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A review of recent advances in lane detection and departure warning system

Sandipann P. Narote [a,*], Pradnya N. Bhujbal [b], Abbhilasha S. Narote [c], Dhiraj M. Dhane [d]

[a] Head of Department (E&TC), Government Women Residence Polytechnic, Tasgaon Sangli, India
[b] Assistant System Engineer, Tata Consultancy Services (TCS), Mumbai, India
[c] Assistant Professor, Smt. Kashibai Navale College of Engineering, Pune, India
[d] Assistant Professor ECE, Indian Institute of Information Technology, Pune, India

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ABSTRACT

Statistics show that worldwide motor vehicle collisions lead to significant deaths and disabilities as well as substantial financial costs to both society and the individuals involved. Unintended lane departure is a leading cause of road fatalities by the collision. To reduce the number of traffic accidents and to improve driver's safety lane departure warning (LDW), the system has emerged as a promising tool. Vision-based lane detection and departure warning system has been investigated over two decades. During this period, many different problems related to lane detection and departure warning have been addressed. This paper provides an overview of current LDW system, describing in particular pre-processing, lane models, lane de Ntection techniques and departure warning system.

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1. Introduction

Among the various accidents which are happening nowadays, unintended lane departure is the leading cause that is risking lives of people. A fatal collision can occur within a split of second due to driver's inattention to the surrounding cars and drowsiness. To reduce the number of traffic accidents and to improve safety, research on Driver Assistance System (DAS) have been conducted worldwide for many years.

Driver assistance systems are systems that provide aid or assistance to the driver while driving. These systems operate by taking input from sensors around the vehicle to compute some form of feedback that is then used to assist the driver of the vehicle. Adaptive Cruise Control (ACC), Blind Spot Monitoring (BSM), Lane Departure Warning (LDW) are examples of driver assistance system. The paper focuses on vision based lane detection and lane departure warning (LDDW) systems.

LDW continuously monitors the position of the vehicle on the lane markers on either side. If the vehicle comes within a certain distance of a marker, the driver is notified and a corrective measure can be undertaken. Using LDDW, unintentional lane departure caused by driver's inattention, distractions, fatigue can be reduced. RALPH [1], AURORA [2], AutoVue and ALVINN are the examples of LDDW system. In lane departure warning system, a camera is mounted high up in the windshield as a part of the rear view mirror mounting block. It captures a view of the road ahead. The driver gets a warning when the vehicle deviates and approaches or reaches the lane marking. The warning may be an audible tone, or a visual alert, or vibrations in either the steering wheel or driver's seat. If the driver intentionally crossing over the lane i.e. the turn signal is on, then there is no warning.

Navarro [3] of the presents effects of an auditory LDW System for partial and full lane departure combined with missed warnings on drivers' performance and acceptance. The study revealed that partial lane departure or reliable warnings are more effective and accepted by drivers than full lane departure or unreliable warnings.

The lane detection system consists of different modules, such as capturing video/image of the road lane marking, lane modeling, feature extraction, lane detection, lane tracking and lane departure warning system. Lane modeling is used to obtain a mathematical description of road lane marking. At feature extraction step, particular lane features such as edge, texture or color etc. are identified. Lane detection is carried out by fitting lane model with extracted features. Finally, lane changes are followed by using lane tracking module. While implementing the system we need to consider different complex conditions such as lane type, daytime, weather and driving scenarios [4]. Recently collaborative strategy is being used

* Corresponding author.
E-mail addresses: snarote@rediffmail.com (S.P. Narote), bhujbalpradnya@gmail.com (P.N. Bhujbal), a.narote@rediffmail.com (A.S. Narote), dmd.ece@iiitp.ac.in (D.M. Dhane).

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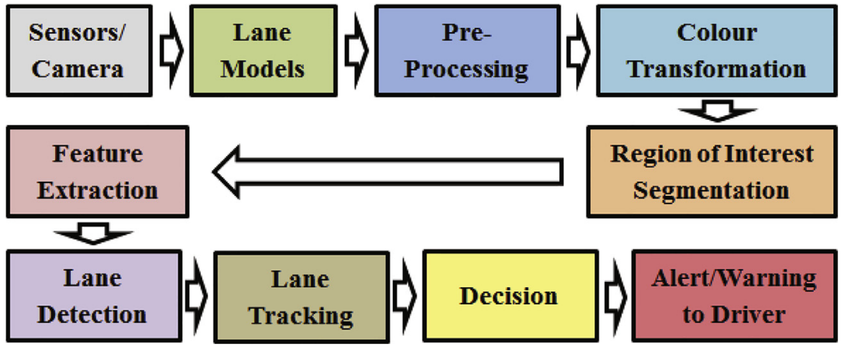

Fig. 1. Block diagram of lane detection and departure system.

for lane change that requires vehicle-vehicle-infrastructure communication (V2X) [5].

The remainder of this paper is organized as follows: Section 2 describes block diagram of lane detection and departure warning system. Section 3 lists the challenging scenarios under which the system will operate. Section 4 presents various pre-processing techniques for noise removal, where Section 5 and dummyTXdummy- 6 describes color transformation and ROI selection respectively. Different lane models are explained in Section 7. Section 8 illustrates different lane detection approaches while Section 9 lists out most commonly used lane tracking methodologies. Section 10 represents various lane departure warning systems. Section 11 gives comparison and summary of different lane detection and departure warning system.

2. Block diagram

Lane detection and departure measurement module are the two major parts of lane detection and departure warning system. First road lane marks are extracted by lane detection module then departure measurement module determines an unintentional maneuver across the lane boundary to prevent lane departure. General block diagram of lane detection and departure warning system is shown in Fig. 1.

The given system first extracts the frame from the video captured by the camera then feeds these raw frames to the lane detection system. Camera systems have limitations due to non-ideal visual conditions. Lane modeling plays an important role when lane detection system fails to detect road lines or interprets other objects such as guardrails as a lane marking. Lane modeling involves mathematical representation of lane marking [4,6] based on information received from various sensors and existing lane detection module [7]. It provides position, angle and curvature of lane marking. At the preprocessing stage, unwanted distortions are suppressed and image features are enhanced for further processing.

After pre-processing, color transformation is performed. As the contrast between lane boundary and normal road plane can be easily seen by the human eyes [8], therefore, for lane detection, most algorithms only consider gray level component. Once the grayscale image is obtained, speed and accuracy of lane detection is improved by ROI (Region of Interest) selection. This will reduce redundant image data based on effective information. In order to enhance the performance, lane models are used to predict ROI of the image plane. Then selected ROI is used for feature extraction. Feature extraction involves extraction of lane features such as color, texture, edge. Contrast between lane marking and road surface, constant width of lane marking, gradients at the marking are considered as the important features for lane detection. Lane detection step ties together the feature extraction and lane tracking stage. With the lane detection module, robust estimation of actual lane position is performed.

At lane detection stage, first line segments are detected from the edge map then detected line segments either classified as left or the right side of lane marking, or reject the detection completely [9,10]. Sometimes object such as traffic signs, zebra crossings, or guard rails which have line like structure may be considered as lane. Therefore, lane verification is performed to remove false lane marking [11]. To select lane marking in which vehicle is driving, information such as length, width and direction of lane marking is used. Lane tracking is applied to follow lane changes. It is used to predict the position of lane marking in the next frame by using the information about lane position obtained from the previous frame. As the vehicle approaches or reaches the lane marking, lane departure system generates a warning.

3. Environmental variability

Intelligent vehicles are equipped with advanced sensing system and intelligent driver assistance systems. A real-time illumination invariant lane departure and warning system robust to bad weather condition and night time is proposed in [12]. It makes use of distinct property of lane colors to lane markers. Zhu et al. [13] presents summary of methods for lane and road detection, traffic sign recognition, vehicle tracking, behavior analysis, scene understanding and performance analysis of these systems.

Due to a vivid environmental conditions of operating working system for lane detection and departure warning system operates, lane detection becomes a challenging task. Therefore, while implementing the system, it is necessary to consider different complex situations such as lane types, road surface, daytime, environmental factors (shadow, rain, fog and sunshine).

1. Types of lane marking: dramatic variation between road lane marking. Road lane markings can be well defined solid lines, dashed/segmented lines, circular reflectors, physical barriers, or nothing [6]. Unlike highways, lane markings of urban roads are not well defined; Background infrastructure (e.g. buildings) or traffic participants may introduce discontinuities in lane marking [14].
2. Road surface: The structured road is painted with lane markings and for unstructured road, road lane marking may be unclear or it may have low level intensity contrast. This leads to a road surface with degraded appearance. Additionally, changing weather conditions, varying illumination make the problem more complex [15,16].
3. Shadow: Lane detection is challenging in variable lighting conditions. It become more trival when road contains both shadowed and non-shadowed areas [16]. Shadow of trees, buildings or other vehicles on road surface leads to false edge creation [17–19].

4. Illumination variation: Illumination variation [20] due to (a) Natural light change- caused by time and weather, (b) Artificial light change- caused by street lamps and vehicles headlights and taillights.
5. Night Scenarios: At night time, the lane visibility is reduced due to which lane detection becomes difficult task. Because of the lack of sunlight, driver uses headlight and street lights to light up the scene in front of the vehicle and uses taillights to signal drivers behind them. Therefore, the system may face difficulties while lane mark extraction due to noise edges caused by those lights. Headlights may cause different part of the image to have different levels of contrast for lane marks [17,18].
6. Rain: In rainy scenarios, because the whole windshield is covered with raindrops, the contrast level of image may be decreased and also, this will introduce noise edges. On a watery road, lane identification becomes difficult due to diverse intensity levels.
7. Fog: In the presence of fog, contrast between lane marking and road surface reduces, which may result in moderate false alarm.

4. Pre-processing

Pre-processing step is an important part of the lane detection and departure warning system, which helps to reduce computational time and improves the result of the proposed algorithm. It is also used to remove sensor noise and errors due to unstable camera motion [21].The input to system is RGB-based color image sequence taken from a camera which is mounted inside the vehicle at the front view along the central line in such a way that it gives a clear sight of the road ahead without obstructing driver's view [22]. To improve the lane detection accuracy, different image preprocessing techniques are applied by many researchers.

