Eye Movement-Based Inference of Truck Driver’s Intent of Changing Lanes

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Abstract: The purpose of this paper is to propose a method to infer a truck driver’s intent to change lanes before initiation of its maneuver. Observation on a truck driver’s behavior in a real world and ordinary drivers’ behavior at a driving simulator indicate common features that the drivers’ glance at the side-view mirror and speed meter becomes frequently when they are going to change lanes in a near future. Based on the observation, a four-level method is developed for detecting driver’s intent to change lanes by using the information of eye-movement. The method is applied to data collected in an experiment. The result shows that driver’s intent is detected at a high level in average 80 percent lane changes when the maneuvers of changing lanes are initiated. Investigations also suggest that a risky lane change may occur if driver’s intent is not detected at the high level. These findings are important to realize an adaptive support system in lane changes.

Key Words: intent inference, lane change, eye movement, driver support system.

1. Introduction

It is vital to improve safety in a long distance driving for a large truck driver. This is because the risk of a traffic accident for a large truck is higher and the damage due to the accident is large. Also, the long-distance driving may make truck drivers fall into a distracted state. Eby and Kostyniuk [1] have pointed out that changing traffic lanes is one of important scenarios that are related with distraction-related crashes. Inagaki et al. [2] have proposed an adaptive support system which modifies its support depending on driver’s psychological state. Their results showed that such support was effective for accident prevention [2]. Note here that the support system works only when the system infers driver’s intent to change lanes correctly. It is important to develop a detection method that is not only to infer driver’s intent correctly but also to be helpful to realize the adaptive support system. Several methods for detecting a lane change have been developed. Pentland and Liu [3] have tried to characterize driver’s behaviors by observing such initial preparatory movements as heading and acceleration of car, and they have achieved 95 percent accuracy at predicting automobile driver’s subsequent action of changing a lane. Kuge et al. [4] has achieved 98 percent recognition rate by using steering angle and steering angle velocity. Oliver and Pentland [5] have extended the Pentland and Liu’s framework [3] for modeling and recognizing driver’s maneuver, and their study has shown that a lane change can be predicted one second on average before a lane change’s maneuver starts. Salvucci [6] has used steering wheel inputs as the basis of detecting driver’s lane-change maneuver, where 80 percent of lane changes have been detected within one second before the vehicle moves a quarter of the lane width laterally. Note that each of these methods aimed to detect or predict an initiation of the lane change’s maneuver, but not to infer driver’s intent of changing lanes before the maneuver.

Mourant and Donahue [7] have examined mirror-sampling behavior of drivers during the 5-second prior to lane change maneuvers, and showed that the drivers glanced at the side and rear-view mirrors more frequently during a 5-second period prior to lane changes. Lee et al. [8] have investigated all of the 8667 lane change behaviors in the real world and have also found that turn signal is only used on average 44 percent. Both Mourant and Donahue [7] and Lee et al. [8] suggest that the eye movements reflect driver’s intent.

This study aims to develop an algorithm to infer the driver’s intent by monitoring driver’s eye-movement prior to the lane change’s initiation. Section 2 gives analyses of time-dependent eye movement prior to a lane change, and describes a detection model and its associated algorithm for intent inference on a lane change. In Section 3, the method is applied to data collected in an experiment and the result shows that driver’s intent is detected at a high level when approximately 80% lane changes are performed out of all of the lane changes.

2. Eye Movement Prior to a Lane Change

2.1 Truck Driver’s Behavior before Changing Lanes

With the cooperation of a transportation company, driving data of four professional truck drivers were recorded in the real world three months [9]. The data included 8,576 lane changes. One of the authors in this paper has observed the eye-movement on the video for one driver out of the four during the time period of preparing a lane change. The findings are:

1. When there is no vehicle ahead, the truck driver always looks forward and rarely looks at the side-view mirror to...
check traffic conditions on the passing lane.

2. When a slower forward vehicle appears, the driver begins to look at the side-view mirror to check traffic condition on the passing lane. The frequency of looking at the mirror is low.

3. As the forward vehicle comes closer, the driver looks at the side-view mirror and the speed meter frequently.

4. Just before initiating a lane change for passing the lead vehicle, the driver looks at the side-view mirror very frequently.

