Robust Lane Change Detection and Tracking in Urban Environment

Saumya Srivastava
Department of Design and Manufacturing
Indian Institute of Science
Bangalore, India
ssaumya@iisc.ac.in

Rina Maiti
Department of Design and Manufacturing
Indian Institute of Science
Bangalore, India
rmaiti@iisc.ac.in

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***Abstract*—Lane detection in autonomous vehicles is crucial for safe navigation, requiring robust methods capable of handling diverse road scenarios, including lane changes. This paper introduces a novel approach integrating adaptive angle constraints and a mark-ROI technique for effective lane change detection and tracking in urban environment, which is capable of providing departure warning signals to the driver and recognizing lane changes. The method involves a series of preprocessing steps to ensure accurate lane localization. These steps include generating an edge map, reducing noise through orientation constraints at the sub-image level, applying the Hough transform for line detection, followed by a mask-based feature extraction to isolate lane markers. A tracking mechanism utilizing a Kalman filter is then employed to maintain detection continuity despite occlusions or missing lane markers. The results demonstrate that the proposed method can detect lane markings in real time across various complex environment.**

***Index Terms*—Lane Detection, Hough Transform, Kalman Filter, Inter-frame Similarity, Indian Roads, Advanced Driver Assistance System.**

I. Introduction

With the advent of technology, autonomous vehicles have emerged to provide assistance to driver and ensure road safety. Various modalities and their fusion have been explored aiming to advance vehicles from level 0 to level 5 autonomy. Vision sensors play a central role in this process, offering a picture-level understanding to computers that closely mimics human vision. Lane and road detection using vision sensors are crucial components of Advanced Driver Assistance Systems (ADAS), helping to define the position of the ego vehicle relative to its surroundings and facilitating motion planning and other essential tasks [1]. Vision-based lane detection methods typically follow a primary sequence of steps: starting with image preprocessing, followed by feature extraction, then fitting a lane model, and concluding with lane tracking. Over the past two decades, numerous researchers [2]–[6] have attempted to localize lane boundaries in various road scenarios. Edge based detection [7] and color based detection [8], [9]are two main techniques used in the feature extraction. However, accurately identifying lanes under challenging conditions—such as occlusion, variable illumination, poor video quality, and adverse weather—remains a significant challenge.

To improve the accuracy, some authors [6], [10], [12], [13] have utilized orientation constraints during feature extraction. These constraints play a crucial role in distinguishing lane markings from other road features and noise by focusing on the expected range of angles associated with lane markings. One of the famous works by Jung et al [14] proposed the combination of edge distribution function (EDF) and Hough transform for detecting the lane boundaries. Hybrid of linear and parabolic model is used to fit the near and far field lane boundaries, respectively. Model provides a robust fit along with being efficient in tracking. However, the EDF fails while dealing with edges of strong aligned shadows that are closer to lane marking.

To further mitigate noise and enhance accuracy, researchers commonly define two types of regions of interest (ROI) for lane detection in the literature. The first type is the road-ROI, which focuses on the image area where lanes are most likely to appear, filtering out irrelevant parts such as the sky and the car's bonnet. Some methods applied vertical mean distribution to delineate the ROI and effectively separating the sky region from the rest of the scene [15], [16]. While others dynamically determine the ROI by first estimating the vanishing point using Hough lines. The vanishing point represents the convergence point of parallel lines, such as lane markings, in the distance. The region of interest is then defined as the area below the vanishing line, which is drawn through the estimated vanishing point [10], [11]. Alternatively, Wu. et.al [13] have defined a fixed ROI based on empirically estimated values. The second type is the mark-ROI, where area around the detected lane marking is search in subsequent frame for the detection of lane marking, as applied in [13], [14], [17]. This method relies on the temporal consistency of lane positions and helps in reducing the computational load by narrowing down the search space to a smaller, more relevant region. To further improve the robustness of lane detection systems, tracking is often implemented to tackle down the scenarios where lane marking detection is not possible [18]–[21]. By maintaining consistency in lane parameters across consecutive frames, researchers can achieve more stable and reliable lane detection, even in challenging conditions.

