Design and Development of Image Based Lane Warning and Anti-Collision Detection System

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ABSTRACT

The increasing rate of car accidents worldwide triggered the necessity to develop a system that can help in reducing that figure. In this paper, an image processing based Lane Departure Warning System (LDWS) and Forward Collision Warning (FCW) were introduced in one system namely smart Inner Rear View Mirror (IRVM). This system will monitor the road parameters and give a warning to the driver to be attentive whenever there is deviation from the lane or possible collision. The novelty of this project relies in reducing the cost of such a system to be affordable to everyone as those systems are currently expensive and exist only in luxury cars. This system utilize OpenCV Inverse Perspective Mapping (IPM), Probabilistic Hough Transform (PHT) and Haar classifier. Raspberry Pi single board computer is used as a platform to process the real-time videos. A preliminary result shows that the system is capable of lane markings detection in different roads condition and traffic situation and able to detect cars in front of the driver with more than 93% accuracy.

Keywords: *Image processing, Smart IRVM, LDWS, FCW*

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Introduction

There is a persistent need nowadays to have a “second eye” to assist the driver on road while driving. Driver’s attention while driving is inconsistent can cause the driver to lose concentration and eventually cause an accident [1]. Lane Departure Warning System (LDWS), Front Collision Warning System (FCWS) and many other safety features can be applied in a single camera using image processing which can be combined and integrated inside the Smart Inner Rear View Mirror (IRVM). Smart IRVM equipped with Advanced Driver Assistance System (ADAS) is proposed in order to assist driver to see rearward image through the vehicle rear windshield. This part usually affixed on top of the windshield or at the front centre edge of the headlining. The inside rear view mirror is mechanically designed to allow it to be adjusted to suit the height and viewing angle of any driver. Below are the 3 most common IRVM in the market:

a) IRVM with antiglare: It will reduce the glare of light of the vehicle behind which would otherwise reflected directly into driver eye at night. It work manually by pushing the lever/knob of the IRVM.
b) IRVM with auto dimming: The function is as same as No. 1. The only different is that it work automatically by using photo sensor & electro chromatic glass.
c) IRVM with display: The rear image from rear view camera installed at the rear of the vehicle will be shown on the screen at IRVM.

The current limitations of IRVM in the market includes lack of advanced safety features as per customer requirement. Even if there an ADAS feature on board, there exist no integrated function between the IRVM and the ADAS modules. The ADAS modules comes with variety of sizes for each different feature which would require extra space in the car dashboard. Current IRVM modules would require modification on its design and weight arrangement to accommodate ADAS modules as part of the IRVM. The durability and robustness of integrated ADAS system and the design of the ADAS warning system are also important when designing the smart IRVM.

Proposed System

We proposed a smart IRVM as an advanced driver aid system that includes ADAS features to help the driver in the driving process. The features that we aim to include as part of the smart IRVM are Digital Video Recorder (DVR), Lane Departure Warning System (LDWS), Forward Collision Warning System (FCW), Auto-Light System, Head Way Monitoring System (HMS), Intelligent High Beam Control (IHC), Rear View Wireless Camera System, Traffic Light and Road Sign Recognition System, Vehicle Monitoring and Tracking System, Pedestrian Collision Warning System, Integrated Mobile Application and Digital Display.

The system prototype consists of processing unit which is a Raspberry Pi 3 SBC with a display panel, camera and Bluetooth connection for monitoring and controlling the features through smartphones as shown in Figure 1. The IRVM panel was designed with sufficient space to house the processing unit as shown in Figure 2 and to be fitted in the vehicle as shown in Figure 3.

