Towards Automated Drive Analysis: A Multimodal Synergistic Approach

R. K. Satzoda, Sujitha Martin, Minh Van Ly, Pujitha Gunaratne and Mohan M. Trivedi

Abstract—Naturalistic driving studies (NDS) capture huge amounts of drive data, that is analyzed for critical information about driver behavior, driving characteristics etc. Moreover, NDS involve data collected from a wide range of sensing technologies in cars and this makes the analysis of this data a challenging task. In this paper, we propose a multimodal synergistic approach for automated drive analysis process that can be employed in analyzing large amounts of drive data. The visual information from cameras, vehicle dynamics from CAN bus, vehicle global positioning coordinates from GPS and digital road map data, that are collected during the drive, are analyzed in a collaborative and complementary manner in the approach presented in this paper. It will be shown that the proposed synergistic drive analysis approach automatically determines a wide range of critical information about the drive in varying road conditions.

I. INTRODUCTION

Naturalistic Driving Studies captures typical day-to-day driving session without artificial features introduced by the controlled experimental studies [1]. As the name suggests, such studies allow capturing the driver behavior and the driving characteristics of the drive or trip in a naturalistic manner of a common road user’s typical vehicle and environment, and not confined to test runs conducted by testbeds in a laboratory drill. NDS such as the 100 car study [2] previously, and Strategic Highway Research Program [1], [3] now have collected enormous amounts of data of more than millions of vehicle miles, ten of thousands of data over 2 to 3 years of time. With advances in data collection techniques using a range of sensors like cameras, CAN, radars, GPS, road maps etc., that can capture naturalistic data from inside and outside the vehicle such as rear and front views of the vehicle, driver face view, cabin view and so on, the challenges in analyzing and extracting meaningful information have increased [3]. A central challenge of using naturalistic databases is the selection of automated data analysis techniques and paradigms that can address relevant research questions [4].

In this paper, we introduce what we term as Drive Analysis, that analyzes automatically the naturalistic data captured in a testbed during a drive. In this paper, we propose a multimodal synergistic approach that brings together data collected by multiple sensors and information sources to analyze the drive data and determine the drive characteristics in an automated way. Fig. 1 illustrates the drive analysis of a typical trip, wherein the drive is analyzed for the types and number of lane changes, areas of the drive (freeway or urban roads), exit and merge drive characteristics etc. using the data collected by different sensing modalities during the drive.

The rest of the paper is organized as follows. In Section II, we presented some related recent work which discuss driving and driver data analysis techniques. The process of data collection that will be subjected to the proposed drive analysis is presented briefly in Section III. In Section IV, we present the automated drive analysis process using data collected from different modalities. The drive analysis is summarized in Section V with some conclusions and ideas for future research.

II. RELATED WORK

One of the earliest works that demonstrates the use and analysis of data from multiple sensors in a vehicle is reported in [5]. Information from camera sensors sensing the vehicle
surroundings is fused with vehicle dynamics data from CAN bus and GPS information to extract useful information about the driver behavior during lane changes. The need for such extensive data capturing, analysis and visualization tools that collaboratively function with each other is established in [5] for Intelligent Driver Safety Systems (IDSS).

In [6], a Looking-in Looking-out (LiLo) framework is proposed to demonstrate how the cameras that are looking inside and outside the vehicle, coupled with other sensing technologies can be used to develop intelligent driver assistance systems (IDAS) like lane departure warning, driver intention and posture analysis. Similar studies have been proposed in [7] wherein multimodal sensory cues are used in a collaborative fashion to predict driver intention.

Analysis of naturalistic driving data for examining the impact of driving style on the predictability and responsiveness of the driver is discussed in [8]. Vehicle dynamics like lateral and longitudinal accelerations and jerks are used to analyze the driving behavior as aggressive or non-aggressive. However, this study does not involve the vision sensor inputs to the system. Similar study was conducted by Derick et al in [9] but it uses the accelerometer and gyroscope sensors of a smartphone to determine the driving styles.

III. DATA COLLECTION FOR DRIVE ANALYSIS

Drive analysis involves data that is captured using different sensors, and/or recorded in different databases. In order to extract as much information as possible from the drive, it is necessary to bring together the different sources of information and analyze the data in a synergistic manner.

