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Vision-based Lane Departure Warning System

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Abstract – *Vision-based Lane Departure Warning System (LDW) is a promising tool to avoid road accidents. In practice, it is exceptionally hard to accurately and efficiently detect lanes due a variety of complex noise such as environmental variability. However, image processing techniques have shown promising and reliable outcome in detecting lanes during non-ideal conditions. Lane detection and lane departure measurement are two important modules in LDW system. This paper explores the gaps and limitations of the existing method in the past 10 years concerning lane detection and departure warning for LDW system.*

Keywords: LDW, lane detection, lane departure

1.0 INTRODUCTION

Driver safety remains a priority in the automotive field. Hence, many efforts are taken to ensure the safety of drivers. One example is the Lane Departure Warning system (LDW), which is designed to warn drivers when their vehicle accidentally drifts out from its driving lane. LDW system is developed to reduce accidents and improve vehicle safety by addressing the various reasons behind road crashes such as driver inattention, distractions and drowsiness. Whether a driver is distracted or tired, LDW system can help to avoid a collision. The system allows the driver to take corrective action that could be the difference between life and death, prevent a minor fender-bender or a serious collision. Another advantage is that the LDW system can help drivers improve their driving behaviour, especially if they are prone to forgetting the signal before changing lanes. Thus, getting an alert will remind the drivers to pay attention and signal their intention so that other road users are aware of it.

Many automobile manufacturers are beginning to equip their vehicles with video cameras located at different places around the body of the vehicle due to the low cost of camera technology. Currently, a camera mounted at the vehicle windshield is the most commonly used LDW system based on image processing as stated in Geetanjali and Mulmule (2016). The camera will continuously capture front view images and these images will be used for processing. It will provide early warning when a driver is about to cross the lane boundary.

The study of LDW system is important as this safety feature has been proven to reduce road crashes (Cario et al., 2017). Driving is a complex action that involves coordinating the eye, hand and foot. A driver tends to feel drowsy and this can cause the vehicle to drift out from its lane and possibly causing an accident. Although there are a lot of proposed algorithms for performance improvement by researchers, due to some factors the LDW system still give false detection. Thus, studies to further develop LDW system which can adapt to various conditions and meet the requirements such as robust, low cost, compact, low dissipation, and real time are important.

2.0 LANE DEPARTURE WARNING SYSTEM

Lane detection and lane departure warning are major elements in LDW system. Based on various studies, a general block diagram of LDW system can be concluded as shown in Figure 1. There are different modules in LDW system such as image capture, pre-processing, feature extraction, lane detection, tracking, departure decision and warning system.

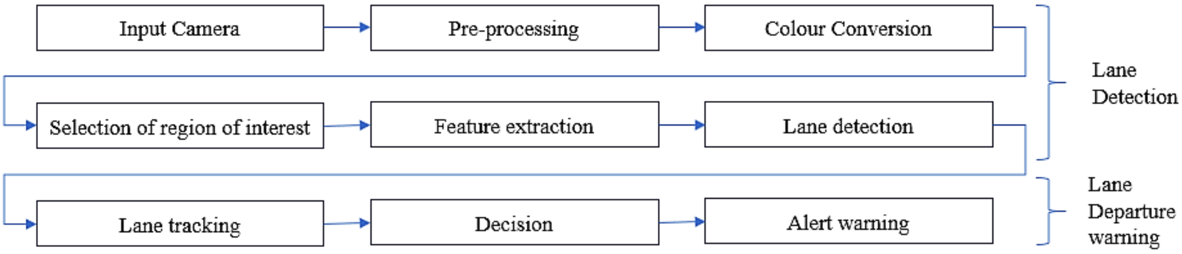

Figure 1: Block diagram of LDW system (Cario et al., 2017)

Firstly, the frame is extracted from the video taken by a camera set up in the vehicle. Pre-processing suppresses unwanted distortion and enhances image features for further processing. Colour conversion is also performed to enhance the image features. Once the converted image is obtained, a particular region in the image is selected to improve performance of the system by reducing computational complexity as feature extraction can be done in selected region of interest (ROI). Lane colour, edges and texture are examples of features that can be extracted from the image to provide information for lane detection. Lane detection works by fitting lane model with extracted feature. At the lane detection stage, lane verification is required to remove false detection. In order to track the change and estimate lane marker position in subsequent frame, lane tracking is applied. If the vehicle approaches the lane boundary, it will sound a warning to the driver.