To perform smoothing operation, mean, median [8] or Gaussian [23] filters are used. In [24], in order to retain the details and to remove unwanted noise Xu and Li first filtered the image using median filter, then to enhance the grayscale image, image histogram is used. In order to cater different light conditions, at preprocessing stage adaptive threshold is performed. Adaptive thresholding is performed using Otsu's algorithm. Then to remove the spot in the image obtained from the binary conversion morphological operations such as erosion and dilation are performed [8,24,25].

In [17,19], a piecewise linear stretching function (PLSF) is introduced to increase the contrast level of lane image when the environment is dim. This function shows robust performance to different lane colors and hence helps to increase the lane detection accuracy under various illuminating conditions.

In [26], FIR filter is applied before Otsu's thresholding. This would help to get rid of effects from noise, non-uniform background illumination etc. Then morphological operations are performed to determine connected objects and the smaller area of region is removed to eliminate the pavement stains to get accurate boundary.

In [22] threshold (λ_T) is computed from histogram of input image as $\lambda_R < \lambda_T < \lambda_L$, where λ_R, λ_L are the intensity values of the road surface ($\lambda_R = \lambda_{\min}$) and lane marking ($\lambda_L = \lambda_{\max}$) respectively. As input image represents white lane marking on black road surface, a histogram consists pixel count peak around the lower quarter of the intensity scale and drops sharply towards minimum and maximum intensity. Since, the majority of pixels in image should represent road surface, global peak in histogram i.e. λ_P correlate to lower bound λ_R. The upper bound is set to $0.9\lambda_{\max}$, slightly smaller than maximum intensity value.

To overcome the impact of brightness variation on lane detection [8] have been used the self clustering algorithm and fuzzy c-means algorithms are used. Based on the intensity profile of roadway these algorithms will calculate two distribution values to separate the light and dark component.

5. Color processing

In lane detection process most of the algorithms have only considered the gray level component. The color of the pixels is originally represented in RGB space that is highly correlated. RGB values can be transformed to YCbCr color space. The reason is that human visual system is less sensitive to the color and the most visually significant information in the color image is reserved in Y component of image. So lane detection procedure is carried out only on Y-component while the chrominance components (Cb and Cr) are discarded as human vision system is insensitive to them. It has advantages of saving data storage and computing time reduction. The formulation of transformation can be described as:

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.275 & -0.321 \\ 0.212 & -0.523 & 0.331 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

In above equation colors are not weighed equally. This will leads to loss of color information while color to grayscale transformation. Therefore, to enhance the quality of the lane mark intensity values, in [18] grayscale conversion is modified as:

$$I = R + G - B \tag{2}$$

6. ROI selection

In order to reduce redundant image data quantity based on effective information the input image should be set on the region of interest (ROI). ROI improves both speed and accuracy of the system. The speed improvement is achieved from reduction in the size of image to be processed. While selecting ROI, the objects having features similar to lane marking are eliminated. This will result into accuracy improvement. As vehicle moving in a forward direction, road is always located in front of vehicle [18]. Therefore, it is advisable to select ROI at the bottom side of image [17–19]. Dong et al. [27] select the ROI about the quarter of the image, at the bottom of the scene. The hood of the car and windshield wiper might affect the lane detection performance by producing false edges. So these parts have to be ignored. Lin et al. [18] used regular or adaptive ROI initialization. If it is possible to detect lane mark form previous frame then adaptive method is used; otherwise, regular method i.e. bottom side of image would be considered as ROI.

In order to save processing time Hsiao et al. [23] used vanishing point to identify ROI. When camera is mounted on a test vehicle in such a way that the optical axis of camera coincides with centerline of vehicle body, and roll angle and tilt angle are 0_0, the vanishing point of the road images appear in center of the vertical direction. Then it is necessary to limit the processing area below the vanishing point because lanes visible in a road image generally lie in that area [28]. In [29], selected ROI is divided into four small regions L_u, R_u, L_l and R_l, where L, R represent left and right lane and u, l stands for upper and lower region respectively. These subdivisions help in searching candidate pixels lying on lane boundaries.

In [30], while ROI selection, line detection procedure is applied independently on the first frame. This initial lane is used to obtain ROI, which will search the area for lane boundaries in subsequent video frames.Tu et al. [31] utilizes strong constraints on the objects, such as shape, width, color and the direction of lane lines, to select ROI which reduces computational load and removes the disturbing objects.

Lane lines appear at the similar position in sequential frames of the video when the frame rate is relatively high. Let l denotes the length of lane line and f is frame rate and vehicle is running at speed v, then number of frames (n) containing the same lane line is given as-

$$n = f\frac{l}{v} \tag{3}$$

Also, the lateral movement of the vehicle between two sequential frames is quite small which results in the lane position only having small differences in these frames. This prior knowledge can be used to predict the lane position in the next frame so that the edge detection algorithm can only consider a small area of the image. This further reduces the computational load.

Most of the time, sky region covers the upper part of input image and much of lane information lies at the bottom side, therefore it is always suggested to select ROI at bottom side of the image

7. Lane modeling

In lane detection and departure warning system, lane modeling plays an important role. Lane modeling is used to obtain mathematical description of road lane marking [4].

Till now, various vision based lane detection techniques propose different rode lane models. To model the road, some algorithms use straight lines; while other algorithms employ more complex models such as parabola, hyperbola, B-spline and clothoid.

In a linear model, lane is assumed to be straight i.e. the lane markings in the detection range are assumed as straight lines. Though the linear model is simple, it limits its application as its only feasible for limited detection range of the camera system. In the lane departure warning system, it is required to calculate the trajectory of the vehicle a few seconds ahead. For a highway accurate lane modeling for 30-40m or more is required, in order to catch the TLC (time to lane crossing) of 1 s. So in this case, complex lane models such as parabolic or a spline based- road model would be better [6].

McCall et al. [6] used a simple parabolic model which incorporates lane position, angle and curvature. Even though, at curves, parabolic model fits the lane better than linear model, still it cannot model lane marking such as connection between a straight lane and circular curves. To describe this type of constant changing curves, higher order lane models are used [9]. But as model order increases, it becomes more sensitive to noise. Therefore, for a robust curve lane detection, temporal filtering is required [9].

In order to detect incoming curve efficiently, Jung and Kelber [30] proposed a linear parabolic lane model. It consists of a linear function in the near field and a quadratic function in the far field. Along with the robustness of straight line model, the linear parabolic model provides the flexibility of parabolic lane model. Jung and Kelber, presented an improved version of linear parabolic model in [32]. Improved linear parabolic model includes constraints related to road geometry. To estimate the condition of road ahead, algorithm computes second derivative of the parabolic part of the model i.e. far field. Due to the introduction of geometric constraints in [32], the improved version performed better than Jung and Kelber [30].

Splines are piecewise polynomial curves. Spline based lane models describe the perspective effect of parallel lines. As compared to straight or parabolic lane model, spline based lane model describes a wider range of lane structures, as it can form arbitrary shapes by a different set of control points [9]. In [33] presents lane model based on Catmull–Rom spline. It is also known as Overhauster spline which is local interpolating spline. In [23,34], spline model further researched using cubic B-spline. At each frame, vanishing point is used for calculation of control points of B- spline. Here, the lane is modeled as a center line with lateral offset. To handle the transition between straight and curve road segments

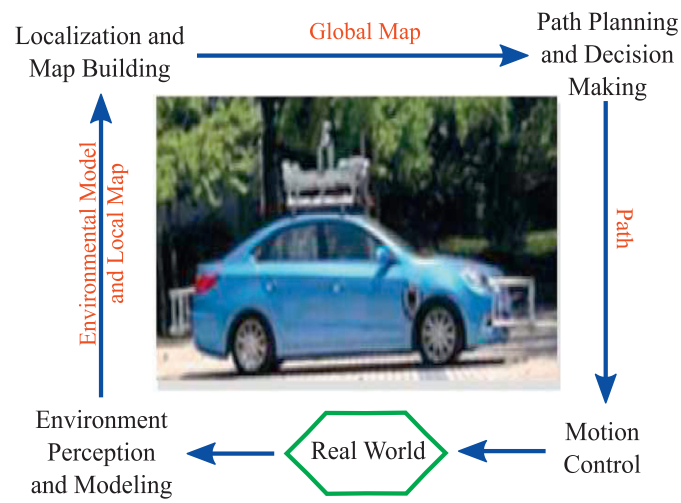

Fig. 2. Technologies in intelligent vehicles [13]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

[35] represents the road lane using extended hyperbola with additional non-linear term.

In case of partial occlusion of lane markings by other vehicle and a very high curvature, prediction of road geometry is a challenging task.Gackslatter et al. [7] proposes a lane model based on clothoid which continuously provides position, angle and curvatures of host as well as its neighboring lane marking. Clothoids are a special type of curve defined by their initial curvature, constant curvature change rate and their total length. It is used to avoid abrupt changes of the steering angle when driving from a straight road to a circular road and vice versa.

Mathematical representation of lane marker is achieved by various lane models, ranging from simple straight line model to complex spline model. Simple models cannot represent lane shapes accurately, while complex lane models result in high computational costs and also increase the detection error.

8. Lane detection

Lane detection is well researched area of computer vision with applications in intelligent vehicle system. Fig. 2 shows the fundamental technologies used in intelligent vehicles. Lane detection plays important role in lane departure warning system. Lane detection system detects lane marking from complex environment and uses them for reliable estimation of vehicle position and trajectory of vehicle relative to the lane. To develop a robust lane detection system that can accommodate the various conditions, the system must be developed by integrating the lane marking detector with lane tracking system [25]. The lane detection task is divided into following steps: Edge detection and lane detection.

8.1. Edge detection

Edge detection method is used to extract the edges of each thresholded feature. Lane boundaries are defined by sharp contrast between the road surface and painted lines. As edge characterizes the lane boundaries, edge detection is considered as an important step in lane detection. This step significantly reduces amount of data by filtering useless information and preserving the important structural properties. The resulting image after edge detection appears as an outline of the thresholded image. In order to detect the edges effectively following criteria should be followed:

1. Low error rate: Low error rate is achieved by detecting all edges in the image but at the same time there should not be response to non-edges.
2. Edge point should be well localized. This indicates that, the distance between the actual edge and edge pixels detected by detector should be a minimum.
3. For single edge point, there should be only one response.

Important steps in Edge detection:

1. First perform image smoothing to achieve noise reduction.
2. Detection of edge points: This is a local operation performed on image to extract all points that are potential candidates to become edge points.
3. Edge localization: At this step, from obtained candidate edge points, only the points which are true members, representing the lanes are selected.

