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Vision Based Lane Detection and Departure Warning System for Advanced Driver Assistance

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***Abstract*— In this paper, a technique for lane detection and identification of vehicle departure to avoid unwanted lane departure is presented. ROI is selected to reduce computational time. Hough Transform is used for lane identification by dividing region of interest (ROI) into two sub regions. Euclidian Distance Transform based measure is used for vehicle departure identification and warning message is generated based on calculated departure measurements. Experimental results indicate that proposed algorithm gives accuracy about 92% and robust against varying illumination conditions, noise, shadow, poor lane marking. The algorithm can detect solid as well as dashed lane markings and works efficiently for real time videos. It is successfully tested on PC platform of 2.4 GHz CPU.**

***Keywords*— Hough Transform (HT), Lane Departure Warning system (LDWS), Lane Detection, Region of Interest (ROI), Euclidian Distance Transform.**

I. INTRODUCTION

The increasing number of road accidents is a serious issue in front of modern society [1], [3], [21], [22]. Driver inattention, fatigue and drowsiness contribute most to the total number of accidents happen [2]. Different measures are being applied by automotive industries in order minimize the accidents by incorporating driver assistant system in vehicles [1]. Nowadays vehicles tend to be more intelligent; intelligent vehicles are the one which applies various advanced technologies to capture real time information which is further analysed to provide comfort and safety for the drivers [3], [23], [25]. Sensor based and machine vision based techniques are most commonly used techniques in intelligent vehicles. Machine vision based techniques are recognized as very powerful and effective for driver assistance system [4], [24]. Machine vision based pedestrian detection; lane detection, parking assistance etc. are most popular features that are extensively used in advanced vehicles. Many a times driver unintentionally deviate from the designated boundary which several times results in accident. Efforts have been done by the several researchers worldwide for developing lane detection and tracking system [3] to avoid fatalities happening due to lane departure on highways.

Lane detection experiences many challenges such as poor lighting conditions, shadowing, varying illumination, varying environmental conditions, road artefects etc. Robust techniques need to be developed to overcome these problems and to increase the efficiency of detection [3], [4].

Lane detection techniques are mainly divided into two parts, feature based techniques and model based technique. Feature based techniques uses painted lines or lane edges for lane detection while model based techniques uses some road parameters for lane detection [12]. Wang, Lin and Chen [3] adopted a method that can be used under different weather conditions, this is done by using fuzzy rules to analyze and design LDWS. Brightness changes are captured using combination of SCA, fuzzy C-mean and fuzzy rule which also improve certain information, canny edge detection algorithm and fan detection are used for lane boundary detection. Then orientation of lane related to vehicle is detected and the departure measurement. Wang, Lin and Chen [2] proposed a method that uses neuro-fuzzy network (FLNFN) model in which fuzzy rules are followed by functional link neural network (FLNN). The algorithm yields robust information about orientation of vehicle and accurate fit to lane boundaries.

Method proposed by Jung and Kelbera [10] uses linear-parabolic lane boundary model for lane departure warning system. The method adopted by Yu, Zhang and Cai [11] uses image preprocessing, dynamical threshold choosing in preprocessing stage and linear-parabolic model fitting which is described in earlier method for lane detection and departure measurement. An efficient and robust weak lane model and particle filter based system for lane detection and tracking measurement is proposed by Ruyi, Reinhard, Tobi, et al. [9]. Weak lane model shows flexibility to different shapes and also gives robustness.

Wang, Wu, Liang and Xi [5] uses innovative algorithm that combines region of interesting (ROI) and random Hough transform (RHT). The algorithm is divided into two stages. In the first stage HT is used for lane detection. Second stage is lane tracking in which Random Hough Transform and ROI are used for improves boundary detection rate.

Method proposed by He, Rong, Gong, et al. [8] uses canny edge detection algorithm for extraction of lane edges, later HT is applied on the selected ROI which detect lanes and also real time requirements. The method is very efficient and accurate.Gaikwad and Lokhande [4] proposed a method which used the same method for lane detection along with PLSF for preprocessing and Euclidian distance transform for departure measurements. Combination of PLSF and Euclidian distance transform improves the detection rate above 97% and keeps false alarm below 3% under different illumination conditions.

