Integrated Vehicle and Lane Detection with Distance Estimation

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Abstract. In this paper, we propose an integrated system that combines vehicle detection, lane detection, and vehicle distance estimation in a collaborative manner. Adaptive search windows for vehicles provide constraints on the width between lanes. By exploiting the constraints, the search space for lane detection can be efficiently reduced. We employ local patch constraints for lane detection to improve the reliability of lane detection. Moreover, it is challenging to estimate the vehicle distance from images/videos captured form monocular camera in real time. In our approach, we utilize lane marker with the associated 3D constraint to estimate the camera pose and the distances to frontal vehicles. Experimental results on real videos show that the proposed system is robust and accurate in terms of vehicle and lane detection and vehicle distance estimation.

1 Introduction

The goal of Advanced Driver Assistance Systems (ADAS) is to improve traffic safety and reduce the number of road accidents. A considerable amount of research efforts on improving automotive safety with automotive vision technologies have been reported. In recent years, vision-based driving assistance systems have received more and more attentions for their low cost and capability of providing information about driving environments. In these systems, robust and reliable vehicle and lane detection is a critical step, and the detected vehicles can be used for various applications, including autonomous cruise control system, lane departure warning system, and forward collision warning systems. These applications usually require applying different techniques in computer vision, such as object detection, line detection and distance estimation. However, most of these basic tasks for ADAS were developed individually. However, the information from different tasks in ADAS can be integrated in a collaborative manner. For instance, the width of two lanes is always larger than the width of vehicle. Otherwise, lane markers should follow a specific pattern according to government rules and this pattern is very useful for vehicle distance estimation. For the reasons, we propose an integrated system that combines vehicle detection, lane detection, and distance estimation altogether in a collaborative manner in this paper.

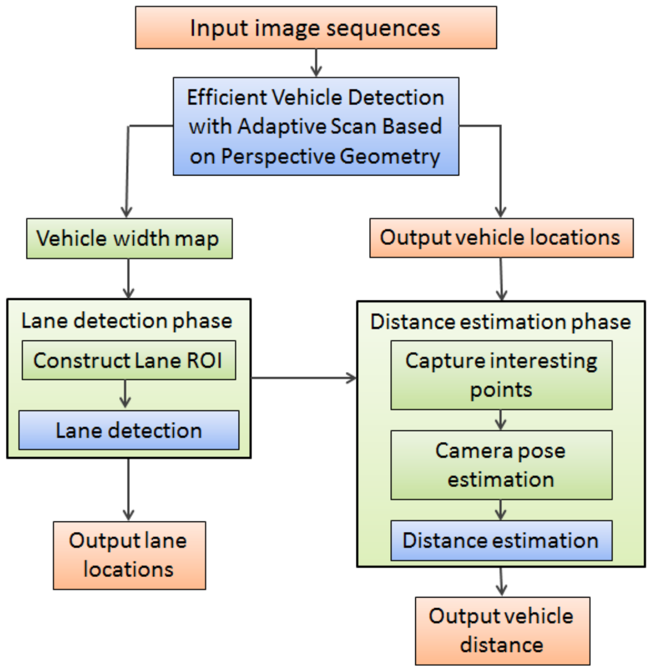

Fig. 1. The flowchart of the proposed system.

In recent years, some research groups utilized additional hardware, such as infrared or radar sensors, to capture additional depth information for the ADAS systems. Without doubt, using the additional depth information can improve the performance of distance estimation and vehicle detection. However, it requires additional cost. Vehicle video recorders have been popularly used to record the video of the frontal scene from the driver's viewpoint. Currently, it is mainly used to provide evidence for car accident. However, it potentially can be used as an ADAS that provides warning to the driver. Therefore, we focus on developing the vision-based ADAS with input videos of traffic scene acquired from a monocular camera mounted on vehicle. The system is able to detect lanes and vehicles, and estimate distances between the vehicles and the camera. In the field of vehicle detection for ADAS, reducing search space based on perspective geometry of the road is efficient to reduce the computation cost. Vehicle width model, a search space reduction manner, was proposed in [1], and our vehicle detection is also based on the same strategy. More details can be found in [1].