There are several ways to perform edge detection such as Sobel [19,22,31,36], Canny [18,33], steering filter [6,37,38], 2D- FIR filter [39], and so on.

8.1.1. Sobel edge detection

Edge linking algorithm is applied on obtained edge image to produce more complete edge link that possibly belongs to lane marks. In [40] the extended edge linking algorithm is proposed with directional edge gap closing. In proposed algorithm, starting point of new edge link is obtained by performing raster scan. With the starting point, edge tracing module trace all edge points associated with the starting point in one orientation. Tracing is done with the 8-connectivity. Once edge links with valid orientation are obtained, directional edge gap closing takes place where edge links are extended by adding new pixel along edge link orientation to fill the gap [40]. In [19], sobel operator is applied to ROI. But still, there are some false edges after edge detection. These points may disturb lane markers fitting finally. Therefore to resolve this, threshold selection is adopted.

In [40] non-local maximum suppression (NLMS) along with sobel operator is introduced to find the edge pixels inside the ROI. To remove noise, the input image is smoothed with 5×5 Gaussian filter before edge detection. Then sobel edge detector is used to find amplitude and direction of edge. Once edge pixels are obtained, weak edge pixels are eliminated using hysteresis thresholds. Finally, NLMS algorithm is applied in which the edge pixels with local maximum along its gradient direction are kept.

8.1.2. Canny edge detection

Canny edge detector is used to find the image gradient. In [8] canny edge detection is used to detect the edges. By tracking the resultant region, the algorithm suppresses the pixel that is not maximum. In hysteresis, two threshold levels T1 and T2 are used. Pixel with magnitude below T1 is set to zero i.e. it is considered as a non-edge. If magnitude of pixel is above T2, then consider it as an edge. If the pixel magnitude is in between thresholds T1 and T2, then pixel magnitude is set to zero if there is no path from this pixel to a pixel with gradient above T2. In [41] canny edge detection is used to segment road area from sky region shown in Fig. 3. The algorithm for vehicle detection is shown in Fig. 4.

In [42] modified version of canny edge detector is introduced where image difference is computed at each pixel only along vertical direction and then NLMS is carried out. The edge points obtained from edge detection are connected based on prior knowledge about lane marking to form edge segment and lane mark segments. In [43], before applying canny edge detection, in order to preserve lane marking information, background subtraction is performed. In background subtraction, global histogram is used to find road surface background. The maximum grayscale around the histogram is taken as background gray. Then the resulting image is obtained from subtraction of background gray from the grayscale image is used for edge detection.

Fig. 3. Road region recognition [41].

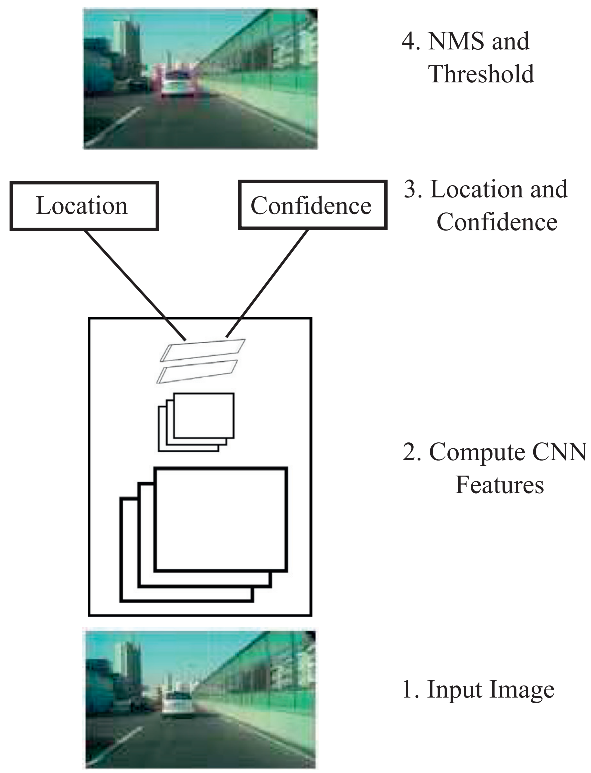

Fig. 4. Vehicle detection [41].

Left mask

1	0	0	0	0
0	1	0	0	0
0	0	0	0	0
0	0	0	-1	0
0	0	0	0	-1

Right mask

0	0	0	0	-1
0	0	0	-1	0
0	0	0	0	0
0	1	0	0	0
1	0	0	0	0

Fig. 5. Masks for left and right edge detection.

Hou et al. [44] applied ensemble learning methods to existing lane change assistance systems to improve the efficiency. In additional work [45] Canny operator is used for edge detection. Noisy edges are removed by scanning for eight neighboring pixels and Progressive Probabilistic Hough Transform (PPHT) is applied to

Fig. 6. Line segments [45].

extract line segments as shown in Fig. 6. Finally Kalman filter is used for tracking. The algorithm is shown in Fig. 7.

Sobel and canny edge operator used for edge detection are not specifically designed for lane detection. Wu et al. [46] defined two 5×5 mask, which identifies lanes based on their degree of stiffness.The edge detection masks shown in Fig. 5. are applied on gray scale image. Then for positive and negative edges, two thresholds are defined. If the pixel value is greater than positive threshold, edge will be set to green color i.e. positive edge. If the pixel value is lower than negative threshold, then edge will be set to red color i.e. negative edge. For the background, black color is used. If the distance between red and green color is less than 5 pixels, white color is used to fill the pixels between two. Finally, binarized image is obtained using black color to fill the pixel in image except the white pixels [46].

In [4] feature extraction is performed by using modified edge extraction method. Result from sobel and canny edge operator contains relatively large set of discrete points. In [4], instead of using these discrete points set, Obradovic used fuzzy points and instead of performing convolution of an image and operator mask, authors applied edge detection on single line.

In [23] the global edge detector is adopted to detect lane marks. For lane detection, peak finding algorithm extracts features points with the help of lane markers characteristics such as brightness and slenderness. Here, line segment is characterized using least square method which helps in reducing lane boundary divergence due to noise [23,47].

In [48] input image is warped into bird's eye view image. Bird's-eye view image is obtained by using the four-points warp-perspective mapping method. All-purpose edge operators like Sobel, Canny and specially designed operators are used for lane detection. An oriented distance transform (ODT) is applied for assigning horizontal distance data with respect to detected edge pixels.

False edge detection due to preceding cars, shadows of guardrails and trees or tire skids is overcome by focus of expansion (FOE) [49]; where, edge pixels of lane markers in the direction of FOE are only considered. Instead of sobel operator, zero crossing method is used to determine angle of edge pixels. Zero crossing method based on brightness of lane marker detects minimum number of edge pixels which are sufficient for lane detection.

Edge based lane marking detection techniques are simple but sensitive to illumination and get heavily affected by shadows. Also, while selecting suitable threshold level, these methods have experienced some difficulties [50]. Parajuli et al. [50] proposed lane detection based on processing of grayscale image with local gradient feature, characteristic spectrum of lanes and linear prediction. Here, conversion from gradient to binary image takes place without any threshold. Therefore, proposed methodology is robust against illumination condition and shadows.

The noise in edge map occurs due to varying environmental and road conditions. The edge detection algorithm should be robust against these factors.

8.1.3. Model based method

In image plane, a point at which a set of parallel lines in 3D space will converge, known as vanishing point [23]. It plays an important role of global constraint for detecting road direction. In [37] suggested edge extraction using steerable filter. Accuracy of lane orientation depends on the edge extraction based on steerable filter. In common edge detection algorithm, local maxima of intensity changes identified as lane orientation; where in [37] orientation of local features at each pixel is calculated using a vanishing point. Once a vanishing point is obtained, a pair of basic filters is applied to the input image which results in an orientation map. Then the orientation map is synchronized to obtain rising and falling edges.

In [11] the horizontal gradient map obtained from edge detection operation, combined with lateral inhibition property and far near adaption. Lateral inhibition property is helpful for lane detection in bad weather conditions as it enhances the response of the edges between lane marks and road surface. Due to perspective projection effect, far lane marks appear to be smaller and more blurred as compared to near lane mark. With the far-near adaption property, it adjusts the far and near edge response.

8.1.4. Histogram based method

In [51] color based segmentation is introduced to distinguish lane marking from road surface. Threshold is calculated as follows-First obtain the histogram of grayscale image, then draw a horizontal line 10*log 20 which intersects the histogram. This will give us most left and right crossover points which are used compute threshold level as, $t = \frac{\sqrt{t_{left}^2 + t_{right}^2}}{2}$.

8.2. Lane detection

Lane detection is an important step as it ties together the feature extraction stage with the tracking stage. In lane detection, estimation of actual lane position is carried out on the basis of extracted features. Once the edge map is obtained, edges that belongs to lane marks can finally be decided. While detecting the lanes, some assumptions are made such as- a. lane marker are painted in brighter color than other parts, b. the orientation of lane marks change are small and smooth along the lane, and c. lane marks are parallel to left and right from the center of lane marks.

There are two types of approaches used for lane detection:the feature-based methods and the model-based methods.

8.2.1. Feature based methods

The feature based methods are usually applied to localize the lanes in the road images by extracting low-level features.

In [52] two stage feature extraction is used for lane detection. It makes use of modified Hough transform to extract small segments of lane contour and clustered using DBSCAN (Density Based Spatial Clustering of Applications with Noise)clustering algorithm. The two stage curve fitting stages are shown in Fig. 8.

In [53] Maximally Stable Extremal Region(MSER)technique is used with the Progressive Probabilistic Hough transform to detect and recognize lane markings. Kalman filter is utilized to track ends of detected line markings.

Partial occlusion of lane marking due to front vehicle affects the accuracy of lane detection. Satzoda and Trivedi [54] proposed ELVIS system which overcome this problem by integrating the results of vehicle detection with lane detection system. In proposed methodology, position of vehicle obtained from vehicle detection module is used to determine the regions of the input image where the lane markers must be detected. HoG transform and SVM classifier are used to detect vehicle where LASeR (lane analysis using selective region) [55] is used to detect lane markings. In LASeR, instead of processing entire ROI, IPM image is divided into number of scan bands. Scan band closest to front vehicle used for lane feature extraction based on steerable filter.

