Drive Quality Analysis of Lane Change Maneuvers for Naturalistic Driving Studies

Ravi Kumar Satzoda¹, Pujitha Gunaratne² and Mohan M. Trivedi¹

Abstract—Analysis of naturalistic driving data provides a rich set of semantics which can be used to determine the driving characteristics that could lead to crashes and near-crashes. In this paper, we introduce “drive quality” analysis as part of the drive analysis process of naturalistic driving studies (NDSs) that we have previously introduced in [1]. In this first work on drive quality analysis for NDS data reduction, lane change maneuvers that are reduced from naturalistic driving data are further analyzed in a detailed manner in order to characterize them. Visual data from multiple perspectives and the data from in-vehicle sensors are used to characterize lane changes based on both the ego-vehicle kinematics and ego-vehicle surround dynamics. According to available literature on NDS and data reduction, this is the first work that presents an analysis of visual data from multiple perspectives to characterize and extract semantics related to ego-vehicle maneuvers in NDSs such as SHRP2.

I. INTRODUCTION

Naturalistic driving studies (NDSs) investigate the contributing factors that result in crashes or near-crashes using the data which is collected from typical day-to-day driving sessions without artificial features being introduced by controlled experimental studies [2]. Unlike on-road prediction systems like [3], NDSs involve offline data analytics [1], [4]. The 100-car study [5] and the more recent Strategic Highway Research Program (SHRP2) [2], [6] are examples of such NDSs. Large amounts of naturalistic driving data is collected in such studies, which is further reduced into specific events and conflicts as defined in the data reductionist dictionary [7]. While data reduction is largely a manual process by trained data reductionists [1], there are increasing number of works that are aimed at introducing automation or semi-automation in this process [1], [8].

In our previous works on automating the data reduction process in NDSs, we have introduced drive analysis in [1], [9], [10]. In drive analysis, naturalistic driving data from multiple sensors is fused and analyzed using the proposed techniques in [1], [9] to detect events that are listed in the data reductionist dictionary [7], which are considered as possible causes for crashes or near-crashes. A detailed drive analysis report is generated for each drive that gives a list of semantics which are related to specific events during the drive. This includes detection of lane change events [1], lane drift events [9], overtaking vehicle detection [11] etc.

While the detection of such precipitating events is critical for data analysis and reduction in NDSs, the events alone might not describe the complete scenario. For example, a left lane change event is detected from the forward view of the ego-vehicle in Fig. 1(a). However, detecting the left lane change event alone does not describe the quality of the drive. If the dynamics of the surrounding vehicles are also considered, then we see that the lane change can be a risky maneuver because there is a vehicle in the left lane behind the ego-vehicle (as shown in the rear camera view in Fig. 1(b)), which is trying to pass/overtake the ego-vehicle.

In NDS drive analysis, characterizing the maneuvers made by ego-vehicle as described above adds higher order semantic information to the events that are identified in the data reduction process. While our previous works on automating the data reduction process through drive analysis focused on “detecting” the events such as lane changes and lane drifts, in this paper the events are further characterized in automated manner to provide more information about the precipitating events in the data reduction process of NDSs.

In this paper, we particularly focus on the drive analysis report that is generated for lane change events during a drive. In [1], lane change event detection was performed for reducing NDS data using the lane detection method proposed in [12], [13], and a drive analysis report was generated to determine the number and type of lane change events during a drive. In this paper, drive quality analysis is performed...
on the detected lane change events to characterize them as aggressive or non-aggressive. In order to do this, we analyze the visual data from two perspectives and analyze the data about the ego-vehicle dynamics within the lane along with the surrounding vehicles that are detected from the multi-perspective views. To the best knowledge of the authors based on open literature on NDS, this is the first work that is analyzing multiple perspectives as stated in NDSs such as SHRP2 [2] to characterize critical events for data reduction. The proposed analysis is applied on real-world NDS driving data and a drive quality analysis report is generated at the end.