Lane detection from images does not seem to be a complicated problem. Tradition methods usually used Canny edge detection and Hough transform to find straight lines. Unfortunately, noisy or misleading edges frequently appear in traffic scenes. For example, shadows, buildings, or traffic signs could degrade the accuracy. On the other hands, Region of Interest (ROI) for lane detection and tracking is also effective to alleviate the problem. Our proposed lane detection method utilizes vehicle width model to reasonably set the ROI of lane. Otherwise, in order to enhance lane detection, we use patch identification to compute the associated confidence. Experiment results show that the proposed method improves the quality by reasonable ROI and patch identification. Distance estimation from road images acquired from a camera mounted in the vehicle is very challenging. Previous works on vehicle distance estimation normally require perform a camera calibration process in advance. Kosecka and Zhang [2]showed that vanishing points can be found automatically and they can be used to estimate the camera intrinsic parameters. Moreno-Noguer et al. [3] proposed to estimate the camera pose from some interesting points detected from an image with their real 3D world coordinates when the intrinsic parameters are given. In this paper, we combine the above two related works, namely, the estimation of intrinsic parameters from vanishing points and 3D camera pose estimation, in an automatic way for vehicle distance estimation. The proposed distance estimation algorithm does not require any human intervention, camera calibration or pose measurement before the distance estimation process. Fig. 1 illustrates the flowchart of the proposed system. The main contribution of this paper is that we construct an integrated ADAS which contains vehicle detection, lane detection and distance estimation in a collaborative manner. The proposed ADAS system can detect vehicles and lanes, and it can estimate vehicle distance from a single road image. Our experimental results also show the proposed vehicle detection with adaptive search strategy based on perspective road geometry is superior to the standard sliding-window search in terms of both speed and accuracy. Our Lane detection is also quite robust under different situations, including complex background. The proposed distance estimation is accomplished from a single road image via 3D pose estimation with the 2D-3D point correspondences extracted from the anchor points in the lane pattern.

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The rest of this paper is organized as follows. In Section 2,the related recent works on vehicle detection, lane detection, and distance estimation in traffic scenes are reviewed. In Section 3, we describe the proposed algorithms for lane and vehicle detection. The vehicle distance estimation algorithm is described in Section 4. In Section 5, we show some experimental results and quantitative

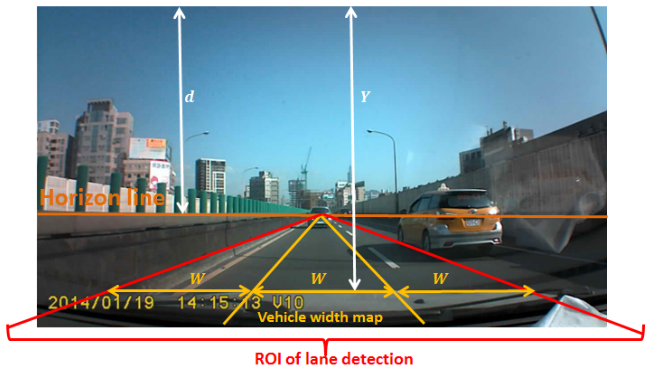

Fig. 2. An example illustrates the relation between vehicle width map and ROI for lane detection. In real traffic scene, the distance between adjacent lanes is always between 2 to 3 times of vehicle width.

evaluation to demonstrate the superior performance of the proposed method. Section 6 concludes this paper.

2 Related work

In the vision-based ADAS, the camera is mounted on the vehicle to capture road images. It is very challenging to detect vehicle in images, due to the wide variations of vehicles in colors, sizes, views and shapes appeared in images. Various feature extraction methods have been used for vehicle detection, such as Gabor filters [4], and HOG [5]. In these methods, SVM or Adaboost are used as the classifiers for the vehicle detectors. In order to reduce computational cost in vehicle detection, several approaches have been proposed [5–7, 1].

Lane detection plays a very important role in ADAS. Detecting lanes from images usually is based on the analysis of edges extracted from images. Unfortunately, there are quite a lot of disturbing edges appeared in traffic scenes, such as vehicles, buildings, traffic signs, shadow, or skid marks. Therefore, lane detection by using traditional straight line detection techniques is prone to errors for real traffic scenes. Some approaches [8, 9] first enhance images with some enhancement filters first and then apply inverse perspective mapping, which transforms images into bird's-eye view images, followed by detecting straight lines on the mapped images. Nevertheless, when lanes are occluded by vehicles, the performance is usually degraded. The determination of the inverse perspective mapping is also a problem, because road images may be acquired by different cameras on different vehicles with different poses. There are some lane detection methods based on using motion information to find the vanishing points and then select the edges that intersect at the vanishing point as the target lanes. Zhou et al. [10] utilized the lane detection result from the previous frame and updated the lane

