

[ME03] Development of driving assistant system for smart vehicle from series of image sequence

Anuar Mikdad Muad, Aini Hussain

Department of Electrical, Electronic and Systems Engineering, Faculty of Engineering, Universiti Kebangsaan Malaysia

Introduction

An autonomous intelligent vehicle system that can interpret traffics situation, provides driving assistance and capable of avoiding collisions can significantly increased driving safety. Such a vehicle system will have to perform several functionalities. In this work, a visual based sensor is used to acquire information by placing a web-camera at the dashboard of a moving car and directed outward in a way to have a similar view with a real driver. The camera captures image sequences where every frame of image provides information pertaining to road and traffic situations.

The aim of this work is to develop a stage of various algorithms that can extract relevant features in every sequence of image and when every one of them is combined, they become as one complete driving assistant system. It is hoped that, when the system is built, it will help to reduce accidents by focusing on keeping a safe distant between trailing and heading car and to avoid uncontrolled lane deviation.

Materials and Methods

Inverse perspective Mapping

The initial processing step is the removal of the perspective effect using Inverse Perspective Mapping, (IPM). IPM is a geometrical transformation technique that transforms each pixel from the perspective view to a bird's eye view (Broggi, 1995). This technique remedies the vanishing point phenomenon in which the road boundaries seem to converge. The IPM model is as shown in Figure 1(a) and (b). Figure 1(a) represents the top view geometrical model while Figure 1(b) represents the side view geometrical model. Two equations were derived using the triangulation and trigonometry of the IPM

model. Figure 2 shows an example of IPM result.

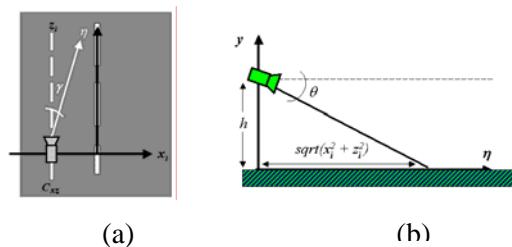


FIGURE 1 The IPM model

$$u(x,0,z) = \frac{\gamma(x,0,z) - (Y - \alpha)}{2\alpha} \quad \dots\dots (1)$$

$$\frac{n-1}{n-1}$$

$$v(x,0,z) = \frac{\theta(x,0,z) - (\Theta - \alpha)}{2\alpha} \quad \dots\dots (2)$$

$$\frac{m-1}{m-1}$$

Where,

$$\gamma = \tan^{-1}\left(\frac{z}{x}\right) \quad \theta = \tan^{-1}\left(\frac{h}{\sqrt{x^2 + z^2}}\right)$$

Lane marker detection

A series of object can be easily perceived and understood by the human but maybe difficult for a computer. This is because the computer calculates each object in the series individually, even though they have common orientation and are align together. For example in Figure 3, we would be able to observe two dashed lines running parallel vertically in the image and interpret it as two straight lines representing the lane boundaries. On the other hand, the artificial vision system interprets each short line of the dashed line as an individual component. This is similar to edge detection, which only highlights the lane marker but has yet to establish knowledge of a

complete line if the lane marker appears as a dashed line.

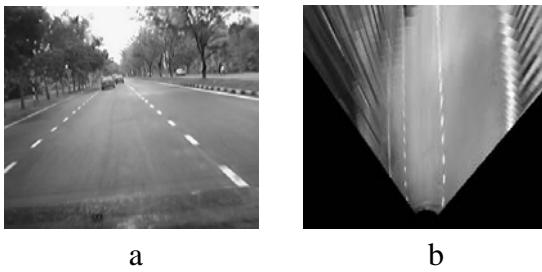


FIGURE 2 (a) Image before and (b) after IPM

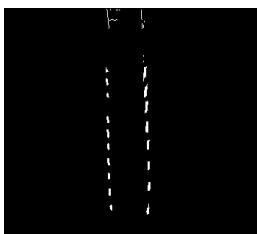


FIGURE 3 Edge detection for 2(b)

