

Lane-Vehicle Detection and Tracking

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Abstract—This paper presents a monocular lane-vehicle detection and tracking system comprising of (i) lane boundary detection, (ii) lane region tracking, and (iii) vehicle detection with a proposed vertical asymmetry measurement. First, a traffic scene image is divided into possible road region. Lane boundaries are then extracted from the region using lane markings detection. These detected boundaries are tracked in consecutive video frames using a linear-parabolic tracking model. Therefore, an approximate lane region is constructed with the estimated model parameters. By integrating the knowledge of lane region with vehicle detection, vehicle scanning region is restricted to the road area so as to detect the shadow underneath a vehicle continuously with less interference from the road environment and non-vehicle structures. A self-adjusting bounding box is used to extract likely vehicle region for further verification. Besides horizontal symmetry detection, a vertical asymmetry measurement is proposed to validate the extracted region and to obtain the center of frontal vehicle. Preliminary simulation results revealed good performance of lane-vehicle detection and tracking system.

Index Terms— Driver assistance systems, Lane detection, Lane tracking, Vehicle detection.

I. INTRODUCTION

Advancement of vision-based vehicle detection has triggered recent development of autonomous vehicular technology in order to automatically localize moving vehicles in complex traffic scene. Generally, the main task of vision-based vehicle detection is to sense a leading vehicle and thus spontaneously alert a driver of precritical conditions with the preceding vehicle, in case he/she makes a sudden break, slowdown driving or uniform movement [1]. Moreover, vehicle detection can be developed to track and follow a preceding car, and at the same time increase the efficient use of driving space. In consequence, an effective visual scanning of frontal road conditions is highly required for vehicle detection system to identify the position of frontal vehicle.

Numerous vision-based techniques have been developed over the past decade to detect vehicles in various road scenes, as described in [1]-[11]. Tzomakas and Seelen [2] detected vehicles based on the shadows underneath them. With the use of entropy, a free driving space was determined and therefore, an adaptive threshold was applied to extract vehicle edges. Chang *et al.* [3] presented a preceding vehicle detection

and tracking system by finding the footprint of a vehicle on road area and tracking the vehicle using the continuity measurement of two consecutive frames. Kate *et al.* [4] combined the knowledge-based methods such as shadow detection, entropy analysis and horizontal symmetry measurement for mid-range and distant vehicle detection without prior knowledge about the road geometry.

Besides that, Khammari *et al.* [5] applied a horizontal Sobel filter on the 3rd level of the Gaussian pyramid to obtain local gradient maxima where a vehicle candidate is located. A temporal filter was used to further remove unwanted pixels and then a bounding box extraction was employed to retrieve a possible vehicle region for symmetry verification. Broggi *et al.* [6] presented a multi-resolution vehicle detection method to localize vehicles with variable sizes. They computed the symmetry property of vehicles in different sized bounding boxes on all the columns of the regions. Liu *et al.* [7][8] detected vehicle region based on the shadow underneath a vehicle and symmetry edges. Additionally, they combined knowledge-based and learning-based methods for vehicle verification. In vehicle tracking, templates were dynamically created on-line and tracking window was adaptively adjusted with motion estimation.

On the other hand, Hoffman [9] performed a multi-sensor fusion approach incorporating 2-D visual features such as shadow and symmetry, with 3-D ground plane information such as camera height for vehicle detection. These fusing features were tracked using Interacting Multiple Model method. Bertozzi and Broggi [10] used stereo vision-based method to detect both generic obstacles and lane positions in a structured environment. They utilized Inverse Perspective Mapping technique to remove perspective effect and reconstruct a 3-D mapping when the camera parameters and the knowledge about road are known. Giachetti *et al.* [11] developed first-order and second-order differential methods to detect vehicle based on the motion.

However, the presence of non-vehicle structures such as over-bridge, fly-over roadway, tunnel, buildings, sign boards etc, in traffic scene may decrease the performance of knowledge-based vehicle detection since these non-vehicle structures possess the horizontal/vertical characteristics identical to vehicle's edges [2]-[8]. Moreover, a complex road environment may complicate the process of vehicle detection as there are many possibilities of human activities along the road side [4]. Frontal vehicle with little relative motion change or stand still has increased the difficulty of vehicle detection based on motion flow [1][11]. Furthermore, the requirement of 3-D transformation and the knowledge of hardware parameters for stereo-based vehicle detection method have highly increased the computational cost and reduced the processing speed [9][10].

