A Real-Time Rear Obstacle Detection System Based On a Fish-Eye Camera

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Abstract—**This paper proposes a rear vision camera-based vehicle detection system which could detect if any rear vehicle exists in ego lane and if any vehicles in adjacent lanes are overtaking. The source image is firstly applied with distortion calibration which helps the following Hough transform to detect the existence of lane lines. The rear vehicle in ego lane is detected by a combination of feature-based approach and appearance-based approach. When a vehicle in adjacent lane is overtaking, the vanishing of its symmetry makes itself very difficult to be detected. Therefore, we propose a new detection algorithm applying corner detection and motion vector whose calculation are based on Local Binary Pattern (LBP) to find if any vehicles in adjacent lanes are overtaking. Our proposed algorithm achieves high detecting rate and low computing power and is successfully implemented in ADI-BF561 600MHz dual core DSP.**

I. INTRODUCTION

According to the statistics from NFTSA, in U.S, 31% of vehicle accidents are due to rear-end collision. A typical scenario is that the in-between distance of the vehicles within the same lane is too close. Rear vision camera becomes more and more popular since it could let drivers directly see if any potential obstacles exist during backing. Actually, it could also be utilized when drivers are driving in highway to enhance safety. Lane departure warning system, which was proposed for a long time, is able to use the image source from rear vision camera. With the help of lane detection result, it is possible to detect if any rear vehicle exists in ego lane and if any vehicles in adjacent lanes are overtaking.

The most common approach to detect vehicle is to use active sensors such as lasers or millimeter-wave radars. Active safety system employing active sensors have shown promising results; however, such sensors are still very expensive. Passive sensors, such as cameras, offer a more affordable solution and can be used to detect vehicles and analyze their behavior. Moreover, visual information is very plentiful and is easy to be utilized in a number of related applications such as lane detection, traffic sign recognition, or object identification (e.g., pedestrians, motorcycles or bicycles).

Several factors make on-road vehicle detection very challenging. The landscape along the road continuously changes while the lighting conditions depend on the time of the day, and the weather. Vehicles' appearance varies in shape, size, and color in image. Moreover, nearby objects may cast shadows or reflect light. Finally, such system always requires real-time processing which makes implementation very difficult.

Both the rear vehicle in ego-lane and the overtaking vehicles in adjacent lanes could be detected even if the image source is from the rear vision camera. There is a great deal of previous researches on front vehicle detection and tracking. The two main steps are 1) to generate vehicle candidates by feature-based approach where the locations of them in an image are obtained by symmetry, vertical edge and horizontal edge calculation [1] [2] and 2) to verify vehicle candidates by appearance-based approach where vehicle features are firstly enhanced, and then classified by a pre-trained classifier. Such detection paradigm is applied by many researchers [3][4][5].

In this paper, the rear vehicle in ego-lane is detected by feature-based approach and verified by appearance-based approach. However, the vehicles in adjacent lanes lose its strong symmetry and vertical edges during overtaking. Therefore, only relative motion could be robustly detected. The lane lines provide a strong determination basis to define the ROI of the rear vehicle in ego-lane and the ones of the rear overtaking vehicles in adjacent lane.

The organization of this paper is as follows. Section II introduces the overview of our system. Section III discusses the distortion calibration of the fish-eye lenses. Section IV describes the algorithm to detect the vehicle in ego-lane. Section V describes the relative motion estimation based on corner detection and motion vector whose calculation are based on Local Binary Pattern (LBP). In section VI, some experimental results of our system are presented. Finally, this paper ends with a brief conclusion.

II. SYETEM OVERVIEW

Our system is implemented in two ADI-BF561 600MHz dual core DSP-based embedded system. In Fig. 1, distortion calibration is firstly applied. The detection of the lane lines being implemented via our previous research [6], the rear vehicle in ego-lane and the overtaking vehicles in adjacent lanes are all based on an undistorted image. The rear vehicle candidates in ego-lane are detected by Sum of Absolute Difference (SAD) and Sobel edge detector. Then, wavelet transform and Support Vector Machine (SVM) are used to verify the vehicle candidates. Moreover, LBP is used to enhance the characteristic of the image for the motion estimation of the overtaking vehicles. The overtaking behavior is detected via corner detection and motion vector.