This involves two cameras that are looking outside (forward and rear facing cameras) to perform the drive quality analysis, and this is the first time (based on publicly available literature on NDS and drive analysis) the two camera views are being analyzed for automated data analysis of naturalistic driving data.

Additionally, it is to be noted that the proposed work in this paper is catered for NDS data analysis, wherein the naturalistic driving data is already collected and is available for analysis. Unlike active safety where the detection or prediction should be done either real time or before the actual event occurs, drive quality analysis is performed on the entire data after it is collected at the end of the drive. This implies that both past and future data from the time of occurrence of an event can be used for data analysis. Also, we will refer to published lane and vehicle detection algorithms in this study, which will be used for characterizing the drive analysis events. Therefore, the detection algorithms are not in the scope of the paper.

III. CHARACTERIZING LANE CHANGE MANEUVERS IN NDS DATA

In this section, lane change maneuvers are characterized for NDS data analytics. The lane change maneuver is first defined followed by the steps to characterize the lane change maneuvers.

![Fig. 2. Overview of proposed drive quality analysis.](image)

**II. OVERVIEW AND SCOPE OF DRIVE QUALITY ANALYSIS**

In this paper, we present drive quality analysis as an additional information gathering step for data reduction in NDSs such as SHRP2. Considering that data reduction involves a few hundred different events in NDSs [7], the scope of this paper is limited to lane change maneuvers of the ego-vehicle. Fig. 2 shows the overview of proposed drive quality analysis. Given the sensor data from multiple sensors such as cameras and in-vehicle sensors that capture the vehicle kinematics, the drive analysis process [1] detects lane change events. The resulting events are further analyzed to generate drive quality analysis reports. The visual data from two cameras is analyzed further for presence of vehicles, and the vehicle detection information is fused with the lane change events and vehicle kinematics to generate drive quality analysis report. In this paper, we limit the study to lane change characterization only, and future works will explore driving styles from the proposed characterization. The detection of lane change events is discussed in our previous work [1].

Before getting into the details of drive quality analysis, we describe the sensor setup framework that is used for this analysis. The sensor suite is similar to the DAS sensor module that is used in the on-going NDS called SHRP2 [2]. This involves two cameras that are looking outside (forward and rear views of the ego-vehicle). Additionally, the vehicle kinematics such as speed, acceleration, steering angle etc. are captured by the in-vehicle sensors through the vehicle CAN (controller area network) bus. The visual information from the forward and rear facing cameras is used to perform the drive quality analysis, and this is the first time (based on publicly available literature on NDS and drive analysis) the two camera views are being analyzed for automated data analysis of naturalistic driving data.

Consider the lane change maneuver timeline shown in [1]. A lane change is usually detected using either of the following two criteria: (a) when the front wheel (left/right) of the ego-vehicle crosses the lane marking, or (b) when the center of the wheel crosses the lane marking. Both the above criteria describe the time instance when the lane change event is detected. However, in order to analyze the lane change maneuver, we need to define the time window of the lane change maneuver.

In order to define the time window $T_{lc} = \{t_{min}, t_{max}\}$ for lane change maneuver, the drift information of the vehicle is combined with the lane change event detection. We will describe this using left lane change and the same can be extended for right lane change events also.

Consider the lane change maneuver timeline shown in Fig. 3. Before the left lane change begins, the vehicle drifts towards the left lane (denoted in red). After the lane change
occurs at \( t_{lc} \) and before the ego-vehicle centers itself on the left lane, there is a period of time when the ego-vehicle appears closer to the right lane (denoted by red in the right most window). Therefore, the ego-vehicle appears to be drifting right before it enters into the lane completely after the lane change maneuver.