3.0 ENVIRONMENT VARIABILITY

Due to various environment conditions such as lane marking types, daytime, road surface and environmental aspects, developing a robust lane detection algorithm has become a tedious task.

i. Lane marking: Distinct solid lines, segmented lines, physical barriers, circular reflectors, or nothing are examples of road markers (McCall & Trivedi, 2006). In addition, there are different colours for road lane marking; in addition to white and yellow which are commonly used (Kumar & Simon, 2015).
ii. Road surface: The road surface can include light pavement, dark pavement, or even a combination of different pavements. The structured road is marked with clear lane markings. Also, lane marking for unstructured road can possibly fade or have low level of intensity contrast. This degrades the road surface. Besides, weather conditions and illumination variant worsens the problem.
iii. Daytime and environment factors: Weather conditions (raining, fog, shadow, sunshine) and time of day have a huge effect on the visibility of road surface. Visibility of the road is reduced significantly at night.
iv. Illumination variant: This is due to change of natural and artificial light. Weather condition and time of day are causes of natural light changes; in addition to artificial light caused by road lamps and vehicle headlight and rear light (Son et al., 2015).

4.0 LANE DETECTION

Various conditions including road and lane appearance, image clarity, and low vision often affect efficiency and accuracy of the lane and road detection. Due to different assumptions of the structured road, various algorithms have been suggested to improve performance of lane detection. In a paper by Zhu et al. (2017), four assumptions are proposed including reliable road surface, ideal lane or road width lane marker appearance or placement that strictly follow the rules and the road is even or strictly follow the elevation change model. Current algorithm applies one or more of these assumptions.

In recent years, many researches have been carried out on lane detection (Zhu et al., 2017). For LDW system, it is important to detect lane correctly. Feature-based is a method to extract lane marking by observable features such as lane edges, colour and intensities.

Haloi and Jayagopi (2015) proposed modified Inverse Perspective Mapping, steerable filter (Freeman & Adelson, 1991) to extract features and RANSAC algorithm to identify and obtain potential lane point position to fit a parabolic curve for lane detection process. In this paper, Lab colour space is used to remove the effects of shadowing and extra sunlight. The experimental result showed satisfactory detection accuracy with average detection rate of 93%. On the other hand, Guo et al. (2015) proposed a method to detect straight and curved lane by using generalized curve lane parameter model. Also, canny edge detector for extracting feature points has been used. An improved RANSAC algorithm was developed and combined with a least square method to compute the lane model parameters.

Son et al. (2015) proposed a method for lane detection in various illumination conditions. An adjustable region of interest is applied to reduce computational complexity. Diverse property of lane colour was utilized to obtain illumination invariant lane marker detection. In addition, YCbCr colour space was used for white lane detection in Y-component and yellow lane detection in Cb-component. Lastly, the main lane was detected using clustering method of lane marker. Result of the experiment showed satisfactory detection rate of 93%.

Aside from the above, Sun et al. (2006) uses lane colour information for lane detection. The RGB is converted to HSI because it is difficult to obtain the lane colour information in

RGB colour space. Characteristically, lane markings on road surfaces are different in term of colour and intensity. Saturation (S) and intensity (I) channels of HIS colour space are sufficient for lane marker detection. Hue (H) channel also provides information for lane marker detection but is less important than S and I channel. The benefits of using HSI colour spaces include reduced computation consumption and increased effectiveness of detection. Tran et al. (2010) proposes an adaptive method for lane detection using an improved HSI colour space. Intensity channel formula for HSI colour space was also enhanced. In a real road scene, there are white and yellow lane markings. Different thresholds are set for white and yellow lane according to their intensity. The proposed algorithm showed good result in maintaining both lanes marking and removing unnecessary information.

A method by regulating CCD parameter to perform lane detection was developed by Ge et.al (2012) to increase the difference between lane line and road surfaces and reduce noise in the image. Hough transform algorithm was enhanced by selection and classification of seed points. Then, a certain restraint was defined to accurately extract the existing lane. The researchers applied the method only on straight line.

In addition, Srivastava et al. (2014) demonstrated different filtering techniques for efficient lane detection algorithm such as median, wiener and hybrid median filter. The hybrid median filter was proposed for detection algorithm. Canny edge detector and Hough transform were used for feature extraction. Based on validation test conducted under different daylight conditions and presence of shadow on the road, such a technique is proven to detect both straight and slightly curved road.

