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A Single Camera Based Rear Obstacle Detection System

Zhang Yankun, Hong Chuyang, Weyrich, Norman

Abstract*—This paper presents a rear obstacle detection system by using a single rear view camera. The system can detect various static and moving obstacles behind the cars. An efficient hierarchical detecting strategy is used to achieve high detection rate and low false positives. The temporal Inverse perspective mapping difference image based coarse detection is used to estimate whether there are obstacles in the predetermined warning area at first stage. Then a novel integral image based segmentation algorithm is developed for fine obstacle segmentation. Finally, the blob analysis is utilized for obstacle representation and verification. Our system achieves 94.2% detection rate and 16% false positives rate on 125 challenging video sequences. The average processing speed of the system is 25fps on a standard laptop.

I. Introduction

With the rapid increasing number of cars in modern world, the number of casualties caused by backing crashes is increasing. Automotive safety is a big concern for consumers around the world and car manufacturers are looking for innovative ways to improve their cars. Many car manufacturers propose rear obstacle detection system for backing up or parking assistance on their cars. This rear obstacle detection systems offer one way of decreasing the risk of accidents by using radar, ultrasonic sensors or camera to monitor the proximity of objects to the car.

The choice of using camera based video system in stead of radar or ultrasonic devices stems from the fact that the driver can see directly the image and can understand what caused the alarm. Rear view cameras based obstacle detection systems have the greatest potential to provide drivers with reliable assistance in identifying obstacles near the car when backing. There are more and more research works about cameras based rear obstacle detection in recent years [1][2][3][4][5].

A robust method for close-range obstacle detection with arbitrarily aligned stereo cameras is presented in [6]. The method based on stereo inverse perspective mapping. Obstacle detection is using the differences between left and right images after transformation phase and with a polar histogram analysis. The system achieves good performance in various environmental conditions.

Stereo vision based methods achieve good performance. But they need two cameras, which require extra costs and space.

In [2], a monocular 3D vision system for obstacles detection is presented. This system uses a single wide angle rear camera and odometry sensors. The odometry sensors are used to get vehicle displacement and epipolar geometry. The feature points detection and matching along epipolar lines. Then structure from motion principle based 3D reconstruction is used for obstacle identification. In [3], an automatic free parking space detection system uses a single camera based structure from motion method for obstacle detection. It doesn't use odometry sensors. The metric information is recovered from the camera height ratio.

Guanglin Ma et all.[4] proposed a rear-view camera based obstacles detection algorithm for backup aid and parking assist applications. It uses three independent methods for obstacles detection and fuses the methods for final detecting. The free-space detection algorithm identifies the road area. The edge-based detection algorithm identifies the vertical or near-vertical edges above the ground plane. The motion (their car motion parameter obtained from CAN bus) based algorithm identifies any moving object.

The work in [4] has some limits. The first limit is it assumes the road boundaries are always in video image. But in most of parking area, such as underground parking area, there are no road boundaries in image. The second is it use color based classifier to eliminate lane marker, but color information is not stable due to illumination change or fading factors. The third limit is shadows and other planar objects on the road surface can't be eliminated if the motion compensation is not accurate. These will produce false positives.

In this paper, we propose a system for rear obstacles detection at various parking areas under various lighting conditions by a single fisheye rear view camera. The definitions of obstacles in this paper are those objects (such as cars, pedestrian, road block, bicycles, etc.) rising from road surface with certain height, which is similar as in [4]. Compared with the work in [4], our system can be applied in various environments. The only assumption for our approach is the road surface is nearly a plane. This is true in most practical environment. Our system doesn't use the motion information of the car. The processing speed is very fast. We use an efficient hierarchical strategy to decrease the false positives.

The paper is organized as followings: Section Ⅱ is the system overview. Section Ⅲ describe the inverse perspective mapping based coarse obstacle detection. A novel multi-scale

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integral image based vertical edge detection algorithm for obstacle segmentation is described in Section Ⅳ. Experiments and conclusion are given in Section Ⅴ and section Ⅵ.

II. SYSTEM OVERVIEW

Our obstacle detection system monitors a warning area behind the car and sends a warning signal to the driver when the car is approaching an object in reverse. The warning area is setting as a 3m * 4m rectangle region (this is the customer requirement) behind the car, see figure 1. If there are obstacles appearing in the rectangle area, the alarm signal will send to driver to warn the driver to keep alert.