In This paper HT is used for lane detection. Hough Transform (HT) is feature based technique for lane detection. Feature based lane detection techniques uses low- level features such as painted lines, lane edges, lane segments from image for localization of lanes[12], [13], [14], [16]. HT is most effective technique for detection of straight line with the advantage of having reduced logic area and memory utilization and high reliability. It is a kind of mapping from image space to parameter space. It efficiently detects the straight lines, have very good fault tolerance and gives robust performance under varying conditions [1], [4], [6], [8], [17], [18].

The paper describes different stages in lane detection and departure warning system. Paper is mainly divided into 6 sections, section I includes introduction to lane detection and departure warning system, section II presents complete framework of the system. Detection of lanes using HT is presented in section III; use of Euclidian distance transform for departure measurement is illustrated in section IV. Experimental analysis is interpreted in section V and conclusion is presented in section VI.

II. SYSTEM ARCHITECTURE

Fig. 1 shows different stages in LDWS. Preprocessing is important step of LDWS, different measures are being applied for preprocessing to make image more suitable for further processing. Firstly image is resized to make images from different databases equal sized. Secondly color image is converted to grayscale image as it gives desired detection rate along with reduced computational complexity. To reduce computational complexity further only the useful area H/2 of an image is selected, by setting ROI which eliminates the useless information from image, where H is height of an image. This reduces computational complexity and reduce error rate significantly. Further selected ROI is divided into right and left halves to detect left and right boundary line of lane using HT as shown in fig. 2(b).

Further thresholding is done which converts grayscale image to binary image in the process noise in the image is reduced.

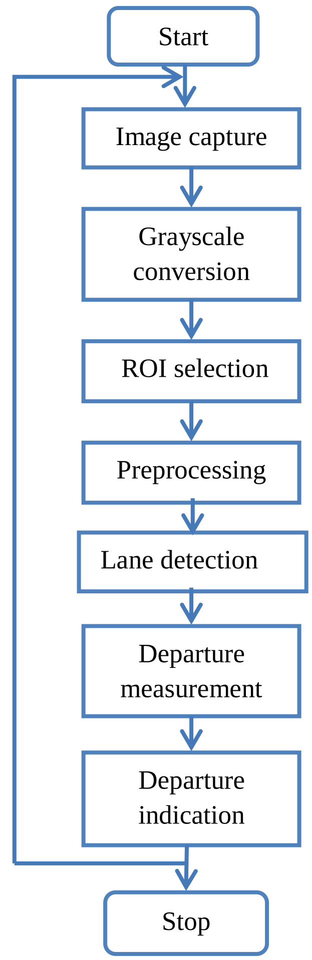


Figure1.Algorithm Flowchart for LDWS

Fig. 2(c) shows that thresholding converts most of the background part of the image into black color and results in enhancing lane boundaries which also enhance detection rate.