In order to determine \( t_{\min} \) and \( t_{\max} \), the lane drift events are also detected while detecting the lane change event using the techniques proposed in [11]. \( t_{\min} \) and \( t_{\max} \) for left and right lane changes are then defined as follows, given the drift events are detected immediately before and after the lane change maneuver:

\[
\begin{align*}
  t_{\min} &= \text{Beginning of left (right) lane drift} \\
  t_{lc} &= \text{Left (right) lane change time instance} \\
  t_{\max} &= \text{Ending of right (left) lane drift}
\end{align*}
\]

B. Lane Change Characteristics using Surrounding Vehicles’ Dynamics

The dynamics of the surrounding vehicles are first used to characterize lane change events in NDS. In this subsection, we will analyze the presence of vehicles in front and rear of the ego-vehicle to determine the drive quality during lane change events. In order to do this, a two-camera setup as shown in Fig. 4(a) is used. This sensor configuration is similar to the sensor setup in the on-going SHRP2 [2] and 100 car study [5]. Therefore, the proposed techniques can be used to analyze SHRP2 NDS data. As noted previously in the introduction, the proposed work in this paper is the main contribution of the paper; however the use of vehicle detection itself is not the main contribution of the paper; however the use of vehicle detection for NDS data analysis is the focus of the paper. Therefore, other vehicle detection techniques can also be used for the proposed data analysis.

Let us assume that a left lane change event is detected. We consider the following two vehicle detection algorithms in this study:

1) Overtaking vehicle detection algorithm [11] to detect the presence of partially visible passing or receding vehicles.
2) Active learning based vehicle detection [14] to detect vehicles in the forward and rear views of the ego-vehicle.

It is to be noted that the vehicle detection itself is not the main contribution of the paper; however the use of vehicle detection for NDS data analysis is the focus of the paper. Therefore, other vehicle detection techniques can also be used for the proposed data analysis.

Let us consider the case when there are no passing vehicles (overtaking or receding vehicles). Let \( S^F_V \) and \( S^R_V \) be the sets of detection windows of the vehicles in the forward and rear views \( I^F_i \) and \( I^R_i \) from the ego-vehicle respectively. Given the lane localization information, which was used to detect the lane change events, the windows in \( S^F_V \) and \( S^R_V \) are then localized within the left lane (considering left lane change event). Among the selected windows, the window that is the closest to the ego-vehicle is denoted by \( W^F \) and \( W^R \) for the forward and rear views respectively. In order to determine the closest window, inverse perspective mapping (IPM) is used to determine the position of the windows in real-world coordinates [15], [16]. It is to be noted that this analysis is meant for NDS analytics. Therefore, camera calibrations are pre-determined and can be used to determine the IPM based estimation of depth of the vehicles. If there is no vehicle in the left lane, then \( W \) is set to null.

Next, the time to distraction \( T_d \) is used to determine the distance from the ego-vehicle, which can be considered as the region where a near-crash or a crash can occur due to the distraction of the driver. According to several studies [17] on driver distraction \( T_d = 1.5 \) seconds is considered as the...
maximum allowable distraction time for the driver to avoid any crash or near-crash. Given the speed \( v \) and acceleration \( a \) of the ego-vehicle from in-vehicle sensors, the distance in front of the ego-vehicle at \( t_i \) \( (t_{\min} \leq t_i \leq t_{\max}) \), which is considered as the region of interest that can pose a threat to the ego-vehicle due to driver inattention is computed using the following equation:

\[
D_{ti} = v_{ti}T_d + \frac{1}{2}aT_d^2
\]  

(2)

Now, given the windows of nearest vehicles in the left lane of the ego-vehicle (for a left lane change event), i.e., \( W^L \) and \( W^R \), the distances of the vehicles are determined using the inverse perspective transformation \([15]\). These distances are denoted by \( d_{ti}^L \) and \( d_{ti}^R \) (illustrated in Fig. 5). \( d_{ti}^L \) and \( d_{ti}^R \) are used to define the risk posed by the vehicles in the left lane in front and rear of the ego-vehicle as follows:

\[
\psi_{ti}^L = 1 - \frac{d_{ti}^L}{D_{ti}}, \quad \psi_{ti}^R = 1 - \frac{d_{ti}^R}{D_{ti}}
\]  

(3)

