PREDICTING DRIVER LANE CHANGE MANEUVERs USING VEHICLE KINEMATIC DATA

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ABSTRACT

One of the challenges of lane departure warning (LDW) systems is to differentiate between normal lane keeping behavior and lane change events in which drivers simply do not use the lane change indicator. Lane keeping behavior differs between drivers and often between driving scenarios, therefore a static threshold of predicting steering maneuver is not an ideal solution. The objective of the current study is to develop an adaptive method of predicting driver lane change maneuver using vehicle kinematic data.

The paper presents an adaptive steering maneuver detection algorithm, which can detect the earliest indication of driver's intent to change lanes. The overall approach was to observe the driver's "normal" lane keeping behavior for a period of time, and seek driver lane keeping behavior which falls outside of what is "normal" for each specific event. We modeled normal driving behavior in this study using a bivariate normal distribution to continuously monitor the vehicle distance to lane boundary (DTLB) and lateral velocity measured in most production LDW systems.

The results of our algorithm were validated against visual inspections of 949 randomly selected lane change events from the 100-Car Naturalistic Driving Study (NDS), in which we compared the time of driver steering initiation estimated by the algorithm against visual inspection. The comparison between algorithm results and visual inspection shows that all steering initiation in lane change events in the sample occurred within 5 seconds of lane crossing. In addition, a sensitivity analysis on the bivariate normal distribution boundary shows that the contour line representing 95% probability produced the lowest average percentage error (2%) with an average delay of 0.7 seconds between the algorithm predicted driver steering initiation time and video inspection. The resultant algorithm was deployed in a large subset of 100-Car and was able to identify the steering initiation time in a total of 53,615 lane change events. The resultant algorithm shows utility in assisting future active safety system in monitoring driver lane keeping behavior, as well as providing active safety system designers further understanding of driver action in lane change maneuvers to improve designs of LDW systems.

INTRODUCTION

In the United States, road departure crashes contribute to more than half of highway fatalities [1]. One emerging active safety technology which may mitigate these road departure crashes is the lane departure warning system (LDW). LDW operates by tracking the vehicle's position with respect to the roadway marking and warns the driver, by either audible, visual, or tactile feedback, of road departure events. Previous studies has shown that LDW systems have the potential to reduce fatalities in drift out of lane road departures in the United States by as much as 28% to 32% [2]. However, driver acceptance remains paramount to the success of LDW systems. Surveys of new vehicle owners consistently report that current LDW systems provide more false alarms then other crash avoidance technologies, such as forward collision avoidance. The result is that some owners disable the LDW system [3]–[5].

One of the challenges of overcoming the false alarms of LDW systems is to differentiate between normal lane keeping behavior and lane change events in which drivers simply do not use the lane change indicator. One potential solution to differentiate between the two maneuvers is to utilize vehicle lateral motion and lateral distance to lane line threshold to predict steering maneuver. This is not straight forward however, as lane keeping behavior may differ between drivers and often between driving scenarios. Therefore a static threshold of predicting steering maneuver is not an ideal solution. The objective of the current study is to develop an adaptive method of predicting driver lane change maneuver using vehicle kinematic data.

Overview of the 100-Car Naturalistic Driving Study

One valuable approach to characterize driver behavior is to use the data from Naturalistic Driving Studies (NDS). NDS involve instrumenting vehicles and continuously recording all normal driving behavior for a period of months to years, therby captures drivers' behavior in a "natural driving environment".

The current study utilizes data collected from the 100-Car NDS to characterize driver lane change behavior. The 100-Car study was a landmark large-scale NDS conducted by the Virginia Tech Transportation Institute (VTTI) from 2001 to 2004 [6].

Drivers were recruited from the Washington D.C. metropolitan area. Few restrictions were used to select subjects, e.g. excluding those with traffic violations. Younger drivers, i.e. under 25 years, and self-reported high mileage drivers were sought and oversampled, however.

