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Estimation of Lead Vehicle Kinematics Using Camera-Based Data for Driver Distraction Detection

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ABSTRACT: Distracted driving has become an emerging concern for road safety in the past decade. Efforts have been made to develop in-vehicle active safety systems that could detect driver distraction. However, most methods focused on detecting a distracted driver of the host vehicle (ego-vehicle). Given that a distracted driver poses increased crash risk not only to him/herself but also to other road users, it may be beneficial to investigate ways to detect a distracted driver from a surrounding vehicle. This paper proposes a method to estimate the kinematics of a lead vehicle solely based on the sensory data from a host vehicle. The estimated kinematics of the lead vehicle include its lane position, lateral speed, longitudinal speed, and longitudinal acceleration, all of which may be potentially useful to detect distracted driving. The method was developed and validated using an existing naturalistic driving study, Safety Pilot Model Deployment, which collected a large scale of driving data in real-world roadways. The method utilizes signals from a camera-based Mobileye® system and other host vehicle sensory channels such as speed and yaw rate. Sensor fusion techniques were used to improve the accuracy of the estimation. The validation results show that the method was able to capture the lead vehicle's kinematics within a fairly small error range. The method could be potentially used to develop in-vehicle systems that are able to monitor the behaviors of its surrounding vehicles and detect distracted or impaired driving.

KEY WORDS: **Electronics and control,** vehicle sensing, distracted driving, driver distraction, sensor fusion, Mobileye® [E1]

1. Introduction

Distracted driving has become an emerging concern of road safety in the past decade, partly due to the prevalence of smartphones and rapid growth of in-vehicle electronic technologies. A survey study found that the prevalence of talking on a cell phone while driving at least once in the past 30 days ranged from 21% in the UK to 69% in the United States, and the prevalence of drivers who had read or sent text or e-mail messages while driving at least once in the past 30 days ranged from 15% in Spain to 31% in Portugal and the United States [(1)]. Indeed, driver distraction has been shown as one of the leading causes of road accidents. According to the United States National Highway Traffic Safety Administration (NHTSA), distracted driving accounted for 3,477 fatalities (10% of overall fatalities) and an estimated additional 391,000 injuries in the U.S. in 2015 [(2)]. In addition, these numbers are likely under-reported due to the difficulties in identifying driver distraction during accident investigation [(3)]. A naturalistic driving study shows distraction of secondary tasks (i.e., those tasks not necessary to driving) account for 23% of all crashes and near-crashes [(4)].

Empirical studies have shown that performing visual-manual tasks while driving may degrade drivers' performance in many aspects such as steering control and lane keeping performance [(5-9)], headway control and braking behavior [(10-11)], and response to sudden or hazard events [(12-13)]. Efforts have been made to develop in-vehicle system that could monitor and detect driving distraction based on measures of different categories that include (1) a driver's eye movements [(14-16)] or head orientations [(14-15)], (2) driver maneuvers such as steering wheel angle [(14, 17)], throttle position [(14)], (3) vehicle kinematics such as lane position [(14-16)] or speed [(14)], and (4) a driver's involvement of a secondary task itself [(17)]. A comprehensive review of driver inattention monitoring systems that include distraction detection can be also found [(18)].

However, most of these effects focused on developing in-vehicle systems that could detect the distraction of the host vehicle (ego-vehicle) driver. Given that a distracted driver poses increased crash risk not only to him/herself but also to other road users in the surrounding, it may be beneficial to develop in-vehicle active safety systems that are able to monitor the driving status of the vehicles in its proximity, and detect potential distracted or impaired driving. To develop such systems, it may not be feasible to directly measure other drivers' eye movements, head orientations, or their inputs to the vehicle such as steering wheel angle or throttle position. However, the vehicle kinematics such as its lane keeping performance has shown to contain useful information regarding the driver's distraction states [(5-9, 14-16)], and it could be potentially measured by the host vehicle from a distance. An anecdotal illustration is that when a driver sees a nearby vehicle making

erratic lane changes or drifting out of the lane, he/she may start to pay closer attention to that vehicle and may even try to stay further away from it.

