

A Blind-Zone Detection Method Using a Fisheye Camera with Combination of Vehicle Detection

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ABSTRACT This paper proposes a novel approach for detecting and tracking vehicles to the rear and in the blind zone of a vehicle, using a single rear-mounted fisheye camera and multiple detection algorithms. A maneuver that is a significant cause of accidents involves a target vehicle approaching the host vehicle from the rear and overtaking into the adjacent lane. As the overtaking vehicle moves toward the edge of the image and into the blind zone, the view of the vehicle gradually changes from a front view to a side view. Furthermore, the effects of fisheye distortion are at their most pronounced toward the extremities of the image, rendering detection of a target vehicle entering the blind zone even more difficult. The proposed system employs an AdaBoost classifier at distances of 10–40 m between the host and target vehicles. For detection at short distances where the view of a target vehicle has changed to a side view and the AdaBoost classifier is less effective, identification of vehicle wheels is proposed. Two methods of wheel detection are employed: at distances between 5 and 15 m, a novel algorithm entitled wheel arch contour detection (WACD) is presented, and for distances less than 5 m, Hough circle detection provides reliable wheel detection. A testing framework is also presented, which categorizes detection performance as a function of distance between host and target vehicles. Experimental results indicate that the proposed method results in a detection rate of greater than 93% in the critical range (blind zone) of the host.

KEYWORDS: Vehicle detection, automotive machine vision, contour detection, Hough circles, Harris corner detection, optical flow, Kalman filter, test framework.

I. INTRODUCTION

ACCORDING to a study by the National Highway Traffic and Safety Administration (NHTSA), lane change maneuvers accounted for 9% of vehicle collisions in the United States in 2007. In 2009, a study carried out by the same organization noted that, “The lane-change task requires drivers to divide their attention between monitoring the forward roadway, their surroundings, steering the vehicle, regulating the vehicle’s speed, and using the turn signal.” It concluded that “Drivers who are pressed to change lanes may exhibit degraded performance in one or more of these subtasks”. In a study by the Royal Society for the Prevention of Accidents (ROSPA), overtaking maneuvers accounted for 6% of all fatal accidents in Britain in 2007.

A blind-zone of a vehicle can be described as “areas around the vehicle that cannot be seen directly by the driver by looking forwards or by using any of the vehicle’s standard rear-view mirrors (internal and external) from the normal sitting position”. (The term blind-zone is used here rather than blind-spot, as the term is used to describe an area up to 10 meters long and 3 meters wide rather than a single spot.) Existing blind-zone monitors involve the placement of either radar or camera sensors on the wing mirrors or at the rear of the vehicle and they indicate to the driver (via an audio warning or a warning light on the rear view mirror) if a vehicle enters the blind-zone of the host vehicle. Radar-based examples of blind-zone monitoring include Audi Side Assist, and Infiniti’s Blind Spot Warning.

However, detection issues have been associated with radar- based systems such as guardrails being falsely identified as vehicles . Radar-based systems provide a high degree of accuracy in detecting longitudinal motion, however lateral movement of vehicles with respect to a sensor in applica- tions such as blind-zone detection can yield inconsistent re- sults . This is evident in situations such as when the overtaking vehicle changes lanes with respect to the host vehicle. Camera-based blind-zone monitoring systems are being increasingly used either as a stand-alone technology or to com- plement radar. Cameras offer significant advantages to radar systems such as more accurate capturing of lateral motion, higher resolution and lower unit costs. One example of this is Volvo's Blind Spot Information System . The use of camera-based systems in vehicles has also increased for other applications such as parking assistance , lane departure warning and traffic sign recognition. Additional functionality can be added to existing camera systems for a minimal incremental cost.