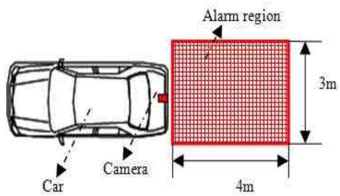


Fig.1 Alarm region behind a car

Our obstacle detection system algorithm diagram is shown as figure 2.

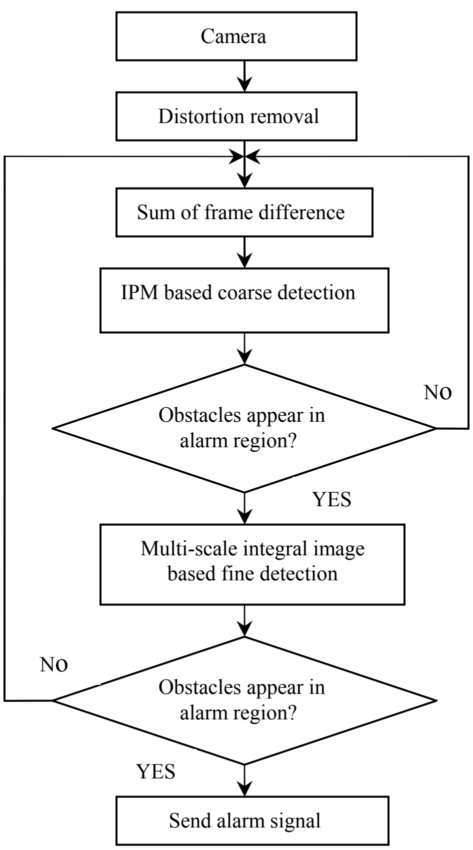


Fig.2. System algorithm diagram

The input for our system is only camera images. A wide angle fisheye camera mounted on the rear car to capture frames from immediate vicinity behind the car. The camera has strong distortion because of wide angle view. The preprocessing is to remove the distortion. Distortion removal is very important because the vertical edge will not "vertical" without distortion removal. Vertical edge is very important for our obstacle detection algorithm. The distortion coefficients are obtained off-line by camera calibration. After distortion removal, system begins coarse obstacle detection between two key frames. The first key frame subtracts the follow consecutive (N-1) (N is key frame interval) frames and sums up the (N-1) difference images to generate a new image. The new image is transformed into inverse perspective mapping (IPM) image by IPM [7]. On the IPM image, coarse obstacle detection algorithm is performed based on polar histogram analysis. Coarse obstacle detection is to determine whether there are obstacles in the warning area of the current frame. If there are obstacles in the warning area, then multi-scale integral image based fine detection is performed on the (N-1)th image for obstacle extraction. Otherwise, the system processes the next key frame. After obstacle segmentation, the blob analysis performs on the binary images for obstacles representation and verification. If obstacles are identified in the warning area at this step, the alarm signal is sent to driver to warn driver to keep alert

III. INVERSE PERSPECTIVE MAPPING BASED COARSE DETECTION

Stereo IPM has achieved good performance for obstacle detection [6][7].The stereo IPM can keep the non-plane objects and remove the plane objects such as lane-markings, shadows by comparing the differences between the left and right remapped image [6]. For a single camera use IPM for obstacle detection, temporal frame difference is used to simulate the effects of stereo cameras [5][8][9][10]. Single camera based IPM methods usually need car ego motion parameter to compensate the displacements between two frames to eliminate false positives [5][10]. However, it is a complicated task to compute the car ego motion parameter accurately.

In our system, the IPM based detection is used as coarse detection. Different with the existing methods in literature, we don't use motion compensation at this step. Because the false positives appear at this step will be eliminated at the next stage. This step must guarantee high detection rate. If IPM based coarse detection finds there are obstacles in the alarm region, it will trigger the multi-scale integral image based fine detection module for obstacle extraction and verification.

