Automated Drive Analysis of Naturalistic Driving Studies with Looking-out Video

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Problem

Large volumes of data from multiple sensors are captured in Naturalistic Driving Studies (NDS) such as in the Strategic Highway Research Program 2 (SHRP2). In order to extract and characterize distraction events leading to crashes and near-crashes, visual data from multiple cameras coupled with other sensory data are analyzed by human data reductionists. This not only requires tremendous human effort and time, it is also subject to human error and interpretation. The research aims at developing novel computer vision and machine learning techniques, which analyze the visual data of the surrounding environment outside the vehicle, and the interactions and movements of the driver and passengers inside the vehicle. In this paper, we present research methods and results for automated drive analysis using looking out videos. Our ongoing research is focused on robust and efficient algorithms for looking-in videos as well.

Method

When looking at the outside surroundings of the ego-vehicle, highly desirable analysis includes estimating the drift of the ego-vehicle, detecting lane changes and their types, determining the types of lanes (i.e. solid or dashed, yellow or white) and determining any road boundary violations. In order to accomplish this, a novel selective region based lane detection algorithm is implemented, which can be deployed in different configurations to determine the various events related to lanes.

Most lane detection techniques involve three main steps: feature extraction, outlier removal and tracking. Figure 1 shows the basic steps in the lane feature detection algorithm. Given an input image frame, an inverse perspective mapping (IPM) is performed resulting an IPM image that gives the lanes in real-world coordinate system. A pre-determined N_b number of bands are selected in the image. Figure 1 shows two such bands that are selected on an IPM image. Steerable filters are applied selectively for a set of angles (currently 180^{o} steerable filters are applied) on each band. The edge maps from the steerable filters are further processed by applying the shift-and-match operation, that eliminates non-lane like features. Therefore, each band is processed using the steerable-like filters and the proposed shift-and-

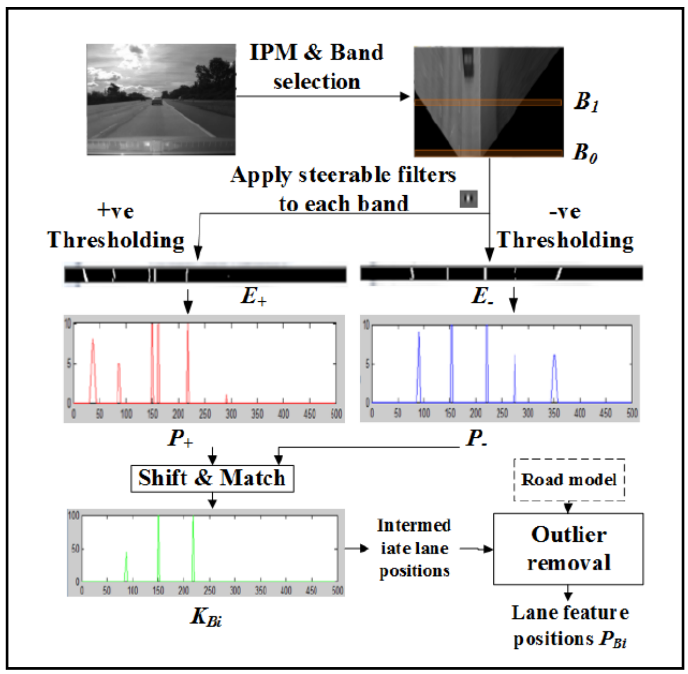

Figure 1 Efficient lane feature detection algorithm (LASeR).

match operation [1]. If there are N_B such scan bands in the IPM image, the left and right lane positions in each band are obtained. However, each band can result in multiple such lane feature positions in each band. The lane features thus obtained are subjected to outlier removal in the next step.

In order to do this, extended Kalman filter is used to track lane positions, which further eliminates the outliers. In addition to the Kalman filtering, road model is also used to combine the lane positions in each scan band to remove outliers. Clothoid lane model is used for this purpose. This entire lane estimation method is called lane analysis using selective regions (LASeR). More details about this method are described in [1].