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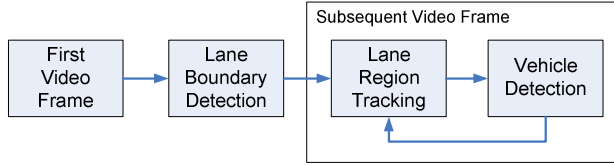


Fig. 1: Proposed lane-vehicle detection and tracking system.

To solve abovementioned problems, a novel monocular lane-vehicle detection and tracking system is proposed in this paper, as the flow diagram is depicted in Fig. 1. Lane boundary detection is performed on road image to locate the left-right lane edges by separating the sky-road region, and analyzing road region to extract the prominent road features such as lane markings. A linear-parabolic lane model without the requirement of camera parameters is constructed to estimate lane geometry. This is followed by lane region tracking to restrict the vehicle searching region on the ground for every continuous frame. As the vehicle region is bounded, vehicle detection based on the shadow underneath a vehicle is repeatedly performed in tracking lane region. In addition, a bounding box extraction method is used to obtain a likely vehicle region for further verification. Besides horizontal symmetry detection, a proposed vertical asymmetry measurement is applied to verify the extracted region and at the same time, the center of vehicle is found.

Section II discusses about the lane boundary detection while Section III explains the lane region tracking technique. The vehicle detection with proposed verification technique is discussed in Section IV. Some simulation results are shown in Section V and followed by conclusion and future works.

II. LANE BOUNDARY DETECTION

Lane boundary detection is important to locate the left-right edges of driving path on a traffic scene image. In this section, a three-stage lane boundary detection is performed, i.e. (i) vertical mean distribution, (ii) lane region analysis, and (iii) lane marking detection.

A. Vertical Mean Distribution

In lane detection process, sky region is not a region of interest (ROI). At the preliminary stage, a traffic scene image $I(x,y)$ is divided into sky region and road region using vertical mean distribution [12]. Vertical mean distribution is measured by averaging the gray values of each row on road image and the row means are plotted in the graph depicted in Fig. 2(a). The threshold value of horizon line is obtained through a minimum search along the vertical mean curve, where the first

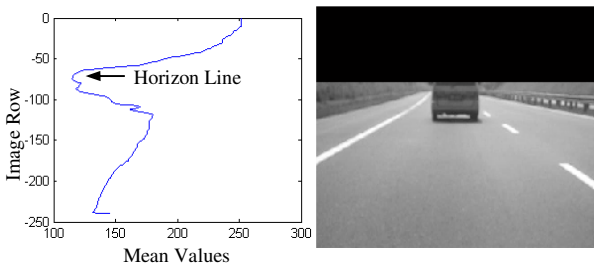


Fig. 2: (a) Vertical mean distribution, (b) Road region image (R_{roi}).

minimum occurs from the upper curve is the regional dividing line. This is because sky region usually possesses higher intensity than road pixels, and it might have a big jump of intensity difference as sky pixels approaches ground. The horizon line threshold is applied to generate a road image (R_{roi}) as demonstrated in Fig 2(b), where all vertical coordinates below the threshold are discarded.

B. Lane Region Analysis

Lane region analysis is performed to further classify road region and lane markings. Usually, the bottom region in a road image contains road pixels. By acquiring a few rows from the bottom of image, the gray value range of road color can easily be obtained and therefore, this color range is applied to further remove road pixels from the R_{roi} map. The lane region analysis steps are shown as follows:

- Step 1:** Pick 30-60 rows from bottom to avoid the possible existence of inner part of a vehicle at the edge of image.
- Step 2:** Build a vote scheme; namely *VOTE* for the selected rows and the maximum vote of the row pixels is recorded.
- Step 3:** Record a global maximum value for the selected rows, as *MAXTHRES*.
- Step 4:** Define the road color range as [*VOTE*-25; *MAXTHRES*+25]. Pixels that fall within this range are denoted as road pixels and a binary map (R_{bin}) is formed as shown in Fig. 3(a).
- Step 5:** Generate a difference map (D_{map}) by differencing R_{roi} and R_{bin} maps. The positive pixel values are retained while the negative values are set to zero. The difference map is illustrated in Fig. 3(b).