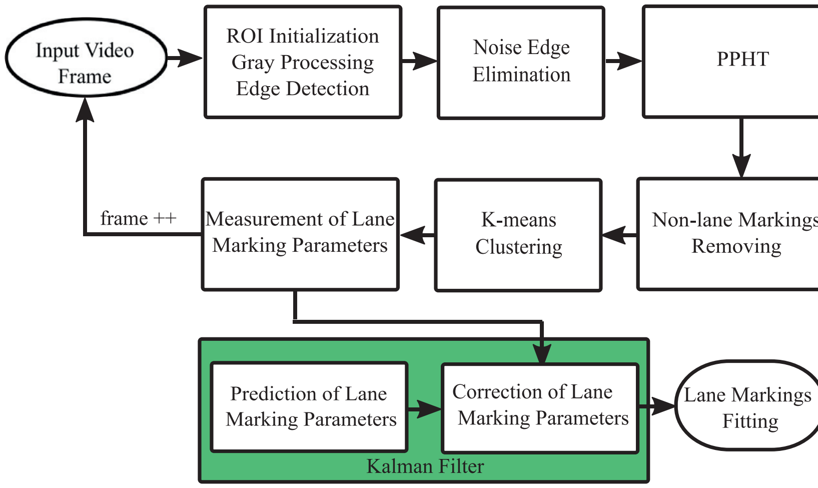

Fig. 7. Lane marking and tracking system [45].

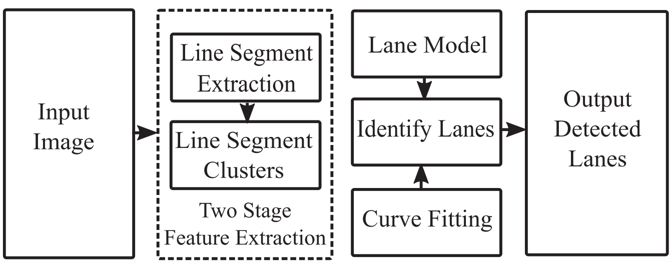

Fig. 8. Feature extraction with curve fitting [52].

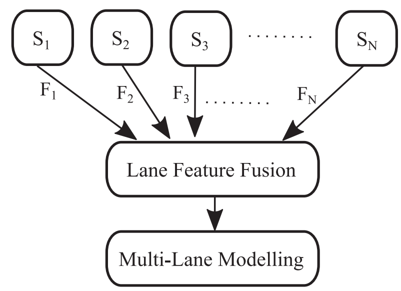

Fig. 9. Multi-lane perception [60].

Monocular camera is used to capture the road images introduce perspective effect in which width of lane marking changes as per their distance from the camera. To remove perspective effect [35,56,57] used inverse perspective effect (IPM) where input image resample and then each pixel is mapped into different position to obtain 2D array of pixels. The above procedure requires priory knowledge about camera parameters and the scene represented in the image. In [58] Xu and Wang proposed a detail methodology to estimate intrinsic and extrinsic camera parameters.

Obradovic et al. [4] performed lane detection using FLDetector where modified fuzzy c-means algorithm is used for clustering a set of fuzzy points. To create on initial set of candidate fuzzy line, for every fuzzy point determine a set of fuzzy coincident points. To reduce computational time instead of checking each point with all other considered only the neighboring points. Finally c-means clustering algorithm is used to create new cluster of fuzzy collinear point. Centroid of a new cluster represents fuzzy line which is collinear with all fuzzy points from the cluster.Tseng and Lin [11] proposed lane marker detection based on conjugate Gaussian model. To remove false positive due to traffic signs and unexpected stripes on the road surface, 3D lane width and relationship between intercept of lane marking with x-axis and angle between lane marking and x-axis are used.

By using the property that lane marking are brighter than road surface, Bertozzi and Broggi [35] proposed a lane detection technique based on horizontal black-white-black transaction. Lane detection procedure starts with filtering of remapped image where brightness value of each pixel is compared with its horizontal left and right neighboring pixels. Then the filtered image is enhanced using morphological dilation. Binerize image obtained from adaptive thresholding of enhanced image is scanned row by row from bottom to up to determine lane marks based on lane width and coordinate of road medial axis.

In [59], lane detection is performed on the basis of stereovision where the assumptions such as flat road, constant pitch angle or absence of roll angle, are eliminated. Here, the lane detection and tracking modules are combined. The algorithm starts with prediction of search region, in which lane parameters obtained from the previous frame and vehicle dynamics are used to predict current lane parameters. This prediction provides search regions for current lane detection. In proposed method, lane detection is carried out on the basis of vertical profile, horizontal profile and roll angle [59].

In [60] real-time approach for multi-lane perception is proposed. It is achieved with using feature fusion based on Graph-SLAM.

As shown in Fig. 9 the $S_1 \ldots S_N$ presents different input sources that collects road information. The features $F_1 \ldots F_N$ are fused together to get advantages of individual features.

Multi-lane detection algorithm based on DARPA Urban Challenge is presented by Revilloud et al. [61]. It detects lanes from bottom to top based on a physical behavior inspired by driver behavior. With extension to this work lane markers are detected in [62]. The results are presented in Fig. 10.

8.2.2. Model based methods

The model based methods use geometrical elements like parabolic curves, hyperbola and straight lines to describe the lanes. The model based methods are popularly used due to its simplicity.

Lane detection system proposed by Lee [28], uses edge information to define edge distribution function (EDF). EDF is defined as the histogram of edge magnitudes with respect to edge orientation angle. With the help of EDF edge related information is connected

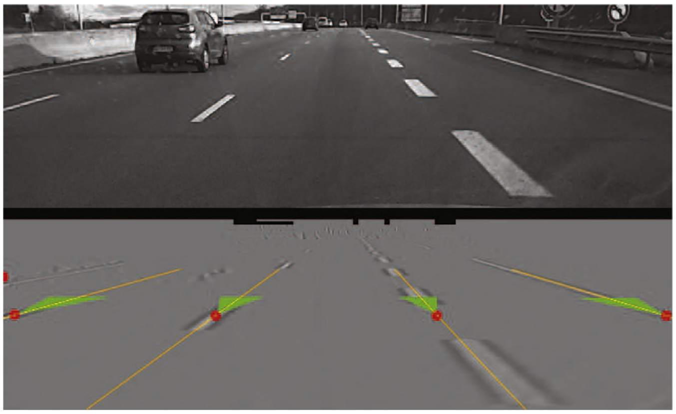

Fig. 10. Red circle: Lane agent. Green triangle: perception triangle of agents. Orange line: road marking estimation [62]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

with lane related information. Lee and co-workers [29,63] proposed modified version of the EDF based lane detection and departure warning system. In proposed methodology, after edge detection, pixels on the lane boundaries are extracted by using lane boundary pixel extractor (LBPE). LBPE uses information such as intensity and edge features of the lane markings. It is based on the property that lane markers are brighter than the road surface. This assumption will help to differentiate actual lane marking from noise edge due to tire skid marks or shadow of guard railings.

Among the various techniques, Hough transform [41] is one of the most robust and extensively used for lane detection. Hough transform is robust to noise and occlusion, as each edge point will be considered independently with respect to other, i.e. removal or introduction of some points will not affect the result of transform. It is used to identify the parameters of lane mark which best fits a given set of points obtained from an edge operator. The Hough transform is implemented as:

$$\rho = x\cos(\theta) + y\sin(\theta); \quad (4)$$

where, (x, y) = coordinates of non-zero pixels in binerize image.

ρ = Distance between the x-axis and fitted line.

θ= Angle between x-axis and normal line.

Applying Hough transform to a set of edge points (x, y) results in a 2D function $A(\rho, \theta)$ which represents the number of edge points satisfying the Eq. (4). The local maxima of $A(\rho, \theta)$ can be used to detect straight line segments passing through edge pixels [27].

Jung and Kelber [30] combined the EDF approach with Hough transform to detect lane markers, where can be obtained from the EDF peak, $\alpha(i.e.\theta = \alpha)$. $A(\theta, \alpha)$ is given as-

$$A(\rho, \theta) = \Sigma_i g(x_i + y_i) \quad (5)$$

where, (x_i, y_i) are edge pixels belonging to $\rho = x\cos(\alpha) + y\sin(\alpha)$.

Instead of counting the number of aligned pixels, addition of edge magnitudes is used to minimize the effect of noisy edges.

In [33], Wang et al. proposed the algorithm, which first detects the vanishing point based on Hough transform by line-length voting then the lane detection is carried out by using maximum likelihood approach. Here the likelihood approach measures the similarity between the lane model and the actual lane present in the image. Wang et al. employed a multi-resolution strategy where the image is down sampled to achieve an accurate solution rapidly.

In [17], the ROI is divided into the left and right sub-region to identify the left and right lane marking. In each sub-region, the lane detection is independently carried out with the help of the Hough transform. Such segmentation of ROI accurately facilitates the identification of the lane marking, with low computations per frames. After the detection of line segment, end points of these line segment are determined which are used to calculate lane related parameters for lane departure identification.

The heuristic knowledge about Hough transform such as double peaks (as there are two lanes right and left), the distance and the height difference between the double peak, angle of the double peaks used to detect the lane in image. In [31] verify the detected lane marks using Hough constraints such as peak height. If the peak height is too low, then it indicates that no lane line is present in the image and the system jumps to next frame; otherwise the system looks for another peak and check whether these two peaks satisfy the constraints of the double peak. If a double peak satisfying all the constraints then the position and direction of the lane line are calculated and stored as predictive knowledge for next frame. In [49] before detecting lane markers using Hough Transform histogram (histogram of angles of edge points) analysis is performed. Histogram consists of double peak structure, representing left and right lane marker. Once peaks are obtained, Hough transform is used to detect the lane boundaries by using edge points which have the same angle.

Dong et al. [27] used the prior knowledge which is obtained from the last frame of video before applying Hough transform for lane detection. The initial and terminal points of lane marker obtained from the last scene, makes frame to frame lane tracking simpler This saves a lot of resources and increase the accuracy of the algorithm.

Environment factors such as rain and heat might wear out the lane marks and the presence of snow on the road might also affect the visibility of road markers. Therefore, it is highly desirable to develop a system that can detect lane marks when they are visible as well as when they become invisible for short period of time. This is achieved in [56] by integrating Lukas–Kanade (L–K) optical flow and Hough transform. The L–K optical flow is used when lane markings are not visible, while Hough transform is used to detect when they are visible. In both cases for lane detection top view images obtained via homography are used. L–K optical flow method used to find out the vehicle's lateral position relative to its position in previous. When no lane markers are found L–K optical flow points tracking is used; as lane markers are found, Hough transform is used to for lane detection.