In this paper, we developed a method to support detecting a distracted driver in a lead vehicle based on the sensory data from the host vehicle. The lead vehicle kinematics being investigated include lane position, lateral speed, longitudinal speed, and longitudinal acceleration, all of which may be potentially useful to detect distracted driving. The estimation of the lead vehicle would be solely based on the sensory data from the host vehicle, so that the method does not rely on any other vehicles to be equipped with any technology to work (unlike vehicle-to-vehicle communication). The method was developed and validated using an existing naturalistic driving study dataset, Safety Pilot Model Deployment (SPMD) [19], which collected a large scale of driving data from real-world roadways. The method utilizes signals from a camera-based Mobileye® system and other host vehicle data such as vehicle speed from the vehicle's Controller Area Network (CAN) bus and yaw rate from an inertial measurement unit (IMU). Sensor fusion techniques were used to improve the accuracy of the estimation. Validations were performed using the real-world driving data from SPMD to examine the accuracy of the estimation method. The potential implications and limitations of the proposed method were also discussed.

2. Methods

2.1. Method overview

The proposed method was developed using an existing dataset from a naturalistic driving study - Safety Plot Model Deployment (SPMD). SPMD was a research program funded by the United States Department of Transportation and conducted by the University of Michigan Transportation Research Institute (UMTRI). The data collection phase of the SPMD was from 2012 to 2015. About 3,000 participants were recruited from the area of Ann Arbor, Michigan. Out of the 3,000 vehicles, about 140 participant-owned passenger vehicles were instrumented with a data acquisition system (DAS) collects a variety of sensor data including four camera views (forward scene, left scene, right scene, and cabin scene) and over a hundred channels of vehicle data such as speed, acceleration, steering angle, and GPS. Most data channels have sampling rates of 10 Hz or higher. A Mobileye® system [20-21] was also installed on the vehicles. The camera-based Mobileye® system monitors the driving context in front of the host vehicle, identifies objects such as motor vehicles or bicycles, and measures the objects' positions relative to the host vehicle. The Mobileye® system had a field of view of 38 degrees, and the data were recorded at 10 Hz into the DAS. The participants used their instrumented personal vehicles for their everyday trips. And the data collection for each participant typically lasted for more than one year.

The data channels used in this paper are summarized in Table 1. Several Mobileye® measurements listed in Table 1 are also illustrated in Figure 1. Similar to the typical methods that utilize sensory channels from multiple sources, data synchronization and interpolation were first performed to the raw time-series data from multiple sensors. Using this method resulted in a synchronized time-series data with a sampling rate of 10 Hz. All calculations in the rest of the paper were based on this synchronized data.

Table 1 Data channels used to estimate lead vehicle kinematics

Channel	Definition	Data source
Range	Longitudinal distance from the host vehicle to the lead vehicle	Mobileye®
Trans-versal	Lateral distance from the center of field of view to the center of lead vehicle	Mobileye®
Lane position	Lateral distance from the centerline of the host vehicle to the (left/right) lane marking	Mobileye®
Curvature	The curvature of the lane ahead	Mobileye®
Heading angle	The vehicle heading relative to the lane heading	Mobileye®
Lane quality	A value indicating how confident the lane detection is	Mobileye®
Speed	Speed of host vehicle	CAN bus
Yaw rate	Yaw rate of host vehicle	IMU

2.2. Estimating lead vehicle kinematics

Lane position: The Mobileye® system mainly used a vision-based method to detect lane markings of the vehicle's current driving lane. And further calculations were made to measure the vehicle's lane position. The system may not be able to detect the lane markings with high confidence in certain conditions such as roads with not well-marked or faded lanes. The system provides a lane quality channel to indicate the confidence of the lane detection. In our method, an estimation of the lead vehicle's lane positon would be calculated only if the system-reported lane quality is high. The system also reports the vehicles' lane position in terms of the vehicle's distance to the left and right lane markings separately. However, based on our observations of the SPMD data, the right lane marking was generally less reliable due to a variety of factors such as right-side road shoulders/edges, right-side merging lanes, etc. (Note the SPMD was conducted in the U.S. which uses right-hand traffic). For this reason, the lane positon based on the vehicle distance to the left lane marking was primarily used in this paper.