Vehicles were instrumented with cameras and inertial measurement devices and equipped with a PC-based computer to collect and store the data. The data collection box housed a yaw rate sensor, dual axis accelerometers, and a GPS navigation unit. In addition, radar sensors were mounted on the front and rear of the vehicle that were able to track other vehicles. The data collection box was usually installed on the roof of the trunk of the vehicle in order to be unobtrusive. . In addition to the on-board instrumentation, vehicle data, such as vehicle speed and brake pedal switch, were collected from the vehicle CAN bus. All data were sampled at a rate of 10 samples per second. Some of the sensors had lower sample rates. These data were still sampled at 10 samples per second but would have multiple samples with equal magnitude.

There were five (5) cameras that offered continuous views in and around the vehicle, as shown in Figure 1. The upper left frame shows a view of the driver's face and upper body, blurred to protect the identity of the driver. The lower left pane is an over-the-shoulder view of the driver, the upper right pane is a forward view out the front of the vehicle, and the lower right pane is split between a view out the passenger side of the vehicles and out the rear of the vehicle.

Figure 1. Combined Video Views from the 100-Car Naturalistic Study

METHODS AND CALCULATION

Driver Selection

A total of 108 primary drivers and 299 secondary drivers were included in the 100-Car study period in which all driving in an instrumented vehicle was recorded. Primary drivers were the primary owners or leasers of the instrumented vehicles. Secondary drivers occasionally drove the vehicles. Primary drivers accounted for 89% of all miles driven during the study period. The entire 100-Car database contains approximately 1.2 million miles of driving. A total of 1,119,202 miles of which were driven by primary drivers in 139,367 trips.

Prior to the analysis, the status of all time-series data was inspected. Instrumentation data, such as the front facing radar, vehicle speed, brake switch status, yaw rate signals, and lane tracking signals, were checked for missing or invalid data. Studies in the following analysis only included vehicles which had valid data in at least 60% of all trips and 60% of all distance traveled.

Lane Change Prediction Algorithm

Our solution to developing an adaptive driver drift out of lane detection algorithm is based on the idea that if we observe the driver's "normal" lane keeping behavior for a period of time, then we may be able to detect when driver lane keeping behavior falls outside of what is "normal" for each specific event. We defined normal driving behavior in this study using a technique adapted from Fujishiro and Takahashi [7]. Figure 2 shows an example from the Fujishiro and Takahashi study, in which driver lane keeping behavior was characterized as a function of distance to lane boundary (DTLB) and later velocity. In the Fujishiro and Takahashi study, a bivariate normal distribution was constructed using the DTLB and lateral velocity time series data. Normal driving behavior was defined as any data within the contour line representing 99% probability, as shown by the magenta circle.

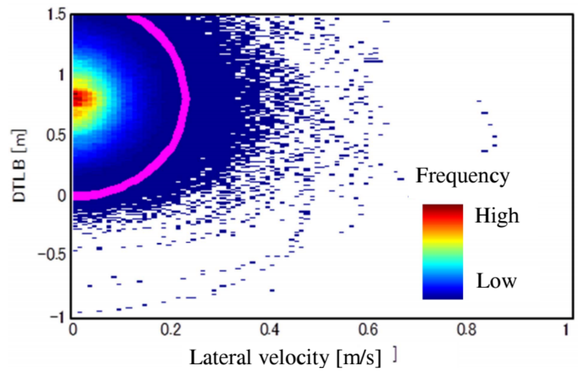

Figure 2. Lateral Velocity and Distance to Lane Boundary (DTLB) Distribution from Fujishiro and Takahashi [7] ***(Reproduced with permission from authors)***

Bivariate Normal Distribution

The bivariate normal distribution is an extension of the univariate normal distribution. Similar to univariate normal distribution, the bivariate extension computes the probability distribution as a function of two variables, and has probability of density function of the following form:

$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}}\exp\left(-\frac{1}{2}Q(x,y)\right) \quad \textbf{(Equation 1)}$$

where the function Q takes the form:

$$Q(x,y) = \frac{1}{1-\rho^2}\left[\left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2 - 2\rho\frac{(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y}\right]$$

(Equation 2)