Standard Hough transform extracts both lane boundaries but with this approach, the artifacts on the road surface such as navigational texts, arrows, tar patches having similar features to the lane marking, often get detected as road lane marker. Therefore to solve this problem [26] firstly extracts midline of the lane based on gradient pairs constraint and then use perspective parallel model to extract lane markers. The algorithm proposed in [26] for lane detection is carried out in two steps. In first step, gradient operator is used to calculate the horizontal gradient and then the midline points are extracted based on gradient pairs constraints. In proposed algorithm parameters of midline are estimated by Hough transform. In second step, according to the midline and edge points of both sides of lane markings, the perspective parallel parameters of the road distance are obtained via another Hough transform. Finally the lane boundaries are robustly extracted from midline and perspective parallel parameters.

The main drawbacks of the Hough transform are its considerable requirements for memory and computational time [37]. To overcome these disadvantages, researchers have made many improvements to the Hough transform. To reduced space complexity of Hough transform Shang et al. [37] used vanishing based parallel Hough transform in which coordinate origin is shifted to the vanishing point as it requires smaller voting method. The core principle of parallel Hough transform presented in [37] is to divide the range of θ into 'n' interval and calculate 'ρ' using 'n 'processing

Fig. 11. Cubical model [64].

engine. Each processing engine contains, a set of pipeline process elements designed to perform Hough transform including calculation, voting and peak detection. In each pipeline only one peak is detected as a candidate. Then the estimated lane candidates are filtered and tracked using lane tracking unit. In order to overcome the computational complexity in [22] Lan et al. proposed sampling based scalable Hough transform. In proposed methodology, image obtained from feature extraction is first divided into N x N non-overlapping blocks. If block contains feature, a Hough transform is performed once only on the central pixel of the block. The methodology reduces the computational time of Hough transform by factor up to N^2 [22].

In [8,25,46], lane detection is carried out using fan scanning detection where the image is scanned from bottom up and middle to both side of image. Fan scanning consist of two steps- in first step edge pixels are grouped into line segments while in second step resulting line segment s are combined to get lane line. Before grouping edge pixels, the first encounter with an edge pixel (white pixel) in each row is saved and all other pixels are set to black. Edge pixels will be grouped into line segments on the basis of difference in coordinates of current and previous edge pixel. If difference is less than threshold then current pixel joins the previous edge pixel in the given line segment; otherwise current edge pixel is used to start a new line segment. At second step, the line segments are linked together to form the lane line.

Shin et al. [48] present particle filter based lane detectors that calculate sequences of isolated points for estimating lane borders. The detector are robust in challenging situations such as suburban roads, country side roads, inner-city roads. The outputs of multiple particle filters are combined into a single particle filter called as super particles.

Jung et al. [64] makes use of temporal consistency of lane width and Hough transform to detect two straight parallel lines that represents lanes boundaries. The detected lane points are fitted to a cubic model (shown in Fig. 11) using a weighted least squares algorithm. It has robust performance as it uses multiple frames to detect lane points.

Lane mark detection is not only an essential task for lane departure warning system, but also an important function for other driver assistance systems; for example vision based forward collision and driver behavior detection, front vehicle detection. From the detail study of various lane detection techniques, it is observed that even though Hough transform has several drawbacks many researchers were used it to detect lane markers. Other lane detection approaches such as DLD pattern, fan scanning, or conjugate Gaussian model provides robust lane detection against shadow effect, occlusion of lane markings, road signs etc.

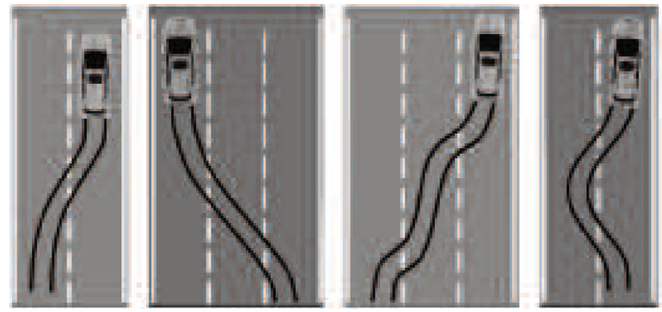

Fig. 12. Lane change models [71].

9. Lane tracking

Estimation of the lane position in the next image is carried out using lane tracking [27]. It allows lane departure system to estimate the vehicle position with respect to road and update the vehicle position as well as vehicle perception of the environment [65]. There will not be much deviation between two consecutive video frames, as there is temporal and spatial continuity between frame sequences. The information about lane position obtained from previous frame is used to guide detection of lane in next frame. In lane tracking, prior knowledge of road geometry put fairly strong constraints on the likely location and orientation of the lane edges in new image [43]. For lane tracking, Kalman filter [4,18,24,66,67], extended Kalman filter [9,68], particle filter [10,42], Annealed particle filter [69], and super-particle filter [70] are used. Wu et al. [71] presents lane-level localization system that detects lane change and analyzes behavior during lane change. Lane change models are shown in Fig. 12.

Kalman filters are used to for object tracking to predict an objects feature location [72]. Because of its recursive nature, new measurements can be processed as they arrive. Kalman filter algorithm contains two steps- state of system is estimated in first step while in second step noisy measurements are used to refine the estimate of the system. Because of simplicity, optimality, tractability and robustness, Kalman filter widely used for lane tracking. But it can be applied to linear system only. This drawback can be avoided by using Extended Kalman filter which simply linearises the non-linear model [73]. In [65], there is an integration of vehicle dynamics and geometric models with Kalman filtering for lane following.

In [42], lane tracking process is carried out using particle filtering, which has the ability to deal with non- Gaussian uncertainties and multi-hypothesis. The lane estimation consists of set of particles, representing a possible lane configuration. In [42], measurements from previous state are used to derived particle state. The particle weight represents the possibility of that particle representing true lane. In [69], H. Zhao et al. performed lane tracking using annealed particle filter in which angle information of edge map is used to measure weights of particle. In annealed particle filter, computational time for each frame is lowered as compared to conventional particle filter.

In [74], LOIS (likelihood of image shape) based on deformable template approach is used to track the lanes from frame to frame. While lane tracking, the information from previous frame is used to estimate lane location in next frame. The output of LOIS includes the curvature, orientation and offset of the current lane. These results are used with Kalman filter to predict the position of the vehicle with respect to the lane. Wang et al. [75] compared the performance of Gaussian sum particle filter (GSPF) with re-sampling (SIR) particle filter and Gaussian particle filter (GPF).

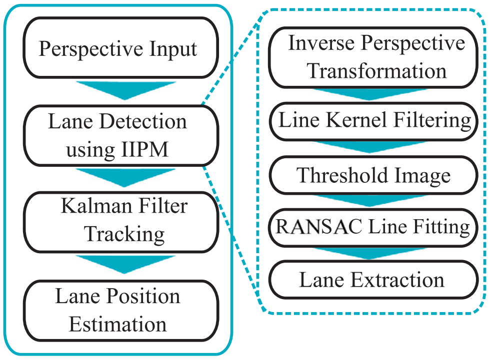

Fig. 13. Lane detection and tracking.

GSPF based on a likelihood function incorporates feature map to obtained better lane tracking.

Hou et al. [45] used Kalman and Particle filter for lane tracking. In [72] Inverse Perspective Mapping (IPM) is used to construct Bird's eye view image. Threshold is applied to detect straight lines i.e lane markers. Random Sample Consensus (RANSAC) line fitting technique is used to estimate parameters of model. Final tracking stage consists of Kalman filter as shown in Fig. 13.

In [5] trajectory planning (polynomial) algorithm is proposed for autonomous lane change. Lotfy et al. [76] proposed lane departure warning tracking system without using Kalman filter instead it uses score mechanism. It uses IPM to construct Bird's eye view of road and extracts edges. Lane boundaries are extracted using simplified Hough transform.

Most tracking algorithm employs various types of Kalman filters and particle filters. As compared to Kalman filters, particle filters and its derivatives required high computational power; but with parallel computing system they can be implemented efficiently.

10. Lane departure

Lane departure warning system constantly monitors the vehicle position with respect to the lane markers on either side and warns the driver when the vehicle begins to move out of its lane [46]. The dangerous lane departure situations resulted from the following two cases [23]:

1. When the vehicle gets too close towards lane boundaries.
2. Rapid departure speed of vehicle i.e. the vehicle approaches the lane boundaries too fast.

Results obtained from the lane detection module are used by decision module to determine the position of vehicle with respect to the nearest lane marking. Decision module uses lane marking on both sides of the vehicle to compute the center of the lane and if the vehicle starts drifting away from the center line, alarm is triggered [22]. To enhance the performance of lane departure warning system, decision module can take input from other sources. For example, based on the presence or absence of the directional indicator, the decision module can conclude whether a lane change is intentional or unintentional.

In [28], lane departure identification is based on symmetry axis and local maxima of the edge distribution function. As the vehicle deviates from the center of its travelling lane, location of axis changes. Though EDF based lane departure identification enhance the performance of system, the algorithm highly depends on the visibility of lane mark and may provide erroneous results for curved road with dashed lane marks. Therefore, in order to increase the robustness of the system, Lee and Yi proposed modified version of EDF based lane departure identification. The new algorithm increase the lane related parameters (such as orientation and location of lane boundaries in an image) and introduced departure ratios to determine the instant of lane departure. Lee and co-workers [29,63] considered θ_l and θ_r and distances ρ_l and ρ_r, defined for left and right lane boundaries. When optical axis of camera and center of lane coincides, they have the values as $\frac{\theta_l}{\theta_r} \approx 1$ $(\frac{\theta_{lin}}{\theta_{rin}}, \frac{\theta_{lout}}{\theta_{rout}})$ and $\frac{\rho_l}{\rho_r} \approx 1$ $(\frac{\rho_{lin}}{\rho_{rin}}, \frac{\rho_{lout}}{\rho_{rout}})$. If the vehicle deviates from center of lane, $\frac{\theta_l}{\theta_r}$ and $\frac{\rho_l}{\rho_r}$ deviates from the value of 1. When the vehicle approaches the left boundary, θ_l and ρ_l decreases at the same time θ_r and ρ_r increases. When the vehicle approaches the right boundary, θ_r and ρ_r decreases at the same time θ_l and ρ_l increases. Regression analysis is used to determine whether the host vehicle has the possibility of lane departure of based on the regression coefficient and sum of square. By fusing the knowledge of regression coefficient and SSE along with departure ratio, it becomes possible to minimize the false edge detection and determination of beginning and ending point of lane departure.