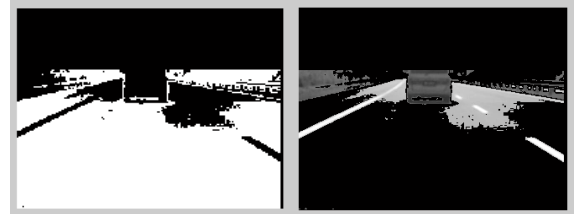


Fig. 3: (a) Lane binary map (R_{bin}), (b) Difference map (D_{map}).

C. Lane Marking Detection

The difference map obtained in the previous stage is, therefore used for lane marking detection. Lane markings are the salient features on road and they are usually used to extract the boundary of road region. Initially, an edge detection using Sobel filter is applied to D_{map} . The gradient magnitude $\nabla D_{map}(x,y)$ and orientation $\theta(x,y)$ are calculated in the following equations [13]:

$$|\nabla D_{map}(x,y)| \approx |D_x| + |D_y| \quad (1)$$

$$\theta(x,y) = \frac{1}{2} \tan^{-1} \left(\frac{\sum_{(u,v) \in R} 2D_x(u,v)D_y(u,v)}{\sum_{(u,v) \in R} (D_x^2(u,v) - D_y^2(u,v))} \right) \quad (2)$$

where u and v are the 3×3 mask coordinates. D_x is the horizontal edge map whereas D_y is the vertical edge map.

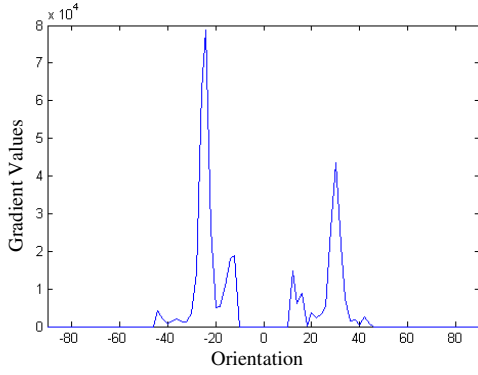


Fig. 4: The edge distribution function.

With reference to the constructed gradient map and its corresponding orientation, a histogram called edge distribution function [13] is build, with its x -axis representing the orientation ranging from $[-90^\circ; 90^\circ]$ and its y -axis representing the gradient value of each orientation bins. The maximum peak acquired in the graph on the negative angle denotes the left boundary angle. Conversely, the maximum peak at the positive region denotes the right boundary angle. Next, these angles are used to determine the weighted-gradient Hough Transform [13] for line construction. In the Hough Transform measurement, the lane's radius $r(\theta)$ is generated based on the following expression:

$$r(\theta) = x_o \cos \theta + y_o \sin \theta \quad (3)$$

where x_o and y_o are the coordinates corresponding to the angles $\theta(x_o, y_o)$ for both left and right lane boundaries. The voting bins for each radius are cumulated with the gradient edge values and the maximum vote is selected. Finally, the measured angles and radii are used to build the left-right lane boundary.

III. LANE REGION TRACKING

As illustrated in Fig. 5, the left right lane of interest (LOIs) is given and drawn in black lines up to sky-road dividing line with T_l -pixel thick where T_l is a varied width for the lane boundaries. These LOIs are lane masks used to obtain possible lane edges in continuous video frame. At this stage, a simple linear-parabolic tracking model proposed in [13]-[15] is used to construct tracked lane region. Initially, an image is split into near and far-field where y_m is the border between near and far-fields. A linear model is applied to follow the straight line in the near-field while a parabolic model is used to mimic the far-field lane border.

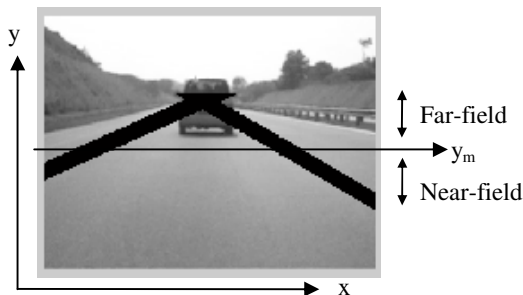


Fig. 5: Detected LOIs in road image

The left lane boundary model $f(y)$ is defined as [14]:

$$f(y) = \begin{cases} a + by, & \text{if } y > y_m \\ c + dy + ey^2, & \text{if } y \leq y_m \end{cases} \quad (4)$$

where $c = \frac{2a + y_m(b-d)}{2}$ and $e = \frac{b-d}{2y_m}$, which are acquired after the imposition of continuity and differentiability conditions on the function $f(y)$.