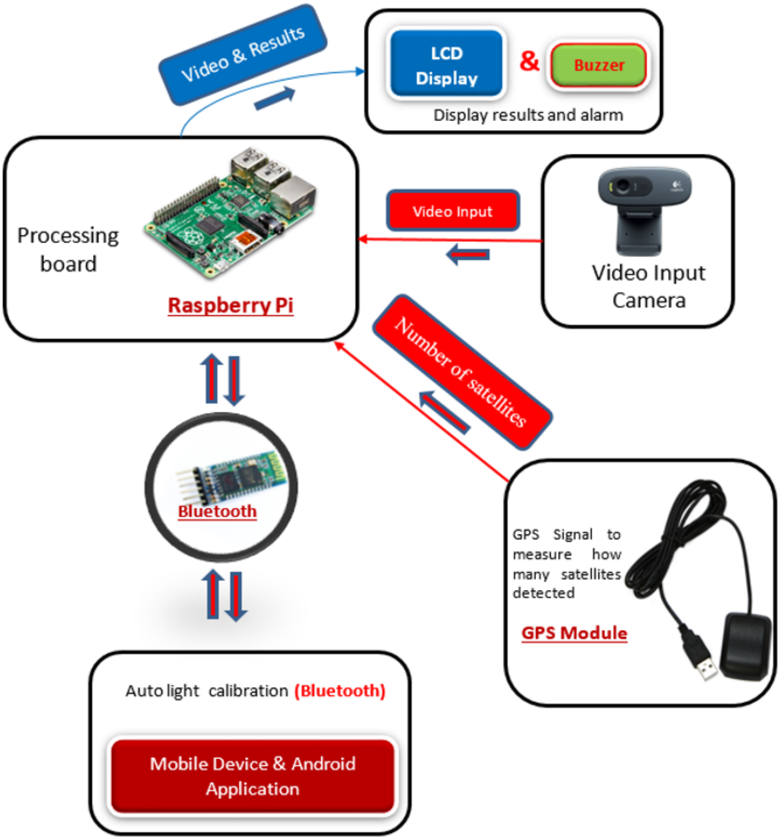
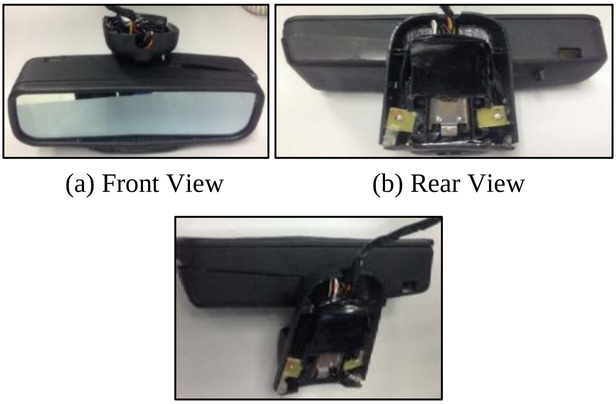


Figure 1: System block diagrams



(a) Front View (b) Rear View

(c) Side View

Figure 2: IRVM Panel

Figure 3: Fitting IRVM on vehicle

System Design

FCW

The FCW is implemented based on the Haar cascade classifier trained for vehicle detection. The training set for the training of the Haar classifier consist of positive images that contain vehicles and negative images which can contain anything but vehicle in it. When classifier is trained, it is being called to search and scan across the image or each frame to look for a match and give either 1 or 0 to indicate detection of the vehicle or non-vehicle respectively. Classifier can be resized during the search process. The cascade classifier will only accept the object to be valid is when it passes all cascade structures [2, 3].

False positive rate (FPR) and true positive rate (TPR) are measures of accuracy of the vehicle detection to know how well the classifier is performing. We tuned the classifier to achieve the lowest FPR and highest TPR. True positive detection indicates the number of the objects identified as a vehicles and therefore matches the reality, however, false positive detection indicates the number of the objects identified as a vehicles when they are not in reality [4]. The formula for TPR and FPR is as the following:

$$TPR = \frac{N_{tp}}{N_{tp}+N_{fn}}, FPR = \frac{N_{fp}}{N_{fp}+N_{tn}} \quad (1)$$

where Ntp is the true positive, Nfn is the false negative, Nfp is false positive and Ntn is the true positive.

LDWS

For the LDWS, the lane boundaries on the road from the camera view look inclined compared to what it is in reality, which makes detecting them is harder than detecting straight lines. Hence we utilized the Inverse Perspective Mapping (IPM) to convert the projection of the camera angle from a front view to top view. This can ease the algorithm used to detect the lines and remove the noise from the perspective effect of the input image [5]. The first half of the algorithm is similar to Wang et al's approach [6].