Lan et al.[22] suggest lane departure detection based on guard zone, where guard zone is placed along the x-axis of image and around the center of vehicle. Selection of guard zone size is crucial task. The size of guard zone should be sufficiently large to respond quickly for vehicle departure from its host lane but at the same time large size of guard zone should not cause frequent false alarm.

In [23], spatial and temporal mechanism is used to identify lane departure. Algorithm defined rectangular warning box to generate departure warning. Driver issued warning on the basis of d_M and d_S, distances from the intercept of left and right lane marking respectively, to the near bottom corners of warning box. The spatial mechanism triggers the alarm if either d_M or d_S larger than $\frac{1}{4}$th width of image. Spatial mechanism is useful when the vehicle is too close to lane boundaries. When host vehicle approaches the lane boundaries too fast, temporal warning mechanism trigger the alarm provide urgent warning before spatial warning. Temporal mechanism verifies whether there is large change in d_M and d_S.

In [73,77], time to lane crossing (TLC) is used as an indicator to predict the vehicle position before lane crossing event (LCE). TLC is defined as the time duration available for driver before a specified part of vehicle crosses the lane boundary. Glaser and Sentouh [78] integrates longitudinal and lateral vehicle dynamics, and vehicle position with TLC to generate departure warning. Due to nonlinearity and limited knowledge about vehicle state and road geometry, in real time accurate estimation of TLC is difficult task. This may leads to excessive false warning which is annoying to driver. One important reason of false warning is intended driver correction, in which vehicle get too close to lane boundary and then return to center of lane. In this situation driver is aware about his behavior and his action is somehow intended; but as TLC based conditions are valid, warning will be activated. At the same time zero or extremely low false alarm rate is undesirable because the driver may not received the warning alarm until the actual crash. Therefore, to reduce excessive false warning of lane departure, system needs to consider drivers behavior [73,77,79].

Angkititrakul et al. [79], proposed lane departure prediction system which predict lane departure before it happen. The proposed technique prevents false warning system by validating the warning signal obtained from TLC based indicator. That is the system distinguishes between unintentional lane crossing event (LCE) or deliberate driver correction event by applying driver behavior model. Core driver model is implemented using Gaussian mixture model and a maximum a posteriori (MAP) is used for driver model adaptation.

In [11] lateral offset is used to measure lane departure. The given algorithm calculates lane departure distance using 3D geometry. Algorithm considered L and R are the distances from the camera set behind the windshield to left and right lane marking, while D_l and D_r are the distances from camera to the vehicle left and right border respectively. Driver would receive departure warning if distance from the vehicle border to lane mark was less than threshold, i.e. If $LD_l < T$ left departure warning, and if $R - D_r < T$ right departure warning. In [20], temporal variations of lane offset and lane mark heading angle used to detect lane departure. Lane offset is depends upon width of lane marking. In [31], To calculate the distance from lane line to the vehicle used the look-up table which represent the relationship between the image distance and physical distance.

Salari et al.[36] used threshold based method to trigger the warning system. In lane departure warning system, first locate the intersection points between the two lanes and bottom lines of image. The distances of these intersection points to the two sides (left and right) of the image determine whether the host vehicle is departing to the right or to the left. If both the left and right distances are less than the threshold value then it indicates that the vehicle has not departed. In case of left(right) departure, left(right)distance is more than the threshold value. The left(right) departure will trigger the warning system, which can inform the driver to adjust the steering wheel to keep the vehicle in the lane.

In [40], lane departure detection determine by using parameters $<\theta, \rho, c, t>$, where 'θ' and 'ρ' indicates lane position in Hough space, 'c 'and 't 'represent color and the type (solid/ segmented) of lane marking. Lane parameter θ is used to define lane departure measure, $T = \frac{\theta_l}{\theta_r}$. In case of no departure, $\theta_l \approx \theta_r$, if left lane departure occur $\theta_l > \theta_r$, while for right lane departure $\theta_l < \theta_r$. If λ is predefined threshold; left lane departure occur if $T \geq \lambda$ while right lane departure occur if $T \leq \frac{1}{\lambda}$.

Once lane markers are extracted using fan scanning, lane departure detection is carried out using angular relationship of lane marker [8,25,30,46]. If θ_{li}= angle of ith line segment measured in an anti-clockwise direction from the horizon to the left boundary and θ_{li} is positive. θ_{rj}= angle of jth line segment measured in clockwise direction from the horizon to the right lane boundary and θ_{rj} is negative [30].Then consider the following three conditions-

1. If the vehicle travels in the center of the straight lane, then there is symmetry in orientation of the left and right boundaries, i.e. $(\theta_{li} + \theta_{rj} = 0)$
2. If the vehicle approaches to the left lane, both θ_{li} and θ_{rj} increase.
3. If the vehicle approaches to the right lane, both θ_{li} and θ_{rj} decrease.

In both second and third case $\theta_{li} + \theta_{rj} > 0$. The trajectory deviation is given by- $\beta = \min(|\theta_{li} + \theta_{rj}|)$

$\beta > threshold$, indicates the vehicle close to the lane boundary and lane departure warning is issued to the driver. While estimating θ_{li} and θ_{rj} temporal filtering is applied to reduce the effect of the noise. In temporal filtering orientation of lane marking in current frame is obtained by averaging orientation in consecutive frames.

In [8,46] lane departure number decides the extent of vehicle deviation from center of lane, based on which different levels of warning signal generated. The lane departure may be intentional (turn signal on) or unintentional (driver falls asleep). In case of unintentional lane departure, driver issued a warning whenever $\beta > threshold$; where in intentional lane change, system waits until lane shift is completed and recomputed lane boundaries. In this situation, no departure warning is issued to driver.

In order to reduce computational time required for lane departure detection, Yi et al. [80] considered only even frames. If the angle of lane marker (left/right) is greater than departure threshold for ten continuous even frames, the system triggers the departure alarm. In [81] lane departure warning system is proposed for mobile devices that uses Hough transform for line detection and fuzzy representation of images to reduce computational time.

Table 1
Comparison of LDW systems.

	LDW [87]		LDW [17]	
	Day	Night	Day	Night
True Lane Detection	97.80%	100%	87. 88%	94.13%
False Lane Detection	3.28%	0.00%	18.75%	5.87%
True Warning	93.5 6%	98.46%	90.50%	96 . 42%
False Warning	6.44%	1.5 3%	9.50%	3.5 7%

Gaikwad et. al. [17] consider four states; No departure, Left departure, Right departure and Danger. Under a no departure state, the vehicle is in the lane. Due to the driver's inattention, the vehicle may drift to either side of the road. In this state, either a left or right departure warning is issued to the driver. If the corrective action is made, then the vehicle returns to the no-departure state or else this might lead to a dangerous situation. The vehicle should not remain in any departure state for long time and should return to the no departure state immediately. For the lane departure identification, a distance based departure measure is computed at each frame and a necessary warning message is given to the driver when such measure exceeds a threshold. The proposed algorithm uses three lane related parameters i.e. Euclidean distance between (a) Hough origin and midpoint of left lane, (b) Hough origin and midpoint of right lane marker, and (c) midpoint of left and right lane marker, to determine departure measure.

Salvucci et al. [82] introduced real time system for inferring human intent, known as 'Mind tracking '. The given architecture provides a computational framework for representing and tracking a person's intentions based on their observed behavior. Based on the behavior of driver resulting from the intention such as lane change, turn or simple stay in the current lane, mind tracking detects a driver 's intention to change lane. Chen and Jin introduced a lane departure detection system that used four parameters such as distance between vehicle and left or right lane marker, the road slope and vehicle yaw angle [83]. When the left (or right) side of the vehicle travels over the lane marker, caused left (right) lane departure. When one of the two (either left or right) departures occurs, the warning module generates a departure warning signal. In order to keep the vehicle in host lane, navigation system provides information about deviation angle of host vehicle and slope of road surface to the driver.

11. Comparison and summary

The commonly used databases for lane detection are LabelMe [84], CALTECH [85] and KITTI road database [86]. The experimentation was carried out using realtime dataset captured by unprofessional photographer by Tata Motors, Pune, India. The videos were captured by three different cameras for six different lighting conditions such as day, night, dawn, sunset, rainy day and fog. The camera was mounted in the middle of front windshield of the vehicle by ensuring all types of lanes are available. More than 200 lane videos were captured for six different scenes with frame rate of 30 frames/sec. The frames in the videos varies among the videos along with datarate with a frame size of 320 x 240. This dataset was The duration of videos varies from 10 sec. to 10 min. The vehicle speed varies from 0 to 100 Km/h.

In our work [87] LDW system based on the Hough transform and Euclidean distance is implemented. Histogram equalization is used to enhance the contrast level of input image. The ROI is segmented using the lower half of image that corresponds to road. Hough transform is used for lane detection in which left and right

Table 2
Summary of various lane detection and departure warning system.

