"Real-Time Lane Detection for Driving System Using Image Processing"

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Abstract: ***In the past decade a lot of research has been done on vision based real-time advanced driver safety system (ADAS). Many OEM car manufacturing companies have stressed their research on ADAS so as to increase the vehicle and driver safety. This work is aimed at developing an algorithm for on road lane departure warning (LDW) system. LDW can be successfully used for dropping the on road accidents which happened due to driver drowsiness or ignorance. In this report a survey has been done for the study and comparison of available algorithm for LDWs. An image processing based algorithm has been developed which uses a single camera mounted on-board. The robustness of algorithm has been tested under various lightning conditions and in the presence of heavy shadowing cast by bridges, vehicles etc. The algorithm is implemented in two steps, first it finds the vanishing point on the road and then a careful selection of line segments have been done by using the information of vanishing point. A smart and robust heuristic feature based filter has been used to validate the detected lanes. Kalman tracker is then implemented in order to track the detected lane and handle the critical sections where the detection algorithm fails. The major challenge for any vision based system has always been to achieve high accuracy and precision along with low computational cost (required for real-time applications).***

1. Introduction

Lane detection and tracking has been a well-researched field from the last decade. Being an important part of ADAS system, various car manufacturing companies have invested to make a robust LDW system. An LDW system can be divided into two sub modules, lane detection and lane tracking. Numerous vision based algorithms and systems have been developed for the intended system

Lane Detection module is responsible for detecting lanes without any prior knowledge. It uses complex image processing algorithms to detect lane boundaries. Most of the available literature for lane detection is based on the plinth of edge detectors. Once, all the lanes are marked, they are then further aggregated into meaningful shapes, termed as lane fitting. Lane fitting algorithms can use complex models such as straight line hyperbola, trapezoid and parabola. Hough transform is a popular technique to detect shapes such as circles, lines and curves. In lane detection algorithms it is used to detect straight lines. Several other techniques, like template matching or neural network can be used as an alternative to hough transform. Once the lanes are detected, vanishing point can be calculated using the lane information. Tracking is the next important part of any LDW systems. Particle filter and kalman filter are two common techniques used for tracking.

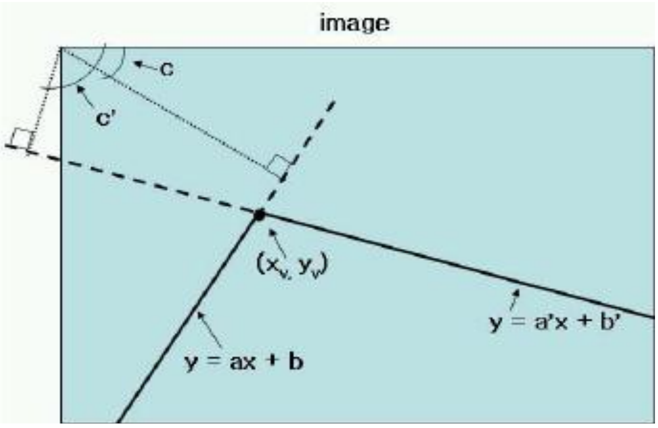
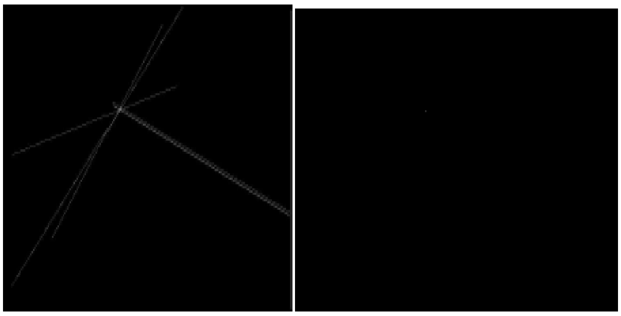


Figure 1. Illustration of road lane model

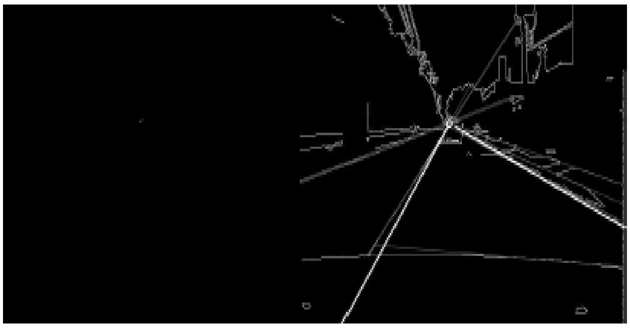
2. Lane Model

Since a road lane consists of two boundaries , the imaged lane is modelled as a pair of lines. The dimension of state space is four: the slope and y-intercept of each line(a; b; a_0 and b_0 in Figure 1). Equivalently, instead of slope and y-intercept, we use the vanishing point coordinates and orientation of each line(x_v; y_v; c and c_0 in Figure 1) as elements of the state vector v which shows more linear