A. Sensors and Information Sources

In this paper, the drive analysis is performed using the information that is captured or recorded by the following modalities:

1) Cameras: The drive analysis presented in this paper relies on cameras as the primary sources of information. With increasing miniaturization of the cameras, they are becoming more ubiquitous and pervasive, especially in automobiles [6]. A wide range of cameras are available at our disposal, in terms of the resolution and accuracy, the field of view, color information etc. Also, cameras can be setup in different positions in the car capturing varied information. In this paper, we use the front facing Pointgrey camera that capture the lanes in front of the vehicle. A $640 \times 480$ resolution video is captured by this camera, which is analyzed for lane markings and other characteristics of the drive, that will be presented in this paper.

2) CAN Bus: Most modern vehicles capture large amount of data pertaining to the vehicle dynamics such as the speed, acceleration, braking pressure, right/left signals, yaw rate etc. CAN bus (for controller area network) is a vehicle bus standard designed to allow microcontrollers and devices to communicate with each other within a vehicle without a host computer. For the drive analysis presented in this paper, we use National Instruments CAN bus to capture the following information of the drive: (a) vehicle speed, (b) yaw rate, (c) steering angle, (d) braking pressure. These different parameters of the vehicle, when combined with the information from other sources give the state of the vehicle during the drive.

3) VectorNav Inertial Motion Unit (IMU): Inertial Motion Unit or IMU captures the state of the vehicle with respect to 10 different axes such as accelerations in all three directions, yaw, pitch, roll, altitude etc. We use a VectorNav IMU that includes an global position system (GPS), accelerometer, gyroscope, magnetometer, barometer and temperature. We particularly use the GPS location information, i.e. latitude and longitude information, yaw, pitch and roll information for the drive analysis in this paper. The GPS unit on the IMU has a sensitivity of up to -159dBm.

4) Digital Road Maps: While the rest of the sources are sensors, digital road maps such as Navteq [10] etc. have enormous amount of pre-recorded information that can be used for drive analysis. Given the GPS locations, these digital maps can be used to extract information like the type of roads, the number of lanes, traffic signals, upcoming turns/exits/merges, warning signals etc. We will show how the digital maps can be used to not only provide more information about the road conditions, but also verify the analysis deductions obtained from other sources.

B. LISA-Q2 Testbed and Data Collection

LISA-Q2 testbed that is equipped with the above mentioned sensors and information sources is employed to collect data during our testdrives. A front facing Pointgrey camera is fixed under the rear-view mirror inside the car, which captures the front-view of the car. Fig. 2 (a) shows the front facing camera that is affixed below the rear-view mirror. The images captured by this camera are analyzed for extracting the visual information that will be used for the proposed drive analysis process in this paper.

In addition to the front camera, we also have a downward facing side camera as shown in Fig. 2 (b). This camera is used to capture the ground truth information about the lanes for validating the lane analysis. As described in [11], this camera captures the lane markings without any perspective distortions unlike the front facing camera. Fig. 2 (c) shows a sample image captured by the side downward facing camera, which can be more readily analyzed for generating the ground truth.

Both these cameras capture $640 \times 480$ resolution video at nearly 15 frames per second as the vehicle moves. The National Instruments CAN bus and VectorNav IMU are connected to an on-board computer, which collect the vehicle dynamics and GPS locations respectively during the drive. Considering that all the three different sensors are capturing independently, we first perform a synchronization of the data from all these three sources with the camera as the reference timeline. For the purpose of drive analysis, the digital road map data is extracted from Google maps offline using the GPS locations that were recorded during the drive. This data is also synchronized with the reference timeline.
IV. AUTOMATED DRIVE ANALYSIS

In this section, we demonstrate how the information from different sensors can be used in a synergistic manner to conduct a detailed drive analysis. We consider cameras or vision sensors as the primary source of information because they capture the maximum amount of data from the scene around the ego-vehicle as seen by the driver himself. We will demonstrate the use of GPS and road map information, in conjunction with camera and CAN data to analyze the drive for information that is either directly not available or more difficult to be extracted from the camera and CAN bus.