Authors	Methods	Advantages	Limitations
Bertozzi and Broggi(1998) [35]	Inverse perspective mapping to remove perspective effect. Lane mark detection is based on horizontal black-white-black transaction.	Due to remapping process, it is possible to locate lane marking even in the presence of shadows or other artifacts.	1. High computational complexity. 2. Detect lane markings in the structured environment (well painted lane marking). 3. When initial assumptions are not met, lane detection cannot provide valid results
Lee (2002) [28]	a: Linear lane model b: Edge operator c: EDF function + Moving sum filter d: Symmetry axis and local maxima of EDF	Road shapes (inclined, declined, wide, and narrow) and vehicle types does not affect the lane detection performance.	1. Highly depends on the visibility of lane marks. 2. Provide erroneous results for road with sharp curved direction. 3. Due to- shadow of a guardrail, warn out road surface, and occlusion by the front vehicles, it becomes difficult to extract the correct local maxima of the EDF. 4. The algorithm does not take into account following factors- vehicle velocity, turn signal, and steering angle.
Otsuka et al. (2002) [49]	b: FOE + Zero-crossing c: Histogram analysis + Hough transform d: Vehicles lateral position.	Robust to changes in brightness. Detect the lane markers regardless of their types (e.g. white lines, raised pavement markers) Robust for various noises such as road signs, shadow of trees and preceding vehicles.	1. Change in lane width causes false edge detection. 2. Zero-crossing method and Hough transform required high computational time and it depends on number of detected edges. 3. FOE assumption cannot be applied be applied on curved road.
Gehrig et al. (2002) [66]	a: Clothoid lane model To detect lane marking uses fusion of two approaches- 1. White lane marking Geometrical Approach (Gradient operator). 2. Reflective lane markers or Bots dot-Bots dot algorithm	Estimate lane marking on poorly structured bots dot road. Also detect lane marking which are degraded due to aging and wear out. Robust prediction of offset and yaw angle.	Requires Camera calibration. Partial occlusion of lane marking may affect lane detection performance; overcomed by stereovision images.
Lee and Yi (2005) [29],[63]	a: Linear model b: Sobel operator + non-local maximum suppression (NLMS) c: Lane boundary pixel extractor (LBPE) + Hough transform d: Lane parameters + linear regression.	Overcome weak points of EDF based LDI system by increasing lane parameters. LBPE improves the robustness of lane detection. Minimize misdetection and false alarm by using linear regression analysis.	As linear model is used for fitting lane boundaries, curve lane may still cause problem.
Jung and Kelber (2005) [30]	a: Linear parabolic model b: Sobel operator c: EDF + Hough transform (Gradient weighted Hough transform) d: Angular relationship of lane marker.	Combines the robustness of linear model with the flexibility of parabolic model. Provides an accurate fit to lane boundaries.	Occlusion of lane marking due to vehicles in front of the camera. Performs well in presence of sparse shadows, provides erroneous results if strong aligned shadows appear close to lane marking.
Lin (2005)[51]	a: Parabolic lane model b: Color based segmentation c: Hough transform + least square method.	Algorithm can deal with straight and curved lane marks, solid and broken line, and obstacle in roadway.	Imperfect lane detection in a) signs drawn on roads b) illumination due to reflection Road color model will change when headlights are reflected by road in rainy day or at night.
Dcruz and Zao (2007) [88]	b: Dilation + component labeling based on 8- connected pixel map. c: scanning of lower half of image + least square method.	As compared to [51], provides robust lane detection under various weather conditions such as rain, bright sun with reflection, and obstacle on road.	If the road signs lies on scanning start point and start point is a white pixel, then algorithm might include this as possible lane marking element.
Chen et al. (2007)[89] and (2009)[90]	a: Parabolic polynomial+projection relation from global coordinates to image plane. b: Intensity of lane marking with its dark-lightdark(DLD)characteristics. d: Lateral offset of vehicle.	Successfully tested on highways, expressways and on urban roads. Works well in sunny, cloudy and rainy condition.	Performance of lane detection warning system will be limited under insufficient light condition.
Lan et al. (2009) [22]	a: Linear lane model. b: Histogram based thresholding + Sobel edge operator. c: Scalable Hough transform. d: Guard zone.	Lane marking have been successfully detected with high accuracy under different complex scenarios such as severe sun glare, poor lighting, and heavy traffic. Reduction in computational time required by Hough transform through scalability.	Fails to detect Lanes with high curvature.
Borkar et al. (2009)[67]	a: Temporal filtering + Inverse perspective mapping(IPM). c: Hough transform + Match filter + RANSAC + Kalman filter.	Tested on different road types (highways, city roads) with different traffic situation. Proposed algorithm provide better performance as compared to earlier algorithm [57]. Modifications in proposed algorithm as compared to earlier method: IPM, RANSAC, Kalman filtering.	Presence of cracks on road surface leads to detection and tracking of false edges. Poor visibility of lane marks due to road aging and wear also causes false edge detection.
Hsiao (2009)[23]	b: Global edge detector. d: Spatial and temporal mechanism.	Hardware: Compact size, low cost, low power consumption. Detect lane under high vehicle departure speed.	Unsatisfactory lane detection results in following cases: 1: lane boundaries are occluded by front vehicle; overcome by incorporating results of vehicle detection. 2: No street light situation.
Xu and Li (2010)[24]	a: Straight line model + Median filtering + contrast enhancement using histogram. b: Sobel edge operator. c: Hough transform + Kalman filter.	Accuracy of algorithm is achieved by introducing failure judgment module.	Lane detection under unstructured road condition is a challenging task. Lane detection fails in shadow and watery situations.

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Table 2 (*continued*)

Authors	Methods	Advantages	Limitations
Lin et al. (2010) [25], [8] and (2012)[46]	a: Brightness compensation by self clustering algorithm, fuzzy c-means clustering, fuzzy rules [8] /Neurofuzzy [25]. b: canny edge detector [25], [8]/ mask of size 5x5 [46] c: fan scanning. d: Angular orientation of lane marker.	Provide an accurate fit to lane boundaries. Road signs, shadow effect, front vehicle does not affect the lane detection performance. In order to correct trajectory of vehicle, system provide sufficient driver to driver.	System fails to detect lane marking when visibility of lane marking get affected by light of bypassing car.
Zhao et al. (2012) [9]	a: Spline based model. c: Extended Kalman filter.	Spline model- Simple, flexible and robust. First time integration of spline based lane model and extended Kalman filter for lane tracking. Support multiple lane tracking and independent tracking.	Light interference at night may degrade the performance.
Obradovic et al. (2013) [4]	a: Set of fuzzy points and fuzzy lines used for road lane modeling. b: Modified Edge extraction. c: Modified fuzzy c-means clustering algorithm (FLDetector).	Tested on PC based platform and smartphone. Performed better and faster than Hough algorithm. Performance is independent of precision of extraction of feature points.	Execution time is depends on position of fuzzy points on an image and number of detected fuzzy lines. Not well suited for applications requiring large number of feature points, where Hough algorithm performed better. As compared to PC based platform, smartphone gives slower execution time.
Tseng and Lin (2013) [11]	b: Sobel edge operator + Lateral inhibition property + far near adaption. c: Conjugate Gaussian model + Geometric constraints. d: Lateral offset estimation.	Edge detector with lateral inhibition give more significant edge response. Robust performance against shadow, windshield wipers and partial occlusion of lane mark by other vehicle. Performed better than lane detection based on fitting of maximum gradient and fitting DLD pattern.	High lane detection rate with extra processing time.
Shang et al. (2013)[37]	a: Series of 2D FIR filter + Gaussian noise reduction. b: Vanishing point based steerable filter. c: Vanishing point based Hough transform. d: Kalman filters + departure warning unit implemented on MicroBlaze Software.	Less storage requirements. Enhance detection capability.	In sharply curved roads, variation in the position of the vanishing point severely affect the lane detection results as follows- 1: As voting of pixels in lines does not accumulate at same peak resulted into series of discrete peaks. 2: Actual vanishing point is not suitable for coordinate origin.
Wu et al. (2014) [18]	a: Linear parabolic model b: canny edge detector + false edge elimination based on gradient orientation and width of lane mark + edge compensation. c: Local adaptive thresholding + lane marking verification based on distance criteria and tracking: Kalman filter.	Detect lane marks in complex scenarios such as- 1: Shadow effect. 2: Night scenarios (street lamps, headlight and taillight of car. 3: Curved lane markers.	Hard to extract lane marks from image sequence which is- 1: Seriously degraded by dense fog. 2: Recorder runs at a very low illuminance level. Working in real time would be critical for proposed method in terms of detection rate and execution time.
Mu and Ma (2014) [19]	a: linear parabolic lane model+ piecewise linear transformation. b: Sobel edge operator. c: Thresholding + piecewise lane fitting.	Piecewise linear transformation enhanced the performance of lane detection when environment was dim. Piecewise lane marker fitting is robust in presence of shadow, lack of lane painting and dashed lane marker.	Intensity changes leads to false lane detection.
Sohn et al. (2015) [20]	a: Vanishing point based adaptive ROI selection+Invariance properties of lane color. b: Canny edge detection. c: Lane clustering and lane fitting based on least square method. d: Lane offset, lane mark heading angle	Handles various illumination conditions due to weather change (rain, fog etc.), streetlamps and headlights of vehicles. Vanishing point based adaptive ROI selection reduce computational complexity.	Difficult to detect lane marking in following conditions- strong light reflection, lane crack, blur lane marks.
Madrid et al. (2016) [81]	a: Fuzzification-representation of the image using triangular fuzzy sets. c: Modified Hough transform based on fuzzification	Provides better results than standard Hough transform with sobel operator. System is reliable and can be used in real time on smartphone.	Provides unsatisfactory results under following conditions: 1. During night. 2. In presence of white cars.
Mammeri et al. (2016) [53]	a,b: MSER(Maximally Stable External Region) blobs used for ROI localization and feature extraction. c: Progressive probabilistic Hough transform d: Kalman filter	HSV color space is used to distinguish lane colors (i.e. white / yellow). 3-stage refinement algorithm applied after MSER remove the other details such as cars, trees etc. MSER based segmentation performs better than edge based segmentation.	Traffic density and lighting system on road may affect lane detection performance at night.
Zhu et al. (2017) [13]	Fundamental technologies in intelligent vehicles like lane and road detection.	The RANSAC line fitting-based method has the highest correct and false positive rates. Straight line is a simple and effective model for short range roads or highway. Splines are good models for curved roads.	To improve performance of system fusion based methods are required which are complex in nature.

Table 3
Detail description of various lane detection and departure warning system.