For parking assistant application, the speed of moving car is usually less than 20km/h. We set the frame interval as 3. (Experiments show the interval as 3~6 almost has no difference to the result). This means the 1, 4, 7, 10, … (3N+1), ... frame as key frame. Suppose F_k is a key frame, F_{k+1}, F_{k+2} and F_{k+3} is the consecutive frames. Using the

F_k subtracts F_{k+1}, F_{k+2} and F_{k+3} and sums them up:

$$D_k = |F_k - F_{k-1}| + |F_k - F_{k-2}| + |F_k - F_{k-3}|;$$

Here D_k is the new difference image. It contains strong edges of obstacles and some false positives. Then the D_k is transformed to IPM image. Similar to the [5][6][8], polar histogram is used to identify obstacles. Here we don't convert the IPM image to binary image for polar histogram analysis. We use the grayscale pixel values directly because it is insensitive to illumination changes. The polar histogram is computed considering every straight line originating from the Focus F (the projection point of the camera onto IPM image called Focus F) and sum up all grayscale pixel values lying on that line.

We use the following rules to find the peaks to identify obstacles:

(1). For each polar histogram, divides its height into N (for our 720*480 image, the N set as 10) equal intervals according to its highest peak value;

(2). Scan the histogram at the first interval, if the width of histogram in this interval large than a predetermined upper limit threshold $T_{\max}$ or less than a predetermined lower limit threshold $T_{\min}$, skip it and scan the histogram at the second interval. Otherwise, suppose W_{half} is the width which is corresponding to 50% of the peak amplitude M, only when $M / W_{half} > 1.5$ (the threshold 1.5 is obtained by experiments) by is satisfied, the peak is identified as an obstacle.

(3). Scan the histogram until it reaches the Nth interval.

Figure 3 shows two examples of IPM based coarse detection. The (d) in fig.3 is the polar histogram. The gray horizontal lines divide the histogram into N intervals. The pink peaks are identified as obstacles by using above rules.

Obviously, the IPM based coarse detection will produce false positives because of no motion compensation. However, it can also help to eliminate some certain false positives (such as the brick texture on road surface, rectangle structure paints on road surface, etc.) based on above rules. Figure 4 shows two types of false positives are eliminated by our IPM based detection. Those false positives can not be eliminated by using vertical edge segmentation based methods.

IV. MULTI-SCALE INTEGRAL IMAGE BASED FINE DETECTION

A. Multi-scale integral image based vertical edge region segmentation

Although the temporal IPM difference image based coarse detection can eliminate some false positives, lots of false positives are still produced because we don't compensate the displacement between two frames by using the car ego motion parameters. So the fine detection is needed to reject false positives. Once the IPM based coarse detection detects the current key frame may contains obstacle objects, it triggers the multi-scale integral image based fine detection module to work.

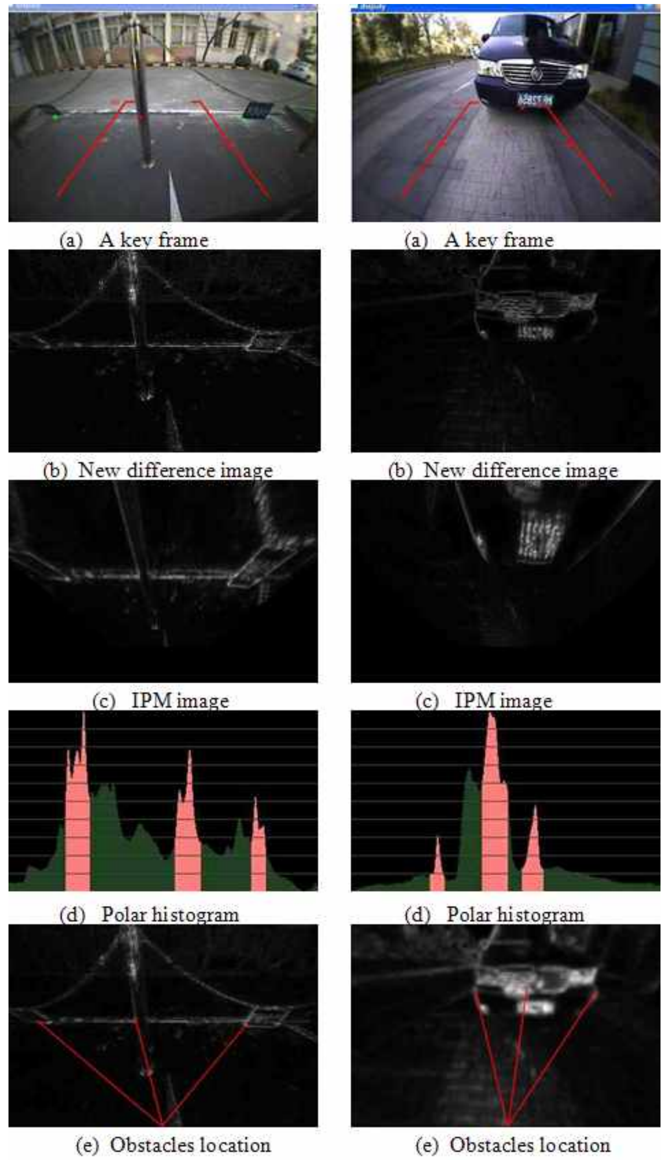
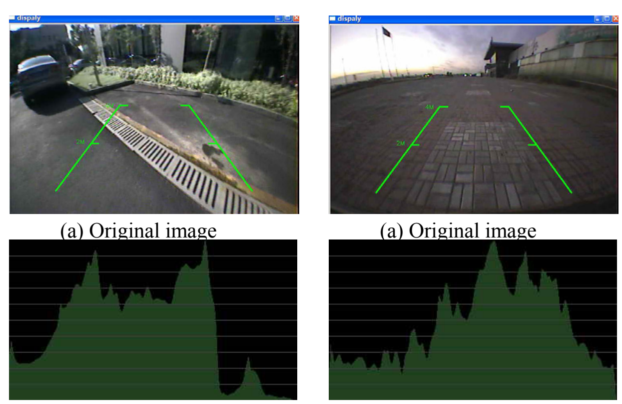