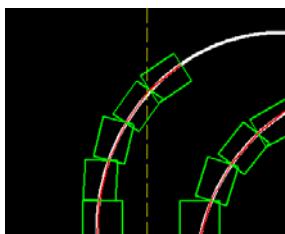


FIGURE 4 Combination between Hough transform and windowing algorithm to perform lane marker detection

Employing Hough Transform (HT) can solve this difficulty. HT associates each short line within the dashed line in the same arrangement and determines the tilt angle (Hough, 1962). HT involves voting technique that selects the overall tilt angle of each short line within a region. The highest voted tilt angle is used as the angle to represent the estimated line segment. This technique also works well for worn out or partly missing lane markers. Since HT is a straight-line detection algorithm, it has a setback to detect curvy and bend line. Besides, a consideration that cannot be neglected is the natures of the road, which exist in various form and orientation. In this work, we propose a solution by decomposing a line into segments. This task is done by windowing algorithm. This algorithm builds a pair of rectangular windows at the bottom center of the image since the pair of lane marker is supposed to lies at that spot. The window clips a small region of image and performs HT to detect straight line and orientation of the line. Windowing algorithm found to be useful by assisting the HT to determined end points of the line. On the other hand, information resulted from HT formulate the construction of subsequent window.

Finally, every end points are linked to form a complete line. A complete sequence of windowing technique with detected lines is shown in Figure 4.

Lane Changing

Lane changing module is a further expansion of lane marker detection with the aim to inform the system that the car is in a process to change its lane and update a pair of new lane marker. The car's position is constantly monitored in every frame by referring the lateral position of the car with x -coordinate of the lanes.

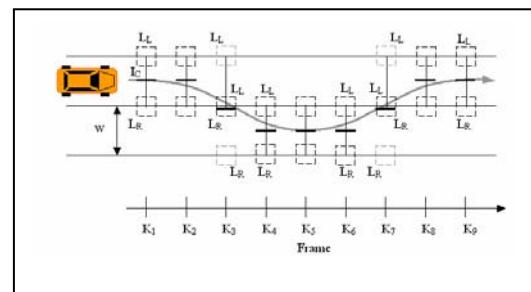


FIGURE 5 Lane change maneuver

The lane width, w is estimated by the lane detection algorithm. The car is inside the lane when both its front wheels are still inside the lane. As soon as one wheel crosses the lane border on its side, the car leaves the lane and moving into adjacent lane. In the n^{th} image, the lane marker detection module detects a parallel line. Speaking in terms of image coordinate, if the module has detected that the center image is crossing either one of the lane borders at n^{th} frame of image, then on the next frame, which is $n+1^{\text{th}}$ frame, the lane marker detection module updates the new lane marker by shifting its lateral coordinate by the width of the lane, w .

Obstacle detection

The criteria used for the detection of obstacles depend on the definition of what an *obstacle* is. The removal of the perspective distortion allows the road surface in the transformed image to be seen perpendicular with viewing angle. If gray level intensity of the road surface is captured from the bottom of the image and propagates upwards, the plot seems to be uniform at one range of level. But if there is a car in front, the gray intensity drop drastically as it indicates that it has reaches the

bumper of the car. The variation of intensity indicates the potential obstacle has been found. The relative distance between the car and obstacle is then measured.

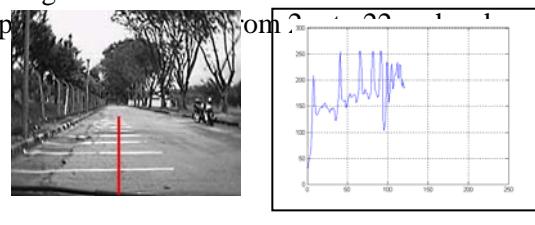
Obstacle tracking

The detection of the obstacle has to be done in the first frame of image sequences and the relative distance then is locked so that it can tracks the location of the obstacle in the subsequent frames. The actual relative distance measured in each frame is then compared with a predicted measurement, and their difference is processed by Kalman filter to generate estimates of the system's error states. The error estimated are then feedback to compensate the tracking system and thus provides an improved estimate of the actual state. This process is iterated for every sequence of images to tracks the location of obstacle (Kalman, 1960).