The next step is selecting a Region of Interest (ROI) where a rectangular zone on the street is highlighted from the input plane to be transformed to another plane. The output image will not be in the same shape as the highlighted one, instead it becomes an inverted trapezoid [7]. This projective mapping can be computed using the homogeneous matrix:

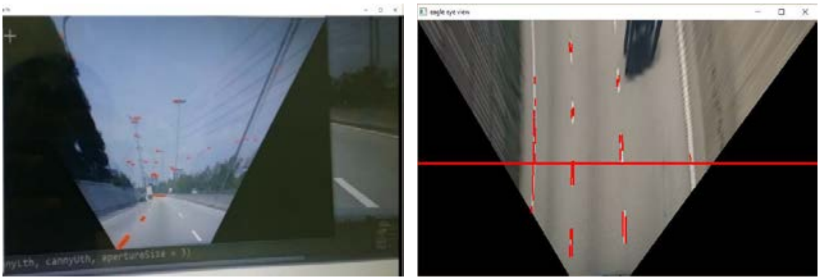
$$P_d = P_s M_{sd} \quad (2)$$

Which is equivalent to the following:

$$(x'y'w) = (u'v'q)\begin{bmatrix} a & d & g \\ b & e & h \\ c & f & i \end{bmatrix} \quad (3)$$

Line detection is done on the binarized image. Image binarization process starts with converting the input image into grayscale, then thresholding is applied on the grayscale image in order to binarize it to black and white colours without having any in-between intensity. According to Bae and Song (2011), this threshold value is calculated by taking the ratio of the highest intensity pixel over the lowest intensity pixel.

Extracting contours and Hough Transform are the next steps to detect the line. We apply the Canny edge detection to get only the edges of the binary image followed by a Hough Transform. Combination of those two operators is enough to generate a basic detection of the road lanes. After lanes are detected, we then draw and connect the discontinuous points to form a line which represents and fits the actual lane markings on the road, restricting this operation to pre-determined region of interest on the frame. The result of LDWS operation is illustrated in Figure 3.



(a) Input (b) Result

Figure 4: input image with ROI and its inverted trapezoid top view

Auto Light System

For auto light system, GPS NMEA data and camera used as input variables to control vehicles headlight. To measure luminance from the camera, we convert the RGB image to HSV and calculate the average of the V values. Distortion filter is applied to the image in order to avoid sudden changes in luminance as proposed in other work. The measured luminance is standardized to the specifications in Table 1. The auto light system controls vehicle head lights in all conditions using GPS NMEA data and the measured luminance from the camera as showed in the Table 2.

Table 1: Luminance requirements

Brightness (LUX)	Action	Delay Time	Adjustable range
200 +/-50	T/L , H/L ON	Immediately	100 – 300
1000+/-200	T/L , H/L OFF	2 seconds	500 - 1500
200-1000(base on #1 & #2 setting)	Maintain previous cond.	Immediately	Base on #1 & #2 setting

Table 2: Auto light control conditions

Input to system	Condition	Action
Time Based Role	Time after 6:45 pm	Head lights ON
	Time after 6:45 pm	Head lights Off
GPS	Tunnel	Head lights ON
	No Tunnel	Head lights Off
Camera Input measuring luminance	Cloudy and raining	Head lights ON
	Sunny and normal	Head lights Off

Experimental Results

FCW

The FCW was evaluated on more than 20 different sample videos. We also mounted the system on actual vehicle and conducted more than 120 on the road trips for real-time evaluation. Results showed that FCW is capable of consistent true positive detection with high accuracy and able to make several detections at once. However, due to the complexity of the road environment, we detected some false positive detections as illustrated in Figure 4.