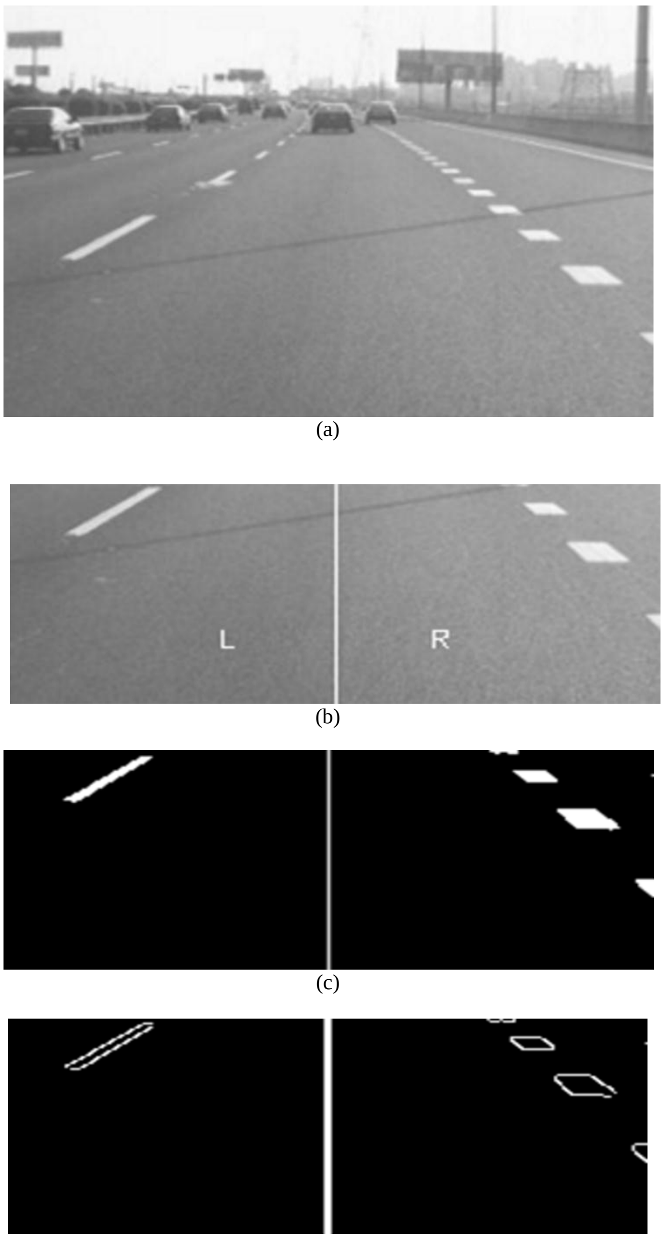
The conversion of input gray values x binary value y is carried out using the following:

$$y = 0 \quad , \qquad 0 < x \le \delta \qquad (1)$$

$$y = 1 \quad , \qquad \delta < x \le 255 \qquad (2)$$

Where δ is the value of intensity threshold used in image thresholding.

Canny edge detection algorithm is used for edge detection which is combination of Gaussian filter for noise reduction, intensity gradient for edge detection, Non-maximum suppression for getting thin edges, Double threshold and Edge tracking by hysteresis to remove small pixel noise and to detect only long edges.



(a)

(b)

(c)

(d)

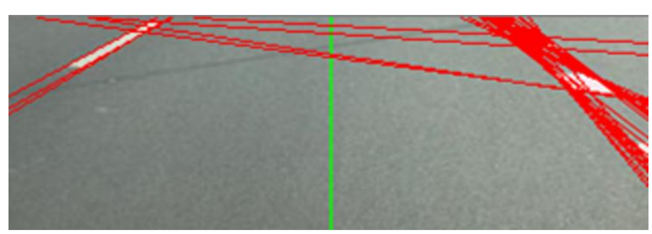
Figure 2. (a) Original image (b) Image after ROI selection (c) Thresholded image (d) Image after application of Canny edge detector

Fig. 2(d) shows results after applying canny edge detector to thresholded image; from figure it is clearly observed that edges of lane boundaries are correctly detected using this algorithm.

III. Lane Detection Using Hough Transform

The HT extracts features from image that are used in estimating straight lane boundaries. Generally straight line satisfy the equation y= px+q where (x,y) is the pixel coordinate, parameter p and q are the values of slope and intercept respectively. The points lying on straight line in image space *X-Y* are mapped to points in parameter space *P-Q*. But for lines having infinite slope this equation cannot be used for representation of lines in such cases normal parameters (ρ, θ) known as Hough Transform space are used for representing lines. Here the pixels belonging to lane marking follows equation $\rho = x \cos \theta + y \sin \theta$, where, θ is the angle between fitted line and origin and ρ is the shortest distance of fitted line from origin [5].

