An Improved Vision-Based Lane Departure Warning System under High Speed Driving Condition

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Abstract. Recently, Lane departure warning system has attracted great attention as it contributes to vehicle active safety. In this paper, a vision-based lane departure warning system under high-speed driving is proposed. The system consists of two functional parts: lane markings detection and vehicle departure identification. The Hough Transform is applied to detect lane boundaries, which is a most effective detection method with high reliability. Based on the road line, a method using several Euclidean-distance-related parameters to calculate vehicle’s position and its deviating status is proposed, which addresses the problem of efficient detection of lane departure under high-speed driving condition. The algorithm is tested and verified in various real driving conditions and proved a reliable and steady performance.

1. Introduction

In this paper, a technique for the identification of vehicle’s unintentional lane departure behaviour is proposed based on vision-based systems. Nowadays, traffic accidents cause hundreds of deaths, thousands of injuries and billions of dollars in loss every year. Among them, unintentional lane departure behaviour as a result of driver’s distraction, drowsiness and fatigue takes quite a considerable proportion [1]. Therefore, Advanced Driver Assist System (ADAS) such as Lane Departure Warning (LDW) system is considered as an effective method to help driver with real-time reminder and assistance. The vision-based LDW system uses cameras installed on vehicle to collect surrounding information and send alarms to driver. For its convenience and its high reliability, it’s in great demand of automotive industry and widely studied in recent years [2].

To generate warning signals for divers, lane departure warning system mainly consists of vision capture, lane detection and departure status identification. There have been many studies in this area over the past decades. Effort have been widely done related to image-based video pre-processing, Hough-based image processing, feature-based and model-based lane detection, vehicle departure identification, etc. [3]. Many other researchers concentrate on any other aspects, such as lighting conditions [4], varying road conditions [5] and driving environments [6]. In the meanwhile, the system should provide precise and timely alerts responding to potential driving dangerous, which is a challenging task. So robust and efficiency need to be recognize as a fatal evaluation of LDW system.

The main contribution of the paper is to provide an LDW system with high accuracy and low complexity under high-speed condition. The figure 1 shows the overall procedures of our LDW system. Since images captured, pre-processing including image conversion, smoothing and edge detection is applied. Then, Region of Interest (ROI) extraction and Hough Transform (HT) are used to extract lane
markings, which is described in Section 2. Based on the lane information, the technique using Euclidean distance parameters to determine vehicle departure identification status is applied, which is presented in Section 3. Finally, Experimental results are shown in Section 4 and conclusion is presented in Section 5.

**2. Lane Detection**

In the LDW system, accurate identification of lanes plays a key role to the overall system. Only when the identification and parameter calculation of the lane markings have been settled, the vehicle position and motion parameters can be accurately determined.

**2.1. Pre-processing**

Pre-processing is a vital step after the original image is captured from monocular camera, as it enhance the frame by reducing the noise and strengthen the contrast. Additionally, image smoothing and region of interest extraction help to remove the unnecessary part with interference information, which can improve the efficiency of calculation.

Generally, the input is firstly converted to grayscale image using a weighting equation to increase the pixel intensity value as follows:

$$I(x, y) = \omega_R R(x, y) + \omega_G G(x, y) + \omega_B B(x, y)$$

Where $R(x, y)$, $G(x, y)$ and $B(x, y)$ are the intensities of the red, green, and blue colours at $(x, y)$, respectively. And $\omega_R$, $\omega_G$ and $\omega_B$ are the weights for $R(x, y)$, $G(x, y)$, and $B(x, y)$, respectively.

**Figure 1.** Block diagram of proposed LDW system

**Figure 2.** (a) Original image captured on Highway (b) converted binary image
By setting a threshold for grayscale, the part with grayscale intensity \( I(x, y) \) larger than the limit is defined as 1 and the rest is set to 0. Therefore, the grayscale image can be converted into a binary image automatically, as shown in figure 2. In order to filter out noise effect, there are many filters used by researchers, such as Median filter, Gaussian filter, dilation and erosion filters, etc. To simplify calculation, a 1D-Gaussian filter is applied to the grayscale image, which smoothing the image considered in X direction and Y direction separately.