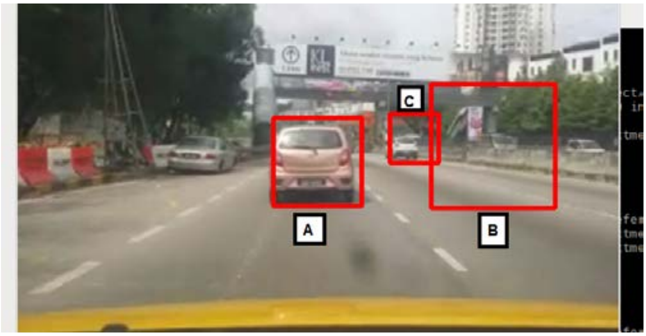


Figure 4: (A) and (C): True positive, (B): false positive.

We use the standard harmonic mean of precision and sensitivity formula to evaluate the performance of the LCW. Sensitivity takes the percentage of true positive samples to the total number cars, while precision gives percentage of true positive cars to both true and false positive (all detected samples) [8]. False negative is the number of vehicles that was not successfully detected. Table 4.1 shows the average percentages of sensitivity, precision and fitness of the LCW on three different videos which are sufficiently good.

Table 4.1: Accuracy measures

Measure	Formula	Percentage
Sensitivity, $\boldsymbol{r}$	$r = \frac{\text{True positive}}{\text{True positive} + \text{False negative}}$	85%
Precision, $\boldsymbol{p}$	$p = \frac{\text{True positive}}{\text{True positive} + \text{False positive}}$	97%
Fitness	$fitness = \frac{2pr}{p+r}$	90.6%

All detections whether they are true positives or false positives were plotted with respect to frames as shown in Figure 5. False positives were monitored and indicated with its corresponding frame. Not all detections represent new vehicle, some are just repeated detections of the same car in different frames. Some low-height vehicles that represent most of the undetected cars weren't detected. Moreover, the position of a car and its distance affect slightly the probability of being detected. However, the overall detection rate was excellent.

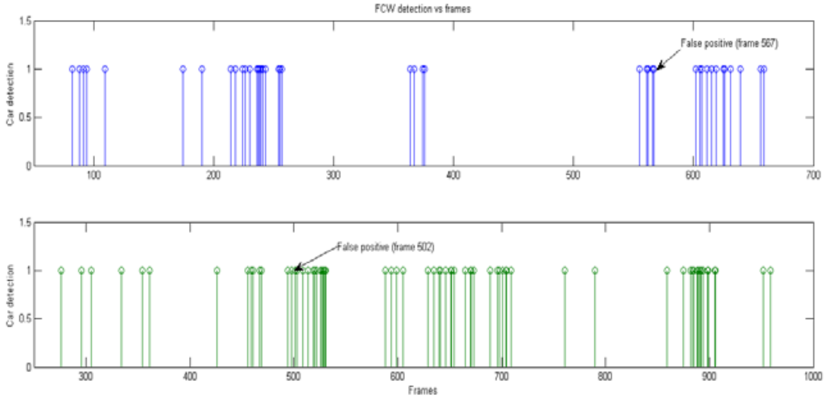
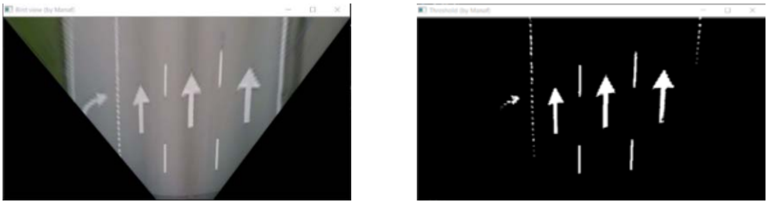