The parameters σ_x σ_y and μ_x μ_y represents the standard deviation and mean of the variable x and y, respectively. The parameter ρ is the population correlation coefficient, which measures the dependence of two variables and is computed based on the covariance of the variables x and y and their respective standard deviation, as shown in (Equation 3.

$$\rho(x,y) = \frac{COV(x,y)}{\sigma_x\sigma_y} \quad \textbf{(Equation 3)}$$

The probability of each x and y combination is calculated by taking a surface integral of (Equation 3, as shown in (Equation 4. Lastly, the desired contour boundary is determined by finding x and y values of the same probability.

$$P(x,y)=\iint_{s} f(x,y)dS \qquad \textbf{(Equation 4)}$$

Steering Maneuver Detection Algorithm

The driver drift out of line detection algorithm follows the three steps shown in Figure 3. The algorithm first detects instances when the vehicle departs the lane line, as shown in Figure 3 (a).

The next step of the algorithm takes available time series data before vehicle lane crossing, and models normal driver lane keeping behavior as a function of DTLB and lateral velocity, as shown in Figure 3 (b). Up to 60 seconds of time series data before vehicle lane crossing to 5 seconds was used to model driver behavior before each excursion. Following the approach of Fujishiro and Takahashi, we defined normal driving behavior by creating a bivariate normal distribution of the DTLB and lateral velocity data prior to vehicle lane crossing and an associated 95% probability contour line. If less than 60 seconds of quality lane tracking data was available prior to the departure, then the algorithm utilized any available data to model normal driving behavior. If the lane crossing occurred less than 5 seconds from the start of the trip, that particular event was omitted from the analysis, as not enough data was available to model driver lane keeping behavior.

The last step of the algorithm, shown in Figure 3 (c), takes the available time series data from 5 seconds before vehicle lane crossing to time of vehicle lane crossing to determine the earliest time point at which the lane keeping behavior was outside of the 95% boundary established in step (b). The process shown in Figure 3 was repeated for each lane change event to create a unique "normal" lane keeping threshold for each event.

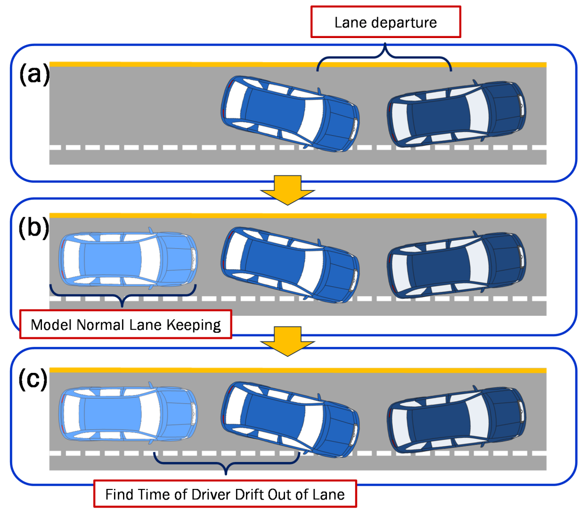

Figure 3. Steering Maneuver Detection Algorithm Procedure

Algorithm Validation

In order to validate the results reported by our algorithm, we compared the algorithm results to manual inspection of video footage of selected lane change events in the 100-Car NDS. A total of 949 randomly selected lane change events from 892 trips were extracted as the validation sample. For each lane change event, a research assistant in our group reviewed the over-the-shoulder camera view to determine the time stamp when the driver begins to initiate steering maneuver. In certain low lighting lane change events, such as nighttime or shadows created by nearby objects, time of steering initiation could not be determined by manual inspection, and therefore was not included in the validation sample.

Figure 4. Algorithm Validation with Manual Video Review

RESULTS

Algorithm Validation

Figure 5 shows the comparison of lead time between algorithm result and visual comparison. In this comparison, lead time is defined as the time between the start of steering maneuver and the first vehicle lane crossing, as shown in Figure 6

The cumulative distribution of lead time compares the result from visual inspection validation sample and the algorithm results from the same events. The analysis of the sample validation was based on quantifying normal lane keeping behavior using a 95% threshold. As shown in Figure 5, the medium lead time based on validation data was approximately 1.8 seconds, while the median lead time based on our algorithm was approximately 0.9 seconds. Both the validation results and the algorithm results shows that all lead times in the sample were less than 5 seconds.