Fig.3. Temporal IPM difference image based coarse detection examples.



(b) Polar histogram (b) Polar histogram

Fig.4. Two types of false positives are eliminated by our IPM detection.

The obstacles usually have vertical edges or nearly vertical edges. The state of the art of vertical edge detection algorithms in literature, such as Sobel operator, Canny operator and Bertozzi's vertical edge detection algorithm [7], can segment the regions which have vertical edges. But they can not eliminate shadows, lane marker or other planar objects in road surface if those objects also appear vertical edges. In order to segment the real obstacles and eliminate such false positives as much as possible, we develop a novel multi-scale integral image based segmentation algorithm.

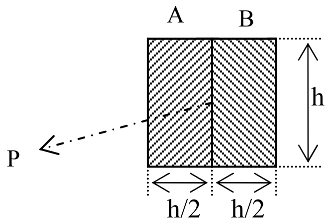


Fig.5 Integral image based vertical edge region segmentation

For each point P in grayscale image, set a rectangle region as P is the center, the height is h, the width is h. Split the rectangle into two rectangles A and B, see figure 5. Sum of all the pixels in left rectangle A and right rectangle B respectively:

$$S_A = \sum_{x^{'} < y, y^{'} < y} p(x^{'}, y^{'});$$

$$S_B = \sum_{x^{'} < y, y^{'} < y} q(x^{'}, y^{'}); \quad (1)$$

Where $p(x^{'}, y^{'})$ and $q(x^{'}, y^{'})$ is the pixel in the rectangle A and rectangle B. The mean value of rectangle A and B is:

$$\mu_A = S_A / n \ ;$$

$$\mu_B = S_B / n \ ;$$

Where n is the pixel number in the rectangle A and rectangle B. Compute the absolute difference of the two means:

$$r = |\mu_A - \mu_B|;$$

$$T = \lambda * \frac{(\mu_A + \mu_B)}{2};$$

Here λ is a constant coefficient which can be obtained by experiment.

Similar to multi-scale haar features used for object detection, multi-scale strategy is used to compute r . Here we use 3 scales by setting the rectangle height h as 4, 6, 8 respectively. The final output for the rectangle center pixel P is:

$$r_k = \begin{cases} r_k, & if \quad r_k > T_k; \\ 0, & otherwise; \end{cases} \quad k = 4,6,8$$

$$P_{out} = \arg\max_k r(k)$$

Here the P_{out} is the final output response for the pixel P.

The major computation of our algorithm is equation (1). It can be computed by using integral image, which is very fast [11]. After we have obtained the edge image, a simple threshold (50) can convert the edge image to binary image for obstacle extraction.