Thus, four levels may be distinguished for the intent to change lanes as: “EXTREMELY LOW”, “LOW”, “MIDDLE” and “HIGH”. In order to characterize each level of intent based on drivers’ eye-movement quantitatively, eye-movement data are collected in Experiment-1.

2.2 Experiment-1

A fixed-base driving simulator is used in the experiment that can simulate driving on a flat, nearly straight expressway with two lanes. Since the host vehicle (HV) is assumed to be a large truck, no visual image is given in the rear-view mirror. Three non-professional drivers (#1 - #3, from 20 to 31 years old) have participated into the data collection. They are recruited from a local society and have agreed on the participation in the Experiment-1. Each participant holds a valid driver’s license. The maximum speed of HV is limited at 90 km/h as speed governor. A total of forty-eight Lane-Change Events (LCEs) and twenty-four No-Lane-Change Events (NLCEs) are given to each participant. The eye-movement data are collected for all events with an eye tracker.

2.3 Characteristics of the Checking Behavior

2.3.1 Statistical difference between LCE and NLCE

In this paper, a ‘checking behavior’ refers to one occurrence of driver’s looking at the side-view mirror or the speed meter, where the mirror or the meter is gazed for at least 0.3 s [10]. For each participant, the average number of checking behaviors, $\bar{n}_{ik}$, is calculated as:

$$\bar{n}_{ik} = \frac{N_{ik}}{T_{ik}}$$

where $N_{ik}$ is the total number of checking behaviors in the $i$-th event for participant #k, and $T_{ik}$ is the time length of the $i$-th event for participant #k.

An ANOVA (analysis of variance) on the average number of checking behaviors, $\bar{n}_{ik}$, shows the significant difference between LCE condition and NLCE condition for every participant (Participant #1-1: F (1, 70) = 28.424, p = .0000; Participant #1-2: F (1, 61) = 18.494, p = .00006; Participant #1-3: F (1, 70) = 28.619, p = .000) (see Fig. 1). As shown in Fig. 1, the number of checking behaviors is greater when a driver has intent of a lane change than when he or she does not. This result is consistent with the result of Lee et al. [8].

2.3.2 Time dependent characteristics of frequency of checking behaviors

A relative frequency of checking behaviors, $r_{fjk}$, is calculated as:

$$r_{fjk} = \frac{n_{jk}}{N_{k}}$$

where $n_{jk}$ is the cumulative number of checking behaviors in time period $j$, $[-10(j + 1), -10j]$, to an initiation time point of changing lanes for all LCEs for participant #k, and $N_{k}$ is the total number of checking behaviors for all LCEs for participant #k.

Figure 2 represents values of the relative frequencies, $r_{fjk}$ ($k = 1, 2, 3$), where the horizontal axis denotes the $j$-th time period to the initiating time point of an origin 0. Figure 2 shows that the frequency of checking the side-view mirror or speed meter becomes higher when the time is closer to the initiation time of changing lanes. The tendency is common to the three participants. Note here that this finding also agrees with the result in Itoh and Inagaki [11] in which they investigated the professional truck drivers’ eye movement.

To characterize the eye-movement quantitatively, we calculate time interval for two consecutive checking behaviors. Let $t_1$ and $t_2$ ($t_1 < t_2$) be the time points of two consecutive checking behaviors. We define the time interval of the two consecutive
checking as $\Delta T(t_2) = t_2 - t_1$. Figure 3 depicts the dynamic change of the time interval for Participant #1-1, where the origin 0 of the horizontal axis is the time point when a lane change maneuver is initiated. It is seen in Fig. 3 that the time interval, $\Delta T$, decreases as approaching to the lane change initiating time point. The similar tendency is also seen for Participants #1-2 and #1-3. In particular, the time interval is short during ten seconds prior to changing lanes (Participant #1-1: Mean = 2.23, Standard deviation (SD) = 1.31; Participant #1-2: Mean = 2.22, SD = 1.80; Participant #1-3: Mean = 3.12, SD = 1.43).

