Review of Lane Detection and Tracking Algorithms in Advanced Driver Assistance System

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REVIEW OF LANE DETECTION AND TRACKING ALGORITHMS IN ADVANCED DRIVER ASSISTANCE SYSTEM

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ABSTRACT

Lane detection and tracking is one of the key features of advanced driver assistance system. Lane detection is finding the white markings on a dark road. Lane tracking use the previously detected lane markers and adjusts itself according to the motion model. In this paper, review of lane detection and tracking algorithms developed in the last decade is discussed. Several modalities are considered for lane detection which include vision, LIDAR, vehicle odometry information, information from global positioning system and digital maps. The lane detection and tracking is one of the challenging problems in computer vision. Different vision based lane detection techniques are explained in the paper. The performance of different lane detection and tracking algorithms is also compared and studied.

KEYWORDS

Advanced Driver Assistance System, Hough transform, Lane detection, Lane departure warning, Lane Tracking

1. INTRODUCTION

Advanced Driver Assistance System (ADAS) provides safe and better driving. It helps to automate, adapt and enhance the driving experience. Most of the road accidents occur due to carelessness of driver. Advanced Driver Assistance System ensures safety and reduces driver workload. Whenever a dangerous situation is encountered, the system either warns the driver or takes active role by performing necessary corrective action to avoid an accident [22]. Lane Departure Warning (LDW) is an important module in Advanced Driver Assistance System. In vision based lane departure warning system, a camera is placed behind the wind shield of the vehicle and images of road are captured. The lines on the road are interpreted and lanes are identified. Whenever the vehicle moves out of a lane unintentionally, a warning is given to the driver. The module is disabled by the turn signal. Lane marker detection is the initial step of lane departure warning system. There are two methods for lane detection; feature based approach and model based approach. The feature based approach use low level features such as edges [1][28][14] whereas model based approach use geometric parameters [12][17][26] for detecting lanes. Figure 1 represents a block diagram of Lane Departure Warning System in a general perspective. Lane departure warning system poses many challenges and issues which includes lane appearance diversity, variation in clarity of image, changes in visibility conditions [23]. Based on the countries, there will be difference in the lane markers used. We have to investigate the type of lane behaviors and the challenges in tracking to solve such lane detection and tracking problems.

Usually yellow and white colors are used for lane markers but reflectors lane are marked with special colors. The number and width of lanes varies with countries. There can be issues related

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to clarity in images due to the presence of shadows. The lane markers may be occluded by the nearby vehicles. When the vehicle comes out of a tunnel, there is an abrupt change in illumination. So the clarity of image is affected by extreme illumination too. The visibility of the lane markers decrease due to various weather conditions such as rain, fog, snow. The visibility can be less in night condition. Figure. 2 shows the challenges in lane detection and tracking.
It is really a tedious task to develop a robust lane detection algorithm.

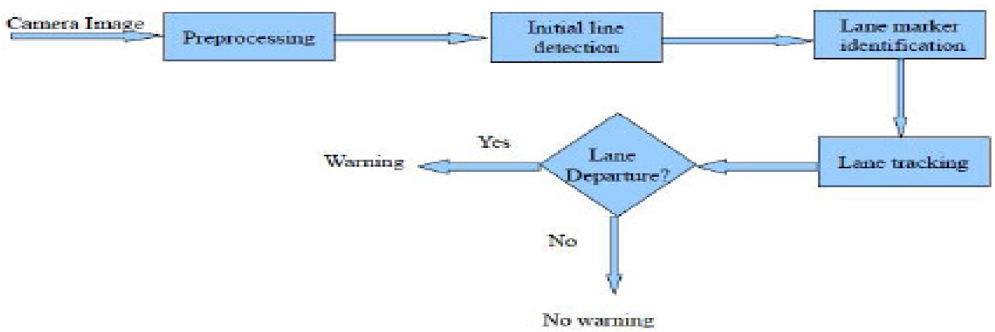

Figure.1. Block diagram of a simple Lane Departure Warning System (LDWS)

Figure. 2 Various challenges in lane detection.[a] A vehicle occluding nearby lane [b] Presence of shadow[c] Rainy road [d] Extreme illumination on left side of image

The paper is organized as follows. Section I describes introduction. Section II explores various lane detection and tracking methods and includes performance analysis of different lane detection and tracking methods. Section III presents performance metrics for lane detection and tracking algorithms. Section IV summarizes the paper.