After the lane feature extraction using the above steps, LASeR algorithm results in lane positions of the left and right lanes denoted by $\mathbf{x}_L$ and $\mathbf{x}_R$ respectively, i.e.,

$$\begin{aligned}\mathbf{x}_L &= [x_{L0}, x_{L1}, \ldots, x_{LN_B-1}]^T \\ \mathbf{x}_R &= [x_{R0}, x_{R1}, \ldots, x_{RN_B-1}]^T\end{aligned}$$

where $\mathbf{x}_L$ and $\mathbf{x}_R$ have the lane positions for the N_B scan bands. The lane positions in the nearest j bands are then used to detect the drift. This is done by finding if the lane positions are found in the drift regions shown in Figure 2. In Figure 2 the L_L and L_R refer to the drift regions corresponding to the left lane drift. Similarly R_L and R_R refer to lane drift regions for right lane drift. These regions are defined based on the fact that as the vehicle drifts to the left, the lane markers tend to move in to L_L and L_R regions. Similarly, when the vehicle drifts to the right, the lane markers shift to the right regions R_L and R_R. These regions can be used to determine the lane drifts using the following formulations:

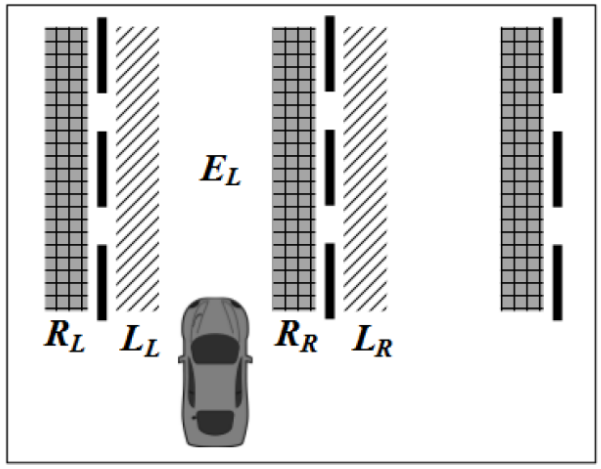

Figure 2. Definition of regions for lane drift detection

$$event = left\_drift \text{ if } \begin{cases} \forall x_{Lj} : L_L^- < x_{Lj} < L_L^+ \\ \forall x_{Rj} : L_R^- < x_{Rj} < L_R^+ \end{cases}$$

$$event = right\_drift \text{ if } \begin{cases} \forall x_{Lj} : R_L^- < x_{Lj} < R_L^+ \\ \forall x_{Rj} : R_R^- < x_{Rj} < R_R^+ \end{cases}$$

$$event = in\_lane \text{ if } \begin{cases} \forall x_{Lj} : R_L^+ < x_{Lj} < L_L^- \\ \forall x_{Rj} : R_R^+ < x_{Rj} < L_R^- \end{cases}$$

In the above formulations, the subscripts L and R represent the left and right regions. The super scripts + and - indicate the left and right bounds of the regions respectively. According to the above formulations, each left and right lane positions are checked if they are present within the left and right bounds of the different regions, which results in the event being classified as left_drift, right_drift and in_lane. More details of the lane drift algorithm are listed in [2].

Results & Discussion

The lane detection algorithm (LASeR) was evaluated on a segment of Toyota Technical Center (TTC) data. The total number of frames is 147. This segment was selected because it resembles the highway scenario similar to the SHRP2 data. The lane position deviation error metric was used for evaluation of lane detection in each frame. Lane position deviation (LPD) is defined as follows. The lane position deviation measures the deviation of detected lane from the actual lanes that are obtained by joining the actual lane markings. It captures the accuracy of the lane estimation process in both the near and far depths of view of the ego-vehicle. Moreover, this measure also evaluates the accuracy of the road model that is used to determine the lane curvature. For a given lane estimation algorithm, the different parameters of the algorithm can be used to determine their effect on LPD.