Figure 5: Vehicle detection vs frames

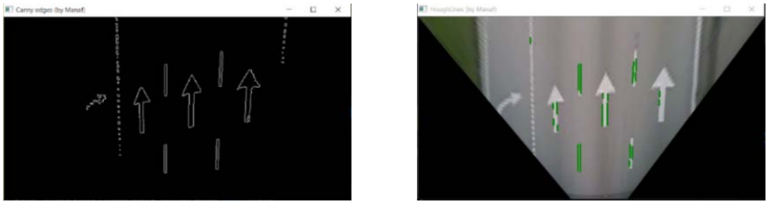
LDWS

The algorithm presents a sequence of steps to reach the result. Firstly, a projection of the top view is generated from the original image (Figure 6b). Secondly, the image is threshold to contain only white and black colours (Binary image) (Figure 6c). Then Canny filter is applied to the binary image to get the edges (Figure 6d). After that, the probabilistic Hough Transform (PHT) is used to extract the lines beside additional built-in function to draw those lines (Figure 6e). Finally, draw the lines with a green or red area between the two lines to show whether the car has deviated or not, where green means safe (Figure 7a) and red means that the car is deviating (Figure 7b).



(a) (b)

Figure 6: Bird's view, Binary image, Canny edges filter, Probabilistic Hough Transform (PHT).



(c) (d)

Figure 6: Bird's view, Binary image, Canny edges filter, Probabilistic Hough Transform (PHT) (continued)

(a)

(b)

Figure 7: (a) Final detection (safe), (b) Final detection (deviation)

Auto Light System

To measure luminance we have conducted several tests at sunset time, night time, and two ways road with vehicles coming from opposite direction to experiment sudden changes in luminance and tunnels. Tests took place at Duke Highway from Batu Caves, Gombak and Jalan Tun Razak in Kuala Lumpur, Malaysia. We have conducted test to Count Satellites in tunnel and parking to give an on signal and test on and off signal based on time. All results were automatically recorded as shown in Figure 8. There are also an on-screen display as in Figure 9. Overall output proved that the system has successfully worked in all conditions including tunnel, parking, night, and sudden luminance changing conditions.

Frame	Location	Time	Output	Condition
40	Tunnel	6.24 pm	OFF	drizzling and cloudy
41	Tunnel	6.25 pm	OFF	drizzling and cloudy
42	Tunnel	6.26 pm	OFF	drizzling and cloudy
43	Tunnel	6.27 pm	OFF	drizzling and cloudy
44	Tunnel	6.28 pm	OFF	drizzling and cloudy
45	Tunnel	6.29 pm	OFF	drizzling and cloudy
46	Tunnel	6.30 pm	OFF	drizzling and cloudy
47	Tunnel	6.31 pm	OFF	drizzling and cloudy
48	Jalan Tun Razak	6.32 pm	OFF	drizzling and cloudy
49	Jalan Tun Razak	6.33 pm	OFF	drizzling and cloudy
50	Jalan Tun Razak	6.34 pm	OFF	drizzling and cloudy
51	Jalan Tun Razak	6.35 pm	OFF	drizzling and cloudy
52	Jalan Tun Razak	6.36 pm	OFF	drizzling and cloudy
53	Jalan Tun Razak	6.37 pm	OFF	drizzling and cloudy
54	Jalan Tun Razak	6.38 pm	OFF	drizzling and cloudy

Figure 8: Auto light test records

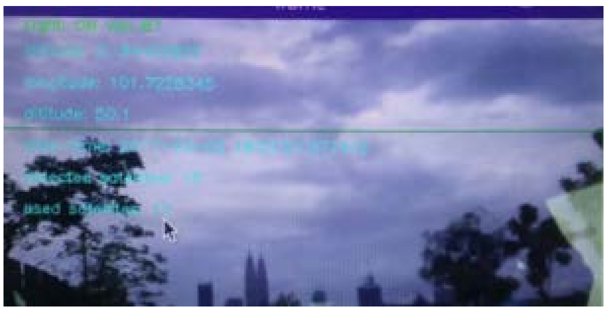


Figure 9: Auto light results on screen

Conclusions

The proposed smart IRVM system is a solid base for future work to complete the rest of the system features. Future work includes developing the remaining features like traffic light recognition system and pedestrian collision warning to achieve the complete product with all the planned features. Current features can be improved in different ways. For LDWS, video stabilization is crucial for a camera to give proper input image. On the other hand, FCW requires more data and vehicle samples to be used in training so that the system can be able to recognize even the non-standard vehicle shapes. Our plan is to include the remaining features stage by stage.

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