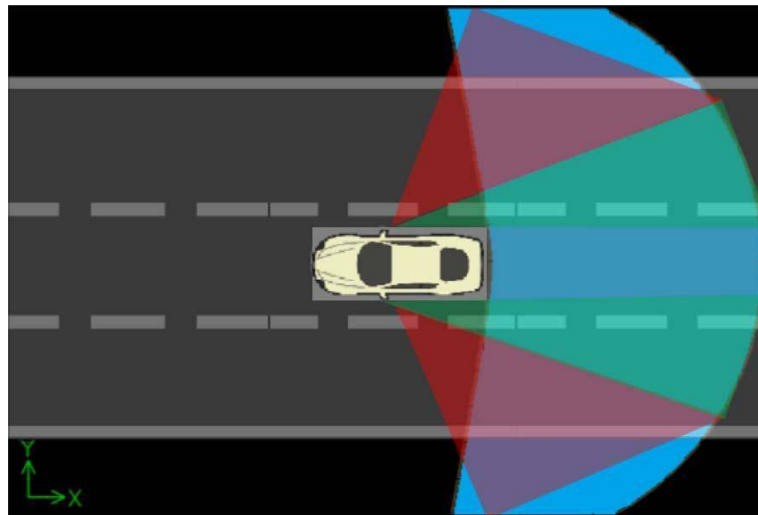


Fig. 1. Visible zones, blind zones and field of view of a rear-mounted fisheye camera. Blind zones are highlighted in red with the visible range of the rear view mirrors indicated in green. The field of view of the rear mounted fisheye camera is shown in blue.

II. VEHICLE DETECTION AND DISTANCE DETERMINATION

A. ADABOOST CLASSIFICATION

This section describes the AdaBoost classification technique used to detect the front-of-vehicle at distances between 10 and 40 meters. To assist in the development, training and testing of the AdaBoost classifier, a database of video footage was collected from a vehicle on the road. The camera used for this database was mounted on the outside of the rear of the vehicle so that it had a clear view of the road to the rear and to the sides of the vehicle. The resolution of the camera was 1280×800 pixels. The camera also featured a fisheye lens with a lateral field of view (FOV) greater than 180° , enabling both rearward blind-zones to be adequately covered by a single camera. Over 60 000 images of vehicles as viewed from the rear of the host vehicle were annotated, and a further 40 000 “negative” annotations consisting of images not containing a vehicle were also added to the data set. The features used to construct weak classifiers are a derivative of “control points” method by Abramson and Steux [62] known as “connected control points”. Arbitrary points are divided into two sets, positive and negative.

These features are favored for their robustness to illumination changes (as shown in low-light performance below) and their low computational overhead, enabling real time performance. The connected control points method applies an additional constraint in that control points must touch another by at least one corner in order to be considered as a feature. These points, produced during training are provided as “weak-learners” to AdaBoost, forming a strong classifier as described in [15]. If a vehicle has been detected using this method during system operation, the target is encapsulated by a bounding box

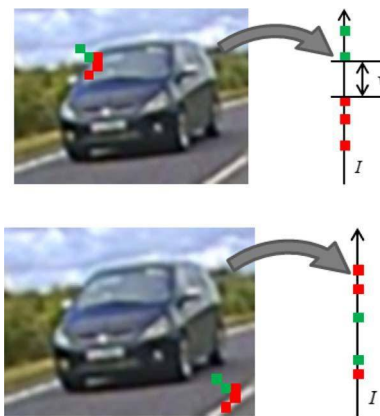


Fig. 2. (a) Positively-classified example with respect to threshold V and (b) negatively-classified example.

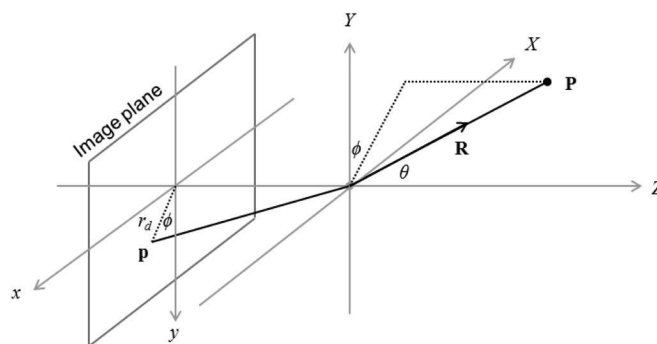


Fig. 3. Projection in fisheye camera.