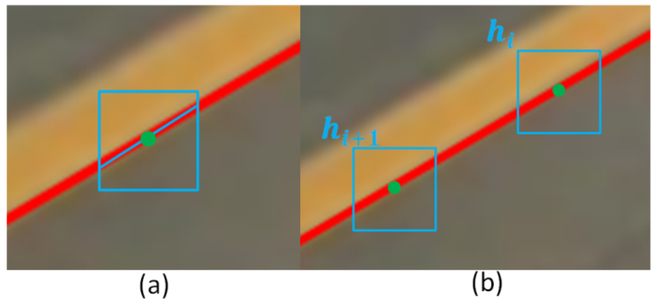

Fig. 3. (a) Patch bisection characteristics and (b) patch similarity characterris-tics for lane detection

detection within a given range. However, the width of lane varies considerably under different image acquisition situations and the tracking range should be different. In [11], they set the ROI empirically. It is not applicable for general cases.

Distance estimation from a single image is very challenging in general. In [12], some samples with known distance and vehicle width in image are used to train a distance estimation model. However, this learning-based approach is very restricted for practical use since the testing and learning data should be acquired under the same setting. If the pose of camera changes or the testing data is captured by a different camera, it would need another setting or new training data to train a new model to overcome this problem. Muller et al. [13] utilized stereo cameras to estimate the distance. But, it requires additional cost in the hardware as well as the computation for stereo matching. Dagan et al. [14] proposed to estimate the vehicle distance by using the relation between the velocity of the camera, which is mounted on a moving vehicle, and the change of width of frontal vehicles in a short period of time. The method works under the assumptions that the velocity of the vehicle is given and the camera is calibrated. In [15], the authors proposed to measure the height and the pose of camera first, and then estimate the vehicle distance assuming the focal length is given. However, it is not easy to measure the pose of the camera mounted in the vehicle in practice. Therefore, automatic distance estimation from a single image is particularly important. Subsequently, we will describe the proposed algorithms for lane detection and distance estimation in the next section.

3 Vehicle and lane detection

3.1 Vehicle detection

In our previous work [1], we proposed a vehicle width model for search space reduction in vehicle detection based on using the perspective geometry in a road image. It is under the assumption that vehicles are on the same ground plane

Algorithm 1 Patch Identification

Input:Each candidate H, patch size SxS pixels, divided into N patch
Output:The confidence of candidate H
Initial:$D \leftarrow 0$
Average select N patches h_1, h_2, K, h_N with size SxS, as in Fig. 3(a), on H .
Foreach $i \leftarrow 1, 2, ..., N$
  $D \leftarrow D+$ Difference(left part, right part), see Fig. 3(b)
End foreach **Foreach** $j \leftarrow 1, 2, ..., N-1$
  $D \leftarrow D+$ Similarity(h_i, $h_(i+1)$), see Fig. 3(a)
End foreach
Confidence = D

and vehicles have the same width. Therefore, the width of vehicles on different y-coordinate in image has the following linear relationship:

$$W = a(Y - d) \tag{1}$$

where W is the vehicle width in an image, a is the parameter that controls the increment of vehicle width, and d is horizon line illustrated in Fig. 2. It is an HOG-based vehicle detection, and the SVM with RBF kernel is chosen to be the classifier.

The system first detects vehicles by a sliding-window search for a few frames, and then it selects a number of pairs of positive detection results with its y-coordinate location and width in the image to estimate the parameters a and d in Eq 1. Finally, the system constructs an adaptive search window strategy based on this linear prediction model. In comparison with the sliding-window search, the adaptive window strategy is more efficient and provides higher accuracy. More details of the efficient vehicle detector can be found in [1].

3.2 Lane detection

For most cases, the distance between adjacent lanes is usually fixed and given. As we can see in Fig. 2, W is the vehicle width in Eq. 1; the red region which contains the left and right lanes is 3 times the vehicle width. For the reason, we construct an ROI for lane detection based on vehicle width. Thus, Canny edge detection and Hough transform are employed to find edges in the ROI. All line segments in the ROI are extended to the horizon and the bottom of the image and then considered as lane candidates. If two lane candidates are very close to each other in the image, then they are merged into one. Since there are several noisy and misleading line segments detected from the road image, such as brake marks or traffic sign, we propose a patch-based identification technique for the lane detection. The patch-based identification is developed based on the characteristic of lanes in images for selecting the correct lanes from the candidates. The detailed patch-based identification is described in the following.