Authors	Lane modeling	Pre processing	Feature Extraction	Lane Detection & Tracking	Lane departure measurement	Advantages & Limitations
McCall and Trivedi (2006) [6]	Parabolic approximation		Steerable filter	For straight lane- Hough transform, for circular reflector statistics of lane marking and Kalman filter		Provide better performance for solid and segmented lane marking than circular reflectors. Occlusion of road lane by vehicle leads to tracking error.
Chen et al. (2009) [90]	Parabolic polynomial lane model	Projection relation from global coordinates to image plane	Intensity of lane marking with its dark-light-dark (DLD) characteristic		The warning signal will be generated when O(y) $\geq$ 0.25W. Where y= desired distance ahead the vehicle, O(y) = lateral offset, W= lane width in world space	Successfully tested on highways, expressways and on urban roads. Works well in sunny, cloudy and rainy condition.
Wang et al.(2010) [8]		Brightness compensation by self clustering algorithm and fuzzy c-mean clustering and fuzzy rules	Canny edge detection	Fan scanning	Angular orientation of lane boundaries	Provide an accurate fit to lane boundaries. Gives robust information about lane boundary orientation. In order to correct trajectory of vehicle, system provide sufficient time for driver.
Qing et al. (2010) [40]	Straight line model	Color verification	Extended edge linking algorithm with directional edge gap closing	Hough transform Classification of lanes (solid/ dashed) by Bayesian probability model	Used parameter vector $< \theta, \rho, c, t > \theta, \rho =$ lane position in Hough space, c= lane color, t= type of lane	Simplify the modeling process- no special requirement of background model or road surface model. Adaptive to various road environment
Xu et al. (2010) [24]	Assume straight line lanes	Median filtering, Contrast enhancement using Histogram	Sobel edge operator	Hough transform, Kalman filtering	Failure and warning judgment module departure information can be judged from the distance between the vehicle and the lane	Challenging in the shadow or watery road situation
Chen and Jin (2010) [83]	Consider straight line model to reconstruct 2D lane	Histogram Equalization	Sobel Edge Detector	Hough transform	Use the distance from the automobile to left and right lane, road slope and vehicle yaw angle to detect lane departure	System fairly exactly detect the real time lane marking
Wu et al. (2012) [46]	Straight lane model		Defined the mask of size 5x 5 to extract edges	Fan Scanning	Angular orientation of lane boundaries	Provide accurate fit to the lane boundaries
Zhao et al. (2012) [9]	Spline lane model			Fast Hough transform	Extended Kalman filter Lateral offset is used for multiple lane tracking	Gives better performance in-adverse weather, for worn out lane marking and for straight as well as sharp curve. Light interference at night may degrade the performance.
Shang et al. (2013) [37]	Cascade of 2 RANSAC is applied to fit and extract lane marking	Series of 2D FIR filter, Gaussian noise reduction	Vanishing point based steerable filter	Vanishing point based parallel Hough transform	Kalman filter, Lane tracking and departure warning unit implemented on MicroBlaze soft core	Less storage requirement. Enhance detection capability. In no lane mark condition and at night give disrupted performance

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Table 3 (*continued*)

Authors	Lane modeling	Pre processing	Feature Extraction	Lane Detection & Tracking	Lane departure measurement	Advantages & Limitations
Obradovic et al. (2013) [4]	Set of fuzzy lines and fuzzy points are used road lane modeling		Modified edge extraction- apply edge detection for single line instead of 2D convolution of an image and operator mask	Modified fuzzy c-means clustering algorithm (FLDetector)		Performed better than Hough transform as it uses small amount of extracted points but not well suited for cases requiring larger no. of feature points
Tu et al. (2013) [31]		Prior knowledge required while selecting ROI	Sobel edge operator	Hough transform, Heuristic knowledge of Hough used to detect whether lane is present or not	Use look up table of Distance Vs Pixels	Build system for robust lane detection with high capture rate and low computational load
Tseng et al. (2013) [11]			Sobel edge operator combine with properties of lateral inhibition of a human visual system and far-near adaption	Gaussian Conjugate model. Lane mark verification by geometric conjugate model	Lateral offset estimation	Does not requires thresholding. Can adapt to various weather conditions, shadow effect. Reduce the effect of occlusion of lane mark. Increase processing time
Aung et al. (2014) [39]		2D FIR filter to remove noise, Auto thresholding	2D FIR filter to detect edges	Hough transform and Kalman filter	Lane change is detected by identifying the change in lane angle	Less processing time. Inefficient detection at poor visible condition especially at night
Gaikwad et al. (2014) [17]	Straight lane model	Piecewise linear stretching function		Hough transform	Euclidean distance	Superior performance for straight lanes. High detection rate and reduce false warning. Lane detection task becomes difficult under rainy condition, tunnel, watery roads, fog.
Srivastava et al. (2014) [43]	Straight line model	Hybrid median filter (HMF). Background Subtraction	Canny edge detection	Hough transform		Effective performance for any kind of noise in the road images. Improvement in HMF against high density noise is required.
Wu et al. (2014) [18]	Linear-parabolic lane model	Regular and adaptive ROI Selection	Canny Edge detection. Eliminate of noisy edges. Local adaptive thresholding.	Verification of candidate lane marks based on distance criteria. Kalman tracking		Detect lane marks in complex scenarios such as curved lane marks, shadow effect, Night time. Hard to extract lane marks in dense fog and low illuminance level.
Mu and Ma (2014) [19]	Linear parabolic lane model	Piecewise linear transformation	Sobel edge operator	Piecewise lane marker fitting		Handle low contrast images. Robust in presence of shadow and lack of lane painting. False lane detection due to change in intensity.
Yoo et al. (2017) [91]	Property of parallel lines		Line segment detector using contrario approach	Vanishing points		Line detection by parametric adjustment. can't be used for unstructured roads.

lane marking are detected independent of each other. Finally, lane departure identification is carried out using lane related parameters, estimated on the basis of Euclidean distance.

Table 1 compares performance of state-of-art methods. As Hough transform is applied on each subregion independently to extract lane marks, number of computations per frame reduced. This reduces computational time required for lane detection. System performed better under different environmental conditions such as rainy condition, nighttime; but the its performance is highly depends on visibility of road lane marking.

Table 2, summarizes various methodologies used in the literature to detect lane markings and to generate lane departure warning signal. These methods are compared on the basis of their performance under complex scenarios such as shadow effect, occlusion of lane markings by other vehicles, arrows marked on road surface and different environmental factors (rain, fog, sun-glare etc.).

Table 3, provides the detailed description of lane detection and departure warning system. The details includes the preprocessing method used, features extracted, method of lane detection and tracking, lane departure measurements and advantages and limitations of reported literature.

The lane detection is highly problematic due to lack of test protocol, performance measure and pubic dataset. Many researcher have reported their results on the basis of structured lane marking urban environment [24,35,51,66], lighting conditions [9,13,18–20,23,28,53,88,89], high curvature [4,22,30,37,49], road condition [67] and computational complexity of lane detection [4,53,81]. Some papers were metric specific [24,30,51,53,63,67,81] using Hough transform and hybrid approach using Hough transform and Kalman filter [24,30,51,53,63,67,81], however computational complexity with Hough transform is high. Few systems were highly sensitive to vehicle departure speed [18,23,81].

Many papers were focused on a lighting environment such as day [28,30,67,89], night [9], rain [24,51], fog [89], dawn [51] and sunset [9,30]. The measure of their success was on the basis of performance measures [24,30,51,53,63,67,81]. As it can be seen from this non exhaustive summary that it is very hard to draw conclusion regarding quality of algorithm and to discriminate the system. However encouraging exception is which draws the conclusion on the basis of various lighting conditions on a larger real time and real scene datasets. Finally this real time datasets results are to be compared with annotated database which will contribute for the development of robust algorithm.

Every method has its own pros and cons. The use of trackers have greatly helped in making this system highly responsive. The main challenge in the field is to implement real-time system that alerts drives in unhealthy conditions. The system must have very low complexity so as the processing overhead is reduced and system responds very quickly to untoward situations that will save life of peoples in cars. Now-a-days due to invention in embedded technology many tools are available that have high processing capability. These tools will emerge many technologies in near future that will assist the driver in every vehicle. With use of high end technological tools to assist drivers the possibility of accidents due to negligence of drivers will be reduced to great extent.

12. Conclusions

In this paper, we have presented the detailed description of various vision based lane detection and departure warning system. In general, the system comprises lane modeling, feature extraction, lane detection, lane tracking and departure warning modules. It has been observed that, in driver assistance systems such as lane departure warning system, lane change assistance and collision avoidance, the lane detection plays vital role. As lane markings are assumed to be feature in the form of edges, feature based lane detection is carried out. In most of the systems, Hough transform is extensively used to detect lane marks; but it requires large computational time.

The paper also highlighted the problem of lane detection under various complex environment involving shadows, dynamic illumination conditions, dense fog, rainy condition, night time and bad condition of road lane marker.

Based on the literature survey so far, different techniques proposed by different researcher achieve good results regarding detection rate, accuracy and minimum false alarm rate; but still, there is scope of lane detection and departure warning system that will have the characteristics mentioned below:

1. The system should be robust i.e. it should detect lanes in all complex situations.
2. Lane detection methods should be fast enough to meet real time criteria.
3. System should detect lane departure under high vehicle departure speed with minimum false alarm.
4. System should be cost effective.

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Sandipann P. Narote received the Bachelors degree (B.E.) and Masters degree (M.E.) both in Communication Engineering from Dr. Babashaeb Ambedkar Marathwada University, Aurangabad, India in 2000 and 2002 respectively, and Ph.D. in Electronics and Telecommunication Engineering (E&TC) from Swami Ramanand Teerth Marathwada University, Nanded, India in 2010. Narote is currently a Head of Department (E&TC) in Government Women Residence Polytechnic, Sangli, India. He is supervisor of four Ph.D research scholars and has supervised twenty Masters thesis. His current research interests include bio-metrics, computer vision, pattern recognition, machine intelligence and intelligent transport engineering. He has authored and co-authored nearly 65 publications in indexed journals and peer reviewed conferences.

Pradnya N. Bhujbal received B.E.and M.E.(Electronics & Telecommunication) from University of Pune, India in 2013 and 2015 respectively. She is currently working in Tata Consultancy Services (TCS), Mumbai, India. Her research areas are image processing and pattern recognition.

A. S. Narote received B.E. (Electronics) in from Shivaji University and M.E.(Electronics) from University of Pune, India in 2004 and 2006 respectively. She is pursuing his research in the field of biometrics and machine vision. She is currently working as Assistant Professor in S. K. N. College of Engineering, Pune, India. Her research areas are image processing and signal processing.

Dhiraj M. Dhane received the Bachelors degree (B.E.) from Govt. College of Engineering Jalgaon, India in 2001, Masters degree (M.Tech) from Visvesvaraya Technological University Belgaum, India in 2006 and Ph.D degree in biomedical engineering from Indian Institute of Technology Kharagpur, India in 2017. Dhane is a graduate student member of IEEE and Engineering in Medicine and Biology Society. He is currently an Assistant Professor at the Indian Institute of Information Technology Pune, India. His current research interests includes image and multidimensional bio-signal processing, pattern analysis and machine intelligence, and intelligent transport engineering.