The lane position of the lead vehicle (LV) was estimated using Eq. (1)-(3) developed based on geometry extracted from Figure 1. The calculation utilizes the lane position of the host vehicle (HV) itself and the lateral distance from the host vehicle to the lead vehicle from the host vehicle's field of view (termed "transversal") with two additional terms, the curve offset and heading offset. The curve offset was to compensate the lateral offset of the lead vehicle that was caused by road curvature. For example, as illustrated in Figure 1, if the lead vehicle is still in the lane, but the road is curved to the left, it may appear from the host vehicle's point of view that the lead vehicle is significantly to the left of the host vehicle. The curve offset can be estimated using the lane curvature and the distance between the host vehicle and lead vehicle (termed "range") using Eq. (2). The heading offset was to compensate the lateral offset of the lead vehicle that was caused by different heading angles of the host vehicle. For example, as illustrated in Figure 1, if the host vehicle is heading to the right side relative to

the direction of the lane, it may appear from the host vehicle's point of view that the lead vehicle is to the left of the host vehicle. The heading offset could be estimated using the heading angle of the host vehicle and the range using Eq. (3).

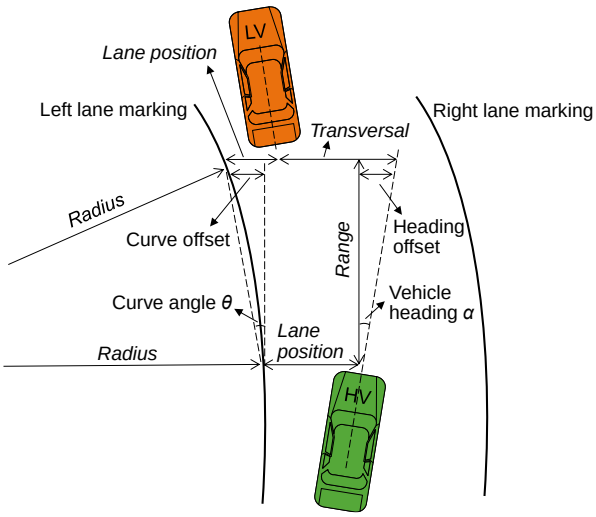

Fig. 1 Illustration of estimating lead vehicle status

$$LanePosition_{LV} = LanePosition_{HV} - Transversal + CurveOffset + HeadingOffset \quad (1)$$

$$CurveOffset = Range \cdot \tan(\theta) \approx \frac{Range^2}{2 \cdot Radius} = Range^2 \cdot Curvature \quad (2)$$

$$HeadingOffset = Range \cdot \tan(\alpha) \quad (3)$$

In Figure 1 the lead vehicle and host vehicle are in the same lane. However, the method could be extended to account for the lane changes made by either the lead vehicle or the host vehicle, so that it would not require both vehicles in the same lane. For this extension the width of the lane would be needed to adjust the estimated lane position of the lead vehicle. The width of the lane could be calculated by summing up the host vehicle's distances to the left and right lane markings. If the lead vehicle moves to the left or right lane (relative to its previous lane), the estimated lead vehicle lane position using Eq. (1) becomes smaller than zero or greater than the width of the lane. The estimated lead vehicle lane position relative to its new lane could be adjusted by adding (if the lead vehicle moves to the left lane) or subtracting (if the lead vehicle moves to the right lane) one lane width. If the host vehicle moves to the left or right lane (relative to its previous lane), the Mobileye® system would automatically update the host vehicle's lane positon values, so that they are relative to the new lane. This lane change by the host vehicle could be identified by the time-series lane position data as the values (i.e., distance to the left lane marking) would jump from a value close to zero to a large value by a magnitude of one lane width (if the host vehicle moves to the left lane) or dive from a large positive value close to one lane width to a value close to zero (if the host vehicle moves to the right lane). When this occurs, the host vehicle's lane position can be adjusted accordingly by adding or subtracting one lane width before applying the method using Eq. (1).

Lateral speed: The lateral speed of the lead vehicle was estimated by taking the numerical differentiation of its estimated lane position. A two-point backward numerical derivatives with first order accuracy was used (see Eq. (4) below). A sampling interval Δt of 0.5 s was used.

$$\dot{x}(t) = \frac{x(t) - x(t - \Delta t)}{\Delta t} \quad (4)$$

Following common practice in calculating derivatives in automotive applications [22-23], a second order Savitzky-Golay filter with a 2.0 s time window was applied to $x(t)$ to smooth the data before getting the derivative. The filter was implemented using the MATLAB *smooth* function.