The introduction of edge detection helps to enhance the contrast and highlight the edge information so that improve the quality of pre-processing. Commonly, edge operators such as Sobel operator [7], Canny operator [8] and steering filter [9] are widely applied to detect edge lines. Since other operators may cause high frequency noise, which affects edge feature extraction and leads to false lane detection, the Sobel operator is applied to edge detection for its strong noise suppression and smooth results.

2.2. Region of Interest extraction

In order to reduce redundant part of the entire input image that contains of useless information, so it is important to extract the Region of Interest to reduce the computational complexity [10]. Faced with the standard lane markings on highway, especially detecting road lanes under high-speed driving condition, we directly complete the ROI extraction by intercepting the partial images in the horizontal and vertical directions, respectively. Although this approach may reduce the accuracy of recognition, it can greatly improve the computational efficiency under high-speed condition.

At the same time, the remaining part of the image is divided into two sub-areas and line feature detection will be completed in each sub-areas independently, as shown in figure 3. The Hough origin \( H_0 \) is located at the midpoint of the lateral width of the ROI. Therefore, the calculation in each sub-areas makes the distance parameters of lanes acquired easily.

![Figure 3. Select of ROI and sub-area segmentation](image)

2.3. Hough Transform

When vehicle is travelling at high speed on the structural road, road lanes can usually be characterized as a straight line. Therefore, HT can be used to extract road information in such case. The HT adopts the form of spatial mapping, which maps the lines in the image space to the points in the parameter space separately [11]. The feature lines can be effectively detected by searching for the point-to-line correspondence, making the system has a great fault tolerance and robustness.

In the pixel space, the point on the edge line can be represented by a polar coordinate equation, as follows:

\[
\rho = x \cos \theta + y \sin \theta
\]

Where \((x, y)\) is the coordinate value of a pixel, \(\theta\) is the angle between the x-axis and the normal line, and \(\rho\) is the distance between the origin and the fitted line as shown in figure 4.

The line to be detected in pixel space corresponds to a certain array \((\rho, \theta)\) in Hough space. After traversing all the points on the edge line, the local maximum accumulator cell \(A(\rho, \theta)\) can be found. Thus, the expression of feature line in the pixel space is obtained.
3. Identification of Lane Departure

3.1. Evaluation measurements of lane departure

Lane identification is just the premise for deviating detection, the identification of the vehicle’s driving status counts more in LDW system. Several evaluation parameters are defined based on the results of former image processing steps. And the Hough origin $H_0$ is the basic reference for all other parameters. The road lines in Hough parameter form is obtained, which is describe in an array ($ρ$, $θ$). Here, $ρ$ is the exact vertical distance from the midpoint Hough origin $H_0$ to the road lane edge. As shown in figure 4, $P_l$ and $P_r$ represents the crossing points of perpendicular lines connecting the Hough origin to the edge line respectively as shown in figure 4.

Thus, position-related parameter $D_l$ is defined as the Euclidean distance between the left crossing point $P_l$ to the Hough origin $H_0$, which is a vector with a direction and its value is represented as follows:

$$D_l = \|P_l - H_0\| = \left(\|P_l\|^2 + \|H_0\|^2 - 2(P_l \cdot H_0)\right)^{1/2} \quad (3)$$

Similarly, another position-related parameter $D_r$ is defined as the Euclidean distance between the right crossing point $P_r$ to the Hough origin $H_0$, which is a vector with a direction and its value is represented as follows:

$$D_r = \|P_r - H_0\| = \left(\|P_r\|^2 + \|H_0\|^2 - 2(P_r \cdot H_0)\right)^{1/2} \quad (4)$$

According to the aforementioned two parameters, the distance-related parameter $\omega(D_l - D_r)$ that determine whether the vehicle has been deviated from lanes is estimated. The parameter is calculated as follows:

$$\omega(D_l - D_r) = \omega \left\|D_l - D_r\right\| = \left(\|D_l\|^2 + \|D_r\|^2 - 2(D_l \cdot D_r)\right)^{1/2} \quad (5)$$

If a certain threshold $\zeta_0$ of the lane departure evaluation $\omega(D_l - D_r)$ is exceeded in several consecutive frames, it can be assumed that the vehicle has been deviated from lane at the current position.