The above formulations for the risk posed by the nearest vehicles will range from 0 (farther away from the ego-vehicle) to 1 (closer to the the ego-vehicle). If no vehicle is found within the \( D_{ti} \) distance from the ego-vehicle, the risk factor is set to 0. The above formulations are meant for the case when there are no passing or overtaking vehicles. If such vehicles are detected, then \( \psi \) is set to 1. Therefore, all the different cases for the risk can be summarized as follow:

\[
\psi_{ti}^L = \begin{cases} 
0 & \text{if no vehicle within } D_{ti} \\
1 - \frac{d_{ti}^L}{D_{ti}} & \text{for } d_{ti}^L < D_{ti} \\
1 & \text{overtaking/receding vehicle found}
\end{cases}
\]  

(4)

The above formulation is for the risk posed by vehicles in front of the ego-vehicle. Similarly \( \psi_{ti}^R \) is computed for vehicles in rear view of the ego-vehicle. The overall risk at time instance \( t_i \) is then defined by

\[
\psi_i = \max(\psi_{ti}^L, \psi_{ti}^R)
\]  

(5)

In this study, we are using the maximum function to define the overall risk. However, other functions such as a weighted average could also be used.

The above risk value is computed for all \( t_i \in [t_{\min}, t_{\max}] \), i.e. the lane change event time window. If the mean risk for the duration, \( \mu_{\psi} \), is greater than a threshold \( T_{\psi} \) then the lane change event is considered to be a risky lane change based on the dynamics of the surrounding vehicles.

C. Lane Change Characteristics using Ego-vehicle Kinematics

In this sub-section, the ego-vehicle kinematics are used to further characterize a lane change event.

1) Steering Angle: Given a lane change event, the steering angle \( \theta_i \) at every time instance \( t_{\min} \leq t_i \leq t_{\max} \) during the lane change is used to create a profile function \( f(\theta_i) \) for the lane change event. Fig. 6 shows the two such profiles of a left lane change and right lane change. The steering angle profile is used to determine change of steering angle at every \( t_i \), i.e.,

\[
\Delta(\theta_i) = \theta_{i+1} - \theta_i
\]  

(6)

The steering angle change is then used to determine the following two measures - cumulative absolute steering angle rate and mean cumulative absolute steering angle rate:

\[
\Phi_\theta = \sum_i |\Delta(\theta_i)| \quad \text{and} \quad \overline{\Phi_\theta} = \frac{\Phi_\theta}{t_{\max} - t_{\min}}
\]  

(7)

\( \Phi_\theta \) gives the total change in steering angle, whereas \( \overline{\Phi_\theta} \) gives the rate of total change in steering angle. Higher values for both \( \Phi_\theta \) and \( \overline{\Phi_\theta} \) usually indicate a sharper lane change event. For the lane changes shown in Fig. 6, the values for the two measures are as follows: (1) \( \Phi_\theta = 8.3, \overline{\Phi_\theta} = 0.23 \), (2) \( \Phi_\theta = 16.4, \overline{\Phi_\theta} = 0.63 \). A higher value of \( \overline{\Phi_\theta} \) indicates that the lane change was performed in lesser amount of time with larger variation in steering angle. It can be seen from Fig. 6 that the duration of the right lane change is shorter and the steering angle variation is higher as compared to the left lane change. These values corroborated with the visual inspection that the right lane change is more aggressive and sudden than the left lane change.

2) Lateral Acceleration: We next look at the lateral acceleration of the ego-vehicle during lane change. Lateral acceleration \( (a_v) \) has been studied in relation with driving styles in \([18]\). In this section, we look at \( a_v \) in relation to lane changes and events in NDS data reduction. In NDS data...
reduction dictionary, lateral acceleration is used in multiple events to determine causes for crashes and near-crashes. For example steering left or right with $a_y > 0.25g$ is considered as a critical event. Similarly, $a_y > 0.4g$ is also an indication for near-crash/crash.