The LPD metric determines the average deviation δ_{LPD} in the x-direction between the actual and detected lane positions $\delta_{LPD} = \frac{1}{y_{max} - y_{min}} \sum_{i=y_{min}}^{y_{max}} \delta_i$, where $y_{min} < y < y_{max}$ is the selected region of the road scene in which the lane deviation is measured. We manually marked the lanes using a GUI in MATLAB, which generates the ground truth information for each input image in the video segment. The estimated lane position by LASeR is then used to determine δ_i for every y position along the vertical axis of the image place between y_{max} and y_{min}.

The evaluation of lane detection algorithm LASeR is presented in detail in [1] and [3]. It is shown that LASeR can detect lanes effectively in varying kinds of complex road and weather conditions. The average lane position deviation was found to be less than 7cm from the ground truth.

Here we evaluate the performance of the lane drift detection presented above. Figure 3 shows sample results of the lane drift detection for a short sequence that is taken from SHRP2 data that is available online. The thumbnails of the frames show the position of the ego-vehicle with respect to the lanes. The right lane position is indicated in the plot below in Figure 3. It can be seen that as the vehicle moves from the center of the lane (Frame 6150) to the right in Frame 6350, the right lane position also shifts in the plot. Similarly, as the vehicle moves to the center of the lane again in Frame 6600, the right lane position shifts such that it is within the acceptable bounds of 0.5m from the normal center of the lane.

The proposed lane drift detection algorithm was tested on NDS data that was collected by Toyota Technical Center (TTC), which comprised of 25000 frames collected at a frame rate of 30 fps (frames per second). This data is similar in nature in terms of perspective to the SHRP2 data. It was seen that the proposed lane drift detection technique was able to detect the drifts in the lane position in more than 95% of the drive as compared to the ground truth (that is generated by manual annotated of lane drift instances). The same was seen on SHRP2 videos that are hosted on the SHRP2 website.

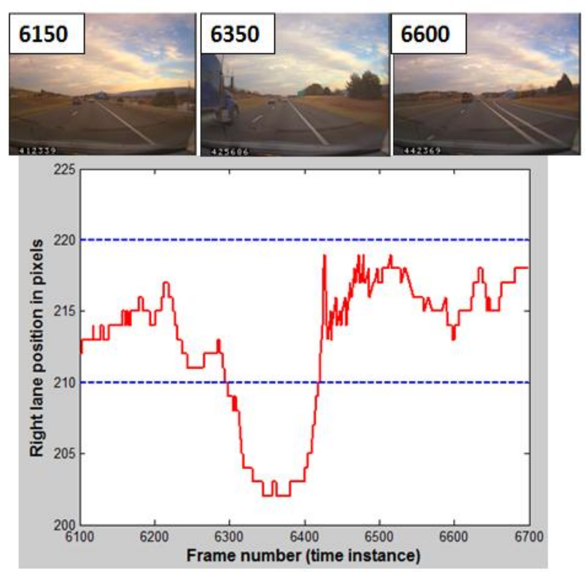

Figure 3. Sample result of the lane drift detection

Summary

Video data collected by the TRB NDS program has great potential to give insights into driver behavior and enhance safety. In this paper, we focus on automated drive analysis using the looking outside camera. The looking out lane drift algorithm was applied on NDS data from UCSD, TTC and SHRP2 as available on the National Academies website, and showed promising results. Future studies are in the direction of incorporating the interactions and movements of the driver and passengers inside the vehicle. Some interesting events include analyzing the driver's interaction with instrument cluster and driver's gaze patterns, injunction with events outside the ego-vehicle.

References

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[2] R. K. Satzoda, P. Gunaratne, and Mohan M. Trivedi, "Drive Analysis using Lane Semantics for Data Reduction in Naturalistic Driving Studies", *2014 IEEE Intelligent Vehicles Symposium*, pp. 293-2983, June 2014.

[3] R. K. Satzoda, and Mohan M. Trivedi, "Performance Metrics for Lane Estimation", *22nd International Conference on Pattern Recognition (ICPR)*, Aug. 2014 (To appear).