2. LANE DETECTION AND TRACKING ALGORITHMS

In this section, Lane detection and tracking algorithms are discussed. Table 1 summarizes and presents a detailed analysis of various lane detection and lane tracking algorithms. This section also investigates the best lane detection and tracking algorithms that can be selected for a specific road conditions.

Yim and Oh [14] developed a three feature based lane detection algorithm. The features used are starting position, orientation and intensity value. In the initial step, a Sobel operator is applied to get the edge information. The lane boundary is represented as a vector comprising of the three features. The current lane vector is calculated based on the input image and the previous lane model vector. Two windows, one for each, is used for left and right boundaries. Assuming N pixel in each horizontal line, N lane vector candidates are generated. The best candidate is selected based on the minimum distance from previous lane vector using a weighted distance metric. For equalization each feature is assigned a different weight. Then a lane inference system is used to predict the new lane vector. If the road width changes abruptly, the current vector calculated is discarded and the previous one is taken as current vector.

A lane detection approach for urban environment is proposed by Sehestedt et al. [30]. Since the lane markers are not clearly visible due to wear and tear, occlusions and due to complex road geometry, a weak model is used for detecting lane markers. In the inverse perspective mapped image, particle filter is applied from bottom row to top. The filter is tuned in such a way to track multiple lanes.

Aly [1] presents a real time and robust approach to detect lane markers in urban roads. It first generates a top view of the road image using inverse perspective mapping for avoiding the perspective effect. Then the top view is filtered using selective oriented two dimensional Gaussian kernel. The filter is tuned specifically for bright lines in dark background with specific width. So it has high response to the line markers and retain only the highest values by selecting q % quantile value from filtered image and removing all values below the threshold. Then the straight lines are detected using simplified Hough transform, which is followed by RANSAC line fitting which provides initial guess to the RANSAC spline fitting step. Then a post processing step is done to localize the spline and extend it in the image. The algorithm does not perform tracking. It can detect any number of lane boundaries in the image not just the current lane.

Kim [24] developed a lane detection and tracking algorithm which can handle challenging scenarios such as faded lane markers, lane curvatures and splitting lanes. In the initial step, a gradient detector and an intensity bump detector is used to eliminate the non lane markers. Artificial Neural Networks (ANN) is applied on remaining samples for lane detection. The detected lane markers pixels are grouped using cubic splines. Hypotheses are generated from random set of line segments. RANSAC algorithm helps in validating the hypotheses. Particle filtering is used for lane tracking.

Cheng et al. [32] introduced a hierarchical algorithm for lane detection. High dimensional feature points are extracted based on feature color extraction. It is used to distinguish structured roads from unstructured roads. Then connected components is applied on the feature points. A feature vector is constructed for feature points exceeding a threshold. Eigen value Decomposition Regularized Discriminant Analysis is done to reduce the variance of the model. Then maximum likelihood Gaussian parameters are estimated. The extracted feature points are used as detected lanes in structured roads. For unstructured roads, the entire scene is divided based on mean-shift segmentation. Each region is considered to be homogeneous and lane markers are detected using Bayes rule.

Initially, color image is converted to gray scale [31] and then shadow removal is performed. Modified Canny edge detector is used for edge detection and then Hough transform is applied on the resultant binary image. Horizon line lane boundary scan is implemented using the edge detection result of Hough transform. The scan starts from the portion where the Hough lines meet the bottom image border. The scan returns data points corresponding to the edges. Then a hyperbola pair fitting is done on the collected data points.