B .POSITION AND DISTANCE DETERMINATION

To determine the position of the detected vehicle in the real world, the fisheye camera calibration parameters must be calculated. We use the equidistant model, as follows.

$$r_d = f\theta$$

C. LIMITATIONS OF CLASSIFICATION WITH FISHEYE

Cameras

This classifier enables detection at relative distances of up to 40 meters between host and target vehicles. However, as the vehicle approaches in an adjacent lane, i.e., during an overtaking maneuver, classification starts to fail. The reasons for this are threefold: First, the view of the vehicle changes significantly depending on whether a target vehicle is located in the blind-zone or at a large distance. Secondly, the curved nature of the fish-eye lens distorts the view of the vehicle as it tends toward the edge of the image. Finally, resolution of the image is also lower in heavily distorted regions of the image. This results in a large region of non-detection of an overtaking vehicle from approximately 0 to 7 meters rearward from the host vehicle. This region lies directly in the vehicle's blind-zone.

This problem could be addressed by training the AdaBoost classifiers to include views of target vehicles from all possible positions. However, as can be seen from Figs. 4 and 5, the view of the vehicle can vary significantly depending on the position of a target vehicle with respect to the camera.

As the vehicle approaches the edge of the frame, the view of a target vehicle is of the side, rather than the front, of the vehicle. Additionally, the effect of the fisheye lens distorts the view of the vehicle, and this effect becomes more pronounced as the vehicle moves to the periphery of the image. The resolution of the image is also lower at the periphery than at the center of the image due to the effects of distortion.

It is infeasible to train AdaBoost to detect in the edge regions because of the wide range of variability in views of a target vehicle. This would require a very significant increase in database size to cater for the range of views possible and it would also reduce the robustness of the system by increasing false positive detection while also increasing computational requirements.

Therefore, this paper proposes that the AdaBoost vehicle detection method is augmented by other detection methods that avail of features other than the front of the vehicle that are visible as the vehicle moves to the extrema of the image, specifically the wheels and wheel arches.



Fig. 4. View from fisheye camera mounted at the rear of a BMW X5 with AdaBoost detection of an approaching vehicle encapsulated in the red bounding box



Fig. 5. Vehicle positioned at the edge of the image

III WHEEL DETECTION: HOUGH DETECTION

As a target vehicle moves from the rear toward the extremities of the field of view of the camera, the vehicle's wheels appear less eccentric and more circular. Hence, circle detection using the Hough Circle Transform as outlined in is used for wheel detection. The Hough Circle Transform is based on the Generalized Hough Transform used to detect lines and curves in an image. Initially, an ROI corresponding to the wheel detection region is passed through a Canny edge detection phase. In this phase, the computed gradient lies between an upper and lower pixel gradient threshold (described in part B). For every pixel corresponding to an edge in the resulting binary image, the slope is considered relative to adjacent edge pixels using Sobel derivatives. A two dimensional accumulator is used to record each pixel co-ordinate corresponding to the line indicated by the slope. Candidate centers of a potential circle are selected based on the x and y pixel co-ordinates that have the highest occurrence in the accumulator (this is based on the assumption that a predefined threshold of required occurrences has been exceeded, further described in Part B). Once a circle has been detected, a bounding box corresponding to this circle is superimposed on the image,



Fig. 6. Detection of front and rear wheels at edge of the image using the Hough Circle Transform.

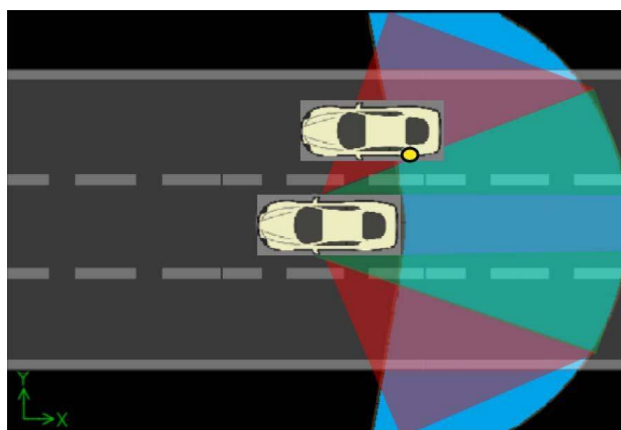


Fig. 7. Detection of rear wheel of a target vehicle with respect to the host vehicle in the context of visible-zones, blind-zones as well as the field-of-view of the rear-mounted fisheye camera.