One hypothesis for the lead time difference between the algorithm and the visual validation is the delay between steering wheel input and vehicle response. Most production vehicles do not respond instantaneously response to the steering input, largely due to weight transfer the suspension and the tires [8], [9]. While our visual inspection denotes the time of steering initiation as the first moment of steering wheel movement, the vehicle do not respond immediately and therefore the algorithm cannot precisely pinpoint the time of steering wheel initiation as reported in the visual inspection.

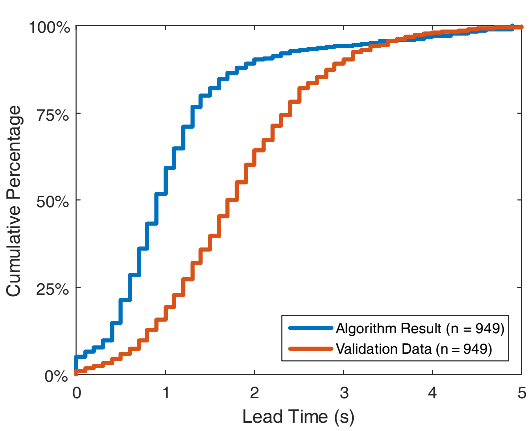

Figure 5. Cumulative Distribution of Lead Time

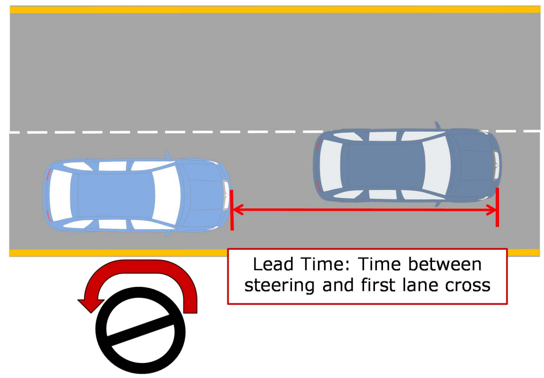

Figure 6. Definition of Lead Time

Sensitivity Analysis The validation sample was also used in a sensitivity analysis to set the probability threshold used in the bivariate normal distribution. In our method, we assumed that a bivariate normal distribution which captures 95% of the normal lane-keeping behavior to be the boundary between normal lane-keeping and lane change initiation. Figure 7 shows the average percentage error of lead time for each confidence interval. Average percentage error is computed as the average of the percentage error, calculated as shown in Equation 5, of all events in the validation sample. As shown in Figure 7, a probability threshold of 95% produced the lowest average percentage error of 2%. No additional benefit is obtained by increasing the probability threshold to 99%.

$$Percentage\,Error = \frac{|\,Leadtime_{a\lg orithmm} - Leadtime_{validation}\,|}{Leadtime_{validation}}$$

(Equation 5)

Sample Algorithm Results Figure 8 shows the steering maneuver detection algorithm performance on a sample trip. The horizontal axis shows the vehicle lateral velocity and the vertical axis shows the distance past edge, or DTLB. The red circle represents the data points used in modeling normal lane keeping behavior, the blue ellipse represents the boundary which captures 95% of the normal lane-keeping behavior, and the blue cross represents the data 5 seconds prior to lane crossing used to determine the start of steering maneuver. The yellow arrow in Figure 8 shows the time progression of driver initiating the lane change maneuver.

