lane changing intent and lane keeping stage. Given the 5-second time window, lane changing intent and lane keeping samples are selected by offline mode. More specifically, by moving forward 5-second from initial time of the lane changes, intent samples could be achieved. Correspondingly, car following behavior, as well as free driving, are cut down to 5 seconds to be lane keeping samples. According to the method mentioned above, ultimately the research group selects 401 lane keeping samples, 406 lane changing intent samples. Among them, the amount of learning samples of lane changing intent and lane keeping are both 200, others are the samples to be identified.

4 Characterization index

4.1 NUMBER OF SACCADES

Generally speaking, when driver shifts his or her attention from one target to another, saccade behaviors may be needed to accomplish the shift process. To some extent, saccade behaviors could reflect complexity of the driving mission, there is a fine linear correlation between them.

Given the 5-second time window length, Figure 3 shows distribution difference of saccade numbers between lane changing intent and lane keeping stages. It seems that there exists significantly more saccade process in lane changing intent than in lane keeping stages, the difference of the two groups is analyzed using independent sample t-test ($p<0.05$), and the diversity is remarkable. The reason may be that compared with lane keeping behaviors, drivers should pay more attention to the surrounding target objects in lane changing intent stages, which leads to the increase of fixation shift process, as well as the saccade numbers.

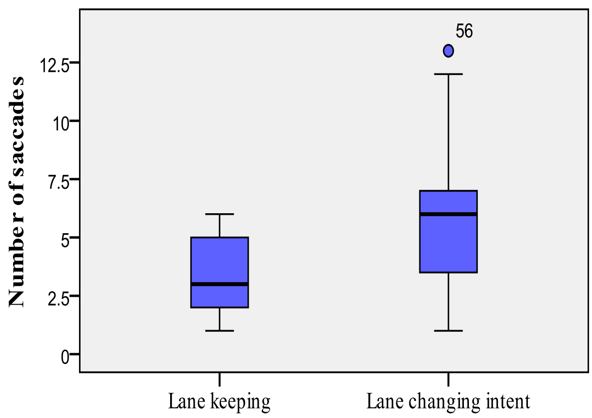

FIGURE 3 Distribution of saccade numbers

4.2 VISUAL SEARCH EXTENT

Underwood G raised that rotation degree standard deviation of the eyes in the horizontal direction could be used to evaluate drivers' visual search extent [13]. The bigger the value is, which may indicate that the more information drivers obtain from the surrounding environment. Figure 4 shows the schematic of rotation degree of the eyes. Where E is the position of the eyeballs, EF is the visual line, α is the rotation degree in the horizontal direction, and β is the rotation degree in the vertical direction.

Figure 5 depicts the distribution differences of visual search extent between lane keeping and lane changing intent stages. It seems that each quartile in lane changing intent stage is remarkably bigger than that of lane keeping stage. Independent sample t-test results ($p<0.05$) shows that the difference between the two groups is remarkable. Further statistics indicates that the average visual search extent of the lane keeping stage is about 4.6°, which is significantly smaller than its lane changing intent counterpart's 12.6°.