Borkar et al. [2] proposed lane detection based on Hough transform and iterated matched filters. RANSAC algorithm is used to avoid outliers due to noise and other artifacts in the road. Kalman filter is used to track the lanes. The first step in the algorithm is to convert the color image to gray scale and temporal blurring then on that image inverse perspective mapping (IPM) is applied. An adaptive threshold is applied on the IPM image to generate a binary image. Each binary image is split into two halves and each one contains one lane marker. A low resolution Hough transform is applied on the binary images. A 1- dimensional matched filter is applied at each sample along the line to find the approximate center of each line. After estimating the center, RANSAC algorithm is applied to the data points for lane detection.

Lin et al. [28] performed lane detection based on lateral inhibition property of human vision system. It enables the algorithm to be robust in various weather conditions. The algorithm is not based on thresholding. It uses 2D and 3D geometric information of lane markers. For lane detection, the positive and negative second difference map of the image is utilized. It provides strong contrast between the road and lane marker. A dual Gaussian model is used to determine whether two peaks corresponding to global maximum on right side of left lane marker and global minimum on left side of left lane marker. After detection verification is performed to judge the correctness of detected lane marker. The verification is done to check the slopes and intercept relationships, actual road width and position of vanishing point.

A lane detection method suitable at night is proposed by Borkar et al. [29]. The algorithm first initializes the Region of Interest (ROI) eliminating the sky and other irrelevant objects. In the next step, a gray scale image is obtained by averaging the three color channels. Temporal blurring is used to elongate the dashed lanes. Adaptive thresholding is done to extract the bright objects. The resultant binary image is divided into left and right halves. Low Resolution Hough Transform is applied on each half for detecting the straight lines. Then a Gaussian kernel is used with iterated matched filter to extract lane markers.

The algorithm proposed by Liu et al. [3] has two steps; initial detection of lanes and their subsequent tracking. The perspective effect is removed from the image using inverse perspective mapping. Then Statistical Hough transform (SHT) is applied on the IPM image for lane detection. SHT works on intensity images and uses multiple kernel density to describe the Hough variables (ρ,θ). As SHT works on every pixel in the image it is computationally expensive and is not suitable to run it on every frame. After initial detection Particle Filter is used to track the detected lanes and update the parameters of the lane model. The parameters of lane model is obtained and updated frame by frame. The SHT is computationally expensive is combined with tracking using Particle Filter. For demonstrating the algorithm straight lane model is used.

Lin et al. [15] proposed a method based on region of interest (ROI). The ROI first initialized and Sobel operator along with non-local maximum suppression is used to find the edge pixels. After obtaining the edge image, an extended edge linking based on directional edge gap closing is done to link those dashed lines in far vision field which are broken due to down-sampling. A raster scan is performed from the bottom of image and the starting point of new edge is found out. Then an edge tracing is carried out and next pixel is added to the edge which is eight connected to the current pixel. For a given starting point the tracing is done in one orientation. The next step is directional edge gap closing. The edge links are extended by adding a user specified number of pixels along the orientation to fill gaps. New pixels are selected from the neighborhood of start and end points. After this those edges with length less than 15 pixels are eliminated. Then two edge link pair are considered and if the distance between them satisfies width of lane mark, then it is regarded as lane mark region.. Next step is lane hypothesis verification, for that the color of lane-marks are checked. After the candidates are finalized, Hough transform is used to determine ρ and θ values.

