A New Vehicle Detection Method For Blind Spot Detection System Based On DSP

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Abstract: Vision based vehicle detection is an important application for vision technique in ADAS. Along with other non-vision sensors, vision sensors can quickly and accurately detect the kind of the moving object due to the increasingly powerful micro-processors. A vision based real time BSD system can improve the driving safety and reduce the accidents. The system analysis the images captured by the vision sensors on the side mirrors, gives warnings to the driver when there is a potential impact. The proposed algorithm uses a prewitt operator for vehicle detection, and the modified template method to verify vehicle's existence. Reducing processing time by setting the ROI and downscaling the image size. The detection ratio of the system is over 96% and itmeets the real time requirements of the ADAS systems.

Keywords: vision camera; blind spot detection; ADAS

I. Introduction

As the economy grows, the amount of vehicles is conspicuously increased for the last decades. But the road accidents have increased as well. Most of the traffic accidents caused by the driver's inattention^[1]. Among all the accidents, there's one common situation: when a vehicle is changing lanes, the driver cannot see all the closing cars due to the blind spot area caused by the side mirrors, cashing with the side closing cars. In order to reduce such evens, a blind spot detection system is needed.

The side vehicle detection methods are divided into the motion-driven detection and the classifier-based detection. The motion-driven detection uses optical flow or feature comparison between consecutive frames^[2]. The classifier-based vehicle detection uses feature vectors such as Haar, LBP, or Hog^[3]. In those scheme, the classifier determines whether an image region is a vehicle or a non-vehicle based on the feature vector^{[4][5]}. The motion-driven detection can only detect closing vehicles from the side-rear region, and its detection ratio is more poor than the classifier-based detection^{[6][7]}. This paper uses classifier-based detection in order to detect vehicles in the blind spot area.

The blind spot detection system(BSDS) is one of the important ADAS systems, which can monitor the blind spot area and gives warning to the driver to avoid the accidents. A BSDS usually use cameras or radar to watch the area around the vehicle and look for vehicles that are nearby. The cameras are always installed on the two side mirrors, as shown on Fig1. In most systems, a light will appear in the side mirror to alert the driver that a vehicle is present. If the driver activates the turn signal while another vehicle is in the blind spot, an audio alert or steering wheel vibration will be activated.

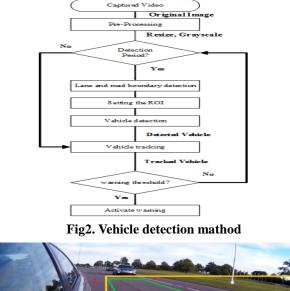


Fig1. Vision cameras for BSDS.

II. Algorithm

This paper proposes a vision based blind spot vehicle detection algorithm. Fig2 shows the processing flow of the algorithm. The video captured by the camera, first resize it to a quarter of the original size to reduce the processing time. Then if it's in the detection period, lane marking and road boundary detection starts. To detect the lane mark and the road boundary, count the whole image's grayscale, mark the sky and lane (gray level is 255) or the shadows (gray level is 0) and then get the road area. Using the detected lane and road

boundary, we can set the ROI (region of interest) region, as shown in Fig3. Once we set the ROI region, we won't have to process all the image area because vehicles outside the ROI region have no effect on the test vehicle, this has reduced a lot of processing time.



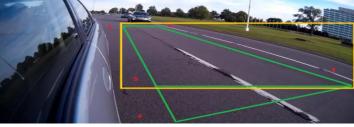


Fig3. ROI region

We can search the vehicle by looking for the edge concentration area. Using priwitt operator to detect edges, the definition of the prewitt operator for f(x,y) is:

 $\begin{array}{l} G_i = |[f(i-1,j-1) + f(i-1,j) + f(i-1,j+1)] - [f(i+1,j-1) + f(i+1,j-1) + f(i+1,j+1)] \\ f_i = |[f(i-1,j+1) + f(i,j+1) + f(i+1,j+1)] - [f(i-1,j-1) + f(i,j-1) + f(i+1,j-1)]| \\ (2) \\ \text{And} \quad \mathbf{P}(\mathbf{i},\mathbf{j}) = \max(G_i,G_j) \\ \text{Or} \quad \mathbf{P}(\mathbf{i},\mathbf{j}) = G_i + G_j(4) \end{array}$

Calculate the horizontal edge and the vertical edge to decide in what area vehicle can exit. And then we can verify the vehicle's existence based on the pattern plate. The correlation formula we use is: $\rho(x, y) = \frac{\sigma(T, R)}{\sqrt{D(T)}\sqrt{D(R)}}$ (5) $\sigma(\underline{T}, R) \text{ is the covariance of the T and R; } D(T) \text{ is the variance of the T, } 2D(T) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \left(T\left(i, j\right) - \overline{T}\right); D(R) \text{ is the variance of the R, } D(R) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \left(R\left(i, j\right) - \overline{R}\right); \overline{T} \text{ and } \overline{R} \text{ represent the average grey value of image T and image R. Substitute the } D(T) \text{ and } D(R) \text{ in the formula (5) and we get:}$

 $\rho(x, y) = (1/mn \sum_{i=1}^{j} (i = 1)^{n} \mathbb{E}_{j}(j = 1)^{n} \mathbb{E}_{T}(i, j)R(i, j) - TR^{J})/(\sqrt{(1/mn \sum_{i=1}^{j} (i = 1)^{n} \mathbb{E}_{T}(i, j) - T^{n})^{2}}) \sqrt{(1/mn \sum_{i=1}^{j} (i = 1)^{n} \mathbb{E}_{T}(i, j) - R^{n})^{2})}$ (6)

-1	0	1	1	1	1
-1	0	1	0	0	0
-1	0	1	-1	-1	-1

Fig4. Prewitt operator

III. Result And Discussion

This paper uses two step to detect the vehicle in blind spot area. First get the approximate area of the vehicle through edge features, then to verify its existence. The modified template method makes it possible to gain the valid result quickly, and the lane mark and road boundary detection reduce the complexity of the algorithm.

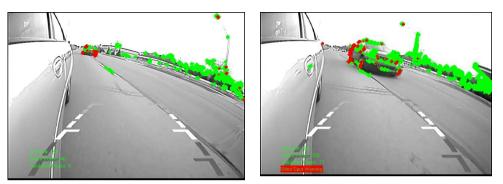


Fig5. Vehicle detection and warning threshold

Fig5 shows the result of the system, when a car gets near from the side lane, the system has detected the vehicle but no warnings has been activated, the vehicle keeps getting closer, and the system keeps tracking, warnings show up when reached the warning threshold. After the real road test, we find that the system detection ratio is over 96% and it meets the requirement of the real-time processing.

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