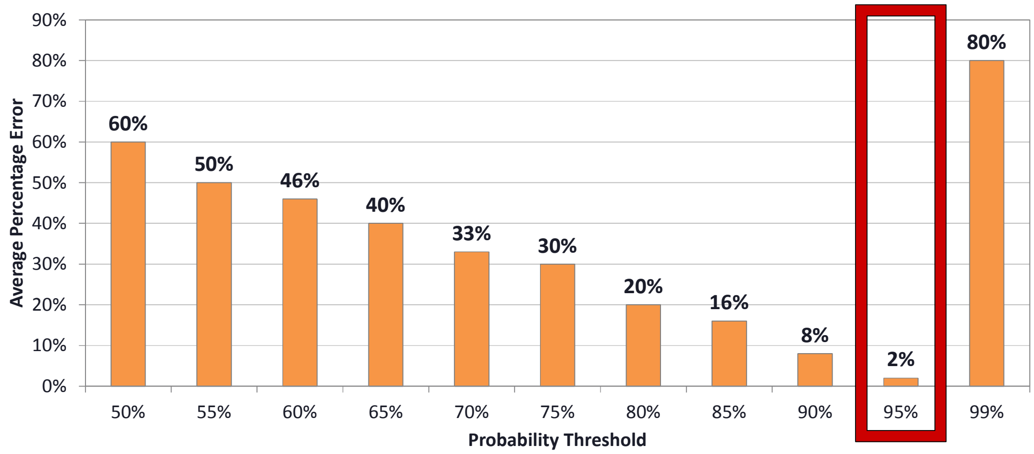

Figure 7. Sensitivity Analysis of Confidence Interval

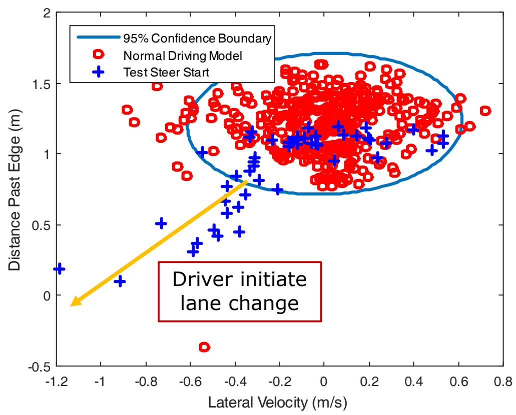

Figure 8. Sample Validation Result

Figure 9 and Figure 10 shows the DTLB and lateral distance for the sample event shown in Figure 8. The orange line in the figure shows the time when the algorithm determined that the data were outside of the normal lane-keeping boundary, while the yellow line in the figure shows when the visual inspection indicated that the driver begin to initiate the steering maneuver. As shown in the figures, the difference in the time of steering maneuver initiation between the algorithm and the visual inspection was approximately 0.2 seconds.