Significant work has also been done on multi-lane detection, as seen in [22]–[25]. In context of multi-lane, ego lane is a host central lane on which vehicle is moving forward. Single lane detection can target only lane departure Warning System (LDWS) and lane keeping assistance system (LKAS), while multi-lane detection provides better understanding of the surrounding of the vehicle. For multiple lane detection, a combination of ridge features and IPM has been used in [24]. In [25], conditional random fields is applied for association of multiple lane marks. Methods works well for both, parallel and non-parallel lanes situation. However, performance of the method degrades in the anomaly of normal weather condition or in the presence of vehicle which occludes lane markings. Zhao et al. [26] needs additional information such as lane width, vehicle speed and direction in order to design a model. However, this additional information requires higher costs. In [27], the authors model the relationships between camera and road geometry with constraint parameters. These approaches are efficient but inaccurate and unstable because the rectified plane can be harmed easily by vibration, tilting, and pitch rate changes of the driving vehicle.

To address the lane departure, Lee [14] proposed a system to detect shifts in a vehicle's direction by determining the lane orientation through an EDF. A lane departure warning system monitors a vehicle's position relative to lane markers and alerts the driver when the vehicle drifts out of its lane [30]. Dangerous situations occur when the vehicle gets too close to or rapidly approaches lane boundaries [31]. The decision module uses lane detection results to determine vehicle position and triggers an alarm if drifting occurs unintentionally [32]. Enhancements include using directional indicators for intentional lane changes [33]. However, methods like the edge distribution function (EDF) may fail on curved roads with dashed lane markings [36]. Lee and Yi improved the EDF algorithm with departure ratios for more accurate detection [34], [35]. Other approaches include guard zones [32], spatial and temporal mechanisms [31], and time to lane crossing (TLC) indicators [36], [37]. Integrating driver behavior models can further reduce false warnings [38].

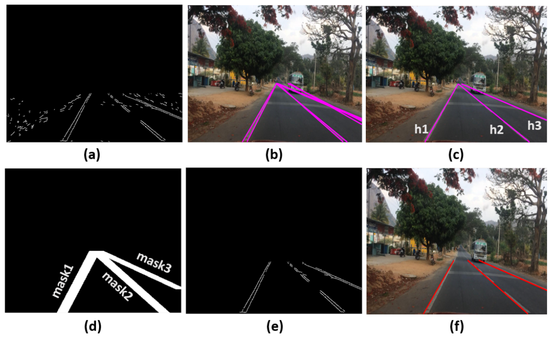

Fig. 1. Primary lane localization involves several sequential steps: (a) Denoised edge-map obtained by extraction of edges while adhering to orientation constraints, as described in [10] (b) Application of the Hough transform to identify lines over the image using the retained edges, (c) Aggregation of the detected Hough lines into three distinct lines labeled as h1, h2, and h3 (d) Creation of masks corresponding to each Hough line, denoted as mask1, mask2, mask3 (e) Overlaying each mask onto the edge image to extract relevant edges, and (f) Plotted lines over each lane marks.

In this paper, we explore a method for multi-lane detection capable of handling both urban and highway scenarios. We introduce a novel algorithm designed to detect multiple lane markings on road, even when the ego vehicle is performing lane change maneuvers. Our propose work has major contribution in the following three directions: (1) We have defined adaptive angle constraint which is capable of extracting lane features during lane change (2) With the aim to maximize the detection accuracy while minimizing the processing of unnecessary parts of the image, we have applied mark-ROI around detection in each frame. (3) We incorporated a modified Kalman filter with correction factor to maintain lane tracking accuracy despite intermittent occlusions and missing lane markings.

II. Proposed work

In the proposed work, we deal with two modules: 1) Primary lane localization, which involves feature extraction and curve fitting and setting up kalman tracker for tracking the fitted line in subsequent frames. 2) Lane change detection, which involves detecting ego lane change maneuver in multi-lane road scenarios.

A. *Primary lane localization*

The process of primary lane localization involves a series of systematic steps to accurately extract lane markings. Initially, the RGB image undergoes transformation into an edge map using the Canny edge detector [28]. This step identifies high-contrast edges that are indicative of potential lane markings. Subsequently, edge map is then partitioned into sub-images and edges within each sub-image that do not

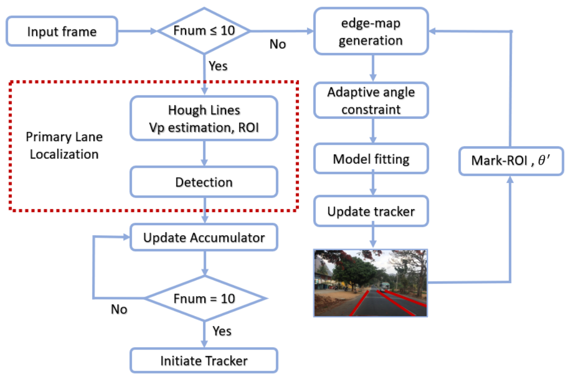

Fig. 2. Algorithm for the detection and tracking of lane markings using mark-ROI and adaptive angle constraint