Longitudinal speed: The lead vehicle longitudinal speed was estimated by the summation of the host vehicle speed and the relative speed between the host vehicle and lead vehicle (termed "range rate"). The host vehicle speed was obtained from the vehicle CAN bus, and the range rate was obtained from Mobileye®. The range rate can also be independently calculated by taking the numerical differentiation of the range using the method described above.

Longitudinal acceleration: The longitudinal acceleration of the lead vehicle was estimated by taking the numerical differentiation of its estimated longitudinal speed. The same differentiation method as described above could be used.

2.3. Sensor fusion

It was observed from the SPMD data that the camera-based system by itself may not be reliable enough to accurately measure the road curvature even when the reported lane quality was high. One of the identified problems was that the system may incorrectly report significant curvature values on straight road. This was demonstrated in Figure 2 below. The erroneous curvature values may degrade the accuracy of the lane position estimation. To improve the accuracy of the proposed method, the road curvature was also independently measured based on the host vehicle's speed and yaw rate using Eq. (5).

$$Curvature = \frac{YawRate}{2 \cdot Speed} \quad (5)$$

The equation was derived based on geometry, and it assumes that the host vehicle is precisely following the curve of the road. The yaw rate could be measured using an inertial measurement unit (IMU) in the host vehicle. With these two independent measures of the road curvature, a simple sensor fusion scheme was proposed. Under the scheme the road curvature was set to zero if the curvature (absolute value) from either of the source was smaller than a preset threshold value (currently set to 1.5 x 10^{-4} m^{-1} or 3,333 m curve radius). Otherwise (i.e., when the curvatures from both sources are above the threshold), the road curvature was set to the curvature measured by Mobileye®. The Mobileye® estimation was selected over the IMU estimation as it seems the Mobileye® system was more accurate when the vehicle was indeed in a curve, as the IMU-based estimation assumes the vehicle is precisely following the road, which would be more difficult to do in a curve. Figure 2

(middle figure) also shows a comparison of the curvatures estimated from the two sources.

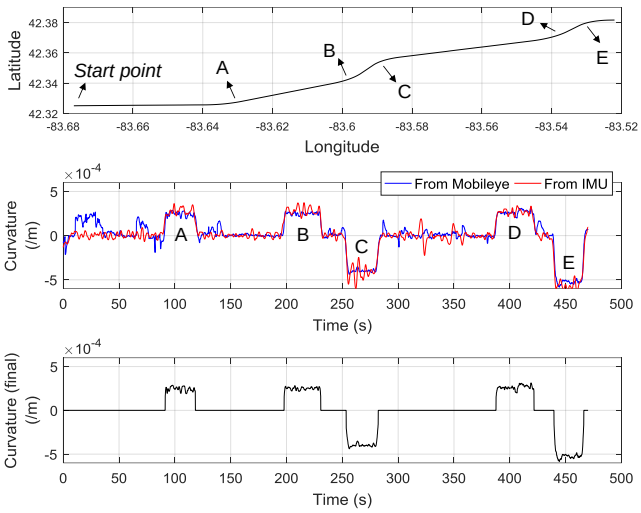

Fig. 2 Demonstration of the sensor fusion in estimating curvature. The top figure is the GPS map of an SPMD driving event, in which five curves (A-E) can be visually identified. The middle figure is a comparison of the curvature estimated by the Mobileye® and IMU. The bottom figure is the final estimated curvature after applying the sensor fusion.

2.4. Validation dataset

To validate the proposed method we aimed to find driving data from the SPMD study in which two instrumented vehicles were driving in proximity with one vehicle (i.e., a lead vehicle) followed by the other vehicle (i.e., a host vehicle). Since both the lead and host vehicles had their driving data recorded, it enabled us to compare the estimation of the lead vehicle status using the sensory data from the host vehicle to the true values directly recorded by the lead vehicle. We queried the SPMD data with the criteria that the distance between the two vehicles calculated from their GPS signals are similar to the distance measured from the camera on one vehicle. Currently, a threshold of 5.0 m was used to define the similarity. This criterion selects the data that the two vehicles are in close proximity and they are not blocked by any other vehicles. After applying this criterion, the forward camera videos of the returned driving events were further reviewed by data reductionists to verify that one vehicle was indeed directly in front of the other. These events were termed paired driving events in which the detailed driving data on both vehicles were available. Figure 3 illustrates an example of a paired driving event, in which the lead vehicle was next to a trailer truck, and it could be seen from the host vehicle camera forward view.