Results

Result for IPM

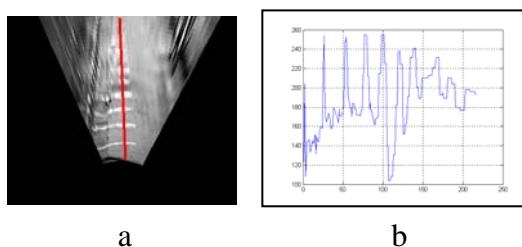
IPM gives a uniform measurement along z-axis. If measured the distance between white tapes from the standard deviation is 39.88σ compared with less deviation in transformed image with 11.42σ . The distance covered after perspective correction is 20m.



a

b

FIGURE 6 (a) Original image with perspective distortion (b) gray level intensity



a

b

FIGURE 7 (a) Transformed image without perspective distortion (b) gray level intensity

Results for lane marker detection

This module is tested in various conditions where the line marker may exist as a solid,

dashed or doubled line and the line is somehow appears as a straight or curve line. A combination of Hough Transform (HT) and windowing algorithm that form the lane marker detection is able to detect a pair or lane marker as shown in Figure 8.

The lane marker detection also proved to has a high resistant towards different climate condition and is not vulnerable when tested under shadowy condition or when road surface is wetted with rainwater. This is due to the robustness of HT.

On some occasion, there is some information painted on road surface like arrow that tells direction and yellow vertical lines that notifies driver to slow their car down. These figures somehow distract the lane marker detection module because they seem to have common intensity and in fact the vertical lines touches with the lane marker. However, as windowing algorithm keeps track the lane marker right from the bottom of the image, the Hough transform have no opportunity to track other features except only the lane marker.

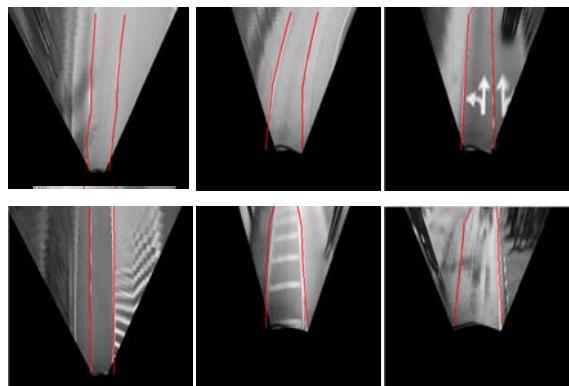


FIGURE 8 Lane detection module results

Result for lane changing

Figure 9 shows three conditions when a car moves in a lane without changing lane, deviate to the right and deviate to the left. The graphs are a function of lateral position against number of frames.

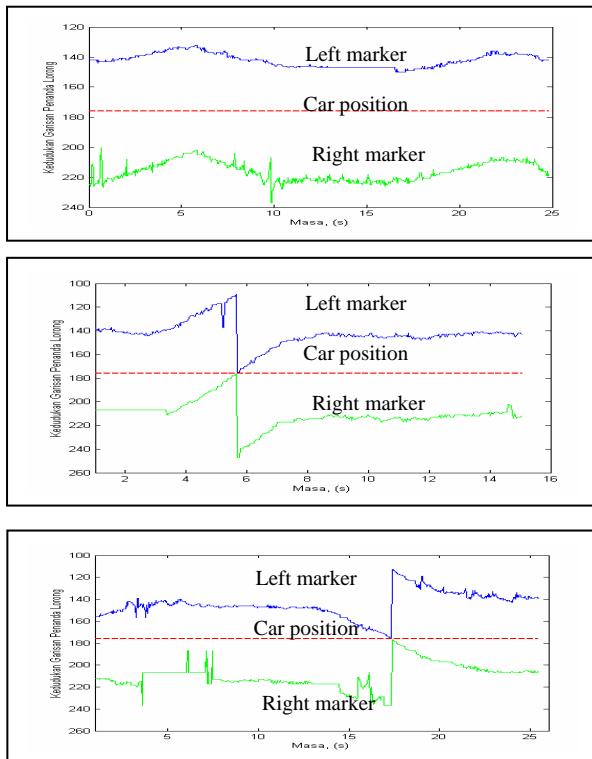


FIGURE 9 Lane change maneuver results

Result for obstacle detection

Based on intensity profile taken from a camera source point to a remote point, the intensity of the road surface is constant at one range before it jumps to drastically when meeting with the shadow of the obstacle' bumper. Through experiments, the gray intensity level for the bumper is below 40.