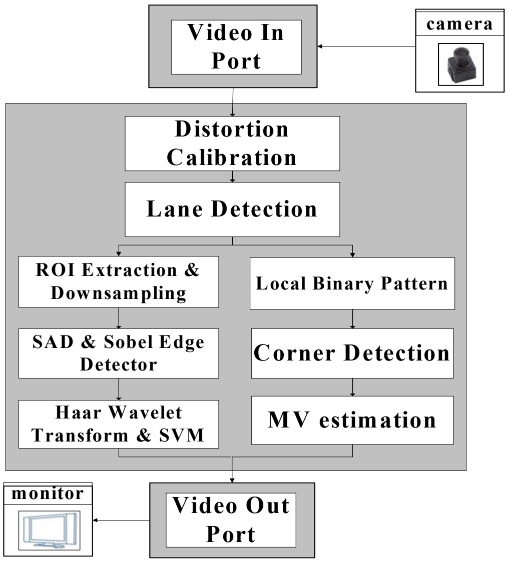
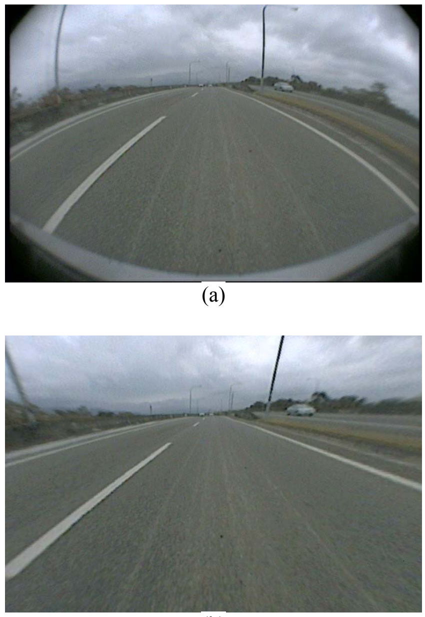


Fig. 1 System overview

III. DISTORTION CALIBRATION

In order to let drivers observe if any obstacles exist on the path of backing, fish-eye lens, which provide visual information as much as possible, are mostly adopted. However, distortion inevitably occurs due to wide field-of-view lens. In order to detect the vehicles in ego-lane, distortion calibration is essential since the strong vertical edges could be straightened. Many distortion calibration toolbox is proposed from literature. In our application, the offline distortion calibration is done by an open source library [7] provided by OpenCV. Fig. 2(a) and Fig. 2(b) are the distorted image and the undistorted image respectively.



(a)

(b)

Fig. 2 (a) distorted image (b) undistorted image

IV. REAR VEHICLE DETECTION

In our proposed algorithm, the rear vehicle candidates are firstly generated by feature-based approach and then verified by appearance-based approach. Feature-based vehicle detection is to detect object, which possesses edge, symmetry and shadow features with default vehicle size inside image. After distortion calibration is performed, the vehicle in the image will possess strong vertical boundaries which are distinct to road. The estimation of the SAD could estimate both the vertical edge and the symmetry of vehicles.

The SAD(x,y) is defined as

$$\frac{\sum_{h_t=1}^{H_t(x,y)} \sum_{w_t=1}^{W_t(x,y)/2} \left| G(x-w_t, y-h_t) - G(x+w_t, y-h_t) \right|}{H_t(x,y) \times W_t(x,y)} . \qquad (1)$$

where G(x,y) is the gray-level of (x,y); H_t and W_t denote the default height and width of the square frame of (x,y). If the results from SAD, and the horizontal edge image using Sobel horizontal edge detector are combined, the vehicle candidate can be located as shown in Fig. 3.