Lane candidates are divided into two sets based on the slope sign computed from the image, because the slopes of two frontal lanes in the images are usually

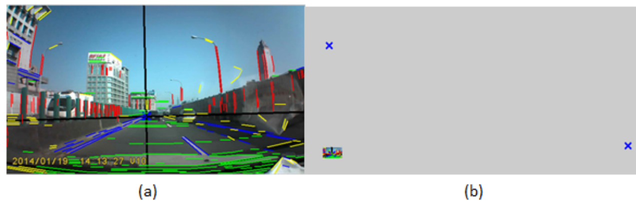

Fig. 4. (a) Detected line segments for three directions. (b) Estimated vani-shing points for three directions.

opposite for road scenes under normal camera settings. For each set $L = l_i$, where l_i are lane candidates, we apply patch identification to determine the confidence for each candidate as follows:

$$c_i = pi(l_i), l_i \in L \tag{2}$$

where Pi is the patch identification function described in Algorithm 1. If the lane candidate is correct, it should have the following two characteristics: First, the left part and right part of each patch (e.g. Fig. 3(a)) are quite different, and the two patches along the line located with a fixed distance (e.g. Fig. 3(b)) are similar to each other. Based on the above two characteristics, we can select the lanes with the highest patch identification score, i.e. the confidence value c_i, from all candidates. The above selection process is performed individually for the two sets of candidate lanes with positive and negative slopes, respectively.

In most situations, the lanes for the positive and negative slopes can be found. Nevertheless, when the lanes are blurred or the driver makes a turn to change lane, the lane detection may fail sometimes. Thus, we take the average of the lane width from the lane detection results in the previous frames. The average lane width can be used in the following cases. If both the positive-slope and negative-slope lanes cannot be identified, the system would preserve the lane detection result from the previous frame. If only one of the positive-slope and negative-slope lanes can be found, the system would use the average lane width to estimate the other lane.

4 Vehicle distance estimation from a single image

In this section, we describe our algorithm for vehicle distance estimation from only a single road image. Our algorithm does not need to calibrate camera or measure the camera pose in advance. We first detect the three vanishing points estimation from an image and estimate the focal length from these vanishing points by using the algorithm by Kosecka and Zhang [2]. We apply this algorithm on the first few frames to estimate the focal length. Fig. 4 depicts an image of the vanishing point detection results.

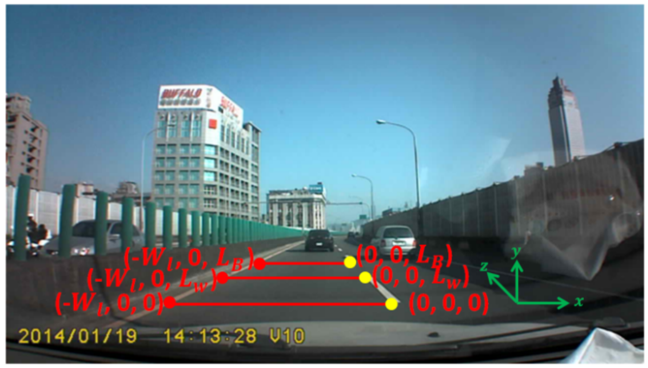

Fig. 5. The anchor points are used to estimate the camera pose.

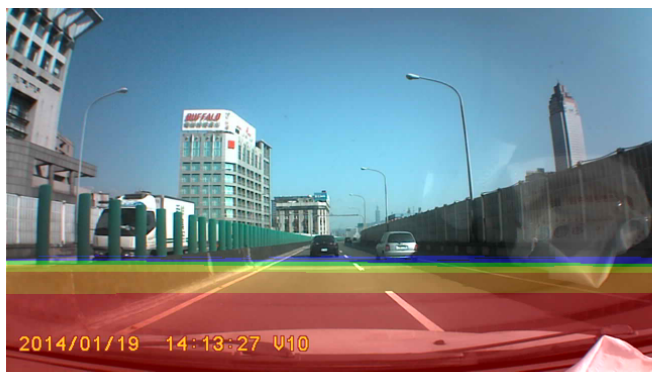

Fig. 6. An example of distance map computed for this image. Each region corresponds to a distance range.