In the meanwhile, the lane departure may happen in a short time when travelling fast, even though it does not deviate at the current moment. Therefore, a status-related parameter is introduced to describe the driving state of the vehicle in the near future as follows:

$$\psi = \frac{d\omega(D_l - D_r)}{dt} = \frac{d\omega \left\|D_l - D_r\right\|}{dt} \quad (6)$$

Where $\psi$ is expressed as changing rate of the above parameters in successive multi-frame images. Only in consecutive several frames can $\psi$ be calculated. With the sliding window detection method, it reflects the tendency of the vehicle to deviate from lanes for some seconds to come. If a certain threshold $\epsilon_0$ of the lane departure evaluation $\psi$ is exceeded, the risk of deviation of the vehicle in the coming seconds can be determined.

3.2. Identification of departure status

Lane departure has been defined as occurring when one of the front wheels of the vehicle crosses a lane marking. The following two parameters are used to identify the lane departure states, which are $\omega(D_l - D_r)$ and $\psi$. The two parameters need to be verified synchronously to estimate the lane departure state.
In the proposed LDW system, if $\alpha(D_l-D_r)$ is less than the threshold $\zeta_0$, the vehicle is considered to remain within the lane at this moment. Simultaneously, if $\Psi$ is greater than the threshold $\epsilon_0$, it is considered that the vehicle may be unconsciously and quickly exiting the current lane due to driver’s fatigue or the like, which may leads to traffic accidents. If $\alpha(D_l-D_r)$ is greater than the threshold $\zeta_0$ for a certain period of time, it is considered that the vehicle has deviated from the current driving lane at this state, at which the driver should be warned in time. When the vehicle is moving at high speed, the state of the vehicle is changing all the time. Therefore, that is not enough only when the position of the current time meets the safety condition: $\alpha(D_l-D_r)$ is less than the threshold $\zeta_0$. It’s necessary to analyse $\alpha(D_l-D_r)$ and $\Psi$ together to determine whether the vehicle is involuntarily deviated in the next period of time.

4. Experimental Results

Being able to evaluate the accuracy and real-time performance of the proposed system, sample lanes on Highway was selected. The test video sequences were captured from a camera mounted on vehicle, whose speed was between 80 and 110km/h. The proposed system was implemented on a computer equipped with a CPU Core i5-6400 2.70GHz in the running environment of MATLAB. The video sequences were pre-processed before lane detection and departure identification. To evaluate the proposed algorithm, different driver’s behaviours with intentional and unintentional deviations was tested.

Table 1. Performance of proposed LDW system.

| Scenarios             | Total Frame | Line Detected Frame | Line detection Rate | Ground truth Departure | Detected Departure | True Warning Rate |
|-----------------------|-------------|---------------------|---------------------|------------------------|--------------------|------------------|
| Left-shifted driving  | 1059        | 1046                | 98.8%               | 106                    | 99                 | 93.4%            |
| Right-shifted driving | 939         | 924                 | 98.4%               | 93                     | 88                 | 94.6%            |
| Straight driving      | 1659        | 1640                | 98.9%               | 0                      | 1 a                | —                |
| Total                 | 3657        | 3610                | 98.7%               | 199                    | 187                | 94.0%            |

a There is a false alarm in straight driving condition.

As illustrated in table 1, the proposed LDW system successfully detects lane boundaries under Highway condition. The proposed algorithm is applied to detect the deviation state at different driving behaviours. For details, lane markings are identified accurately among left-shifted, right-shifted and straight driving conditions with a total true detection rate of 98.7%. In addition, the performance of vehicle departure identification tested in the same three experimental scenarios. The result shows that the system works on well in different deviating conditions with a total true warning rate of 94.0%. Compared with other state-of-art LDW systems, algorithm based on the two parameter criterion performs a better true warning rate than [10] does, which fits more under high speed condition. Therefore, the proposed algorithm is proved to achieve a fast processing with high accuracy.

5. Conclusion

In this paper, a novel vision-based lane departure warning system with low computational complexity and high accuracy has been presented. The system is approved to detect road lanes and identify unintentional lane deviation behaviours effectively, especially under high-speed condition. When verified, the frame sequences captured from real-time driving condition are processed through image conversion, ROI segmentation and Hough Transform. For vehicle position and motion status identification, an algorithm with several Euclidean-distance-related parameters criterion is proposed. The system performs well with a 94.0% true warning rate, which demonstrates that the proposed method
for lane departure system is effective and accurate. Since the approach presented only has a minimal requirement of information to characterize driving status, this reduce the amount of calculation and makes it more feasible in a real-time embedded system application.

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