2.4 Algorithm for Detecting Driver’s Lane-Change Intent

According to the observation in Section 2.1 and the investigations in Section 2.3, an algorithm is developed to infer driver’s intent via monitoring checking behaviors.

This inferring method is described as a state transition diagram as shown in Fig. 4. In order to decide how to detect a current level of driver’s intent, two detection conditions are defined:

1. time length of each glance on checking the side-view mirror and the speed meter that is to distinguish a checking behavior. the value is set at larger than 0.3 s [2], and
2. frequency of the checking behaviors that is to decide at which level driver’s intent is by counting the number of checking behavior within last fixed time period $T$ s. Let $T$ be detection duration that we set at 10-15 seconds according to the analyses in Sections 2.2 and 2.3.

An arrow between two levels denotes a transition from one level to the other, and the value shown on each arrow is the minimum number of the condition (2) for occurrence of a transition to the other level of driver’s intent. Let ‘reset’ denote that the detected intent level changes from HIGH, MIDDLE or LOW to EXTREMELY LOW. The dotted lines in Fig. 4 denote the ‘resets’ from each intent level to EXTREMELY LOW.

From a viewpoint of the number of driver’s intent state, it is possible to think 2-state approaches (e.g. only “EXTREMELY LOW” state and “HIGH” state) to infer driver’s intent. However, 2-state approaches are not suitable to realize the adaptive support system to a driver to change lanes. Suppose that a driver begins to be aware of a slow forward vehicle that is approaching to the host vehicle. In this case, the driver’s intent is detected at “LOW” in terms of the proposed method, but may be detected at “EXTREMELY LOW” by a 2-state approach. If the host driver tries to initiate changing lanes even at “LOW”, the support function may have to remind the driver at the moment. However, any reminder can be not supplied to the host vehicle in case of a 2-state approach.

3. Evaluation of the Proposed Method

3.1 Experiment-2

The purpose of Experiment-2 is to evaluate the effectiveness of the proposed method to infer driver’s intent.

Apparatus

A motion-base driving simulator is used in Experiment-2. It can simulate driving in a car-cockpit, expressway with two lanes (see Fig. 5). The ‘host vehicle (HV)’ is set as a large truck so that no visual image is shown in the rear-view mirror.

Participants

Twelve females and eight males have participated in Experiment-2. Each participant holds a valid driver’s license. The ages of the 20 participants range from 20 to 55 years old (Mean = 34.5, SD = 8.43). They have been recruited from a local society and have agreed to participate in Experiment-2.

Driving task

In Experiment-2, participants are requested to drive on the cruising lane at the driving simulator when there is no slower lead vehicle. The maximum speed of the host vehicle (HV) is limited at 90 km/h and the speed of the lead vehicle (LV) is set at 80 km/h. When there is a slower lead vehicle, a participant should pass it safely. Eight types of Lane-Change Events (LCEs #2-1 - #2-8) are provided in accordance with traffic conditions. Figure 6 depicts initial conditions of LCEs #2-1 - #2-8.

In addition to LCEs #2-1 to #2-8, eight types of NLCEs also

![Fig. 5 Motion-base driving simulator in Experiment-2.](image)

![Fig. 6 Initial traffic conditions of lane change events in Experiment-2.](image)
occur in the experiment. In each NLCE, the vehicles on the
passing lane drive at the same initial conditions as LCEs. The
difference between an NLCE and its corresponding LCE is that
a forward vehicle drives at 90 km/h (i.e., the host vehicle
can not pass the lead vehicle) in an NLCE.

Eight Scenarios #2-1 to #2-8 are given to all participants. For
each scenario, two LCEs and two NLCEs occur. Table 1 de-
scribes the events in each of eight scenarios.

Procedure
All participants are asked to fill out the Driving Style Ques-
tionnaire (DSQ) sheet [12] in order to investigate dependence
of driver behavior on the driving style. The DSQ [12] performs
eight principal components to describe the driving style: (1) ‘con-
fidence in driving skill’, (2) ‘hesitation for driving’, (3) ‘impa-
tience in driving’, (4) ‘methodical driving’, (5) ‘prepara-
tory maneuvers at traffic signals’, (6) ‘importance of automo-
bile for self-expression’, (7) ‘moodiness in driving’ and (8)
‘anxiety about traffic accidents’. The value of each item may
range from one to four.