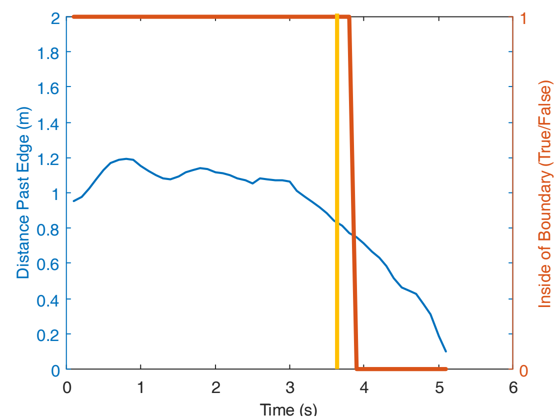

Figure 9. Sample Event Distance Past Edge

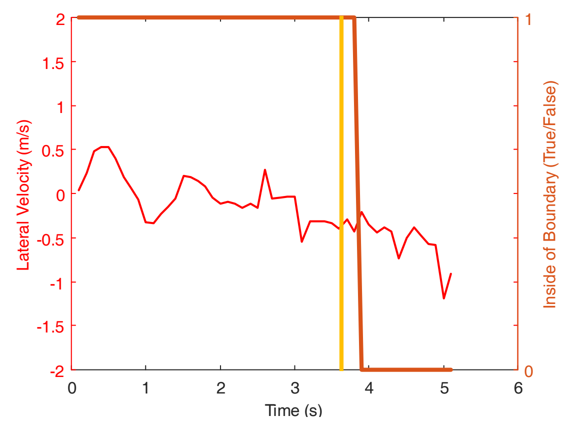

Figure 10. Sample Event Lateral Velocity

Algorithm Application: Detect Steering Initiation in Lane Change Events

One of the uses of the algorithm is to detect steering initiation in lane change event in which the driver does not use the turn signal. Previous studies have utilized 100-Car NDS to characterize driver lane change maneuver, in an effort to improve the triggering threshold of active safety systems [10]. Using the steering maneuver detection algorithm, we were able to compute steering initiation time for 53,615 lane change events from the 100-Car NDS.

Figure 11 shows the cumulative distribution of the lead time between steering start and lane edge crossing. The median lead time in the population of lane change was approximately 1 second.

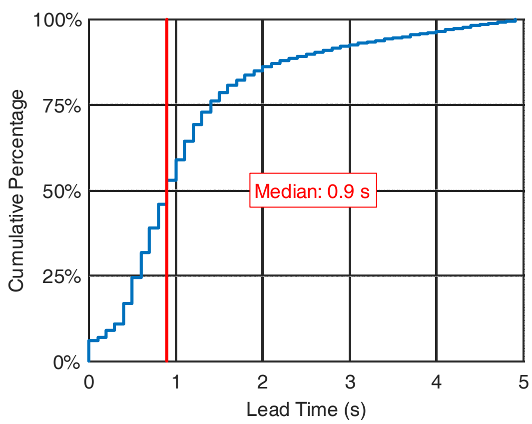

Figure 11. Cumulative Distribution of Lead Time

In addition to characterizing the lead time between steering maneuver initiation and lane crossing, we also compared the difference in driver behavior during steering initiation and lane change crossing in lane change events during car following events. Driver lane change behavior was quantified using Time to Collision (TTC) with respect to the lead vehicle. For each lane change event, TTC was computed at the time of steering initiation as well as the time of vehicle lane crossing, as shown in Equation 6:

$$TTC = \frac{-V_r - \sqrt{V_r^{\ 2} - 2 * A_r * D}}{A_r} \qquad \textbf{(Equation 6)}$$

where Vr is the relative speed, obtained from the reported radar range rate, between the two vehicles. Ar is calculated as the time different of Vr, and is the relative acceleration between the vehicles. Lastly, D is the distance between the two vehicles, which was obtained from the reported radar range rate.

We utilized the General Extreme Value Distribution (GEV) to characterize the probability of driver lane change for a continuous range of TTCs. The GEV distribution was previously determined to be the best fit distribution to describe driver lane change behavior, based on minimizing the Akaike information criterion (AIC), and Bayesian information criterion (BIC) [11]. Figure 12 show the GEV distribution of TTC at the start of steering maneuver. The distributions were computed separately for each 10 mph vehicle speed. For each vehicle speed bin, the GEV distribution provides continuous probability of steering initiation with respect to TTC.

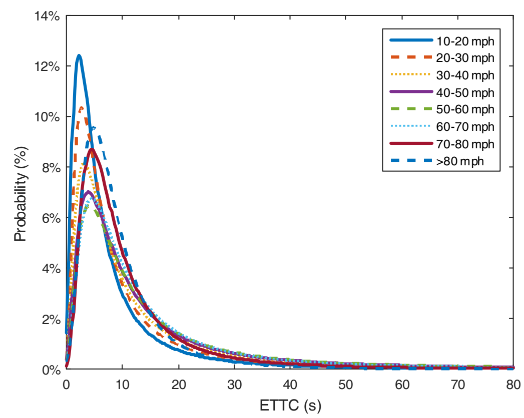

Figure 12. GEV Distribution of TTC at Start of Steering Maneuver

The GEV distributions shown in Figure 12 can also be characterized by their mode, or the TTC values corresponding to the maximum probability in each distribution. Figure 13 shows the modes of GEV distributions of TTC values at the start of steering and start of lane crossing. The comparison of GEV distributions modes between the start of lane crossing and start of steering shows that the modes of the TTC distributions are higher at the start of steering for all speed ranges, and the modes generally increase with vehicle speed.