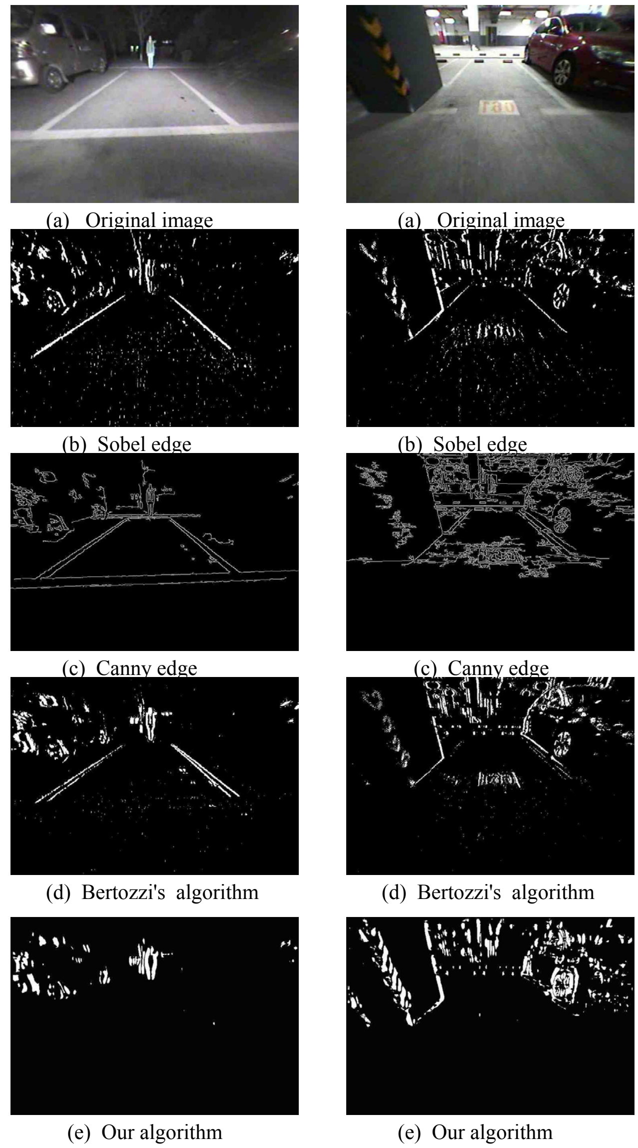


Fig.6 Comparison of our algorithm with other vertical edge detection algorithms for obstacles segmentation. Our algorithm uses a simple threshold (50) to convert the edge image to binary image, and other edge detection algorithms use adaptive threshold method.

Our algorithm has superior advantages compared with other vertical edge detection algorithm for obstacles segmentation. The first advantage is our algorithm can eliminate lots of planar objects (such as some shadows, lane marker, text paints, etc.) in road surface even if they have vertical edge. The second advantage of our algorithm is insensitive to illumination change.

The figure 6 shows some results of our algorithm comparing with other vertical edge detection algorithms for obstacles segmentation. From figure 6, we can see our algorithm obtained good performance for obstacle segmentation. Most of planar objects (such as lane mark, text paints) on the road surface are eliminated by our algorithm.

B. Obstacle representation and verification

Once the obstacles are segmented, we perform blob analysis on the binary image for further analysis. First morphological operations on dilation and erosion are used to eliminate the isolate points and merge the adjacent points. Then fast connect component labeling is used to merge close components and deletes the objects that are smaller than a certain area threshold (40). Finally, each blob is represented by the smallest ellipse that completely encloses its contour. Figure.7 shows the obstacle representation in two images.

(a) Original image (a) Original image

(b) Binary image (b) Binary image

(c) Obstacle representation (c) Obstacle representation

Fig.7 Obstacle representation

After fine obstacle extraction, there are still some false positives. We use the following property to eliminate them. The property is: the prolongation of the edges of obstacles should pass the Focus F on IPM image [5]. We use F as midpoint to set an interval by using a threshold Th(10). We check the prolongations of the principal axis of each ellipse. If the prolongations fall into the interval, the ellipse is identified as an obstacle.