A. Lane Change Analysis

In order to perform the drive analysis, we first consider the vehicle localization information from the relative position of the vehicle with respect to the lanes. Lane detection and tracking can be used to find the ego-vehicle position with respect to the lane markings [12], [13]. We employ VioLET lane estimation and tracking method as described in [11], which employs the steps shown in Fig. 3. Lane features are first extracted using steerable filters that are generated by finding double derivatives of 2-D Gaussian kernels $G(x,y)$ in different directions, i.e. $G_{xx}(x,y)$, $G_{xy}(x,y)$ and $G_{yy}(x,y)$. Therefore, given:

$$G(x,y) = e^{-\frac{(x^2+y^2)}{\sigma^2}}$$  (1)

$G_{xx}(x,y)$, $G_{xy}(x,y)$ and $G_{yy}(x,y)$ are computed in [11]. Maximizing the filter responses in the direction of the lanes extracts the lane features and non-lane features are rejected. A road model and Kalman filtering are then used to perform outlier removal and also track lanes from one frame to the other across time. The Kalman filter used for tracking lanes in this paper uses the following state variables:

$$x_{k+1|k} = Ax_{k|k}$$  and  $$y_k = Mx_k$$  (2)

where $x$, $A$ and $M$ are defined as follows:

$$x = [\phi, \tan \theta, W]^T$$  (3)

$$A = \begin{bmatrix} 1 & v \Delta t & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} ; \quad M = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$  (4)

In the above equations, $\phi$ is the lateral deviation of the car from center of the lane, $\theta$ is the yaw angle of the car, $v$ is the vehicle speed and $W$ is the width of the lane. It can be seen from the above equations that the visual information from the camera is supported yaw and vehicle speed data by the CAN bus to determine the vehicle localization information with respect to its lane.

Let us consider the vehicle localization information obtained from a 7 minute drive as shown in Fig. 4, involving 7100 frames captured at 10-15 frames per second. Fig. 4 shows the vehicle position relative to the left and right lanes indicated by the dotted lines. If the vehicle is in the middle of the lane, the vehicle position is seen at 0 on the y-axis. If the vehicle drifts to the right, the vehicle position increases above 0 and vice versa for the left drift. The black solid lines show the thresholds $T_L$ and $T_R$ at $y = 1.2m$ and $y = -1.2m$ respectively. If the vehicle center goes beyond $T_L$ or $T_R$, a left or a right lane change is indicated respectively. It should be noted that in Fig. 4 the vehicle position in the lane after every lane change is with respect to the center of the new lane. From Fig. 4, which are generated from camera and CAN sensing modalities, we can see that the drive involved both right and left changes at different instances of time.

We now introduce the road map data as an additional layer of information to the vehicle localization and lane change information that we have in Fig. 4. The road map information is obtained from the GPS locations of the vehicle that are recorded during the entire drive using the IMU. Fig. 5 shows the map data using these GPS locations for the drive.
maps APIs written in Javascript were used to plot the path on the street map as shown in Fig. 5. The markers on the map in Fig. 5 correspond to the different time instances during the drive. We use the GPS locations that are recorded during the drive to also obtain information about the road from the digital map database. This includes the type of road, speed limits and warnings that are seen at different points during the drive. On combining the vehicle localization data in Fig. 4 and the road map data from Fig. 5, the lane change activity information shown in Fig. 4 can be examined more accurately. According to the road map data in Fig. 5, the vehicle is entering an exit ramp at $t = 5646$ and we see a right lane change indicated at $t = 5615$ in Fig. 4. Therefore, it is possible that the lane change that is being flagged by the camera at $t = 5615$ could actually be an exit into the exit ramp on the right. The GPS data collected from the drive can be used to further confirm this deduction as shown in Fig. 6 (a). The GPS locations between $t = 5615$ and $t = 5715$ collected during the drive are used to determine the actual path of the vehicle as shown in Fig. 6 (a). It can be seen that the ego-vehicle is the right most lane at $t = 5615$ and is exiting the freeway into the exit right ramp. A similar analysis is performed using the GPS information of the drive to analyze all the lane changes that were indicated by the camera and CAN data. This analysis showed the right lane change that is indicated in Fig. 4 at $t = 5900$, is due to the vehicle moving into the right lane at the junction. A left lane change is shown in Fig. 4 at $t = 6447$. However, the road map data at $t = 6447$ indicates a junction and a sharp right turning that took place at the junction, as shown in Fig. 6(b). Therefore, the false positive lane change maneuver from the camera data is discarded by using the GPS and road map data of the drive.