(a) Original image (b) Canny edge image



(c) Hough line Image (d) The intersection of Hough line(white point) current frame t



(e)Vanishing point probability as an accumulated histogram on frames from t - ▼t to t. The histogram is properly scaled for visualization

(f)detected lane boundaries and the vanishing point marked as a white thick lines and circle respectively

Figure 2. Intermediate images during lane detection.

Input : Sequential Canny edge images $\{E_t\}$ (See Figure 2(b) and accumulated 2D histogram O (see figure 2(e))
Output : Left(q_L) and right(q_R) lines of imaged lane boundaries and vanishing point v
Set count C zero ($C = 0$)
Set all the bin values of o zero ($o\ (m) = 0$; *for all m*)
foreach *time t* **do**
Hough transform E_t to detect a set of lines, K_t (See Figure 2(c))
foreach *line* $i \in K_t$ **do**
Compute the orientation n_i of the line.
end
foreach *pair of lines i and j* ($i; j \in K_t$ *and* $i \neq j$)
do
Find their intersection $m_{i;j}$
Increase histogram value $h_t\ (m_{i;j})$ by 1 (See Figure 2(d))
end
if max ($h_t\ (m)$) > T_h **then**
Add the current histogram to the accumulated histogram ($o = o + h_t$)
Increase the count C by 1
if $C > T_C$ **then**
find the vanishing point if exists as well as left and right boundaries. (Algorithm 2)
end
end
else
$C = 0$
$o\ (m) = 0$; *for all m*
end
end
Algorithm 1: The lane detection algorithm by histogram of line intersections

3. Lane Detection

The lane detection method used in this paper is based on the Hough-based vanishing point detection method which is most popular in this purpose. The main idea is to wait until the vanishing point is detected at the same position for some consecutive frames. The pseudo code of the detection module is described in above Algorithm where T_h; T_C; T_o and T_D are thresholds whose values are properly set. The addition and subtraction between histograms h_1 and h_2 of the same size is defined as following.

$$h_1 \pm h_2 := h_1\ (m) \pm h_2\ (m)$$

where m is the index of a bin.

Input: Set of detected lines K_t at the current frame t and histogram of line intersections o
Output: vanishing point v, left(q_L) and right(q_R) lane boundaries if exists. Updated histogram o
$m_* = \arg\max(o\ (m))$

if $o\ (m_*) > T_o$ **then**
Set vanishing point v as m_*

foreach ($i; j$) *such that i; j 2* K_t; $n_i > 0$; $n_j < 0$
do
Get distance D from $m_{i;j}$ to v
if $D < T_D$ **then**
Add the pair ($i; j$) to the set R
end
end
(i_*, j_*) = arg min $n_i - n_j$
Set q_L and q_R as i_* and j_* respectively (See Figure 2(f)).
Break
end
Subtract the histogram of t - T_C from the accumulated histogram ($o = o - h_{t - T_C}$)

Algorithm 2: Estimation of the vanishing point as well as both lane boundaries.

4. Results

In this paper, the algorithm performance has been analyzed using output results. The proposed algorithm has been tested under several challenging scenarios. Different cases has been discussed in details in the following sub sections.

4.1 Clear Lane Marking

The algorithm is working fine under the normal scenario where both the right and left lanes are present and can be distinguished properly. The detected lane marking have been marked using a dark grey colour which can be seen in output image.

4.2 Scenario with Single Lane

One of the issues for LDW system is to correctly detect both lanes even when one of the lane is partially or not present. The application of canny edge detector can be understood in this scenario as it can detect the edges of the distant lane marking. Due to canny edge detector the correct lane marking can be retained.

4.3 Shadowing Effect Scenario

As discussed in section 1. 3, shadowing effect is one of the biggest challenge for any algorithm. In this case, Kalman tracker and Canny together help the algorithm to retain the lane boundaries. Kalman hold the value of vanishing point while canny try to extract each and every possible edge. This scenario also proves that Canny can handle the change in image intensity.

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