IV. WHEEL ARCH CONTOUR DETECTION (WACD)

The AdaBoost classifier-based algorithm described in Section III was evaluated in conjunction with the Hough Circle Transform on test video of overtaking maneuvers. It was noted during this testing that, as expected, AdaBoost classification began to fail as the vehicle moved toward the edge of the image. However,

in the region in which the AdaBoost algorithm started to fail, the wheel appeared elliptical rather than circular in the image, due to the perspective effect. The result is that Hough Circle detection encountered difficulties detecting wheels located in this region. To bridge this gap in detection, a novel method of detecting wheels at distance was required. Hence, a new detection algorithm (WACD) has been developed. The algorithm operates by initially passing the ROI generated by AdaBoost into a Canny edge detection algorithm once the tracked vehicle reaches the point at which AdaBoost is known to start experiencing difficulties. Fig. 10 shows an example ROI, after Canny edge detection has been applied. The presence of a wheel can now be determined by the detection of a triangular shaped contour in the ROI. This is carried out by calculation of the deviations between adjacent vertices of the contour.

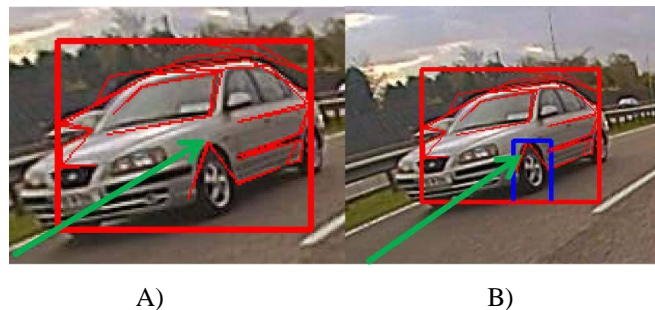


Fig. 8. (a) The Douglas-Peucker algorithm applied to contours within the ROI defined by the AdaBoost algorithm. Green arrow indicates contour of interest. Following processing of the contour, the wheel is located (b). The vertices of the polygon centered on the wheel arch are used to delimit the wheel bounding box (green arrow).

V. VEHICLE TRACKING

Previous sections have discussed the detection of vehicles at distance using AdaBoost, and detection at closer range using Hough Circle detection and wheel arch detection using a new approach. Both of these approaches operate at the level of individual frames, therefore, in order to increase robustness against occasional front-of-vehicle and wheel detection failures, and to increase computational efficiency, the front of a target vehicle, and front and rear wheels are tracked using a combination of Harris corner and optical flow algorithms. When an initial detection occurs, a tracking structure is created containing the dimensions of the bounding box, type of object detected (front of vehicle, front or rear wheel) and the method of detection (AdaBoost, Hough, Contour). Harris Corner detection is applied to extract a set of features (corners) that correspond to the most significant points of interest within the bounding box. These points are further refined using subpixel corner locations according to the method outlined. The detected features from the previous frame are matched with features detected in the current frame using optical flow. The vector deviation of all matched points is calculated and the bounding box is adjusted according to this deviation. Fig. 13 shows examples of matched points for both front of vehicle and rear wheel. method is used based on the Kalman filter. The Kalman filter uses previous positional measurements to form a Gaussian model with mean and standard deviation of future position. An overall object confidence metric (CO) is also maintained for each detected vehicle to indicate whether the vehicle is still present in the image or not. The metric is initialized as soon as detection is confirmed by the AdaBoost algorithm for an approaching vehicle to the rear. This confidence metric is incremented with each detection instance and decremented when frame-based detection or optical flow tracking fails, and the Kalman filter is required.