Jung et al. (2016) carried out lane detection based on spatiotemporal image as shown in Figure 2. The spatiotemporal image is generated along the time axis by accumulating the pixel. The trajectory lane point resulted from the constancy of lane width is identified by applying Hough Transform on binary image of the aligned spatiotemporal image. The positions of identified lane points were used to estimate the predicted alignment offset of the scanline in the following frame. In each frame, the detected lane points were fitted by simple cubic model. The result showed that it was robust to missing lanes when using temporal consistency.

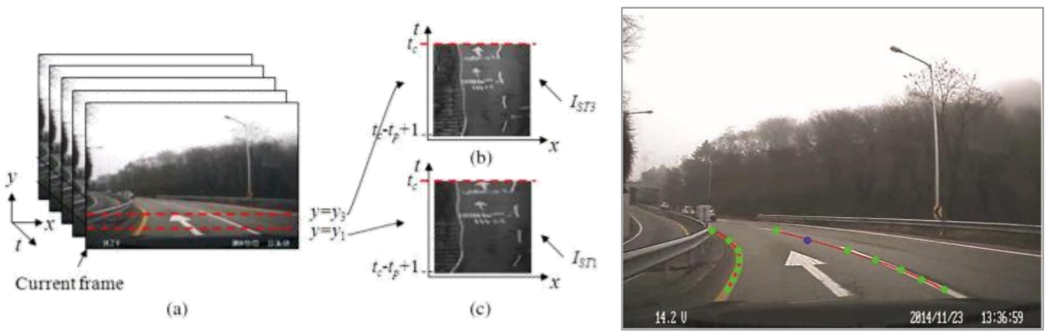

Figure 2: Spatiotemporal image process and cubic model for lane fitting (Jung, 2016)

Kortli et al. (2017) used Hough transform for lane and vanishing point detection as shown in Figure 3. Vanishing point detection was used to obtain region of interest (ROI) that will reduce complexity of algorithm for the next frame. The Otsu’s threshold was implemented to overcome illumination variant problem.

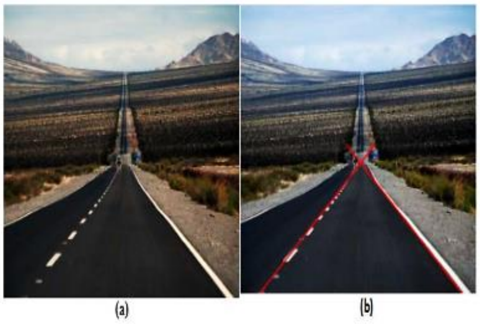

Figure 3: Result of lane detection after reducing false detection of straight line and its vanishing point (Kortli et al., 2017)

Additionally, Yoo et al. (2017) in his paper proposed a vanishing point-based method of detecting lanes as in the projected 2-D image parallel line meeting at the vanishing point. In another paper by (von Gioi et al., 2010) the line segment detector was used to extract line. The strength of the line is determined because the pixel alignment error may occur during line segment extraction. Figure 4 shows the intersection points of line segments extracted did not meet at the vanishing point. Thus, the probabilistic voting procedure was applied. During the vanishing point estimation process, the Gaussian distribution was computed. This method had a computational cost. Thus, a method using lookup table was proposed. Next, the line segment was filtered by geometric constraint. The outlier was removed in the candidates of the line segments using proposed score function, so the host lane could be determined. Experimental result shows the proposed method can detect lane in various conditions. However, there were errors in detection if the shadow or any repaired mark had similar orientation with road lanes.

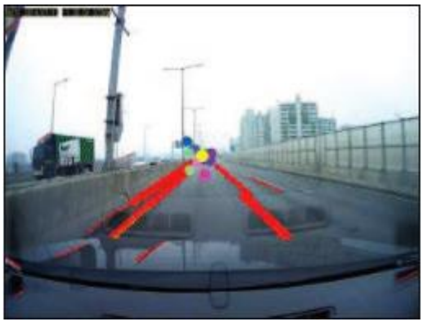

Figure 4: The circles of different colours indicates line segments intersection point and the yellow circle indicates lanes vanishing point (Yoo et al.,2017)

For lane detection, numerous methods have been used depending on various assumptions. Many features have been studied for LDW system. A better solution for it to be adaptive is by combining numerous algorithm to attain reasonable outcomes. Straight line is the easiest and effective way for model fitting to represent straight line and for short range of highway. Table 1 summarizes the lane detection methods that have been studied in this paper.