Let (x_{ni}, y_{ni}) and M_{ni} for $i = 1, \dots, m$, denote the m coordinates of the non-zero pixels of the edge image and its corresponding magnitudes in near-field. On the other hand, let (x_{fj}, y_{fj}) and M_{fj} for $j = 1, \dots, n$ represents the n coordinates and the n edge pixels in far-field. Subsequently, the expression in (4) can be rearranged into the $n+m$ formula below:

$$f(y) = \begin{cases} a + by_{ni} = x_{ni} & , i = 1 \dots m \\ \frac{2a + y_m(b-d)}{2} + dy_{fj} + \frac{(b-d)}{2y_m} y_{fj}^2 = x_{fj} & , j = 1 \dots n \end{cases} \quad (5)$$

The approximated solution can then be found by minimizing the error function as in (6).

$$E = \sum_{i=1}^m M_{ni} [x_{ni} - f(y_{ni})]^2 + \sum_{j=1}^n M_{fj} [x_{fj} - f(y_{fj})]^2 \quad (6)$$

The error is minimized when the following 3×3 linear system is solved:

$$A^T W A c = A^T W b \quad (7)$$

Where

$$A = \begin{bmatrix} 1 & y_{ni} & 0 \\ \vdots & \vdots & \vdots \\ 1 & y_{nm} & 0 \\ 1 \dots \frac{1}{2y_m} (y_{f1}^2 + y_m^2) \dots - \frac{1}{2y_m} (y_{f1} - y_m)^2 \\ \vdots & \vdots & \vdots \\ 1 \dots \frac{1}{2y_m} (y_{fn}^2 + y_m^2) \dots - \frac{1}{2y_m} (y_{fn} - y_m)^2 \end{bmatrix}$$

$$W = \text{diag}(M_{n1} \dots M_{nm} \dots M_{f1} \dots M_{fn})$$

$$c = [a, b, d]^T$$

$$b = [x_{n1}, \dots, x_{nm}, x_{f1}, \dots, x_{fn}]^T$$

Hence, the left boundary parameters are estimated and used to construct the left lane model. A similar operation is employed to the right boundary. After the tracking system is completed, the construction of lane region is needed to limit the vehicle detection boundary. The linear tracking model is applied to construct the lane region as demonstrated below:

$$LROI = \begin{cases} I(x, y) & , \text{if } x \geq a_r + b_r y \text{ \& } x \leq a_l + b_l y \\ 0 & , \text{if } \text{others} \end{cases} \quad (8)$$

where (a_l, b_l) and (a_r, b_r) are the estimated parameters for left and right linear lane models while $I(x, y)$ denotes the original image. The detected lane region of interest (LROI) is used to restrict the vehicle searching area, which largely reduces the computational time.

IV. VEHICLE DETECTION

After the retrieval of the lane region from the lane region tracking in Section III, the system proceeds to vehicle detection in order to locate the position of frontal vehicles. Three stages are needed in identifying a vehicle: (i) shadow detection, (ii) bounding box extraction and (iii) proposed verification.

A. Shadow Detection

The LROI produced in previous section is used to detect the shadow underneath a vehicle. At first, a gradient edge transformation is applied to the LROI image with a certain edge threshold as the binary image is shown in Fig. 6(a). The remaining region might be a shadow or some noise produced by lane edges. Further steps are taken to remove the noise. A group of connected pixels which has more than T_2 pixels in horizontal is defined as the possible shadow region where T_2 denotes as the threshold value for shadow detection. Therefore, this process removes the pixels connectivity that is less than T_2 pixels remaining those possible pixels that are larger than T_2 pixels and those remaining pixels are defined as pixels of interests (POIs), as depicted in Fig. 6(b).