Fig 3(a). Shows that application of HT on considered road image gives lines corresponding to lane boundaries as well as some lines which do not correspond to lane boundaries resulting in false detection. Different modules are being applied to minimize such false detection and to increase accuracy of lane detection. Fig. 3(b) detection results after applying HT and angle constraint on detected Hough lines. Lines corresponding to lane boundaries lie in certain range of θ. Hence lines which do not fall in that range are eliminated to minimize false detection. This condition makes system robust against shadowing and road irregularities and results in increasing the accuracy of detection. Even after applying angle condition detection results show multiple lines belonging to lane markings causing ambiguity regarding considering exact line for departure measurement which is subsequent step of lane detection. To solve this problem only the innermost line from left and right sub regions is used for drawing detected boundary line and for departure measurement as shown in fig 3(c).



(a)

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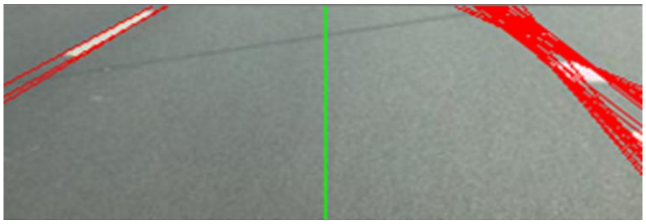


(b)

(c)

Figure 3. Detection results after applying (a)Hough Transform (b) Angle constraint (c) Inner boundary selection

IV. Departure Measurement

Euclidean distance transform is used for departure measurement of vehicle. O_H is taken as Hough origin and MP_L, MP_R are taken as midpoint of left and right lane boundary line respectively.

TABLE I
Conditions For Departure

Departure Type	Condition for Departure
Left Departure	$\epsilon_L - \epsilon_R > +\alpha$
Right Departure	$\epsilon_L - \epsilon_R < -\alpha$
No Departure	$-\alpha < \epsilon_L - \epsilon_R < \alpha$

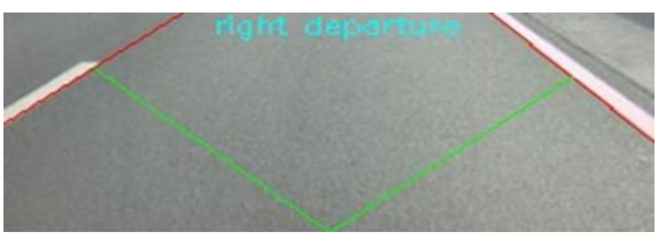


Figure 4. Detection result for departure measurement

For finding departure, Euclidian distance between Hough origin and both the mid points is calculated. ϵ_L denotes Euclidian distance between Hough origin to left boundary and is calculated using equation:

$$\epsilon_{L}= \sqrt{(O_{Hx} - MP_{LX})^2 + (O_{Hy} - MP_{Ly})^2} \tag{3}$$

Euclidian distance between Hough origin to right boundary and is calculated using equation:

$$\epsilon_{R}= \sqrt{(O_{Hx} - MP_{RX})^2 + (O_{Hy} - MP_{Ry})^2}. \tag{4}$$

The difference between above two Euclidian distances gives the departure direction. The distance between Hough origin and the lane boundary in the direction of vehicle departure will be less than other Euclidian distance. For this parameter $\emptyset$ is calculated as follows

$$\emptyset = \epsilon_L - \epsilon_R \tag{5}$$

If the value of $\emptyset$ is greater than $+\alpha$ that means ϵ_R is less than ϵ_L, results in issuing right departure indication. Conversely, if $\emptyset$ is less than $-\alpha$ that means ϵ_L is less than ϵ_R, results in issuing left departure indication. If value of $\emptyset$ is between $+\alpha$ and $-\alpha$ no departure indication is issued as shown in fig. 4

V. Experiments And Discussion

Proposed algorithm is tested on various videos and standard databases. Algorithm is implemented on Intel Core i3 central processing unit 3110M, with 2.4 GHz processor. Table II lists specifications of platform. A digital camera near a rearview mirror in a vehicle is used to capture video. Video sequence1 used for algorithm testing was 20 sec long and contained 600 frames with a resolution of 320×240 and frame rate 30 fps. The size of video sample was 7.52 Mb with a data rate of 3000 kbps.