The lane detection algorithm is proposed by Zhou et al. [12] has three modules: lane model generation, parameter estimation and then matching. The lane is modeled using the middle line and three parameters lane width, original orientation and the road curvature. The parameters in the model is reduced using middle line model which provides the starting location, orientation and curvature. Using the lane width the final lane models is obtained. The algorithm is focused on the near field of view. For estimating the lane model parameters vanishing point is detected. The vanishing point detected based on Gabor texture analysis, which helps to estimate the orientation of each pixel in ROI. Finally all these pixel orientations vote for locating the vanishing point. Each pixel votes for more than one vanishing point due to the presence of artifacts. A Gaussian model is used to maximize the likelihood and obtain a single vanishing point. After vanishing point detection the width and orientation of lane is estimated. For that road boundaries are detected using Canny edge detector and Hough transform. Each lane model candidate have different curvature. To estimate the curvature a model matching algorithm is used. A Gabor filter is used along each candidate and the one with maximum votes is the best fit.

Daigavane et al. [13] developed a lane detection method based on ant colony optimization (ACO) is proposed. Initially, the input image is resized to 255 X 255 pixels for reducing the computation time. The three channel RGB image is converted to single channel grayscale image. Then, median filter is used to filter out noise and to preserve the edges. Next the edges are detected using Canny edge detector. The output binary image is given as input to ant colony optimization. It generates the additional edge information that is lost in Canny edge detection. ACO uses a number of ants which move based on the intensity variation in the image. Using a probabilistic approach, each ant moves until it reaches another line segment. After those edges are properly connected Hough transform is used to find out straight lines. The lines corresponding to highest peaks in Hough space is extracted as lanes.

Guo et. al [5] proposes a method where the input image is first converted to inverse perspective image. Next multiscale lane detection is done in parallel on both sides of image. To find the similarity of corresponding pixels in either sided of the road Normalized cross correlation (NCC) is done. To check whether the detected lane markings are painted or not machine learning algorithm is used. ANN classifier with two layers and seven hidden nodes is applied on a small image patch of 9X3 windows around each and every preserved road marking pixels. Integrating the intensity and geometry cues a weighted graph is constructed, with weight corresponding to the confidence of a pixel to be a lane point. The lane boundary is estimated using particle filter, for that Catmull Rom splines model is used. It is suitable for curved lanes, lane changes, splitting and merging lanes.

Y.-C. Leng, et. al [8] proposes a lane detection system for urban roads. The edges are detected using Sobel operator. Then Hough transform is implemented to detect straight lines. In the road image lanes appear to intersect. At different height of the image width of lanes differ. The minimum lane width is defined as minw and maximum lane width as maxw . The width of a lane at each region wi (i=0,1,...4) should always between minw and maxw . For each left and right lane candidate a matching is done based on the width of each candidate pair. If the width of pair in different height does not satisfy the criteria is eliminated. After the extraction of left and right boundaries lane departure can be determined by position of lane boundary.

Liu et al. [4] presents an improvement of traditional particle filter [3]. It is suitable for linear-parabolic lane model. Initially, the Inverse Perspective mapping (IPM) of images are obtained. Certain descriptors are used such as color, position, gradient are used to detect lane markers in IPM image. The probabilistic distribution of straight line parameters is modeled as multi-kernel density and three candidates are found using Statistical Hough Transform. SHT can be extended to detect parabolic structures. Then the vertical edges are found out using Sobel edge extraction. The number of particles depends on the dimension of the particle state. The algorithm is done in hierarchical manner. The linear part is estimated first and then the parabolic part is estimated. The linear part is assigned more particles than the parabolic part. To make the algorithm robust, a constant percentage of initialization samples is introduced in every iteration. The linear part estimation is done in two steps. First the state is predicted using a random walk probability model. The second step is re-sampling using a specific observation. Only the particles with high weight values are kept. In similar way particles are estimated for parabolic part also. If the lanes in vision field have high curvature, then the estimation error increases.

Borkar et al. [6] developed a method based on the parallel nature of lane markers. First Inverse Perspective Mapping is performed. Then the IPM image is converted to gray scale image. Then the image is filtered using Normalized Cross Correlation. Now find out a collection of straight lines using Polar Randomized Hough Transform (RHT). Each best fitting lines have high scoring coordinates or peaks in(ρ,θ) space. To determine if two lines are parallel lines peaks with identical θ value can be paired. Usually the lane markers are parallel but due to some imperfections in lens, captured image variation in lane marker placements etc it may not be parallel always. So the constraint of identical θ value needs to be loosened. This can be achieved by applying a tolerance window. The video is tested in real time videos and obtained good results. Common difficulties face in lane detection such as presence of shadows neighboring vehicles and surface irregularities are greatly reduced in this approach. There is difficulty in detecting worn out lane markers.