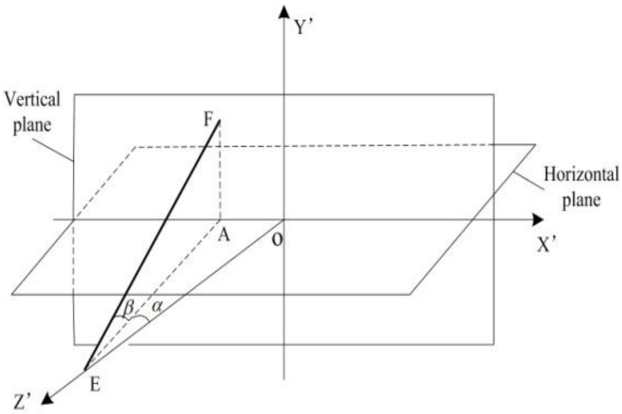

FIGURE 4 Rotation degree of the eyes

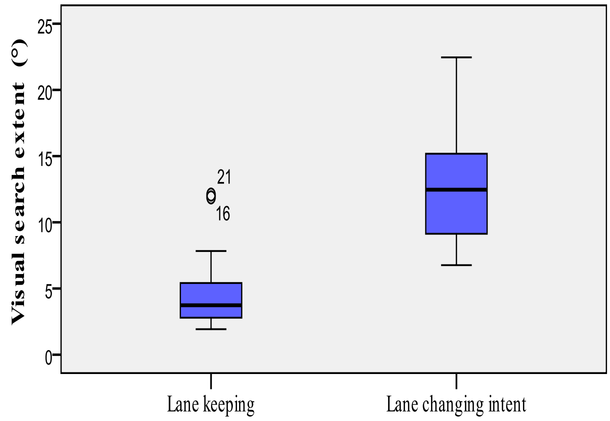

FIGURE 5 Visual search extent under different driving stages

4.3 SACCADE AMPLITUDE

The angle between adjacent two fixation points is defined as saccade amplitude (Figure 6). The bigger the value is, the farther between the two fixation points. Suppose that there exists several saccade processes in the given 5-second time window length, mean of the values is defined as average saccade amplitude of the learning sample.

As shown in Figure 7, each quartile of saccade amplitude in lane changing intent stage is remarkably bigger than lane keeping stage. Further data processing results indicates that the average of all the lane keeping learning samples is about 12.5°, which is obviously smaller than lane changing intent stages (about 25.6°). One reason may be that there are more fixation shift routes in lane changing intent stages, for instance, the shift route from forward view to side mirrors, which is accompanied by large saccade amplitude, thereby confirming the safety before lane changing operations.

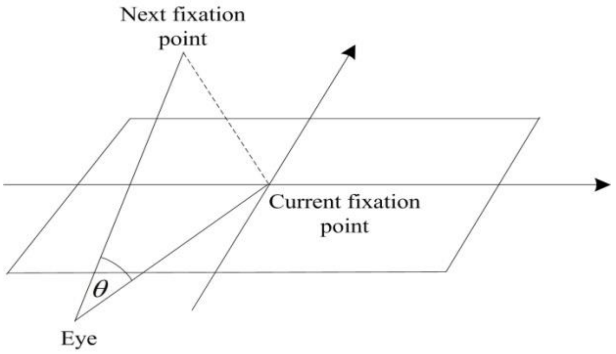

FIGURE 6 Schematic of saccade amplitude

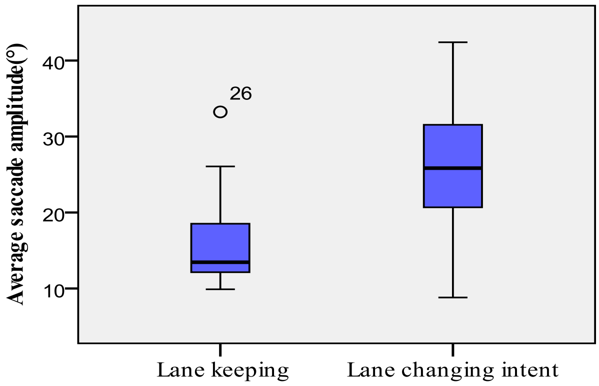

FIGURE 7 Distribution of average saccade amplitude

4.4 HEAD ROTATION DEGREE

Besides eye movements information, faceLAB 5 can also track drivers' head movement status. Head rotation degree in the horizontal direction could reflect drivers' operational intention to some extent [9]. This paper uses Std (standard deviation) of HRD (head rotation degree) in the horizontal direction to depict the discrete degree of the head movements.

Figure 8 depicts Std of HRD distribution difference in the horizontal direction, showing that each quartile in lane changing intent stage is remarkably bigger than that of lane keeping stage ($p<0.05$). The average of HRD Std in lane keeping stage is 1.5°, which is significantly smaller than counterpart's 8.8° in lane changing intent stage. The reason for the difference may be that drivers need head movements to compensate the eye movements in the lane changing intent stage, so as to accomplish the fixation shift process, which is accompanied by large saccade amplitude.