In this work, we assume that the principle point is located at the image center and the image distortion is not considered. With the estimated focal length, we have the camera calibration matrix K. Then, we can estimate the camera pose from 6 2D-3D corresponding points, i.e. image coordinates and associated 3D world coordinates, by the 3D pose estimation method [3]. In the proposed method, we detect the anchor points along the dash lanes (e.g. Fig. 5, yellow points) by using the template matching method. The other three points are the corresponding points on the other lane (e.g. Fig. 5, red points), with known lane width W_1 (approximately 3.75 m) in 3D world distance. The 3D word coordinates of these six points can be determined according to the fixed lane pattern from the local traffic regulation. Therefore, we can estimate the camera pose, i.e. rotation matrix R and translation vector T, from the six pairs of point correspondences. We combine them into the projection matrix M.

When the system detects a vehicle with the middle bottom of the window located at (u, v) in image coordinate, we can use M to estimate the position of the car in real world coordinate (X, Y, Z) . Because we assume the vehicle be located on the road plane, Y is 0 at all times. Thus, we have

$$s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = M \begin{bmatrix} X \\ 0 \\ Z \\ 1 \end{bmatrix} \tag{3}$$

The three unknowns X, Z, and s can be easily computed by solving Eq. 4. We determine the distance between the real world coordinate of the vehicle and the translation of camera T in the z-coordinate to be the frontal vehicle distance.

$$\begin{bmatrix} m_{11} & m_{13} & -u \\ m_{21} & m_{23} & -v \\ m_{31} & m_{33} & -1 \end{bmatrix} \begin{bmatrix} X \\ Z \\ s \end{bmatrix} = - \begin{bmatrix} m_{14} \\ m_{24} \\ m_{34} \end{bmatrix} \tag{4}$$

Sometimes, shadows or lane occlusion by frontal vehicles may cause false results in detecting the lane anchor points. In order to reduce the false distance estimation, we construct a distance map for each frame by computing the distance at each pixel below the horizon line (see as Fig. 6), and take the average of the distance maps from previous frames and use it when false distance estimation is detected.

5 Experimental Results

In our experiment, we evaluate the performance of the proposed method on several image sequences captured by us by using a monocular vehicle video recorder. The sequences were acquired under different situations, as described in Table 1. TP-Day1 video does not contain changing lane situations, and there is no shadow effect. TP-Day2 video is more challenging, because it contains changing lane and shadows of builds on the road. Shadows make the intensity of lane in the images more difficultly to detect. TP-Day3 video contains some hills, and it potentially can cause problems for lane detection, because hills will change the locations of the vanishing points. Therefore, the methods based on vanishing points may cause unpredictable problems. The ground-truth lanes are labelled manually, and the lane detection results are correct when the distance between the ground-truth lane and the detected lane computed at horizon line and the bottom of image is smaller than a threshold.

We compare our lane detection method with the vanishing- point-based method [10]. Furthermore, we apply the vanishing point-based method within the same ROI to improve their lane detection performance. Table 1 shows that the lane detection within ROI significantly improves the detection accuracy, because it reduces some unreliable edges. Our lane detection algorithm dramatically outperforms the vanishing-point-based method [10] with and without using ROI on these three road videos of different situations. This proves the proposed

Fig. 7. It illustrates how the ground truth of distance estimation is obtained. The images are acquired from a vehicle video recorder. There are markers placed at 4, 6, 8, K, 18 m away along the side lane.

Table 1. THE accuracy of lane detection under three different conditions

Data	**frames**	**Situation**	**Acc. of [10]**	**Acc. of [10] with ROI**	**Acc. of ours**
TP-DAY1	500	No shadow, no changing lane	0.758	0.832	0.952
TP-DAY2	2160	Shadow, changing lane	0.690	0.784	0.835
TP-DAY3	605	Rugged, no changing lane	0.603	0.711	0.921

patch-based identification approach is quite robust for lane detection under different road conditions. For vehicle distance estimation, we fix the camera in the car for capturing our testing data, and the ground truth of distance estimation can be obtained by using some markers placed along the side lane, finding them in the image, and computing the distances at different locations in the image. Fig. 7 illustrates how the ground truth is obtained. Fig. 8 shows the accuracy of distance estimation at different distances by using the proposed 3D pose estimation method. In this work, we focus on the distance lower than 20 m in our experiments. The distance estimation results are compared with the ground truth distances. As expected, the farther the distance of the frontal vehicle is, the larger the distance estimation error is. Since we usually pay more attention to near vehicles during driving, the performance characteristics of the proposed