Tran et al. [7] uses a horizontal line detection to find out the sub-region in image which is under the horizontal line where the lanes are present. A vertical mean distribution method is used to determine the first minimum that occur in the upper curve. This minimum position is considered as the horizontal line position. In day time the minimum and in night time maximum search along the vertical mean curve is considered. Then on the bottom sub-image Canny edge detector is applied. Based on the threshold fixed there can be lanes and noise candidate in the edge image. Then k-means clustering and RANSAC algorithm is used to detect the lanes. After the left and right lane boundaries are obtained, the intersection point between them is used as a horizontal line position for next frame of sequence. The algorithm focus on current lane only. When there is a crossing then also detection is not correct.

Table 1. Comparison of various lane detection and tracking algorithms

Method	Preprocessing	Detection	Tracking	Evaluation	Comments
Y. U. Yim and S.-Y. Oh (2003) [14]	Sobel operator	Hough transform and three feature vector	Temporal predictor is used to predict current lane vector	Works fine for rainy and shady road	Apriori information on road is not needed
S. Sehestedt, et al. (2007) [30]	Inverse perspective mapping	Weak model based	Clustered particle filter	Robust in difficult lighting conditions	Suitable for both straight and slightly curved urban roads

Z. Kim (2008) [24]	Edge detector, Intensity bump detector	Artificial Neural Network ANN)	Particle filter	Robust in presence of leading vehicles and low illumination	Suitable for both straight and curved roads
M. Aly (2008) [1]	Inverse perspective mapping, Selective oriented Gaussian filters	Hough transform and RANSAC spline fitting		Comparable results to algorithms using both detection and tracking	In presence of stop lines at cross walks, nearby vehicles detection not proper
H. Y. Cheng et al. (2008) [32]	Based on color extraction	Eigenvalue Decompositio n Regularized Discriminant Analysis		Robust in various weather conditions	Suitable for structured and unstructured roads
A. Assidiq et al. (2008) [31]	Canny edge detector	Hough transform and hyperbola fitting		Robust in shadows	Suitable for painted and unpainted curved and straight roads
C.W. Lin et al. (2009) [28]	Vertical edge detector	Positive and negative second difference maps		Robust in various weather conditions and presence of shadows	Verification step reduces false positives
A. Borkar et al. (2009) [29]	Adaptive thresholding	Low resolution Hough transform and matched filter		Robust in night time	Not suitable for day time operation
A. Borkar et al. (2009) [2]	Inverse perspective mapping, Adaptive thresholding	Hough transform and iterated matched filter	Kalman filter	Robust in noise and artifacts in road	Absence of lane markers leads to false detection and tracking
G. Liu et al. (2010) [3]	Inverse perspective mapping, Adaptive thresholding	Statistical Hough transform	Particle filter	Computational ly expensive	Straight road model is used

C. Guo et al. (2010) [5]	Cascade lane feature detector	Catmull Rom splines	Particle filter based on weighted graph	Robust in various lighting and weather conditions.	100 samples are generated for both left and right lane respectively
Lin et al. (2010) [15]	Sobel operator with non maximum suppression	Directional edge gap closing and Hough transform		Adaptive to various road conditions	Lane departure warning included
S. Zhou et al. (2010) [12]	Lane model is obtained based on camera parameters	Gabor filter based lane matching algorithm		Robust in noise and shadows	Based on flat road assumption
P. Daigavane and P. Bajaj (2010) [13]	Canny edge detector and Ant Colony Optimization	Hough transform		Not robust in shadows	Suitable for painted and straight roads
Y.-C. Leng and C.-L. Chen (2010) [8]	Sobel operator	Hough transform		Successful detection in worn-out road surface, signs, graphs, warning lines and image shaking	Suitable for urban roads
A. Borkar et al. (2011) [6]	Template matching	Polar randomized Hough transform		Not robust in worn out lane marker	Suitable for straight roads
T. T. Tran et al.. (2011) [7]	Canny egde detector	k-means clustering and RANSAC		Focus on current lane	At lane crossing inaccurate detection
R. Gopalan et al. (2011) [9]	Pixel hierarchy feature descriptor	Learning based detection	Particle filter	Robust in shadows and occlusion	Based on static motion model