Fig. 3. A mark-ROI is defined around the detected lane mark, defining the angle θ' as an angle constraint to selectively filter out irrelevant edges in the next frame.

conform to the specific orientation constraints of lane markings, as outlined in [10], are filtered out.

$$\text{constraint} = \begin{cases} \text{left mark}, & 20^\circ < \theta < 70^\circ \\ \text{right mark}, & -20^\circ < \theta < -70^\circ \end{cases} \quad (1)$$

This step removes irrelevant vertical and horizontal edges caused by shadows, trees, vehicles, buildings etc and produces a denoised edge map. Next, the Hough transform is applied to detect lines within the edge map generated from the previous step. This method allows for robust detection of linear features, which are crucial for identifying lane markings. Multiple Hough lines contributing to the vanishing point estimation are shown in Fig. 1(b). The area above the vanishing point is removed from the edge map, as illustrated in Fig. 1(a). Detected Hough lines are then grouped and aggregated into three distinct categories, denoted as h1, h2 and h3, based on their spatial arrangement and orientation relative to the image frame as depicted in Fig. 1(c). Each of the Hough line is then translated into a corresponding mask—specifically, mask1, mask2, and mask3 (Fig. 1(d)). These masks are overlaid onto the previous denoised edge image to extract pertinent lane marking edge features as seen in Fig. 1(e). This process effectively enhances the visibility and isolates the lane markings from residual noise and other visual distractions. Finally, a linear line is plotted using the RANSAC [39] over the extracted features, as shown in Fig. 1(f).

B. Tracking

Our research operates under the assumption that lane markings are consistently present on the road surface. However, these markings can become occluded by vehicles, pedestrians, or motorcyclists, or may degrade due to wear and tear, resulting in their absence in certain frames. To enhance the robustness of our algorithm in these scenarios, we employ a tracking mechanism for each mark-ROI. When a lane marking is either undetectable or deviates from its expected position by more than a predefined threshold within mark-ROI, a Kalman filter is utilized to generate a predictive output. This is achieved by setting the correction factor C to zero in the following equation:

$$\hat{s}_k^+ = \hat{s}_k^- + C \times KG_k(Z_r - H\hat{s}_k^-) \quad (2)$$

where $\hat{s}_k^+$ and $\hat{s}_k^-$ are updated and predicted state estimates respectively, Z is measured value, providing the observed data and KG is kalman gain, which adjusts the influence of the measurement on the state estimate. By relying on this predictive mechanism, the algorithm maintains accurate lane tracking despite intermittent occlusions or missing lane markings. Given that both process noise (v_k) and measurement noise (w_k) are assumed to follow a multivariate normal distribution with a mean of zero, covariance matrix Q_k for the process noise has diagonal values of 0.5 as

$$w_k \sim \mathcal{N}(0, Q_k), \quad Q_k = \begin{pmatrix} 0.5 & 0 \\ 0 & 0.5 \end{pmatrix} \quad (3)$$

Similarly, covariance matrix R_k for the measurement noise has diagonal values of 0.05 as

$$v_k \sim \mathcal{N}(0, R_k), \quad R_k = \begin{pmatrix} 0.05 & 0 \\ 0 & 0.05 \end{pmatrix} \quad (4)$$

C. Mark-ROI setup using adaptive angle constraint

Once the accumulated data confirms the presence of lane-marks,considering the relatively stable nature of the lane mark positions from one frame to the next, tracker is initiated and a region of interest (mark-ROI) is delineated around each identified lane mark. This ROI serves as a designated search area in the subsequent frame of video data. By confining the search to these predefined regions, computational resources are optimized, and the tracking algorithm can swiftly and accurately locate the corresponding lane marks in subsequent frames, even amidst varying environmental conditions or minor deviations in camera perspective. However, existing lane detection algorithims [10], [12], [13], [29] primarily focus on