The lane changes also include steering left or right. Therefore, the lane changes in NDS data are characterized using the lateral acceleration. Fig. 7 shows the profiles of absolute values of lateral acceleration during two lane changes. The mean value $\mu_y$ of $a_y$ is computed for the segment of the drive when a lane change occurs, i.e., between $t_{min}$ and $t_{max}$. The mean value is then used to characterize the lane change as aggressive or non-aggressive. For example, referring to Fig. 7, the $\mu_y$ is determined as $0.21g$ and $0.15g$ respective for the right and left lane changes. If we set a threshold of $T_y = 0.2g$ to classify a lane change as aggressive or non-aggressive, the right lane change is considered as an aggressive lane change.

IV. DRIVE QUALITY ANALYSIS FOR NDS: VISUALIZATIONS AND REPORT GENERATION

In this section, the drive quality analysis report is generated for naturalistic driving data. First, we consider one lane change event and demonstrate all the different measures that were formulated in the previous sections. The visual data from the two cameras and the vehicle kinematics data from the in-vehicle sensors are combined using the proposed formulations in order to generate the different profiles as shown in Fig. 8.

Fig. 8(a) shows the risk posed by the nearest forward and rear vehicles (with respect to the ego-vehicle) in the left lane during the lane change interval. It can be seen that the risk from the rear-vehicle is consistently higher compared to the forward vehicle during the lane change maneuver. However, after the lane change event occurs, the forward vehicle seems to be posing higher risk. This was corroborated by manual inspection of the visual data, which showed that the ego-vehicle accelerated (longitudinal acceleration) towards the end of the lane change maneuver. Fig. 8(b) shows the overall risk, which is the maxima function that was described in Section III-B. The overall risk ensures that the risk posed to the ego-vehicle is determined by the nearest vehicle for every time instant.

Next, the profiles of steering angle and lateral acceleration of the ego-vehicle during the same lane change event are visualized in Fig. 8(c) & (d). It can be seen from the steering angle profile in Fig. 8(c) that the lane change event did not involve sudden steering angle movements because a maximum deviation of about $5^\circ$ occurred during the lane change event. However, the lateral acceleration profile shows that the ego-vehicle moved at lateral accelerations over 0.2g for most of the lane change event.

The profiles in Fig. 8 can be used by the data reductionists in NDS as tools to visualize the lane change event. The metrics described in Section III derived from the profiles in Fig. 8 are then used to generate reports. First, individual reports for each lane change event are generated. Table I lists the different measures related to this particular lane change event, and it also tags the event as either aggressive or non-aggressive. It can be seen from Table I that 2 of the 4 metrics characterize the lane change event to be aggressive.

Next, all the lane change events in a given drive from naturalistic driving data can be characterized to generate detailed reports related to the quality of drive based on the metrics presented in this paper. Table II shows one such report, which one can use to deduce the following. It can be seen that there are more high risk left lane changes as compared to right lane changes. In the context of right side driving in US, this means that the drive involved more high risk lane changes towards faster moving traffic. Furthermore, there were 10 lane changes that are tagged as high risk due to ego-vehicle kinematics. This shows that the driving style itself could be aggressive and a contributing factor for high risk lane changes.

V. DISCUSSION, REMARKS & FUTURE DIRECTIONS

This section is deliberately titled as discussion and remarks, and not as conclusions. This is because we believe that the analysis presented in this paper is only a first step towards more such studies for automatically analyzing naturalistic driving data, that could enable a multitude of solutions for driver safety, traffic safety systems and controllers for intelligent vehicles. In this study, we characterized lane change maneuvers that are detected in naturalistic driving data based on two camera views, ego-vehicle dynamics and in-vehicle kinematics information. Semantics such as the aggressive nature of the lane change maneuvers are extracted to generate drive quality analysis report. Further work needs to be done to involve more contributing factors to the characterization of the lane change maneuvers, such as the presence of vehicles in blind spots, surround view information such as traffic signals, traffic lights etc.
Additionally, considering that lane and vehicle detection are being explored for implementation on embedded processors [16], [19], [20], online drive analysis using mobile computing platforms in order provide the driver an analysis of the drive in real-time is a possible future direction.

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REFERENCES