Each participant is requested to practice driving for approxi-
mately 10 min. to acquire familiarity with the operation of the
driving simulator. In the first half of data collection, all partici-
pants experience the four Scenarios #2-1, #2-2, #2-3, and #2-4.
After a 15-minut break, the other four Scenarios #2-5, #2-6,
#2-7 and #2-8 are given to them.

One ‘trial’ is defined as that an event is practiced. Each of
LCE trials lasts for approximately 2 min. and each of NLCE
trials lasts for approximately 30 s.

Dependent variables
During the experiment, we collect data on the driving be-
haviors (e.g. steering angle, velocity and headway distance),
information of eye-movement (e.g. time length of checking be-
havior). These data are recorded at 10Hz. The steering angle
is used to determine the time point of initiating a lane-change.
The headway distance is also recorded when the HIGH level
intent is detected. The eye-movement data are used to infer
drivers’ intent.

Let $t_D$ denote the time point when a HIGH-level intent to
change lanes is detected (the origin $O$ is the event’s start), and
let $t_I$ denote the time point when the maneuver is initiated. If
the HIGH-level intent is kept until a lane change is initiated,
the detection is defined as ‘successful’. On the other hand, a

\[
R_d = \frac{N_s}{N_{trial}} = \frac{N_1 + N_2}{N_{trial}}
\]

(3)

where, $N_s$ is the number of successful trials, $N_{trial}$ is the
number of all LCE’s trials, $N_1$ is the number of the trials of TYPE1
detections, and $N_2$ is the number of the trials of TYPE2
detections.

For all trials in NLCEs, false positive rate, $R_{fp}$, is calculated as:

\[
R_{fp} = \frac{N_{fp}}{N_{trial}}
\]

(4)

where $N_{fp}$ is the number of the trials of TYPE2, and $N_{trial}$ is the
number of all NLCE’s trials, respectively.

The detection rate, $R_d$, and the false positive rate, $R_{fp}$, for
each participant under a condition of $T = 12$ seconds are shown
in Fig. 8. The mean detection rate is 80.2% (SD = 0.164) and
the mean false positive rate was 13.7% (SD = 0.171). The result
shows that driver’s intent was detected at HIGH-level when ap-
proximately 80% lane changes out of all the lane changes were
initiated.
In order to investigate to what extent detection duration $T$ can be made shorter, we investigated cases in which $T$ was set at 10 s. The result shows that the detection rate under $T = 12$ s is higher than that under $T = 10$ s (Mean $= 0.693$, SD $= 0.212$). We also tested $T = 15$ s in order to investigate whether detection rates may be improved if driver behavior is monitored a bit longer. The result that the detection rate under $T = 15$ s (Mean $= 0.807$, SD $= 0.165$) is not higher than that under $T = 12$ s.

3.2.2 Checking behavior

Because large individual difference is shown on the detection in Fig. 8, we investigate the checking behavior in terms of the detection rate. Firstly, all the participants are divided into different groups according to their detection rates. Figure 9 indicates a dendrogram obtained from a hierarchical clustering on the detection rates. Let HIGH_R denote a cluster that consists of Participants #2-5, #2-10, #2-12, #2-17 and #2-18. The detection rates are high (Mean $= 0.975$, SD $= 0.034$) for HIGH_R participants. Let LOW_R denote a cluster that consists of Participants #2-4, #2-6, #2-8, #2-9, #2-16 and #2-20. The detection rates are low (Mean $= 0.599$, SD $= 0.109$) for LOW_R participants. That is that approximately 40% lane changes were performed when driver’s intent was not detected at the HIGH-level. Let MID_R denote a cluster that consists of the others, and their detection rates range from 0.800 to 0.875 (Mean $= 0.847$, SD $= 0.029$).