Following criteria were further applied to ensure the data quality: (1) the lane quality reported by Mobileye® was high for both the lead and host vehicle, (2) the range is less than 60 m since the Mobileye® measurements are less accurate when the object is further away, (3) the speed of the host vehicle was higher than 60 mph (97 km/h) which aimed to limit the data to freeway driving in which the lane quality is generally high.

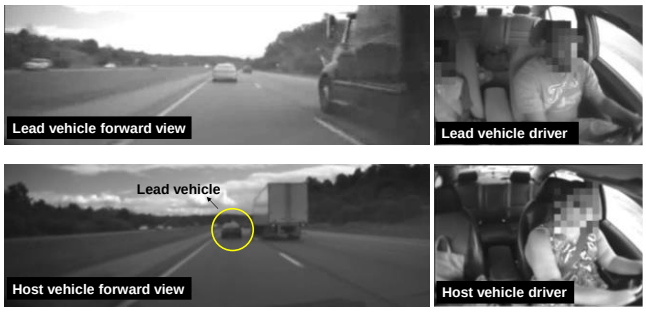

Fig. 3 Illustration of the paired driving events

Since in the paired driving events the lead vehicle was also fully instrumented with the DAS, the true values from the lead vehicle were obtained in similar ways to how the measures were obtained from the host vehicle. The true speed of the lead vehicle was obtained from its CAN bus. The true lane position of the lead vehicle was obtained from the Mobileye® system that was equipped in the lead vehicle. The true acceleration and lateral speed was calculated based on the true speed and lane position with the numerical differentiation method described above. All data processing in this paper were performed using MATLAB®.

3. Results

There were 16 paired driving events with a total of 48 minutes of driving data identified from the SPMD database. After applying the three additional criteria, 38 minutes of the driving data (N = 22,895, 80% of total data) were remaining for validation. Figure 4 shows the estimation result for one of the paired driving event that lasted for over 9 minutes. As can be seen for the lane position and longitudinal speed, the estimations matches the true values fairly well. During the event the lead vehicle made two lane changes, firstly moving to the left lane at around 320 s, secondly moving back to the right lane at around 345 s. The host vehicle made two corresponding lane changes following the lead vehicle. As can be seen from the figure, these lane changes were accounted for by the estimation method.

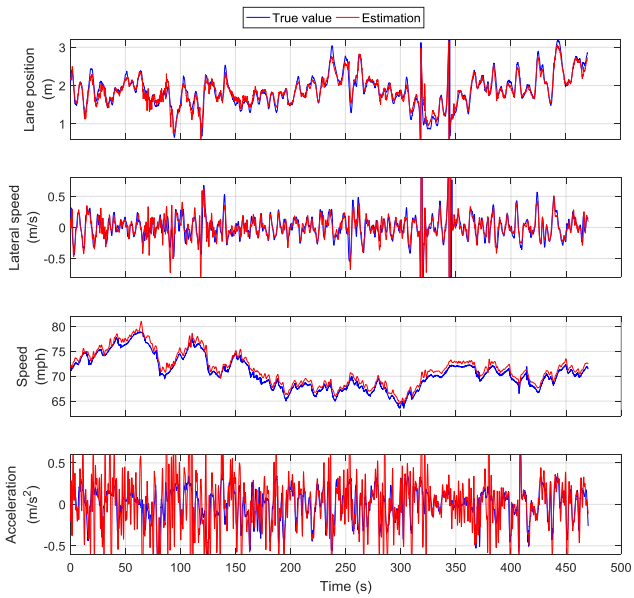

Fig. 4 Estimation result for one of the paired driving events

There seem to be larger errors when estimating the lateral speed, and even more so for the longitudinal acceleration. This was expected as they were calculated by taking numerical differentiation of the estimated lane position and speed of the lead vehicle. Any noise or imprecision of the estimated lane position or speed may be amplified in the differentiation process. To access the usefulness of these two measures, we applied an additional moving average filter to the lateral speed and longitudinal acceleration after the differentiation, and examined the effects of filters with varying time window widths on the accuracy of the estimations. The filter was implemented using the MATLAB *smooth* function. Note no moving average filter was applied to the true values. The results using the same paired driving data are shown in Figure 5 and 6.

