ISSN 2348 – 7968

Lane Changing Assistance Using Image Processing (LCA)

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Abstract

This paper aims at real-time video analysis to detect and track the vehicle behind using a rear-view camera to assist the driver to change lanes without having to look in the side mirrors or without the need of other person hence preventing the accidents caused due to human errors. Information received from the video stream is speed of the vehicle following, position of the vehicle. Calculating the speed and the distance of the vehicle following, the system makes a decision to suggest or not to suggest the driver to change the lane in the direction in which he has given a turning signal.

1. Introduction

Sensing vehicles behind during changing lanes on a highway are important aspects in safe driving, accident avoidance. We designed a system that is capable of identifying vehicles behind, moving in the same direction as our car, by tracking them continuously with a rear-camera. The fundamental problem here is to identify vehicles in changing environment and illumination. Although there have been numerous publications on general object recognition and tracking, or a combination of them, which have been implemented for real-time using in-car or a front-view camera, which has to process the input stream on-the-fly during vehicle movement there is not yet any system that processes the rear-view input to assist the driver when the vehicle is moving in the forward direction.

This paper introduces an effort to design and implement real-time oriented systems that are highly adaptive to the road and traffic scenes based on domain-specific knowledge on road, vehicle and control.

System introduced here consists of the three parts: camera frame segmentation, car distance estimation, car velocity estimation. Combining the output from all the three parts our system makes a decision that should the driver change the lane or not. If the system calculates and finds that the driver can safely change the lane the system approval and indicating the driver that he can change the lane safely.

The rear-view camera is a camera facing backwards which is the simplest and widely deployed system on modern cars that have rear parking facilities.

2. Dominant motion estimation

The estimation of the 2D parametric motion model accounting the dominant image motion is achieved with a robust, multi-resolution, and incremental estimation method exploiting only the spatio-temporal derivatives of the intensity function Quadratic motion models. Since the near car environment free of obstacles is formed by the road which can be considered as a planar surface, the image dominant motion due to the car motion can be exactly represented by a 2D quadratic motion model involving eight free parameters. Let us denote

$$\Theta = (a_0, a_1, a_2, a_3, a_4, a_5, a_6, a_7),$$

The velocity vector

$\mathbf{W}_\Theta(P)$ At pixel $P = (u, v)$

Corresponding to the quadratic motion is given by:

$$W_\Theta(P) = \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} + \begin{bmatrix} a_2 & a_3 \\ a_4 & a_5 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} + \begin{bmatrix} a_6 & a_7 & 0 \\ 0 & a_6 & a_7 \end{bmatrix} \begin{bmatrix} u^2 \\ uv \\ v^2 \end{bmatrix} \quad (1)$$

Dominant image motion estimation to estimate the dominant image motion between two successive images It and It+1, we use the gradient-based multiresolution robust estimation method described in [6]. To ensure robustness to the presence of independent motion, we minimize a estimator criterion with a hard-redescending function. The constraint is given by the usual assumption of brightness constancy of a projected surface element over its 2D trajectory. Thus, the motion model estimation is defined as:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}}\ E(\Theta) = \underset{\Theta}{\operatorname{argmin}} \sum_{P \in R(t)} \rho(\mathrm{DFD}_\Theta(P)) \quad (2)$$

$$\text{with } \mathrm{DFD}_\Theta(P) = I_{t+1}(P + W_\Theta(P)) - I_t(P). \quad (3)$$

ρ(x) is the Tukey'sbiweight function. The estimation support R (t) can be the whole image. In practice, it will be restricted to a specific area of the image. The minimization is embedded in a multi-resolution framework and follows an incremental scheme. At each incremental step k, we can write:

$\Theta = \widehat{\Theta}_k + \Delta\Theta_k$, where $\widehat{\Theta}_k$ is the current estimate of the parameter vector Θ. A linearization of $\mathrm{DFD}_\Theta(P)$ around $\widehat{\Theta}_k$ is performed, leading to a residual quantity $r_{\Delta\Theta_k}(P)$ linear with respect to $\Delta\Theta_k$:

$$\begin{aligned} r_{\Delta\Theta_k}(P) &= \nabla I_t(P + W_{\widehat{\Theta}_k}(P)).W_{\Delta\Theta_k}(P) \\ &\quad + I_{t+1}(P + W_{\widehat{\Theta}_k}(P)) - I_t(P) \end{aligned}$$

Where $\nabla I_t(P)$ denotes the spatial gradient of the intensity function. Then, we consider the minimization of the expression given by

$$E_a(\Delta\Theta_k) = \sum_P \rho\left(r_{\Delta\Theta_k}(P)\right). \quad (4$$

This function is minimized using an Iterative-Reweighted-Least-Squares procedure. It means that the expression (4) is replaced by:

$$E_a(\Delta\Theta_k) = \frac{1}{2}\sum_P \omega(P) r_{\Delta\Theta_k}(P)^2, \quad ($$

And that we alternatively estimates $\Delta\Theta_k$ and update the weights $\omega(P)$ (whose initial value are 1).This method allows us to get a robust and accurate estimation of the dominant image motion (i.e., background apparent motion) between two images.

2.1 Obstacles detection

The previous step supplies two sets of information:
1. The motion parameters θ corresponding to the dominant motion;

2. The map I_ω of the weights $\omega(P)$ used in (5) which account for the fact that pixel P is conforming or not to the computed dominant motion. The maps I_w will be used to detect the obstacles from the image sequences. Let us recall that the considered quadratic motion model is supposed to correspond to the apparent motion of the road surface. Therefore, each pixel that is not conforming to this estimated motion can be considered as belonging to an obstacle, either static or moving (or to another part of the scene, if it does not lie on the road).

The outliers map I_w is thresholded and mathematical morphology operators are applied in order to suppress noise. Pixels are then merged into group of pixels according to various criteria (distance or motion-based criterion). Concerning the distance criterion, two pixels or regions (group of pixels) are merged if they are convex or if the distance between these two groups is below a given threshold. Concerning the motion similarity criterion, two regions Ri and Rj are merged in a single region Rf if the motion within region Ri is consistent with the motion in Rf and if the motion in Rj is consistent with the motion in Rf . It is defined as:

$$C = C_{if} + C_{jf} \quad (6)$$

Where reflects the motion similarity between regions $R_{k|k=i,j}$ and R_f:

$$C_{kf} = \frac{1}{Card(R_k)} \sum_{P \in R_k} \left| d^u_{\widehat{\Theta}_k} - d^u_{\widehat{\Theta}_f} \right| + \left| d^v_{\widehat{\Theta}_k} - d^v_{\widehat{\Theta}_f} \right| \quad (7)$$

Where $\mathrm{d}_\Theta = (d^u_\Theta, d^v_\Theta)$ denotes the displacement of pixel $P = (u, v)$ According to the motion model Θ, and $\widehat{\Theta}_k$ designates the parameters of the motion model estimated within region R_k using the same method as the one described in Section 2. $Card(R)$ Is the number of pixels in region R.

2.2 Obstacle tracking:

We then obtain for each obstacle (or, more precisely, for each area in the image that is not conforming to the dominant motion) a bounding area. In order to improve the efficiency of this approach and to limit the number of false alarms, these areas are tracked over successive frames. A comparison between obstacle areas detected in two successive images is then necessary. Two tests both based on motion similarity have been investigated. The first one exploits the criterion defined in (6). The second, which assumes that the two regions overlap, and evaluates the motion consistency in the intersection of the two regions.