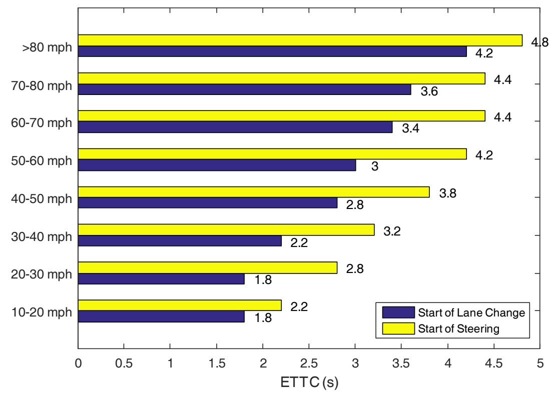

Figure 13. Comparison of Modes of GEV Distributions for TTC in Lane Change

CONCLUSIONS

The overall objective of the current study was to develop an automated algorithm to detect the start of steering initiation in lane change events.

The overall approach in the methodology was to model the normal lane keeping behavior using the distance to lane boundary and lateral velocity of the vehicle prior to the lane change event. The start of steering maneuver was defined as the first time when driver lane keeping behavior reaches outside 95% of normal lane keeping behavior.

The results of the algorithm were validated against manual video inspection of 949 randomly selected lane change events. During the manual inspection, the researcher review of the over-the-shoulder camera view to determine when the driver initiated the steering maneuver during the lane change. In certain low light lane change events, such as night time driving or shadows casted over the driver, time of steering maneuver could not be determined.

The comparison of lead time, or the time between the start of the steering maneuver and the vehicle crossing the lane edge, showed that the median lead time for the algorithm was approximately 0.9 seconds shorter than the lead time reported by visual inspection. We hypothesize that the difference in lead time is largely due to the play in the steering wheel and the fact that vehicles do not immediately respond to steering wheel input. Lead time was less than 5 seconds for all lane change events in the validation sample, suggesting that detecting steering wheel input within 5 seconds prior to lane crossing was a reasonable assumption in our algorithm.

The algorithm validation sample was also utilized in a sensitivity analysis of the confidence interval. Confidence intervals between 50% and 95% was selected to represent normal lane keeping behavior, and the performance of the algorithm was compared against the results from the manual inspection. According to the average percentage error of lead time between the algorithm output and the manual inspection, a 95% confidence level best described the normal lane keeping behavior in our algorithm, and was therefore selected in the final methodology.

We were able to compute steering initiation time in 53,615 lane change events. The distribution of lead time, or the time between steering initiation and first lane crossing, was approximately 1 second. In approximately 5% of the events, the lead time identified by the algorithm was 0, suggesting that in a small percentage of events, driver are very close to the target lane when they initiate the lane change maneuver. For all lane change events, the result of the algorithm shows that drivers begin steering maneuver for a lane change within 5 seconds of the vehicle crossing the lane. This shows that, in certain cases, we can potentially detect drivers' intent to change lanes as far as 5 seconds in advance.

Lastly, a probability distribution was fit to the population of TTC values using the general extreme value distribution. The modes, or peaks of the probability distributions, shows that TTC generally increase with vehicle speed. The comparison of modes of probability distribution shows drivers have higher TTC at the start of steering maneuver than the first lane cross. This suggests that drivers generally decrease the following distance between vehicles as the overtake maneuver progresses.

One of the major limitations of the current algorithm is the dependency on lane line availability. In most rural or suburban driving environments, lane lines are poorly marked or not available, therefore in these scenarios, our algorithm did not have sufficient information to model normal driver lane keeping behavior.

In summary, the current study developed a valuable methodology to estimate the start of steering maneuver in lane change events in the 100-Car NDS. Steering input was not directly recorded in the 100-Car NDS, and the current method provides an important tool in improving driver lane change characterization, and the resultant characterization of lane change events at the start of steering improves the previous study using first lane cross as the start of steering maneuver.

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