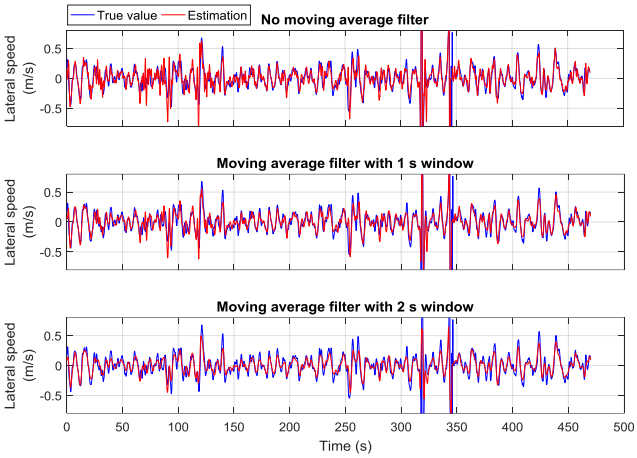

Fig. 5 Estimated lateral speed with different filter window width

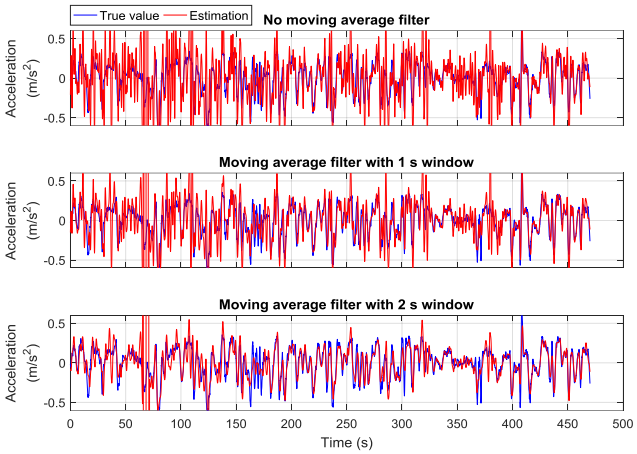

Fig. 6 Estimated acceleration with different filter window width

As can be seen from Figure 5 and 6, the noises from the estimations were greatly reduced when the moving average filter was applied for both lateral speed and longitudinal acceleration. And the estimations matched the true values fairly well when the filter with the 2-s time window was applied, even for the lead vehicle acceleration.

The estimation error was calculated for the entire data at every time point (N = 22,895) as the difference between the true value and the estimated value. The summary of the estimation errors for each of the measures are shown in Table 2. The error is reported as the 5th percentile and 95th percentile of the entire data. In other words, 90% of the data fall within the error range.

Table 2 Summary of estimation errors

Estimated measures	Estimation errors [5th percentile, 95th percentile]
Lane position	[-0.38, 0.29] m
Speed	[-2.2, 1.0] mph or [-3.5, 1.6] km/h
Lateral speed (no filter)	[-0.28, 0.27] m/s
Lateral speed (1-s filter)	[-0.26, 0.25] m/s
Lateral speed (2-s filter)	[-0.23, 0.22] m/s
Acceleration (no filter)	[-0.62, 0.61] m/s^2
Acceleration (1-s filter)	[-0.49, 0.49] m/s^2
Acceleration (2-s filter)	[-0.35, 0.34] m/s^2

Lastly, to demonstrate the potential use cases of the proposed method, Figure 7 shows a paired driving event from the SPMD data in which the lead vehicle driver was using his cell phone with significant eyes-off-road time (as can be seen from the lead vehicle cabin view). The lead vehicle was slightly drifting off the lane to the right side (as can be seen from the lead vehicle forward view). The estimation of the lead vehicle lane position (in this case the distance to the right lane marking was shown) successfully captured this minor lane departure.