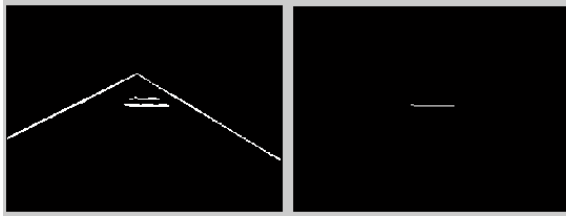


Fig. 6: (a) Shadow detection, (b) POIs after noise filtering

B. Bounding Box Extraction

Vehicle verification is an important process in order to test the detected region whether it is vehicle or non-vehicle. First, an extracting box is used to determine the vehicle's ROI, where the POIs exist. Since the bottom pixels of possible vehicle's shadow are detected, the height from the detected shadow pixels to the top image is calculated as H_{pix} while the image height is defined as H_{img} . So the ratio of the image is calculated as follows:

$$V_{ratio} = \frac{H_{pix}}{H_{img}} \quad (9)$$



Fig. 7: Vehicle's ROI after the adaptive bounding box extraction.

The ratio has the advantage that, if the car is at far-field, the ratio is smaller and if the car is getting nearer, the ratio becomes larger. This adaptive ratio is then multiplied with a threshold (T_3) to obtain the possible vehicle ROI's height and width for evaluation, as depicted in Fig. 7.

C. Proposed Verification

For further verification of vehicle's ROI, symmetry detection is performed horizontally and followed by the vertical symmetry detection. The horizontal grayscale symmetry axis can be found in [3] with the formula below:

$$HS(j) = \sum_{j=X_l}^{X_l+W} \sum_{i=Y_h}^{Y_h+H} \sum_{\Delta x=1}^{W/2} |G(i, j+\Delta x) - G(i, j-\Delta x)| \quad (10)$$

$$j_{sym} = \arg \min HS(j)$$

where $HS(j)$ is the horizontal symmetry measurement with the symmetry axis located at $x=j$. As illustrated in Fig. 8, the horizontal symmetry axis of the possible vehicle region occurs at the local minimum where the point $x = 31$.

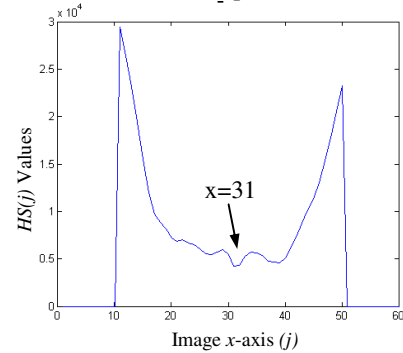


Fig. 8: The horizontal symmetry measurement.

The same idea is applied on the vertical asymmetry detection with some modifications. Instead of analyzing the grayscale symmetry, the vehicle region is turned into an edge difference map by differencing all the columns to its first column of the possible ROI and the difference map formula is defined as follows:

$$VS(i) = \sum_{i=Y_h}^{Y_h+H} \sum_{j=X_l}^{X_l+W} |G(i, j) - G(i, 1)| \quad (11)$$

$$i_{sym} = \arg \max VS(i)$$

where $VS(i)$ is the vertical asymmetry measure with the asymmetry axis located at $y=i$.

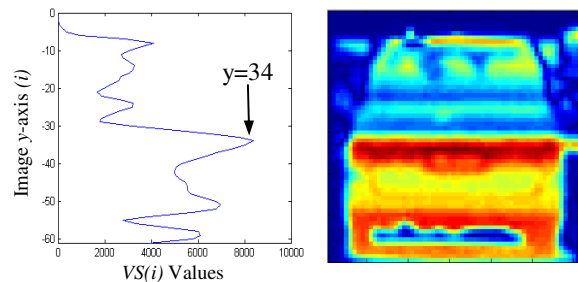


Fig. 9: (a) Vertical asymmetry measurement, (b) Vehicle's difference map.

As illustrated in Fig. 9(b), the color distribution at the center row has the largest intensity compared to others due to the great dissimilarity of vehicle's region to surrounding environment. The sum of each row is plotted on the graph, and at the same time, the global maximum in the graph is selected as the vertical asymmetry axis. As depicted in Fig. 9(a), the peak occurs at the center of vehicle region where the vehicle center is largely differentiated to others at the point $y = 34$. Finally, the results of symmetry and asymmetry axes are plotted on the vehicle's ROI as shown in Fig. 10. The center of vehicle can easily be obtained after the horizontal symmetry and vertical asymmetry analysis and it can be extended for vehicle tracking.