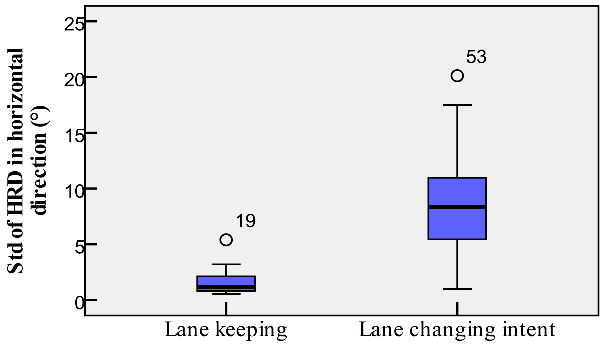

FIGURE 8 Standard deviation of head rotation degree

5 Lane changing intent identification

5.1 BINARY LOGISTIC MODEL

The logistic model is quite different from traditional regression analysis, it could be better suited to solve the regression case with discrete dependent variable than the latter one. The logistic model needs fewer restrictions of the independent variable's distribution characteristics. By means of nonlinear transformation, linear combination of the independent variable could be transformed to the probability value of the dependent variable [14]. For lane changing intent identification (define it as event *Y*), the identification results may be a dualistic problem, that is, "lane changing intent" (*Y*=1) or "lane keeping" (*Y*=0), so binary logistic model could be used to solve lane changing intent identification problem. The logistic model could be defined as follows:

$$\log it(p) = \ln \frac{p}{1-p} = b_0 + b_1 x_1 + \ldots + b_n x_n \,, \tag{1}$$

$$p = \frac{e^Z}{1+e^Z} = \frac{1}{1+e^{-Z}} \,, \tag{2}$$

$$Z = b_0 + b_1 x_1 + \ldots + b_n x_n \,, \tag{3}$$

where, p is the probability of drivers having lane changing intent, $p \in [0,1]$, x is the independent variable related to the event, b is the regression coefficient of the independent variables, and e is the natural constant. When $p \geq 0.5$, we consider that drivers intend to execute the lane changing behavior (*Y*=1). Otherwise, the judgement results would be lane keeping behavior (*Y*=0).

5.2 INTENT IDENTIFICATION

Based on the analysis of characteristic parameters in the intent time window, characteristics indexes for lane changing intent identification are determined as number of saccades (x_1), visual search extent (x_2), saccade amplitude (x_3), and Std of head rotation degree in the horizontal direction (x_4). The basic idea of the intent identification is to determine the regression coefficient of the logistic model by extracting the learning sample's characteristics, then applying to the multi-parameter fusion identification of the samples to be recognized. For each learning sample, depending on the statistic analysis, characteristic values of the identification indexes in 5-second time window may easily be determined. According to the attributes of the learning samples (200 lane keeping samples, 200 lane changing intent samples), binary logistic regression model is built by the SPSS statistic analysis software, the expression is as follows:

$$p = \frac{1}{1+e^{-(-17.88+1.547x_1-0.223x_2+0.239x_3+2.228x_4)}}, \quad (4)$$

where, p is the probability of drivers having lane changing intent, x_1 is the number of saccades, x_2 is visual search extent, x_3 is saccade amplitude, x_4 is std of head rotation degree in the horizontal direction.

After establishing the intent identification model, we should verify the efficiency of the model before its real application. Goodness-of-fit test results based on Cox & Snell RCS^2 and Nagelkerke RN^2 are shown in Table 1. The nearer RCS^2 and RN^2 approximates to 1, the better model's fitting effect to be. Results show that both RCS^2 and RN^2 are greater than 0.75, which verifies the excellent classification efficiency of the logistic model.