Fig. 3 The result after applying SAD and Sobel edge detector

Once any vehicle candidate is obtained, it will be verified by the appearance-based approach which involves both feature extraction and classifier training operation to distinguish the vehicle candidate as vehicle or nonvehicle. Here, we adopt wavelet features and SVM which are proposed by [8] for verification. Moreover, the Haar wavelet coefficients are suggested to be quantized based on an observation that the actual values of the wavelet coefficients might not be so important. The experimental result in the literature proves that such simplification is more efficient. The SVM training tool that we adopt is LIBSVM [9] which is free, popular and extensively used to solve many practical classification problems.

V. OVERTAKING VEHICLE DETECTION

The vehicles in adjacent lanes generally lose their strong vertical edges and symmetry. Therefore, it is difficult to detect them when they remain static. However, overtaking behavior would be comparatively obvious to be detected. Here, the detection of the overtaking vehicles is implemented by firstly calculating LBP of each pixel and then applying corner detection and motion vector estimation.

LBP was proposed in [13] for the first time. The standard version of the LBP of a pixel is performed by thresholding the 3X3 neighboring pixels with the center pixel. Fig. 4 illustrates the basic LBP operation. If the gray level of center pixel is greater than one of the surrounding pixels, the corresponding bit is set to 1. Other bits will be set to 0 if the corresponding pixels are smaller than the center one. Finally, all the results are combined to get an 8 bit value.

After each pixel is processed by LBP, LBP(x,y) will be compared with its surroundings including LBP(x,y-3), LBP(x+1,y-3), LBP(x+2,y-2), LBP(x+3,y-1), LBP(x+3,y), LBP(x+3,y+1), LBP(x+2,y+2), LBP(x+1,y+3), LBP(x,y+3), LBP(x-1,y+3), LBP(x-2,y+2), LBP(x-3,y+1), LBP(x-3,y), LBP(x-3,y-1), LBP(x-2,y-2) and LBP(x-1,y-3) as shown in Fig. 5. If over 9 successive LBP of surrounding pixels possess difference over default degree with the center one-LBP(x,y), LBP(x,y) will be considered as a corner. Here, the difference is calculated based on Hamming distance.

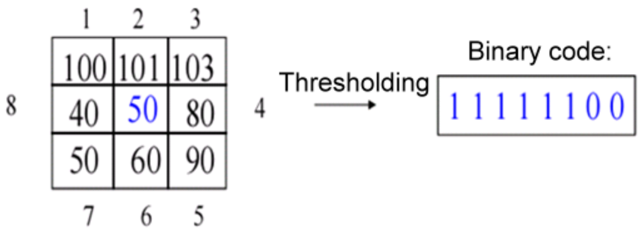


Fig. 4 Illustration of LBP operator

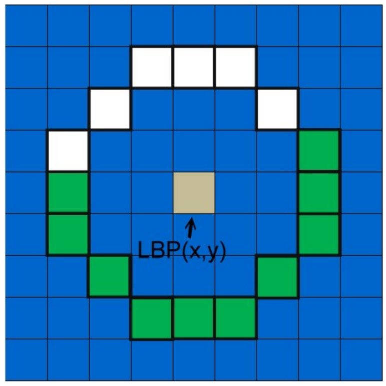


Fig. 5 Corner Detection based on LBP

When LBP(x,y) is considered as corner at frame i, its motion will be determined by performing block matching. Considering the fact that the movement of a corner in any frame-pair is mostly small, the motion vector is estimated by performing block matching around its neighboring pixels as shown in Fig. 6.