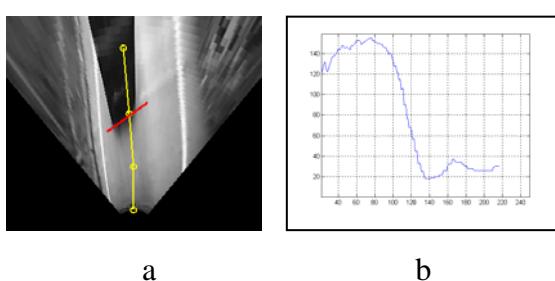


FIGURE 10 (a) gray level intensity is captured from bottom part of the image to the obstacle's bumper (b) graph of the intensity profile

Result for obstacle tracking

Q is set to 0.0027 based on covariance of the first two measurements and R is set to 0.27. From graph it is shown that Kalman filter requires a period of 1.4 as a responsive time before closely tracking the moving obstacle and estimating distance one step ahead.

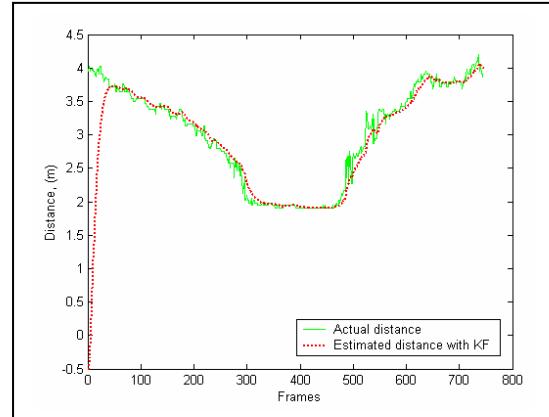


FIGURE 11 Actual distance and estimated distance using Kalman filter

Kalman filter demonstrates a stable performance because it tracks the actual distance closely and the profile of Kalman gain plot does not diverge as shown in Figure 11and 12 respectively.

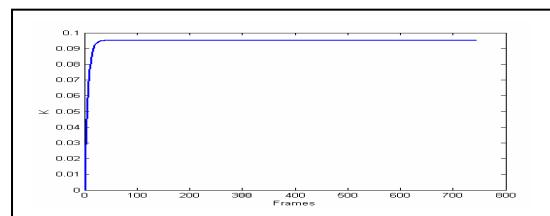


FIGURE 12 Kalman gain

Discussion

The usage of vision technique instead of other sensors shows that this technique can detect other information that other sensors cannot afford to accomplish.

Inverse perspective mapping allows image to be seen from another viewpoint. Apart from preserving the distance uniformly along the z -axis, it also acts as image segmentation by focusing on the surface of the road and removing other object in image like sky, clouds, trees, bush and other features.

The combination between Hough Transform (HT) and windowing algorithm supplement each other in performing lane detection task. HT found to be robust and insensitive towards noise but has setback because of its inefficient to determine end points since this algorithm assumes that a line is infinity. Windowing algorithm clips the line and determines the

end points from the intersection between the line and window's boundaries. The construction of subsequent window is then guided by line orientation, which is detected by HT.

At this stage of work, the lane-changing module act as lateral position guidance for a car assist in term of visualization by highlighting the lane and update it when car has change its lane. Further improvement can be made. If any further improvement has to be made, it has to be inputting the information resulted from this module to the steering control mechanism. As a consequence

A sequence of above module narrows the region of interest and increases the probability of finding the desired obstacle within this area.

From results, this approach proved to be encouraging where merely inspecting gray level intensity is enough to determine the obstacle and its position.

We can measure the relative distance in one frame and on another frame, measure the distance again but we have not got a clue about kinematics relationship between those two frames. From result, in order to track the distance, Kalman filter offered a recursive solution to track and control the distance optimally. By exploiting the time frame duration of the camera used, the filter provides dynamics information like position, velocity and acceleration. The stability of this filter is possibly made by fine tune its covariance values.

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