**B. Drive Analysis using Vehicle Dynamics Information**

In this section, we use vehicle dynamics from CAN bus as the primary source of information and analyze the drive for useful information by complementing the CAN data with inputs from camera, GPS and road maps. Let us analyze speed of the vehicle which is one of the basic information that is directly obtained from the CAN bus. Fig. 7 plots the vehicle speed (in miles per hour) that is recorded by the CAN at every frame. Now, let us combine this information with the information from the cameras, GPS and road maps. The GPS and road map data that was shown earlier in Fig. 5 indicates that the vehicle was on a freeway till $t = 5600$ and then entered urban road. The speed limits during this stretch of the drive are obtained by using the GPS locations of the vehicle and road map data, which are shown in Fig. 5. According to this road map data for the drive, the vehicle should ideally have a speed of no more than 65mph till $t = 5600$, and reduce to 50mph on the urban road after $t = 6000$. The speed data from CAN shown in Fig. 7 shows that the vehicle remained within speed limits during most part of the drive. The sudden drop of speed at around $t = 6100$ is because of the vehicle stopping at the junction as corroborated by the camera and GPS data previously. Therefore, by combining the GPS and road map data with the speed data, we can find out the number of times and/or the amount of time the vehicle was above the speed limits during the drive.
We now analyze the drive for another vital information about the drive. The curvature of the road at different points in time can also be found using the vehicle dynamics information. Curvature $C$ at any point is defined by the following:

$$C = \frac{d\theta}{ds}$$  \hspace{1cm} (5)

where $d\theta$ is the change in angle of the tangential motion vector of the vehicle and $ds$ is the distance traversed by the vehicle along the curve. We determine $d\theta$ using the yaw angle information from the CAN bus. Similarly, we get the $ds$ using the speed and time information from the CAN bus.

Fig. 8 shows the curvature (in degrees/m) of the road that was covered during the drive. We have clipped the curvature magnitudes between 1 and -1 so that the curvatures of subtle curves can be amplified. If $C > 0$, then the road is curving to the right and vice versa for left curves. The analysis from Fig. 8 shows that there are at least 6 right curves and 2 left curves during the drive. This is corroborated by our camera and road map data, which show that there are curved roads during the time instances shown in Fig. 8. We also notice that there was one sharp right curve at $t = 6100$ giving curvature value more than 1 and a significantly sharp right curved road immediately after $t = 6300$. These correspond to the turning that the vehicle makes at the junction at $t = 6100$ and the vehicle passes through another sharped curved road immediately after that. We can combine the speed and curvature information together to see how safe the drive was. Accidents during the curves occur because of overspeeding on curved roads. An analysis of the two curves in Fig. 7 and 8 together shows that the vehicle speed is in this particular drive is usually under control during the curved parts of the drive.

### TABLE I

**Drive Analysis Summary**

<table>
<thead>
<tr>
<th>Drive analysis characteristics</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of right lane changes</td>
<td>4</td>
</tr>
<tr>
<td>Number of left lane changes</td>
<td>1</td>
</tr>
<tr>
<td>Time spent on freeway</td>
<td>4.27 mins</td>
</tr>
<tr>
<td>Time spent on urban road</td>
<td>1.90 mins</td>
</tr>
<tr>
<td>Total distance</td>
<td>5.906 miles</td>
</tr>
<tr>
<td>Average speed on freeway</td>
<td>64.50 mph</td>
</tr>
<tr>
<td>Average speed on urban road</td>
<td>40.21 mph</td>
</tr>
<tr>
<td>Number of stops</td>
<td>1</td>
</tr>
<tr>
<td>Number of right turns</td>
<td>1</td>
</tr>
<tr>
<td>Number of left turns</td>
<td>0</td>
</tr>
<tr>
<td>Number of freeway entries</td>
<td>0</td>
</tr>
<tr>
<td>Number of freeway exits</td>
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<tr>
<td>Time spent on single lane</td>
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<tr>
<td>Number of right curves</td>
<td>5</td>
</tr>
<tr>
<td>Number of left curves</td>
<td>2</td>
</tr>
<tr>
<td>Average distance from center of lane</td>
<td>35cm</td>
</tr>
</tbody>
</table>

### V. Summarizing the Analysis & Conclusions

We now put together all information that we gathered from different sources about the drive. Table I summarizes the findings from the drive analysis that was performed on the sample drive that we discussed till now. The information from cameras, GPS, digital road maps and the CAN bus are used in a synergistic manner as described in the previous sections to determine the different aspects of the drive that are listed in Table I. We have demonstrated an automated drive analysis approach that not only aids in getting extensive information about the drive but also helps in verifying the findings from different sources. Such a multi-modal drive analysis can be applied to data that is being collected as part of naturalistic driving studies like SHRP2 to understand the driver behavior, road conditions, vehicle dynamics under different road conditions etc. Such kind of analysis also allows researchers from different disciplines like human factors etc. to extract information that is relevant to their specific field of study. As part of future research, it is envisaged to perform this drive analysis while the data is being collected.

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### REFERENCES