G. Liu et al. (2011) [4]	Color, position and gradient descriptors and Sobel operator	Statistical Hough transform	Partitioned particle filter	Computationally expensive	Suitable for both straight and curved roads
M.Tan et al. (2013) [26]	Patch based feature extraction	Based on linear parabolic model and geometric constraints	Particle filter	Robust in shadows and illumination variation	Classification of lane markers included
S. C. Tsai et al. (2013) [27]	Sobel filter	Tracing circular mask	Probing circular mask and third order polynomial fitting	Works in blurred and broken roads	Suitable for both straight and curved roads
G. Liu et al. (2013) [10]	Sobel operator	Statistical Hough Transform	Partitioned particle filter	Robust in shadows and occlusion	Suitable for both straight and curved roads
H. Zhao et al. (2013) [17]	Bar filtering and color based segmentation	Based on a robust lane model	Annealed particle filter	Similar result as particle filter but the computation time is reduced	Suitable for both straight and curved roads
H. Yoo et al. (2013) [11]	Adaptive Canny Edge detector	Hough transform and curve model fitting		Robust in illumination changes	Suitable for both straight and curved roads
H.Jung et al. (2013) [25]	Steerable filter	Haar like features		Robust in illumination changes	Lane departure warning included
J.Wang et al. (2014) [20]	Segmentation	K-means clustering and B-spline fitting		Not susceptible to interference effect	Urban lane detection

H. Tan et al. (2014) [21]	Improved river flow	Hough transform		Robust in vehicle occlusions	Suitable for both straight and curved roads
U. Ozgunalp, and N. Dahnoun, (2014)[16]	Symmetrical Local Threshold	Hough transform	Kalman filter	Robust in shadowsand night	Suitable for both straight and curved roads
Y.Li et al. (2014) [18]	Canny edge detector	Hough transform	Kalman filter	Poor performance in heavy traffic, confusing road textures and uneven illumination	Suitable for straight roads
V. S.,Bottazzi et al. (2014) [19]	Histogram	Segmentation	Lucas-Kanade tracking	Robust in illumination changes	Based on Triangular prior model

Gopalan et al. [9] models the contextual information shared between lane marker with the surroundings is modeled using a pixel hierarchy feature descriptor. Here lane detection is done using a learning based approach. The situation can be modeled as a two class detection problem corresponding to lane marker and non -lane marker. Instead of using the local features of object in isolation here the information shared by the object with its surrounding scene is used. The pixel -hierarchy based descriptor is used to hierarchically analyze several visual features like intensity patterns, textures and edges based on the region surrounding each pixel corresponding to the object. Then from the contextual features the relevant features are selected using a robust boosting algorithm. For tracking the lane markers in subsequent frames particle filter is used. For tracking a static motion model is used to represent the state of particles.

Liu et al. [10] uses a top down approach for detecting lanes. First IPM is performed to remove the perspective effect. The probability distribution of lane parameters is estimated by multiple kernel density, and the uncertainties of visual cues are modeled using Gaussian kernels Statistical Hough Transform which was initially used for estimating straight lines is extended in this paper to detect parabolic and linear parabolic cases. After deriving likelihood function a partitioned particle filter (PPF)is used for lane detection and tracking. The PPF uses prior knowledge to generate a number of hypothesis or particles. Then the hypothesis is verified by derived likelihood function called measurement function using nearby data. Since PPF maintains multiple hypotheses of lane parameters it can handle several challenging situations such as occlusions, shadows and lane changes. To detect lane markers, image descriptors based on appearance features is defined. Multiple kernel density is used to estimate the probability distribution of lane parameters. The multiple kernel intensity is used to estimate straight lines, parabolic and linear parabolic shapes. The PPF kernel model is robust against occlusion and noise.