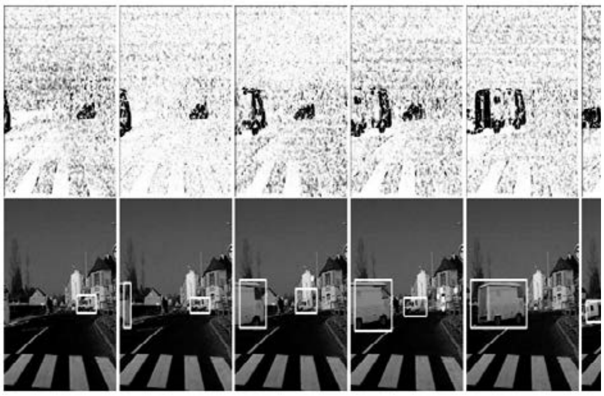


Figure 1. Obstacle detection from a motionless vehicle. The first and third rows display the outliers maps, fourth rows contains the detected obstacles (see text for details)

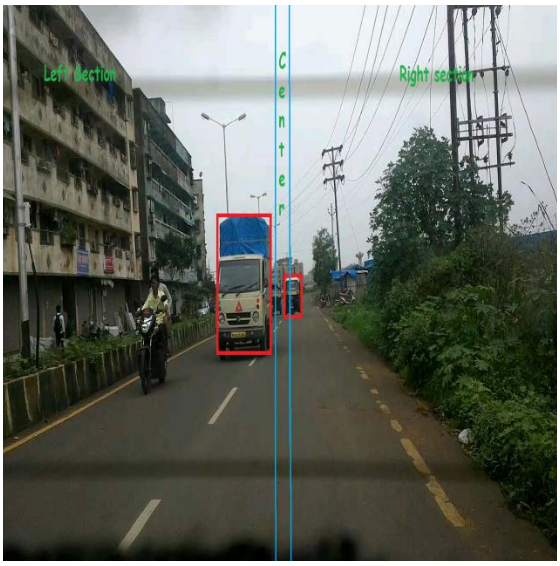
It can be expressed as follows:

$$C_{ij} = \frac{1}{Card\left(R_i \cap R_j\right)} \cdot \sum_{P \in R_i \cap R_j} \left| d^u_{\hat{\Theta}_j} - d^u_{\hat{\Theta}_i} \right| + \left| d^v_{\hat{\Theta}_j} - \right.$$

This short term temporal tracking allow us to suppress false detections that could arise in a one-frame analysis. At this step we have a set of obstacle areas validated in the current frame and specified by their bounding rectangular boxes, and their position in the previous frame.

3. Camera frame segmentation

In this part image is divided into 3 different sections i.e. left, centre and right.



This division is performed based on the resolution of camera. In each of this section detection of car is done using high vision algorithm for object detection. Now if car is detected in left section then it is in first lane and at right side of driver; if car is detected in right section then it is in third lane and at left side of driver. This method provides us with a robust technique of detecting, on which side of the driver the car lays. Hence using this method even when the car is on the road without white strips the system can detect from which side the car is approaching from.

4. Car Distance Estimation

We characterize a car by its location and shape, which we formally define as

$$\left(\begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix}, \begin{pmatrix} \sigma_x \\ \sigma_y \end{pmatrix} \right),$$

Where (μ_x, μ_y) denotes the centroid and (σ_x, σ_y) denotes the spatial standard deviation of the group of pixels.

ISSN 2348 – 7968

A standard formula for computing the distance Z to an object of known size simply consists of the focal length f multiplied by the ratio between the size L of the real object and the size l of the object's projection on the image plane. This assumes that the road can be considered planar, which is true in most cases. Then

$$Z = \frac{f \cdot L}{l} = \frac{f \cdot W_{\text{real}}}{W_{\text{sensor}}}, \qquad (9)$$