TABLE II
Specification Of Platform

CPU	Intel Core i3 3110M 2.40 GHz
Processor cores	2
Memory	4 GB DDR3 SDRAM
OS	Windows 7 Ultimate
System Type	64 bit operating system
Frame rate	30 fps
Resolution	320×240

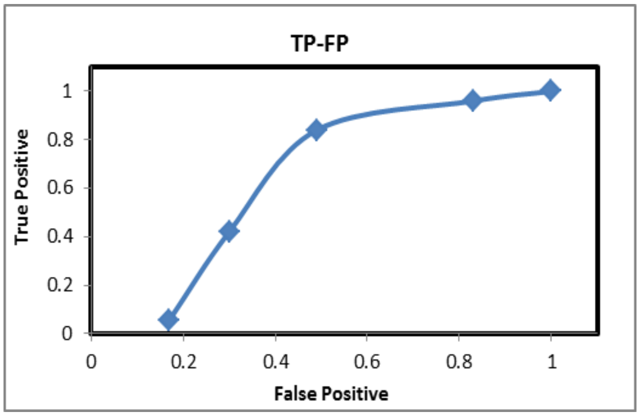
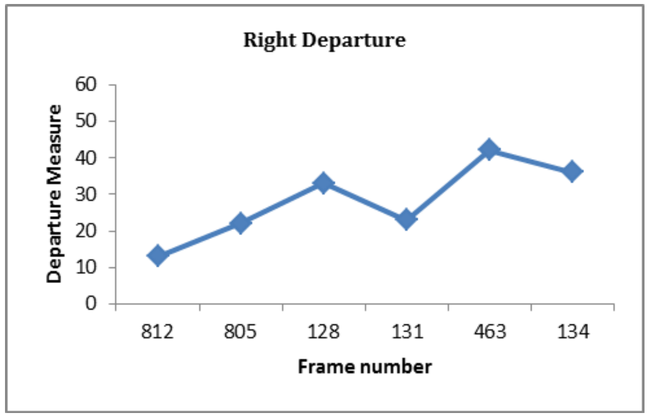


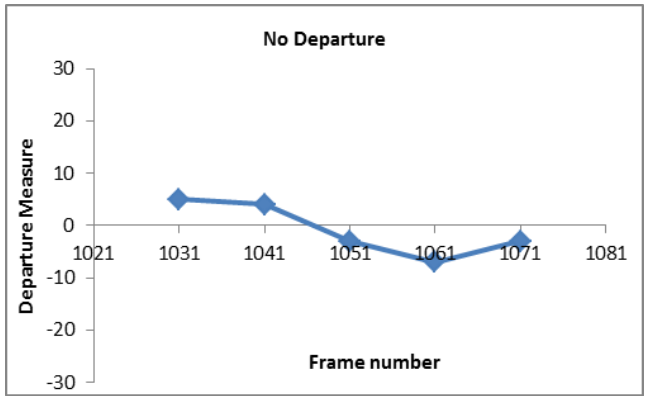
Figure 5. Graph of True positive versus False positive

LABEL-ME database contains two databases one database contains 633 highway images with a resolution of 320×240 and other contains 600 urban road images with resolution of 360×240. Algorithm is tested using corodova1 database from CALTECH lane database containing 249 road images with resolution of 640×480.