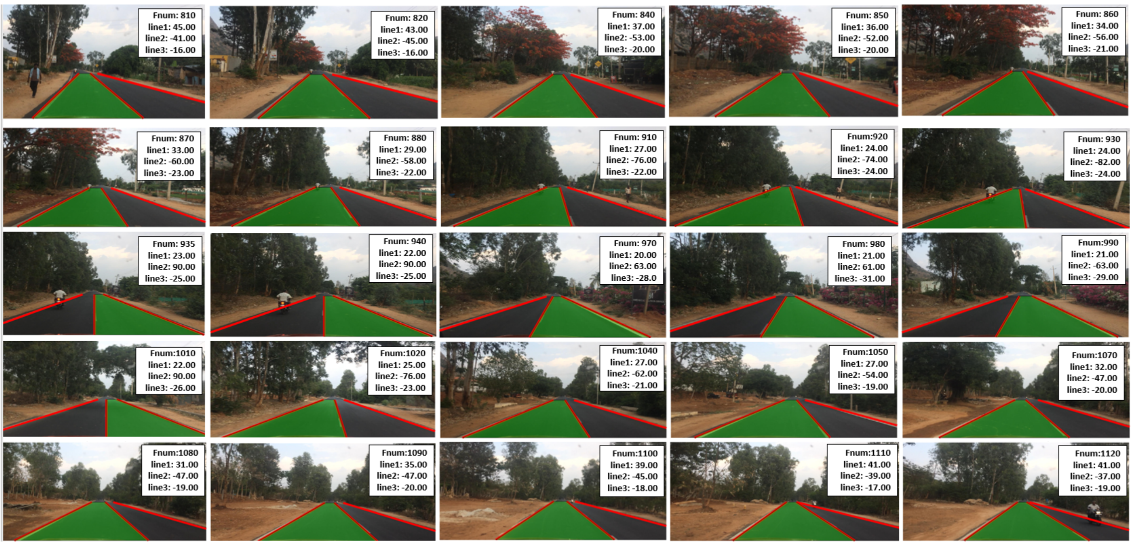

Fig. 4. Lane change maneuver. Initially, the ego vehicle is in the left lane (row1). The vehicle gradually shifts to the right lane to overtake a motorcyclist (fnum:880-1010) and, after a few frames, shifts back to the left lane (fnum:1090-1120). Shaded green portion defines the host lane for ego vehicle.

evaluating algorithms based on hard thresholding on orientation, neglecting the robustness of lane changing models against lane changing maneuverings where angle constraints of lane marks are invalid. To address this issue, we create mark-ROI with width 25 pixels on both left and right side of marking along with adaptive angle threshold θ calculated as

$$\text{adaptive constraint} = \begin{cases} 1 & \varphi_1 < \theta < \varphi_2 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where $\varphi_1 = \theta' - 15°$ and $\varphi_2 = \theta' + 15°$. By utilizing the mark-ROI approach as shown in Fig. 3, we eliminate the need for Hough transform, which requires extensive computation to detect lines over the entire image. Meanwhile, the mark-ROI method leverages the spatial consistency of lane markings between consecutive frames. Fig. 2 shows the algorithmic flow chart for detection and tracking lane markings, where till 10 frames, lane detection is done based on hough lines and generated mask. However, at the 10^{th} frame, the tracker is initialized, establishing the mark-ROI and adaptive angle constraint, which subsequently guide the detection process in the subsequent frames.

D. Lane Departure Detection

The proposed work focuses on continuously monitoring the orientation of lane markings using the methods described previously. This monitoring is crucial for detecting potential lane departures. The system tracks the angle and alignment of lane markers relative to the vehicle's position. If the driver does not signal an intention to change lanes, indicated by the absence of a turn signal (blinker), the system remains vigilant. It compares the detected orientation of the lane markings against a predefined threshold. In our case, this threshold is set at a value of $80°$. When the orientation of the detected lane markings approaches or exceeds this threshold, the system interprets it as a potential unintended lane departure. Consequently, it triggers a warning to alert the driver.

III. Results and Discussion

The experiments are conducted on PC equipped with 3.00 GHz Intel Core i9 CPU and 32 GB RAM and images are scaled to size 640×340. Our dataset was captured with an iPhone at a frame rate of 30 fps and a resolution of 1334×750 pixels. The camera sensor, attached to the rear-view mirror, is aligned with the vehicle's central axis. For lane detection purposes, the images are resized to 640×320 pixels. The dataset encompasses two scenarios: daytime and nighttime, with images taken on highways and urban streets. Our dataset also include images with frequent lane change. Lane change is a fundamental maneuver in vehicular dynamics, performed to navigate roads efficiently and maintain traffic flow. This maneuver involves the lateral movement of a vehicle from one lane to another and is necessitated by various driving scenarios, including overtaking slower vehicles, avoiding obstacles, merging onto highways, or positioning for an upcoming turn or exit.