Secondly, the time length of each checking behavior and the frequency of checking behaviors as a function of time are calculated for LOW_R and HIGH_R participants. The mean time length of checking behavior, $\Delta T$, in each trial for each participant was calculated as:

$$\Delta T_{ik} = \frac{\sum_{l=0}^{N_{jk}} \Delta t_{ikl}}{N_{jk}}$$  \hspace{1cm} (5)$$

where, $\Delta t_{ikl}$ is the time length of the $l$-th checking behavior in the $i$-th trial for Participant #k, and $N_{jk}$ is the number of checking behaviors in the $i$-th trial for Participant #k.

An ANOVA on $\Delta T_{ik}$ shows a highly significant difference among the three Clusters ($F (2, 288) = 31.408$, $p = 0.00$, see Fig. 10). This result indicates that the LOW_R participants have spend less time on checking the side-view mirror or the speed meter in comparison with MID_R and HIGH_R. As mentioned in Section 2.3.1, the checking behavior is counted when the glance is not less than 0.3 s in Experiment-2. The result in Fig. 10 suggests that the LOW_R participants might check the side-view mirror or the speed meter less than 0.3 s. The glance less than 0.3 s can not be recognized as a checking behavior even if they intend checking the traffic condition. The number of checking behavior for the LOW_R participants may become small. Thus, the proposed method may fail in inferring a lane change’s intent of this type of drivers. Therefore, it is necessary to modify the definition of a checking behavior for the LOW_R’s type of drivers.

The frequency of checking behaviors, $f^C_j$, is made for LOW_R and HIGH_R participants as:

$$f^C_j = \frac{\sum_{k \in C} n_{jk}}{N_{trial-p} \cdot k_C}, \hspace{1cm} C = LOW_R, \hspace{0.5cm} HIGH_R$$  \hspace{1cm} (6)$$

where,

- $n_{jk}$ is the cumulative numbers of checking behaviors at
time period \( j \) for Participant \( #k \) in cluster \( C \).

- \( k_C \) (\( = |C| \)) is the number of participants in cluster \( C \),
- \( N_{trial-p} \) is the number of the trials for each participant.

Because a linear LMS analysis shows significant correlations between the checking-behavior’s frequency and the time to the initiation for the respective types of participants (HIGH\(_R\): \( r = -0.9633, p < 0.01, \text{slope} = -0.0382 \); MID\(_R\): \( r = -0.9579, p < 0.01, \text{slope} = -0.0307 \); and LOW\(_R\): \( r = -0.9599, p < 0.01, \text{slope} = -0.0237 \)), we conduct an ANCOVA (analysis of covariance) among the three Clusters. The result showed a highly significant difference on the frequencies (\( F(2, 24) = 24.543, p = 0.00, \text{see Fig. 11} \)). The result indicates that even though a LOW\(_R\) participant tends to take a lane change, the frequency of checking behavior still keeps at low values. It is suggested that such driver as the LOW\(_R\)’s participant might drive at a risky situation, e.g., lack of enough checking behaviors. Therefore, it is necessary to adjust the frequency condition as stated in Section 2.4 in the inferring algorithm to this type of drivers.

3.2.3 Discussion of improving the proposed method

According to the investigation in Section 3.2.2, this section gives investigations how to improve the proposed method by adjusting the two detection conditions as mentioned in Section 2.4, respectively.

**Approach-1.** Researchers tried to adjust the limitation of glances in condition (1) from 0.3 s to 0.2 s. This adjustment results a significant increment. The mean detection rate is 93.4\% (\( SD = 0.105 \)) for all of the participants. One the other hand, an error of measuring instrument might contribute to one of factors error of the great improvement in terms of the adjustment.

**Approach-2.** Also, we tested an adjustment that the HIGH-intent is detected when the number of the checking behaviors is 3 instead of 4 as mentioned in Section 2.4. The adjustment also resulted in an increment that the mean detection rate is 86.3\% (\( SD = 0.129 \)) for all of the participants.

Figure 12 indicates the detection rates in terms of the original method, Approach-1 and Approach-2 for the three Clusters. The result shows a statistical effect of the adjustments for the Clusters of LOW\(_R\) (\( F(2, 15) = 6.857, p < 0.1 \)) and MID\(_R\) (\( F(2, 21) = 12.826, p < 0.01 \)). The significant improvements are operated for the Clusters of LOW\(_R\) and MID\(_R\), but not for HIGH\(_R\). This result implies that it is necessary to decide the value of each of conditions according to different situations.