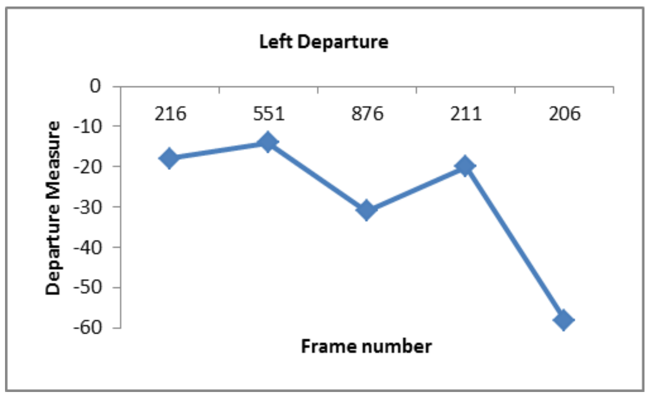
Fig. 5 shows graph of True Positive(TP) versus False Positive(FP). The graph does not depend upon accuracy of detection, however it depends upon number of frames considered for analysis. Graph illustrates that initially for small amount of frames taken TP increases rapidly with FP. As we increase number of frames further TP shows slight increase with respect to FP. Fig. 6 is plot of departure measure of different frames under different departure conditions. Depending upon threshold conditions set over departure measure appropriate warning is generated. Small agnitude of departure measure indicates less deviation of vehicle from center of lane whereas higher magnitude of departure measure indicates greater deviation from center of lane. Fig. 6(a) shows left departure condition. frame 463 shows highest magnitude of departure measure hence maximum deviated from center whereas frame 812 shows minimum magnitude of departure measure hence least deviation from center. For departure measure values between -10 to there is very small deviation from center and vehicle approximately can be considered at the center of lane.



(a)



(b)



(c)

Figure 6. Plot of (a) Right Departure (b) No Departure (c) Left Departure

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Hence in such cases no departure indication is generated. Therefore frames in fig. 6(b) give no departure indication. Fig. 6(c) with the frames having departure measure shows right departure condition. Figure 7 is a graph of departure measure for video_seq1 which illustrates that departure measure for first 200 frames mostly lies between middle part -10 to 10 hence many frames belongs to no departure condition whereas major part of frames between 400 to 500 are part of lower portion of graph hence member of left departure condition. Maximum portion from rest of frames falls in upper part of departure measure hence belongs to right departure criteria.

TABLE III
RESULTS AND ANALYSIS FOR DIFFERENT DATASET

Dataset	TP(%)	FP(%)	MD(%)	CP(ms)
LABEL-ME(Highway)	91.7	8.06	0.158	26.2
LABEL-ME(Urban)	90.33	9.17	0.5	25.4
Video_seq1	92.17	7.67	0.17	29
Corodova1	92.36	7.63	0	53

TP – True Positive, FP – False Positive, MD – Missed Detection, CP – Computation Time

Table III shows performance of proposed method for different dataset.

Corodova1 dataset shows highest TP with maximum computation time than other dataset. It also shows lowest FP and MD compared with other dataset. LABLE_ME(urban) shows least TP and computation time along with maximum FP and MD. Higher value of TP and lower value of FP and MD illustrates higher detection accuracy, hence maximum accuracy is achieved for Corodova1 dataset. Least value of computation time illustrates fastest detection, hence fastest detection is achieved for LABLE_ME(urban) dataset. Proposed method gives accuracy of about 91.64 % with average computation time of 33.4ms.

Figure 7 is a graph of departure measure for video_seq1 which illustrates that departure measure for first 200 frames and frames between 400 to 500 mostly lie in lower portion of graph hence member of left departure condition. Most of the frame between 500 to 600 lies between middle part -10 to 10 hence many frames belongs to no departure condition Maximum portion from rest of frames falls in upper part of departure measure hence belongs to right departure criteria Fig. 8(a), (c) illustrates that algorithm accurately detects continuous as well as dotted lane markings under normal lighting conditions. Fig. 8(d), (e), (f) are the lane images during shadowing, nighttime, under tunnel and wet road; under these conditions intensity level belonging to road surface and lane markings changes drastically which makes lane detection very difficult under such conditions. Proposed algorithm gives good detection results under such varying conditions and generates appropriate warning signal.