Table 1: Summary of lane detection methods

No.	Research Study	Pre-Processing	Feature Extraction	Model Fitting	Performance	Advantages and Disadvantages	Evaluation
1	Guo et al. (2015)	Select ROI and convert to Grayscale image	Canny Edge Detector	Improved RANSAC algorithm + Least Square Method	Dataset: Tongji and Caltech Lane Dataset Results: Tongji Lane Dataset 88.82% Caltech Lane Dataset 95.17% Processing time: 0.025s (Corei5@ 3.0GHz,4GB RAM)	Advantage: the proposed method can reduce noise point obtained by using Canny algorithm.	Robust in various distraction (shadow, non-lane marking line, occlusion) and low illumination. Limitation: Blur lane mark
2	Haloi & Jayagopi (2015)	Inverse Perspective Mapping	Steerable Filter	RANSAC	Dataset: KITTI, Caltech, Indian road Dataset Results: KITTI 94.26% Caltech 97.14% Indian Road 90.58% Processing time: 0.029s with 4 Core@2.3GHz	Disadvantage: Complex feature extraction	Works in various condition (robust to shadow effect)
3	Ge et al. (2012)	ROI Selection	CCD parameter	Improved Hough Transform	Test on real highway Results: Sunny 98.51% Cloudy 99.20% Average processing time: 0.025s	Advantages: The proposed Hough transform method can detect in lower processing time and higher accuracy. Disadvantage: Hough Transform are not be able to detect curve lane.	Works in various condition (strong brightness, cloudy and sunny day) Limitation: curve lane

No.	Research Study	Pre-Processing	Feature Extraction	Model Fitting	Performance	Advantages and Disadvantages	Evaluation
4	Son et al. (2015)	Colour conversion to Y-CbCr colour space	Use colour information i.e. white lane detection in Y-component and yellow lane detection in Cb-component	Least squares line fitting for each centre obtained from each cluster	Dataset: DIML's database2, Caltech Dataset, SILD 2011 Results: Caltech 93.6% DIML2 94.3% SILD 2011 94.2% Processing time: 0.033s		Works in various illumination and environmental condition. Limitation: faded lane marking, strong light reflection, low angle of sun situation, lane crack
5	Tran et al. (2010)	Colour conversion to HSI colour space	Use colour information, set threshold of intensities and saturation	-		Advantage: Do not require any filter and noise reduction module.	It shows good result in maintaining both lanes marking and removing the unnecessary information
6	Jung et al. (2016)	Spatiotemporal image	Hough Transform	Cubic model	Dataset: Borkar, Yoo, and authors' dataset Results: Borkar 79.61% Yoo 82.30% Proposed 88.70% Computational efficiency: 0.117s to process 1s video (4G RAM @ 2.8GHz)		Robust to missing lanes (in particular), Satisfactory result with sharp curvature, night road, lane changes, obstacle and lens flare. Limitation: Error occurs due to changes of lane abruptly
7	Kortli et al. (2017)	Otsu thresholding, Sobel operator	Hough Transform	Determine vanishing point	Straight lanes 97.84% Curved lane 93.6% Processing time: 0.028s (Corei3@3.2GHz)		Works in various condition Limitation: Blur lane mark, uneven surface of the road, curve lane
8	Yoo et al. (2017)	Grayscale Image	Line Segment detector	Using the probabilistic function to estimate vanishing point.	Dataset: Caltech and authors' Dataset Results: Caltech 87.97% Proposed: 92.43% Processing time: 0.18s (4.0GHz @ 32GB RAM)	Disadvantage: High computational time	It shows good result on various condition Limitation: shadow or any repaired mark have similar orientation with road lanes

5.0 LANE TRACKING

Lane tracking is carried out to predict lane position in the subsequent frame and to update its position. Previous frame information will guide lane detection in the subsequent frame. Tracking is done to reduce detection noise, interpolate lane boundary position during short periods where the incorrect detection occurs and estimate the upcoming position of lane boundaries. Cualain et al. (2012) and Chanho and Moon (2018) used Kalman filter, a least-square approximation of linear movement for lane tracking implementation.

The Kalman filter usually assumes that the object moves with constant or linearly varying speed between successive frames. Thus, by considering a dynamical linear model affected by random measurement noise, the Kalman filter is the optimal estimator if the noise is white, zero mean, and uncorrelated with the process variables (Cario et al., 2017).