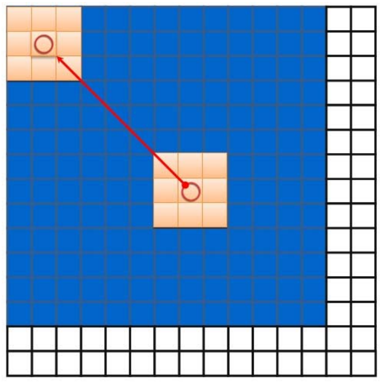


Fig. 6 Block matching for estimating Motion Vector

VI. EXPERIMENTAL RESULTS

The processing time of lane detection, rear vehicle detection and overtaking vehicle detection are all within 33ms and this meets the need of real-time operations. The whole system is used to continuously monitor the traffic scenes at the driving speed over 60km/hr. i.e., the whole system will only activate at highway. The size of each frame of grabbed image sequences is 720 pixels by 480 pixels per frame. Our proposed algorithm is capable of detecting a variety of vehicle type (sedan, van, jeep…etc) as shown in Fig. 7, Fig. 8 and Fig. 9. When the overtaking vehicles in adjacent lanes are detected, the yellow square will indicate that such behavior is happening as shown in Fig. 10 and Fig. 11.

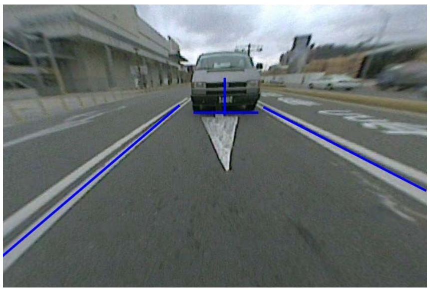


Fig. 7 A detected sedan

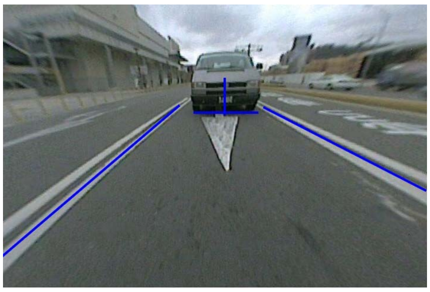


Fig. 8 A detected van

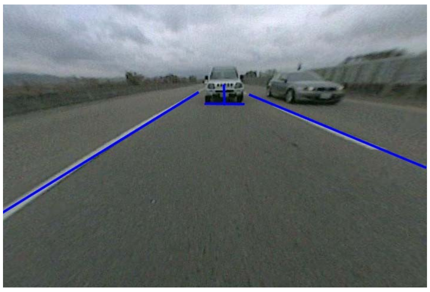


Fig. 9 A detected jeep

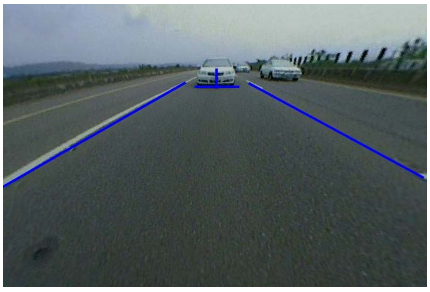


Fig. 10 A vehicle before overtaking

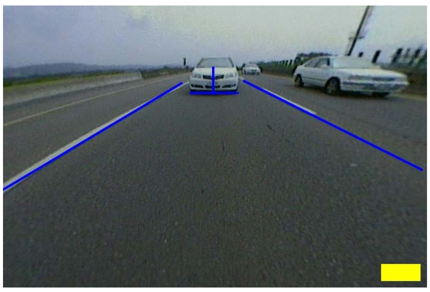


Fig. 11 An overtaking vehicle

VII. CONCLUSION

In this paper, we have proposed a new system which could simultaneously detect the rear vehicle in ego-lane and the overtaking vehicles in adjacent lanes. Not only the driving safety is enhanced but also an added value is given to the rear vision camera. The proposed algorithm can effectively satisfy the demand of real-time processing with 30 frames per second. The detection accuracy is already acceptable for being popularized in vehicle industry. In the future, we will try to develop weather-adapted algorithm which is capable of functioning robustly under severe weather such as heavy rain or dense fog.

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