V. Experiment Analysis

A. Setup

A fish-eye camera is mounted on the back of a car to collect experiment data in real parking environment. A laptop is linked to the camera to record the video files. The camera resolution is 720*480. The frame rate is 30fps. The configuration of the camera on the car is shown as figure 8. The pitch angle is 30^0 and no yaw angle and roll angle. The height of the camera frame above the ground surface is 0.90cm. These parameters are used to compute the IPM image [12]. The video files are collected under various road environments at different time (morning, noon, afternoon and night). We place some obstacles in some parking areas. The obstacles include pedestrian (moving and static), cars (moving and static), bicycles, road block, etc. The testing video files contain 125 different parking sequences. There are total 137 obstacle cases in these video files. The warning area of our system is a 3m * 4m rectangle region on road surface behind the back of car, see previous figure 1. The rectangle region is corresponding to a trapezoid in video frames. We draw the trapezoid in each video frame with initial color is green. The definition of the correct detection of our system is: when obstacles appear in the trapezoid region in video images, the green color turns to red color.

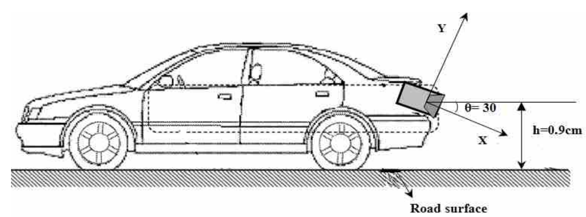


Fig.8 the configuration of camera mounted on the car

B. Result analysis

The experimental results are shown in table I. Our system achieves nearly 94.2% correct detection rate and about 16% false positive rate. The system has nearly 100% correct detection rate for pedestrian and cars whether those obstacles are static or independent moving. Figure 9 shows some of our correct detection examples.

Table I Results of experiment

	Correct detection	False detection	Missed detection
Obstacle objects	129	22	8
rate	94.2%	16%	6%

Most of the missed detection cases are the walls which have uniform texture. For those cases, there is no edge information, so the detection is failure. Actually, most of single camera based methods will fail on these cases. The false positives include some moving shadows, long lane marker with arrow, sudden lighting changes, etc. The figure 10 shows two missed detection examples and two false positive examples.

Our system runs on a 1.73GHz laptop, 1G RAM. The IPM transform is implemented by a look-up table. The average processing speed of our system is about 25fps. During the detection process, it only needs to store one frame. So our system is very efficient for embedded system.

VI. CONCLUSION

We propose an efficient rear obstacle detection system for parking assistant application. The system can be applied in various parking environments. Instead of using the car ego motion parameters to compensate the displacements between two frames, the system uses a hierarchical strategy to reject the false positives. The system is easy to implement. The IPM transform can implement by using a look-up table. The multi-scale integral image based fine detection can be implemented by using fast integral image computation. Only one frame is needed to store during the detecting process. Those characters indicate our system is very efficient for embedded system.

Further works we will decrease the false positives rate below 10% and port the system to QNX platform.

Fig.9 Correct detection examples

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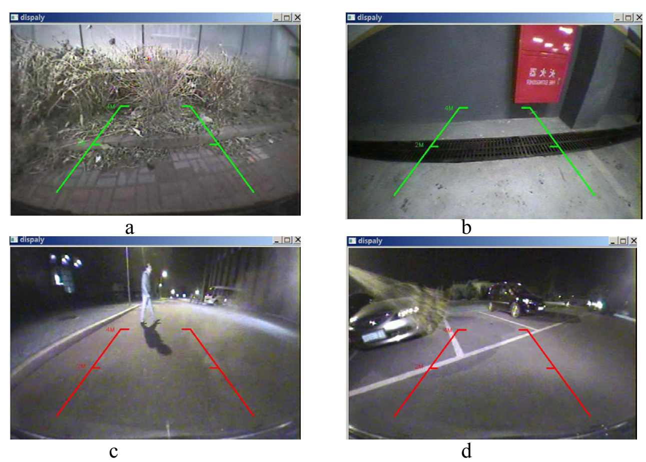

Fig.10 The missed detection examples and false positive examples. (a) and (b) are the missed detection examples. (c) and (d) are false positive examples. (c) is due to moving shadow of pedestrian, (d) is due to sudden lighting change.