Besides that, Gopalan et al. (2012) use particle filters to track lane markings without information of vehicle speed and assume the lane markings to be stationary through the video sequence. Particle Filter algorithm works by initializing the particles initially set and then predict the particles in current time frame. Finally, the particles are resampled based on the weights, which uses the observation model (Liu et al., 2010). Zhao et al. (2013) use annealed particle filter (APF) for lane tracking by using angle information of edge map to calculate weight of particle. APF has annealing run at each frame in the video sequence compared to conventional particle filter that uses single factored sampling.

6.0 LANE DEPARTURE WARNING SYSTEM

LDW system will continuously monitor the vehicle position based on the lane markers and alert the driver when the vehicle begins to depart its lane. The warning system will use the information from lane detection to approximate the vehicle when it unintentionally crosses the lane boundary within the next few seconds. There are two circumstances which are resulted from dangerous lane departure:

i. When the vehicle is near to the lane boundaries
ii. When the vehicle quickly approaches the lane boundaries

Lane departure decision can be made using detected lane position. Cualain et al. (2012) determined the lane departure by observing the distance of the vehicle to the detected lane boundary. Perpendicular distance, d from detected lane boundary is calculated. The warning system is issued when d = (width of vehicles track /2) is met. According to Son et al. (2015), in order to detect lane departure, temporal differences of lane offset and lane marking heading angle are measured. From the database obtained, the road width is determined. If the offset variance is more than half of the road width, it is considered as lane departure hence the alarm signal is sent.

Other than position information, lane departure can be determined by using angle information. In a study by Yi et al., (2015), angle information is used to decide lane departure condition. In order to reduce computational time, prediction is made only in even frames. For every continuous 10 even frames, the angle is calculated. The departure begins when the angle of the left lane line exceeds the departure threshold set value or angle of the right lane line is less than the value set for departure threshold. Haloi and Jayagopi (2015) approximate the departure angle using current vehicle position with respect to lane offset and optical flow computation as illustrate in Figure 5. Horizontal optical flow is a robust feature for undesirable horizontal velocity, which may be a clear signal of lane changing or passing, except for curved lane.

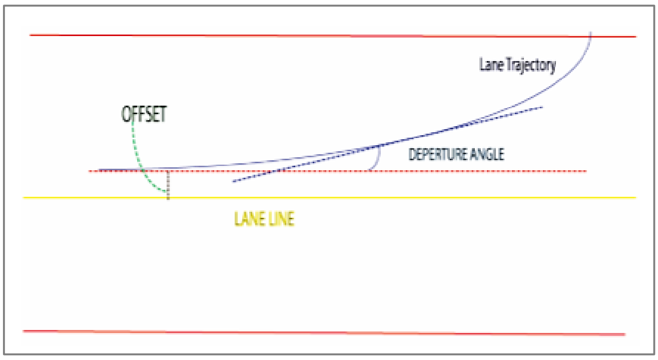

Figure 5: Lane departure idea (Haloi and Jayagopi, 2015)

6.1 Type of Warning Alert

There are three types of warning alert for LDW system; namely audio, vibration and visual alert. The auditory warning signal produces a beeping sound as warning when the car crosses a solid or dotted lane marking, then mutes itself once it is away from the lane edge. This form of alert will easily catch the driver attention but cannot always be heard over background noises. Another form of alert is Haptic feedback warnings. The steering wheel or seat cushion will vibrate as a warning sign. Seat cushion feedback can vibrate either on the left or right side in order to catch driver's attention.

Virtually every car shows a visual indicator that the car is drifting out of the lane. Typically, it is a pair of striped lane markings with yellow or green lines that indicate LDW is active. Red colour or flashing indicates that the car has departed from the lane. In most cars, the instrument panel indicator is not big enough to capture the driver's attention in a hurry, thus the need for audible or haptic feedback. At present, a lane departure warning icon is placed in the head up display, where it is more likely to be noticed by the driver.

7.0 CONCLUSION

Lane Departure Warning (LDW) system plays an important role to assist drivers. There are various methods for lane detection and departure warning. Based on literature review presented in this paper, various techniques have been proposed that produce good result in terms of accuracy, detection rate and lowest incorrect alarm rate. However, further research is needed to reduce the complexity of algorithm and its computational time.

This research will be helpful to researchers to develop their own algorithm by integrating the stated algorithm to improve system performance. In the available Original Equipment Manufacturer (OEM) product or aftermarket product such as MobileEye, the algorithm used cannot be obtained and is inaccessible for performance comparison. In the future, lane departure warning system for advanced driver assistance system (ADAS) must be designed.

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