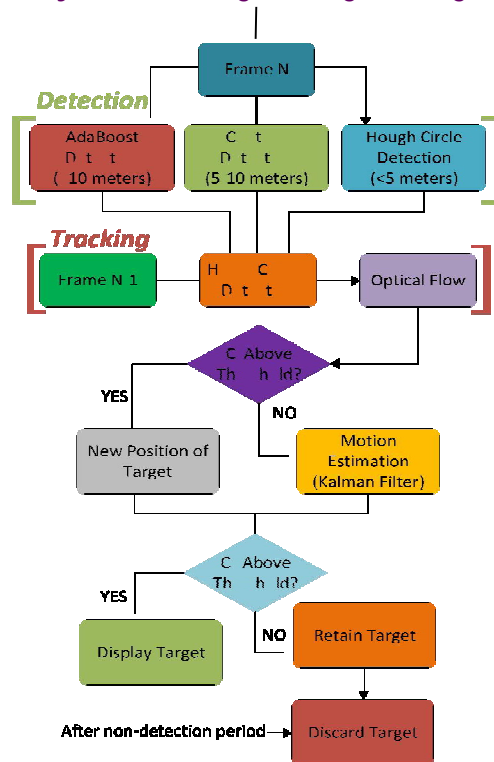


Fig. 9 Summary of operation of all detection and tracking algorithms.

Thresholds/Parameters

The key parameters that affect tracking are the inputs to the Harris Corner and Optical Flow algorithms. Harris Corner calculates the autocorrelation matrix of the second derivative images over a small window around each point. By Harris’s definition, corners are areas in the images where two large eigenvalues are returned, corresponding to a large gradient in two directions.

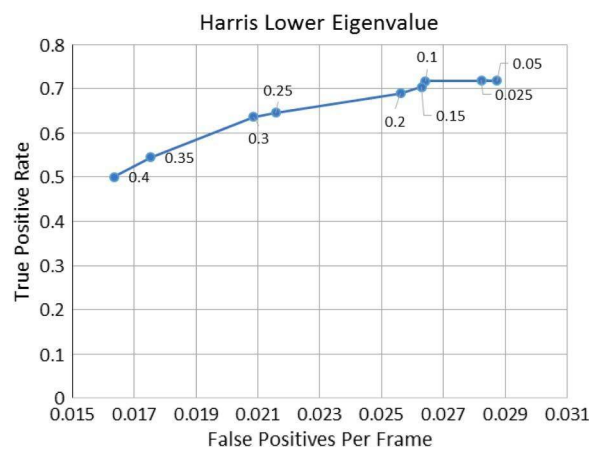


Fig. 15. Effect of changing Harris Corner Tracking Lower Eigenvalue on TP and FPPF across entire AdaBoost range.

The effect of changing this parameter is shown in Fig. 15. The value of the lower eigenvalue is selected at

0.1 since this delivers the best TPR to FPPF ratio. The primary threshold that determines performance in the Optical Flow calculation operates in a very similar way. It is based on the special gradient matrix proposed by Bouget. The minimum eigenvalue calculated using this method is used as a threshold below which points are discarded. This removes points which do not appear to match the points selected using the Harris method in the previous frame. Fig. 16 illustrates that based on our testing, there is little improvement in True Positive Rates for an error threshold beyond 200. Hence, this value is used, since a higher value impinges on computational effort as more points require tracking.

VI. CONCLUSION

This paper has proposed a novel approach for detecting and tracking multiple vehicles at the rear of a vehicle using a single rear-facing fisheye camera. Detection is achieved at distances of between 15 and 40 meters using an AdaBoost classifier trained on a database of annotated images, based on the front-view of target vehicles. Limitations in the AdaBoost method become apparent as vehicles move toward the edge of the image when approaching from the rear in an overtaking maneuver. The paper has addressed this through the use of wheel detection using the Hough Circle Transform and a novel contour-based detection method entitled WACD designed to detect wheel arches. Each method has been extensively tested using a testing framework which evaluates the true positive rate and false positives per frame of each detection methodology as a function of distance from the rear of the vehicle. Moreover, the test data used in this paper are particularly challenging due to the fact that significant radial distortion is present owing to the use of a fisheye lens. The system is particularly useful in situations where vehicles approaching from the rear move into the host vehicle blind-zone, a situation that is a significant cause of collisions, where the combination of multiple algorithms provides better performance than each algorithm individually, as evidenced by the high true positive rates, and low false positives per frame. The proposed system provides robust vision-based blind-zone detection while only requiring a single camera. This allows for the implementation of other ADAS systems such as RCW, Parking Assistance and Lane Departure Warning without requiring additional hardware. Through the use of additional temporal analysis e.g., derivatives, the relative velocity between host vehicle and approaching target vehicle may be calculated.

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