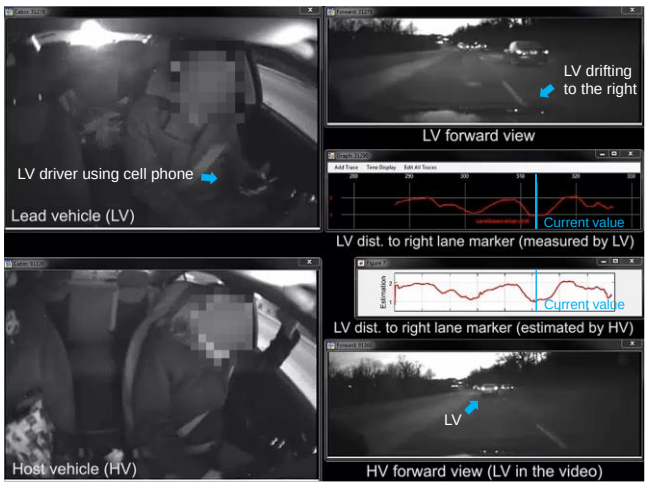

Fig. 7 Demonstration of using the method to detect a lead vehicle lane departure due to lead vehicle driver cell phone use

4. Discussions

This paper proposes a method to estimate the kinematics of a lead vehicle solely based on the sensory data from a host vehicle. The method was developed and validated using real-world driving data from a naturalistic driving study, Safety Pilot Model Deployment. The method utilizes signals from a camera-based Mobileye® system and other host vehicle sensory channels such as speed and yaw rate. The validation results show that the method was able to capture the lead vehicle's kinematics including lane position, lateral speed, longitudinal speed, and longitudinal acceleration within a fairly small error range. Since the numerical

differentiation is sensitive to small noises in the estimated lane position and speed, the estimations of the lead vehicle lateral speed and longitudinal acceleration are more challenging as numerical differentiation are performed on the estimated lane position and speed, respectively. Nonetheless, after applying low-pass filters to the data both before and after the differentiation, the lateral speed and longitudinal acceleration show agreement with the true values directly recorded from the lead vehicle.

It is noted that although the method was currently developed using s specific vehicle implementation setup (i.e., SPMD) with a specific camera-based system (i.e., Mobileye®), the method shall be applicable to other hardware and implementation setups as long as the input channels meet the definitions described in the paper. It was illustrated in the Result section that the method could be used to detect a lane departure event of a lead vehicle caused by the lead vehicle driver using cell phone. However, essentially the method could be used to detect any driving behaviors of a lead vehicle that can be captured using the four estimated kinematics metrics (i.e., vehicle lane position, lateral speed, longitudinal speed, and longitudinal acceleration). This may include distracted driving, impaired driving, aggressive driving, or drowsy driving, etc.

There are several limitations in the current study. First, the vision-based method relies on the camera to see the lane markings to estimate the lead vehicle's lane position. Thus it would not work in conditions when the system can not reliably detect the lane markings, for example, on deteriorated road surfaces with not well-marked or faded lane markings, in adverse weather such as heavy rain or snow. The validation experiment had focused on the freeway driving when the lanes were generally well marked. Secondly, even when the lane markings are successfully detected, the algorithm needs to be further advanced to cope with some more complicated road configurations such as merging lanes, ramp split, etc. Thirdly, in this study we focused on the vehicles in front of the host vehicle within a fairly narrow field of view range of 38 degrees. It would be potentially useful to develop methods to monitor a wider range of surrounding vehicles such as vehicles from adjacent lanes or even behind the host vehicle. These potential functions could help to create a wider range of safety zone for drivers who may be warned for potential risks from different directions.

5. Conclusions and future work

This paper developed a method to estimate the kinematics of a lead vehicle solely based on the sensory data from a host vehicle. The lead vehicle kinematics being investigated include lane position, lateral speed, longitudinal speed, and longitudinal acceleration, all of which could be potentially useful to detect distracted driving. The method was developed and validated using an existing naturalistic driving study dataset, Safety Pilot Model Deployment, which collected a large scale of driving data in real-world roadways. The method utilizes signals from a camera-based Mobileye® system and other host vehicle data such as vehicle speed and yaw rate from an inertial measurement unit. Sensor fusion techniques were used to improve the accuracy of the estimation. The validation results show that the method was able to capture the lead vehicle's kinematics within a fairly small error range. The proposed method could be potentially used to develop in-vehicle active safety systems that are able to monitor the driving behaviors of its surrounding vehicles and detect distracted or impaired driving.

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