As illustrated in Fig. 4, where initially the vehicle is situated in the left lane of the road. However, gradually over the successive frames vehicle shift towards the right to overtake the motorcycle and slope of line2 undergoes a notable change from frame number 840 to 930, transitioning from -41° to -82°. This shift signifies that line2 is approaching a vertical orientation, as evident by frame 935 in Fig. 4. Once

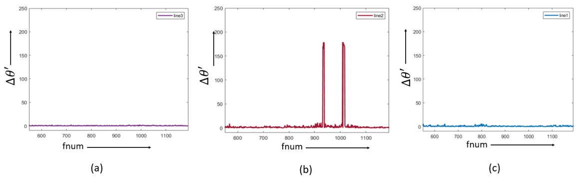

Fig. 5. Analysis of slope changes for detected lines (a) change in slope for line1 (b) change in slope for line2 (c) change in slope for line3

the vehicle aligns its position, resulting in line 2 becoming vertical, any further rightward movement leads to an increase in the slope of line2. As the vehicle continues its trajectory to the right, the positive slope decreases from 90° to 61° between frames 940 and 990. Conversely, as the vehicle progressively returns to its original left-lane position, the slope of line 2 crosses 90° and gradually reduces to 37° (absolute value), observed at frame number 1120 in Fig. 4. This behavior reflects the vehicle's changing position relative to the lane markings and highlights the dynamic nature of the slope as an indicator of the vehicle's lateral movement. As can be seen in Table I., Yoo's [12] method struggles to adapt to lane changes due to hard thresholding criteria on angle to remove noise. However, we have achieved high performance by applying adaptive angle constraint through established mark-ROI.

TABLE I. COMPARISON OF DETECTION RATE ON OUR DATASET

Clips	Frame nums	Yoo's [12]	Our method
clip1	651	92.40	**96.50**
clip2	453	90.21	**100**
clip3	501	88.10	**99.86**
clip4	501	91.25	**96.83**

Fig. 5 illustrates variation in the slope of line1, line2, and line3 across different frame numbers. The slope remains relatively constant, indicating minimal changes in the lane marking corresponding to line1. Similar to line1, slope of the line3 remains relatively stable, suggesting that the lane marking corresponding to line3 does not undergo significant changes across the frames. However, there are significant variations in the slope values, particularly around the mid-section of the frame range. This indicates a notable change in the lane marking, possibly due to a lane change maneuver when vehicle shifts from left side to ride side and then to left side again, slope of line2 drastically change around fnum 930 and fnum 1010. Our dataset, annotation and results are available on https://sites.google.com/view/lanechange.

IV. Conclusion

In this paper, we presented a comprehensive approach to multi-lane detection, designed to handle both urban and highway scenarios, with a particular focus on scenarios involving lane changes. Our method leverages adaptive angle constraints and a mark-ROI framework to enhance the accuracy and efficiency of lane detection. By implementing a tracking mechanism with a modified Kalman filter, we have ensured robust lane detection even in the presence of occlusions and challenging conditions. The proposed system is capable of providing departure warning signals to the driver and recognizing lane changes. When the system detects that the vehicle is unintentionally drifting out of its lane, it promptly issues a warning to alert the driver, helping to prevent potential accidents. Additionally, the system accurately identifies when a lane change is occurring, distinguishing between intentional maneuvers and unintended departures. The evaluation on our dataset showed a significant improvement, particularly in scenarios involving lane changes, as evidenced by the analysis of slope changes for detected lines and the high detection rates across various clips. However, proposed method has following detection issues: 1) It is ineffective on curved road markings due to the straight geometry of the mask-ROI. 2) It can mistakenly identifies edges of curb or other vehicles within assigned mask-ROI, and can result in the continued presence of false ROIs in subsequent frames, as shown in Fig. 6. Future research could explore the integration of additional sensor data, such as LiDAR and Radar, to further enhance the robustness of the system.

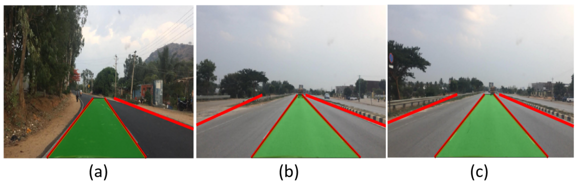

Fig. 6. (a) The proposed method is ineffective on curved road markings due to the straight geometry of the mask-ROI. (b) Aligned edges of the curb are detected instead of the faint left-most marking within the mask-ROI, leading to erroneous detection. (c) This can result in the continued presence of false ROIs in subsequent frames.

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