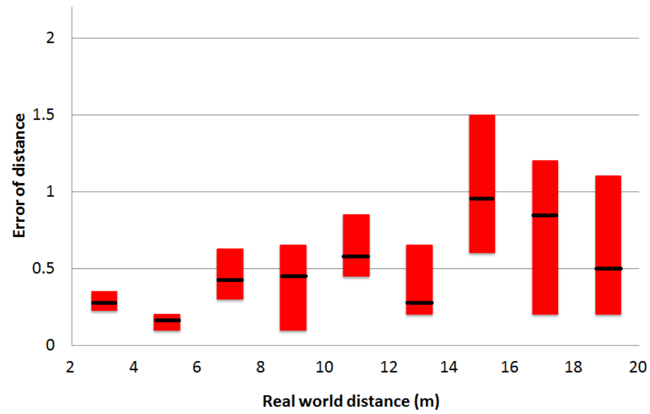

Fig. 8. Distance estimation result. The error is smaller than 2 m in all testing data, and the error is lower when the frontal vehicle is closer to the camera.

distance estimation algorithm is quite effective to assist drivers to obtain more information of frontal vehicles.

For the integrated ADAS system, we combine the vehicle detection, lane detection, and distance estimation in a collaborative manner. Vehicle width model is used to constrain the region of lane detection with an appropriate ROI. After we detect lanes, the anchor points along the lanes can be easily found and used for vehicle distance estimation. This combination not only reduces the cost of the pre-processing in each part of the system, but also improves the accuracy and Fig. 9 depicts some sample results of our ADAS for each sequence in each row. The results of lane detection are quite good, and the errors of distance estimation are lower than 1 m in average.

6 Conclusion

In this paper, we proposed an efficient advanced driver assistance system that combines vehicle detection, lane detection, and distance estimation. The information of each part can be used to improve the performance for another part. The proposed ADAS can be applied for different data captured from different cameras with different camera poses. The proposed system can detect lanes as well as vehicles and then estimate the distances of the detected vehicles from a single image. Therefore, the proposed approach can be widely used in general conditions. For the future work, it is practical to implement the ADAS on a multi-core platform, such as GPU, to achieve real-time performance. In addition, converting the real-time ADAS system into a program running on a mobile computing platform, such as a smart phone, is very convenient for drivers to improve driving safety.

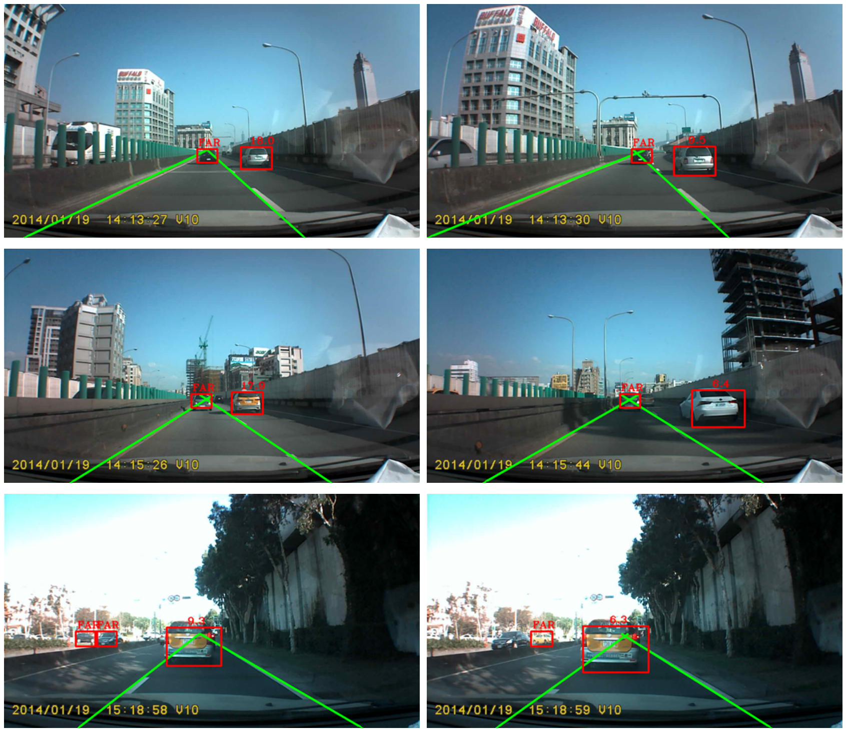

Fig. 9. Sample frames of the ADAS, each row for each sequence.

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