Where W_{real} is the real width of the vehicle, which is assumed to be constant for all vehicles, and W_{sensor} is the
Vehicle's width on the imaging sensor, which is derived from the camera calibration and the vehicle's width in pixels W_{pixel} that can be computed using the light, patches location as

$$W_{\text{pixels}} = (\mu_x^{\text{right}} + 2 \cdot \sigma_x^{\text{right}}) - (\mu_x^{\text{left}} - 2 \cdot \sigma_x^{\text{left}}). \quad (10)$$

Knowing the depth Z of the plane in which the vehicle is situated, Eq. 11 can be derived from it. This defines the lateral shift X between the camera's center and the vehicle's position, assuming that other vehicles travel in a direction which is approximately parallel to the camera's optical axis:

$$X = \frac{Z \cdot S_{\text{sensor}}}{f},$$

Where sensor is the horizontal distance on the imaging sensor between the detected vehicle's centre and the image centre and can be computed with the help of camera calibration.

5. Car velocity estimation

In this section we make the estimation of the speed of the car behind our car. Here we use a basic speed and time calculation to find the speed.
Derivation:
Let the speed of car A and car B is V1kmph and V2kmph.
Distance covered by car A in 1sec
=1sec*V1
=1sec*V1mps*1000/3600
=0.277V1 metre
Distance covered by car B in 1sec
=1sec*V2
=1sec*V2mps*1000/3600
=0.277V2 metre
Consider the Distance between car A and B is d1 at some instance
After 1sec-
A is ahead of B by (d1+0.277V1) metre and B travels a distance of 0.277V2 metres.
The new distance between A and B is d2 which is given by,
d2= (d1+0.277V1)-0.277V2……(g)
So the relative change in distance=d1-d2
Now if we know:

1) Velocity of car A (V1mps) is the velocity of our car, which is known from the speedometer.
2) Distance between car A and B at some instance (d1).
3) Distance between car A and B after 1sec (d2).

From equation (g) we get

d2 = (0.277V1 + d1) – (0.277V2)
V2 = (0.277V1 + d1 –d2)/0.277

$\boxed{V2 = V1 + (d1 + d2)/0.277}$ …. (c)

6. Working

Detecting the car using the detection algorithm in section 2 and using the data from section 3(Car in which direction?), section 4(Car distance from our car) and section 5(velocity of the car behind us)

1. Data from section 3 we conclude:

- If the car is in (left segment) OR (left and centre segment) then the car is to the right of the driver.
- If the car is in (centre) OR (centre and left and right segment) then it is exactly behind the driver.
- If the car is in (right segment) OR (right and centre segment) then the car is to the left of the driver.

2. Data from section 4 we conclude:

- The distance from our car at an instance.
- Distance of the car after every interval of 1sec.

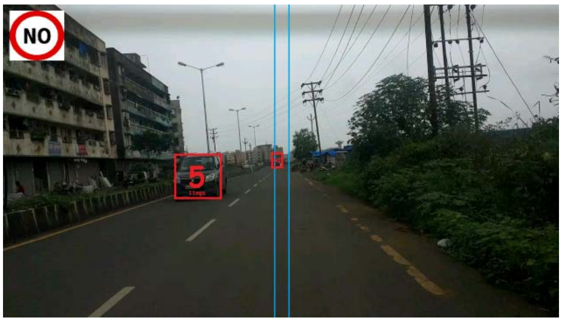
3. Data from section 5 we conclude:

- Velocity of car coming from behind.

Our system combines all this conclusion and we get the lane in which the car is approaching, the time it will take to reach our car which is calculated by:

Time for approach
=Distance (section 4)/Velocity (section 5)

Hence our system can assist the driver, if it is safe to change the lane based upon the maximum time to change the lane (threshold=5sec) and the time for approach.



If Time for approach <= to threshold, then the system does not allow the driver to change the lane.

7. Conclusion

In this paper, Lane Changing Assistance using Image Processing is presented for helping the driver to change the lane by using Camera frame segmentation. It will also calculate the Distance and velocity of the car behind from our car so the chances of accident due to human error will be reduced.

8. References

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