Jung et al. [25] proposes a lane detection algorithm which uses Haar like features to obtain candidate lane points. The image is divided into two rectangular regions. Diagonally directional steerable filters are used, as lane marker appears diagonal due to perspective effect. Approximated steerable filter is used to the Haar like features and maximal response is obtained. The left and right lanes are computed. As the lanes are parallel, they will converge at vanishing point. This hypothesis is verified to check the correctness of detected lanes. After detection lane departure can be determined based on the distance between vanishing point and the horizontal central line. If the distance increases there is a lane departure.

Tan et al. [26] developed a method for lane detection and classification. The lanes markers are detected based on a linear parabolic model. The lane marker pixels are assumed to have higher intensity than the pixels on the pavement. A small rectangular patch is used to extract the statistical properties between the lane marker pixels and pavement related pixels. In each frame the consistency of each pixel in the patch corresponding to lane marker with the distribution of pavement pixels are checked to distinguish pavement and lane marker pixels. After detection cascade classifier is used to classify the lane marker. Four binary classifiers are used which will classify the detected lane marking into five classes: dashed, dashed-solid, solid dashed, single-solid, double-solid.

Tsai,et al. [27] proposes a novel boundary determination algorithm for lane detection. It is based on local gradient direction. Sobel edge detector is used for finding out the gradient magnitude and direction. Then two circular masks namely tracing mask and probing mask, are used to collect limited samples of gradient orientation. The initial gradient is determined based on the largest histogram bin for orientation. The probing circular mask is used to avoid deviation. A third order polynomial fitting is also used.

Yoo et al. [11] generates lane gradient maximized image from a color image based on linear discriminant analysis. This produces strong edges to the lane boundary in various illumination. Then Canny edge detector is applied to get edge image. After edge detection Hough transform is applied to get initial lane detection. The Hough transform cannot represent curved lanes, so curve fitting is used for detecting curved lanes. Three parameters of the quadratic curve are used to estimate the lane model. For the first frame the training data is given manually and for remaining frames the training data are updated for adapting illumination changes.

Zhao et al. [17] proposes a method which uses annealed particle filter for lane detection and tracking. A bar filter is used as the lane marker can be described as black white-black bar like object. Since the lane marker usually have white or yellow color, the color cue is also used. To better distinguish the colors RGB images are converted to HSV space. These cues are processed separately before using annealed particle filter. Instead of single factored step in conventional particle filter annealed particle filter an annealing is done at each frame in the video sequence. A stationary motion model is used. The particles moved to the region of high probability. In the correction step, the angle information of edge map is used to measure the weights of particles. The annealed particle filtering has three main steps including re-sampling, correction and weight normalization. For the lane detection and tracking a robust lane model is also used. It can be applied to both linear and curved roads.

Ozgunalp et al. [16] uses Symmetrical Local Threshold (SLT) algorithm. It is based on dark - light-dark transition property of lanes. For each input point the average intensity value of all pixels to the left (within a range) in same row is calculated and, then average intensity is calculated for the right hand side. If the intensity of pixel is greater than both left and right averages then it is considered as a lane feature point and labelled in the feature map. Then a connected component analysis is applied. One either side of the feature points are searched for lane borders. If orientations of both the borders are close to each other, then the average of the angles is considered as the orientation of the detected lane border. Otherwise the point is eliminated from the feature map. To reduce the noise a distance transform is used. The distance of each feature point from the nearest non feature point in feature map is calculated and a weight is assigned. Thus the lane markers have higher weight than the isolated pixels. Also the center of lane marker have a high value. Next Hough transform is applied and rho values is calculated for theta values close to the orientation of feature points thus the computation speed is increased. Both the left and right lane are detected in a frame and after that these lanes are tracked.