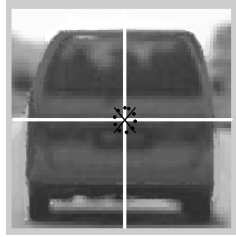


Fig. 10: Detected vehicle regions with symmetrical and asymmetrical axes.

V. SIMULATION RESULTS

All results were generated using Matlab 2006b with the Core 2 Duo processor at 1.8GHz with 1GB RAM. A video sequence was captured under sunny day condition at around 12 p.m. in a highway environment using Canon IXUS 65. The first image, as depicted in Fig. 11(a), was used for the lane boundary detection while the consecutive 12 video samples showed in Fig. 12 and Fig. 13 were used for the evaluation of lane tracking model and the vehicle detection. Initial values of the following parameters, $T_1 = T_2 = 8$ and $T_3 = 100$ were set in these experiments.

The application of lane detection on road image is a critical step since it determines the results and performance of the following stages - lane tracking and vehicle detection. The detection results demonstrated in Fig. 11(a) retrieved the driving path successfully in frontal view. The detected lane boundaries were therefore used to estimate the left-right LOIs in the next step. Some other lane detection results were demonstrated in Fig. 11(b) & (c) (obtained from WWW.) and left-right lane boundaries were expected in the images.

The employment of previously detected lane outputs on the

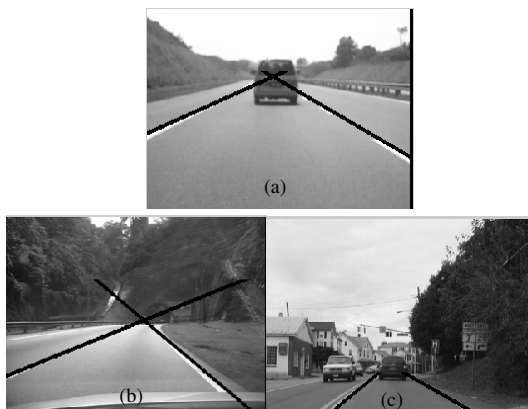


Fig. 11: The result of lane detection (a) for the first sample of video frame, (b) before tunnel, (c) in city.

first frame has activated the lane tracking process. The purpose of lane tracking system is to predict the possible lane model based on the detection result in order to reduce the computational cost in a video frame. The linear-parabolic lane model was applied to the video sequence. As a result, the lane tracking algorithm extracted the lane region successfully, as depicted in Fig. 12. However, the lane tracking method was only an estimation using a lane model and it could not follow the path exactly. As we could observe in Fig. 12(b)-(g), the lane boundary was slightly above the lane markings, but at this stage, road region was of interest since it was used to restrict the vehicle searching region. With this knowledge of lane region, the presence of vehicle could be detected in continuous frames.

After the lane region was obtained and tracked for every frame, vehicle searching area was limited to ground area because vehicles were always found on the roadway. This greatly reduced frontal vehicle scanning time and removed noises that looked similar to be the priori knowledge of vehicle regions such as horizontal/vertical structures of buildings and edges. As demonstrated in Fig. 13, the vehicle region was successfully detected in every frame and each frame indicated the vehicle region with a self-adjusting bounding box. The drawing of a box is based on an adjustable image ratio and it was always well fitted to the vehicle region. At the same time, the horizontal symmetry and vertical asymmetry measurement described in Section IV were analyzed for vehicle verification. The intersection of horizontal symmetry axis and vertical asymmetry axis denoted as the vehicle's center. Every video frame obtained the center of vehicle correctly with the symmetry analysis except for the Fig. 13(i).

VI. CONCLUSION

A monocular lane-vehicle detection and tracking system has been presented in this paper with an integration of three components, i.e. (i) lane boundary detection, (ii) lane region tracking, and (iii) vehicle detection with a proposed vertical asymmetry measurement. The advantages of lane-vehicle detection and tracking system are, (i) the reduction of vehicle searching time, and (ii) the increase performance of the vehicle detection based on the priori knowledge regardless to the environmental interference caused by non-vehicle structures and sky region. At the same time, lane detection and tracking system without any camera parameter can be applied to other driver assistance function for the determination of ROIs. Furthermore, horizontal symmetry analysis with an assistance of vertical asymmetry analysis can easily obtain the center part of vehicle and this center point can be used for vehicle tracking in future. In the future, further investigation will be carried out on lane-vehicle detection and tracking system under various road conditions.