3.2.4 Driving behavior

The investigation in Section 3.2.2 shows that the LOW\(_R\) participants have spent less time on checking behaviors when they tend to take a lane change. This might cause that a lane change is initiated under a risky situation because of insufficiency of checking behaviors for LOW\(_R\) participants. Let \( \Delta_t \) be time length from the start time (0) of each event to the initiation time (\( t_I \)) of changing lane. Let \( \Delta_{D-I} \) be time length from the detection time (\( t_D \)) to the initiation time (\( t_I \)). Figure 13 depicts the values of \( \Delta_t \) and \( \Delta_{D-I} \) for the three Clusters, respectively. An ANOVA shows significantly differences of the time length, \( \Delta_t \) (\( F(2, 251) = 11.167, p < 0.01 \)) and the time length \( \Delta_{D-I} \) (\( F(2, 251) = 4.338, p = .014 \)) for the three Clusters. The shorter time length \( \Delta_{D-I} \) for the Cluster of LOW\(_R\) implies that the LOW\(_R\)’s participants might take lane changes under a relatively risky situation. Therefore, inferring driver’s intent, especially for such a driver as the LOW\(_R\) participant correctly is vital to avoid and prevent traffic accident in lane changes.

Researchers also collected time headway (THW) at which driver’s intent was detected at LOW level and HIGH-level. Figure 14 depicts cumulative percentages of detections at LOW-level and HIGH-level as a function of THW. It is found that the LOW-level was detected when THW = 4.18 s (\( SD = 1.20 \)), and the HIGH-level was detected when THW = 3.27 s (\( SD = 1.28 \)). The above finding suggests that the participants begin to check the traffic condition around because of the slow lead vehicle when THW is approximately 4.2 s. The result is a clue of when a driver starts to tend to change a lane. This might be useful to investigate an issue of whether a driver drives at a...
risk situation, or not.

3.2.5 Dependence on driving style

The above analyses showed that the three Clusters performed the checking behavior in the different ways. This suggests that the three Clusters’ participants might be at different driving styles. Via investigating the scores of eight items in DSQ [11] among the three Clusters’ participants (see, Fig. 15), it is found that some of the items show different tendencies, such as (4) ‘methodical driving’ and (8) ‘anxiety about traffic accidents’. The result showed that the LOW‐R’s participants have a lower value of the item (4) and a higher value of the item (8). On the other hand, interviews with the participants in Experiment-2 indicated that such a participant as LOW‐R has a tendency to fall into a distracted situation. The result suggests that examining the scores of DSQ is helpful to discuss the issue of distraction in lane changing behavior.

4. Conclusions

This paper proposed a multi-state detection method to infer drivers’ intent by monitoring drivers’ eye-movement. Four levels of driver’s intent were distinguished: EXTREMELY LOW, LOW, MIDDLE and HIGH. In verification by a driving simulator experiment, the result showed that driver’s intent was detected at HIGH-level when approximately 80% lane changes were initiated out of all of the lane changes for all the participants. The analyses also indicated that those participants, whose intent was detected at not HIGH-level when approximately 40% lane changes were performed, spent less time on checking traffic conditions. This result suggested that the lane-change behavior might be risky if driver’s intent is not detected at the HIGH-level. The investigation of driver’s behavior indicated relations between driving behavior and the detection at each of levels. This finding may assist in understanding driver’s decision-making during lane changes. It is suggested that the proposed method is helpful to discuss the issues of the adaptive support system, e.g., whether and when a support function should be activated.

The observation and the interview in Experiment-2 with the participants showed that traffic condition and distraction may affect the driver behavior. Therefore, as a future work, the authors will try to reveal an effect on the eye-movement by traffic conditions and distractions in order to realize an adaptive method to infer driver’s intent correctly under different conditions. The result of DSQ’s scores implied that the participants, who might be in a distracting situation, have a different tendency of the driving style from the others. This will be helpful to discuss of adjusting the method in accordance with driver’s state and style in the future.

References


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