To detect the edges in ROI, Canny edge detector is used in [18]. The straight lines are detected from the binary output of Canny edge extractor using Hough transform. To eliminate effect of noise local maxima features are searched along the estimated lane boundary. Then RANSAC algorithm is applied to eliminate outliers. The final local maxima features are fit into a straight line. Next Kalman filter is used to track the lanes in remaining frames.

Bottazzi et al, [19] proposes a histogram based illumination invariant lane detection method. A dynamic region of interest (DROI) is defined using a prior triangle model. First the histogram of the whole image and road frame are calculated. The difference between the two is used to find out the illumination changes. From the ROI lane markers are segmented. The algorithm uses Lucas Kanade tracking to track the lanes.

Wang et al. [20] uses overall optimal threshold converting the input image to binary. Inverse perspective mapping is done to avoid the perspective effect. Then K means clustering is performed to partition n samples to k clusters. Considering all the points in a cluster as control points, B-spline fitting is implemented to obtain lane marker.

The ROI is divided into near vision field and far vision field [21]. The input image is converted into IPM image. The local Hough transform is applied on near field of vision to detect the straight lines. In the far vision field an improved river flow method is used to extend the points detected in near vision field or the curve line detected in previous frame. The start flowing point is the top point in the detected straight line. The detected feature points are the fitted into a Hyperbola pair model using RANSAC.

3. PERFORMANCE METRICS USED FOR LANE DETECTION AND TRACKING

For evaluating the performance of lane detection and tracking algorithms the result is compared with ground truth data set and a check is done to determine whether there is true positive (TP) or false positive (FP) or false negative (FN) or true negative (TN). True positive occurs when there exist a ground truth and it is detected by the algorithm. False positive occurs when the algorithm detects a lane marker when there exist no ground truth. False negative occurs when ground truth exist in the image and the algorithm misses it. True negative occurs when there is no ground truth in the image and the algorithm is not detecting any.

The most common metrics used for evaluating performance of lane detection algorithms are Precision, Recall, F-score, Accuracy [34], Receiver Operating Characteristic (ROC) curves and Dice Similarity Coefficient (DSC)[33]. Precision is the fraction of detected lanes markers that are actual lane markers. Recall is the fraction of actual lane markers that are detected. F-measure is the measure that combines precision and recall and is the harmonic mean of precision and recall. Accuracy is the measure of how well the actual lane markers are correctly identified and true negatives are excluded. The metrics are represented as shown in equations (Eq. 1-5). The ROC curve is obtained by plotting True Positive Rate (TPR) versus the False Positive Rate (FPR) for different values of the extraction threshold. If area under the curve is larger than the detection is good.

Precision=TP⁄((T P +F P) (1)
Recall=TP⁄(TP+FN) (2)
F−measure=2*Precision*Recall⁄(Precision + Recall) (3)
Accuracy=(TP+TN)⁄(TP+TN+FP+FN) (4)
DSC=2*TP⁄((TP+FP+P) (5)

Where TP is the number of true positives, FP is the number of false positives, TN is the number of true negatives, FN is the number of false negatives and P is the number lanes detected.

3. CONCLUSION

In this review, a detailed analysis of various lane detection and tracking algorithms is discussed. The different methodologies investigated by different authors for lane detection and tracking during the last decade are presented in the paper. Various performance evaluation metrics are also discussed in this paper. Lane departure warning is an inevitable module in the advanced driver assistance systems. In the last decade several advancements occurred in the lane detection and tracking field. Vision based approach is a very simple modality for detecting lanes. Even though lot of progress has been attained in the lane detection and tracking area, there is still scope for enhancement due to the wide range of variability in the lane environments.

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