TABLE 1 Validation of the model

Step	Cox & Snell RCS^2	Nagelkerke RN^2
1	0.783	0.923

After the efficiency verification of the logistic model, then we can carry out the lane changing intent identification process depending on the built model. For the lane keeping and lane changing intent samples to be identified, supposing that the properties of the samples are unknown, we scramble them to the "gray box". For any one of those samples in the "gray box", extract the characteristic values of the indicators in the identification time window, then putting into the logistic model, finally the identification properties of the samples could be determined. By comparing samples' identification results and their real properties, we can verify the identification performance of the logistic model, which is shown in Table 2.

TABLE 2 Classification efficiency of the logistic model

Samples to be identified	Identification results		Success rate
	Lane changing intent	Lane keeping	
Lane changing intent 206	True Positive (TP) 189	False Negative (FN) 17	91.75%
Lane keeping 201	False Positive (FP) 22	True Negative (TN) 179	89.05%
Sum 407	Positive samples 211	Negative samples 196	90.42%

When lane changing intent samples are precisely identified to be "lane changing intent", we define it as "true positive". If lane keeping samples are mistakenly identified to be "lane changing intent", the identification results may be defined as "false positive". Similarly, "true negative" and "false negative" could be defined in turn. Generally, we use "sensitivity", "specificity" and "accuracy" (overall identification success rate) to evaluate identification performance of the model, they are calculated as follows:

$$Sensetivity = \frac{TP}{TP+FN} \times 100\%, \quad (5)$$

$$Specificity = \frac{TN}{FN+TN} \times 100\%, \quad (6)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100\%. \quad (7)$$

According to the identification results in Table 2, sensitivity of the logistic model is about 91.75%, specificity is 89.05%, and overall identification success rate is about 90.42%, which indicates that the logistic model could effectively identify drivers' lane changing intent.

The existing lane changing assistance system regards turn signal as the main basis to identify drivers' lane-changing intention. The research group obtains drivers' use of turn signals based on the experiment under real road environment, which is shown in Figure 9. Origin of the horizontal axis represents the initial time of the lane changing behavior, the negative values corresponds to the time of lane changing intent stages, and the positive values corresponds to the time after lane changing operation. Figure 9 shows that by the initial time of lane changes, turn signals usage is about 48.6%, subsequently increase to 76% by 5-second after the lane changing operation. If we regard turn signals as the main basis to identify drivers' lane changing intent, the identification success rate even below 50%, which is far lower than its counterpart of the logistic model built in this paper.

Comparing to other lane changing intent identification methods, the logistic model built in this paper could effectively avoid the uncertainty caused by overly dependent on drivers' maneuvering characteristics [15-16], and the identification success rate surpasses 90%. Once the research results are applied in the development process of lane change auxiliary system, both working performance and reliability of the system could be remarkably improved, thereby guaranteeing the safety of the lane changing process.

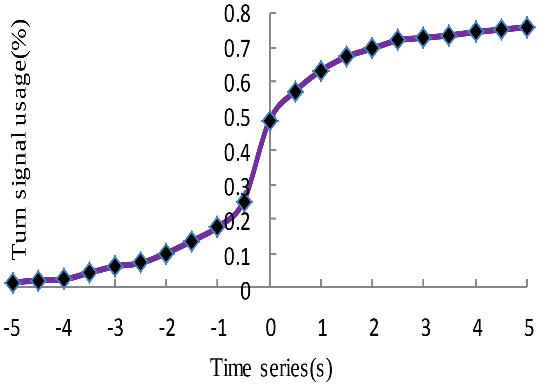

FIGURE 9 Turn signal usage rates in time axis

6 Conclusions

In this research, we propose a logistic model to identify lane changing intent by monitoring drivers' eye and head movements. Lane changing time window is determined by extracting drivers' fixation characteristics of the rearview mirrors before lane changing operation. Based on the differential analysis of the visual characteristics and head movements between lane keeping and lane changing intent stages, characteristic index system is further constructed. By building the logistic model, drivers' lane changing intent is precisely identified, and the identification success rate may reach 90.42%. The research results may provide important theoretical foundation for the improvement of intelligent vehicles' active safety technology, as well as the optimization of lane changing assistance system.

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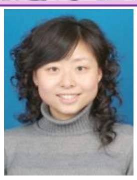

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