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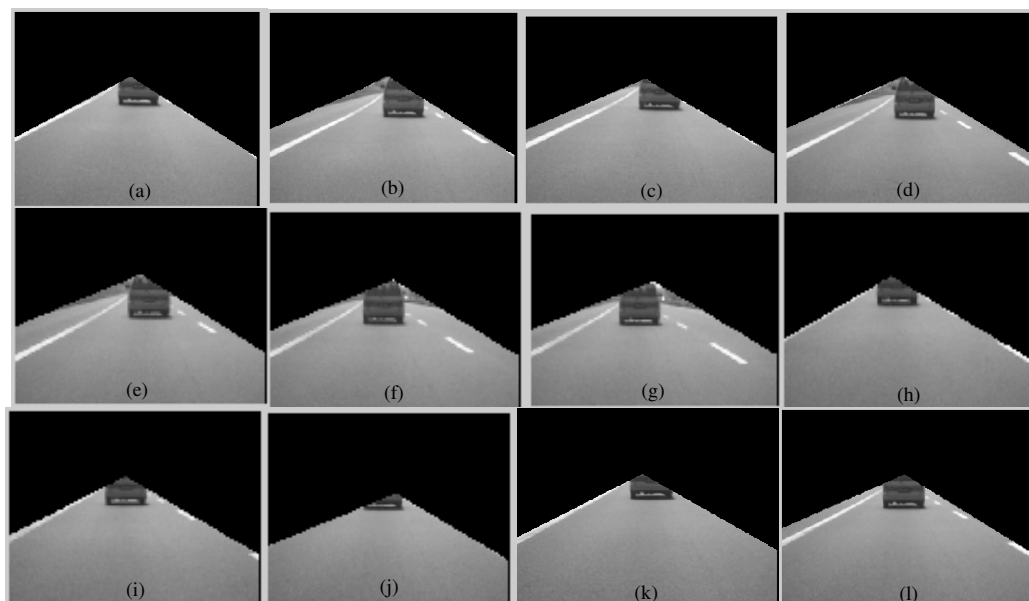


Fig. 12: Lane region tracking results in frame sequences.

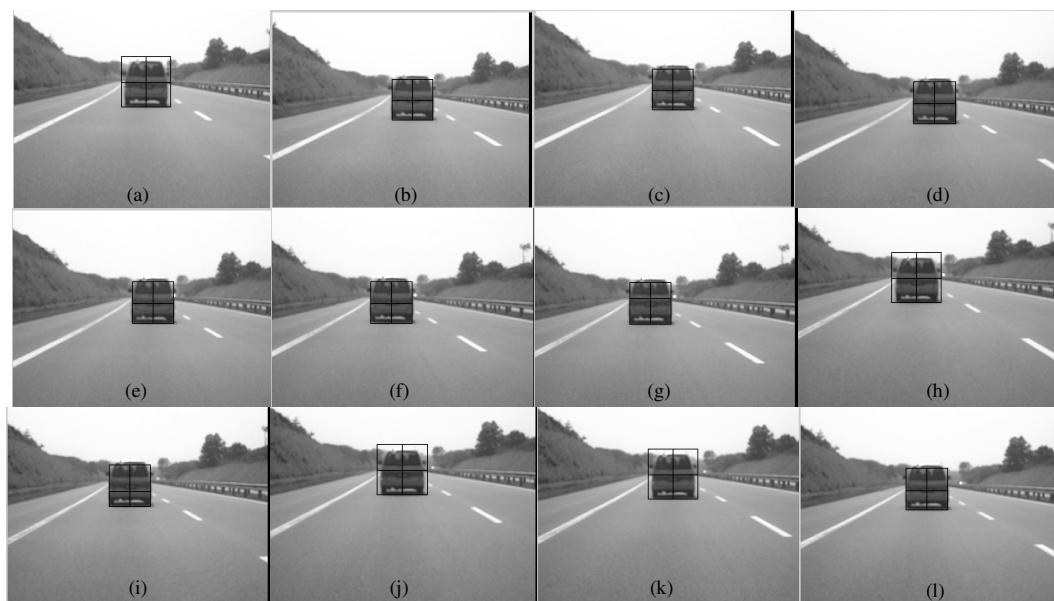


Fig. 13: Vehicle detection results in frame sequences.