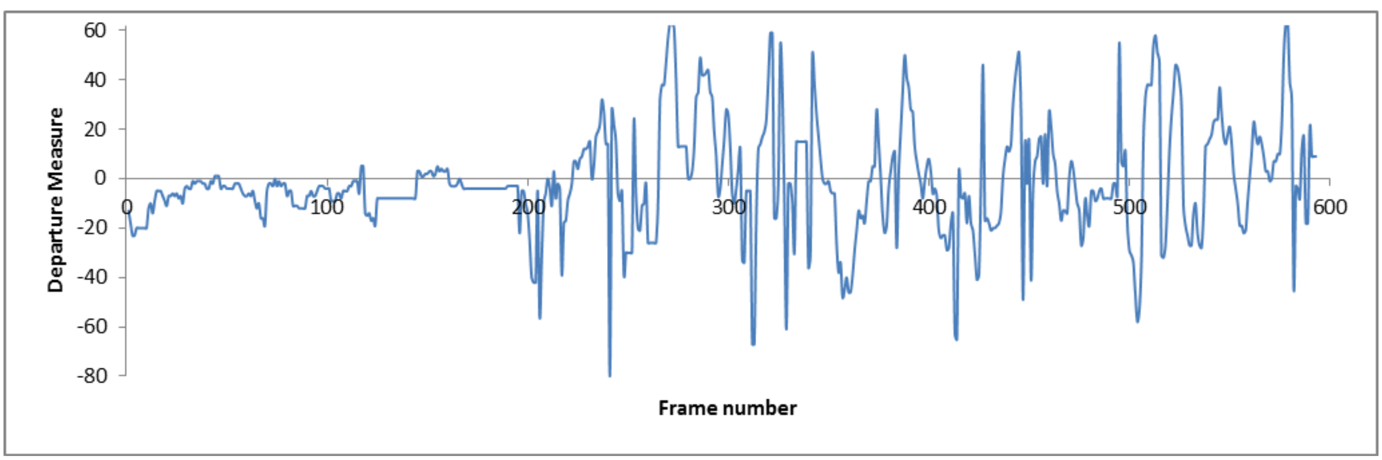

Figure 7. Graph of departure measure for video_seq1

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Figure 8. Detection results for various conditions (a) Normal lighting (b) Shadow (c) Dashed marking (d) Nighttime (e) Tunnel (f) Wet roads

TABLE IV
Comparison of Proposed Method with Other Algorithms

Method	TP (%)	FP (%)	MD (%)	CT(ms)
Hamdi et al.	87.5	9.5	3	100
Wang et al.	95	-	-	50
Gaikwad	97	-	-	
Lin	92.3	-	-	40
Bhati	88.61	-	-	37.76
Proposed	91.64	8.13	0.2	33.4

TP – True Positive, FP – False Positive, MD – Missed Detection, CP – Computation Time

Table IV shows that method proposed by Hamdi gives lowest detection rate whereas that proposed by Gaikwad gives highest detection rate with the use of PLSF and HT. Out of the methods presented in the above table the one presented by Hamdi requires highest computation time.

The method presented in this paper gives good detection rate with lowest computation time of the methods compared above using HT and Euclidian distance transform for lane detection and departure measurement respectively.

VI. Conclusion

In this paper, a new method for LDWS is presented based on Hough transform and Euclidian distance based departure identification to improve computational time while maintaining good detection rate. Initially ROI is selected to remove unwanted part from image and to reduce computation time as well as false detection. Division of the ROI into two sub-regions unable detection of lane boundaries on both sides. Canny edge detector is applied on image to increase the detection rate and removes noise using Gaussian filter. HT is used for robust lane detection. Further missed detection is reduced by applying angle constraint on detected Hough lines and inner boundary selection. Lane departure parameters are estimated using Euclidian distance transform. The method performs better in the presence of challenging situations like shadowing, night-time, tunnel condition and wet road surfaces and gives high detection rate with less number of false warnings. Experimental results show that the algorithm is suitable for real time detection and varying lighting conditions. Further work will concentrate on extending proposed method to integrate road model with the proposed method to make system more flexible to lane shapes. This will also facilitate the real-world coordinates of a vehicle with respect to both lane boundaries and unable car to take control over steering wheel to prevent accidents and autonomous driving.

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