American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)

ISSN (Print) 2313-4410, ISSN (Online) 2313-4402

http://asrjetsjournal.org/

Real-time Road Obstacle Detection Using Association and Symmetry Recognition

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Abstract

This paper presents a fast road obstacle detection system based on association and symmetry. This approach consists to exploit the edges extracted from consecutive images acquired by a stereo sensor embedded in a moving vehicle. The algorithm contains three main components: edges detection, association detection and symmetry calculation. The edges detection is achieved by using the canny operator and point corner to extract all possible edges of different objects at the image. The association technique is used to exploit relationship between the edges of two consecutives images by combining it with the moment operator. The symmetry is used as road obstacle validation; the road obstacles like vehicle and pedestrian have a vertical symmetry. The proposed approach has been tested on different images. The provided results demonstrate the effectiveness of the proposed method.

Keywords: Obstacle detection; Vehicle detection; intelligent vehicle; edges detection; Association.

1. Introduction

An intelligent vehicle (IV) can achieve road obstacle detection by knowing its environment. Obstacle and Vehicle Detection play a basic role. In fact, an intelligent vehicle must be able to detect vehicles and potential obstacles on its path. Advanced driver-assistance systems intend to understand the environment of the vehicle contributing to traffic safety.

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It has been considered important that intelligent vehicles identify obstacles around a host vehicle and estimate their positions and velocities precisely. In this context, many systems have been de-signed to deal with obstacle detection in various environments. Radars [1,2], laser range finder [3,4], stereovision [5,6,7,8,9,10] and multisensory fusion are used on structured roads. Several approaches to obstacle detection based on the localization of specific patterns (features such as shape, symmetry, or edges).

In [11,12] the stereo matching is used in many applications, like obstacle detection, 3D-reconstruction, autonomous vehicles and augmented reality The vision-based obstacle detection for the outdoor here we provide a brief review of the state of the art in vision-based obstacle detection. The vision-based obstacle detection for environment can be classified into monocular and multi-camera methods. In Monocular vision-based methods we find some techniques like optical flow was used for robotics obstacle detection in [13] and Appearance-based method [14] applied only appearance or color feature to discriminate the obstacles. Recently, some researches on 3-D reconstruction from single still image were presented to detect obstacle [15,16,17]. However these methods have weak points in estimating an obstacles position, velocity, and pose, and this has been considered one of the most challenging tasks in computer vision for a long time. The V-disparity and G-disparity image [24,25,26,27], was designed to detect obstacles by estimating the disparity of the ground plane automatically.

In this paper, we focus on edges Association and symmetry obstacle detection. That is, detecting the road obstacles ahead of the vehicle using a stereo-camera in real time.

This paper describes a new detection vehicle approach based on edges detection and association [28,29]. This approach is composed of extracting the interest edges and possible shapes features, extracting possible vehicle from association image in the successive frame. Our approach is able to detect most of the obstacles in the road scene by using the association between the two consecutive frames by combining it with the symmetry operator to detect the vehicles on this scene. This approach provides a good and robust representation of the geometric content of road scenes and it can detect and locate the road vehicles. The remainder of the paper is organized as follows: After reviewing the introduction in the section 1. The improved vehicle detection method is given in Section 2. Then some experimental results will be shown in Section 3 to demonstrate the advantages of our system. Finally, conclusions and discussions of this study will be given.

2. The vehicle detection Process

This section describes the steps of the proposed method for vehicle detection on road scene. The principle of the new approach is to exploit the link between the two consecutive frames in the temp. This exploitation consists of finding the association between the contours of two frames in order to build the association image to extract all useful information for vehicles detection. The following notations will be used in the rest of the article. I_{k-1}, I_k denote the images of the frame f_{k-1} and f_k acquired at time $k-1$ and k. Dep($\mathbf{C_k^i}$) is the edges displacement value along both x and y abscises.

2.1. Edges detection (point corner/ canny)

In this work, we are interested in using edge points and point corner for extracting significant features from the consecutives images. The Canny edge detector and The Shi corner detectors [18,6] are regarded as one of the best edge detectors and point corner currently in use. It provides continuous edge curves, which are essential to the proposed detection method. Consequently, we use the Canny operator for edge (points and curves) detection from the consecutives frames. Using the Canny detector in the current work allows the detection of more edge points for obstacles detection and especially a vehicle that has a well-known shape compared to other forms such as trees etc ...

The reason we used the Harris operator to detect corner points is that a vehicle has a similar shape of a rectangle. Subsequently, the existence of corner points will be stronger. After calculating the point's corners, a simple thresholding was performed to remove small items from other objects that have a different shape to the shape of a vehicle, points corners in a vehicle are much more compared to trees or features of the road. The last step is to find all the contours that pass through these corner points in order to limit the calculation of the association and the moment of the edges for the two consecutive images.

2.2. Association between edge points of consecutive images and The moment computation

2.2.1. Association between edge points

As before mentioned; the main idea of the proposed approach is to exploit the relationship between consecutive frames. We propose to use the association to achieve this goal [28,29].This subsection describes the method used to find the association between edge points of consecutive frames association of the images I_{k-1} and I_k . Let us consider two edge points P_{k-1} and Q_{k-1} belonging to a curve C^i_{k-1} in the image I_{k-1} and their corresponding ones P_k and Q_k belonging to a curve C^j_k in the image I_k (see Figure. 1). The associate point to point $P_{k-1}$is defined as the point belonging to the curve C^i_k whith the same y-coordinate as P_{k-1}. Two associate points are two edge points belonging to two corresponding curves of two consecutive images of the same sequence and having the same y-coordinate. From Figure 1, we remark that point Q_k constitutes the associate point of P_{k-1}.

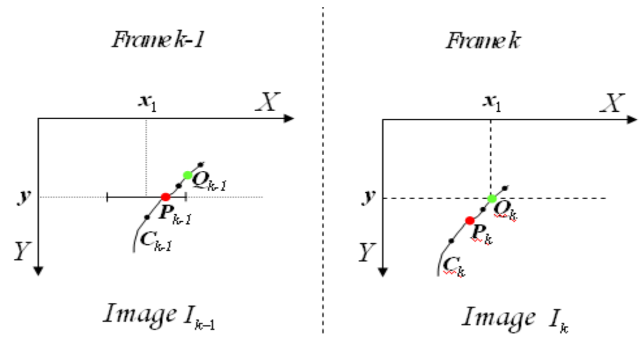


Figure 1: I_{k-1} and I_k represent successive images at t0 and t1. The point P_{k-1} in the image I_{k-1} constitutes the associate point of the point Q_k in the image I_k. The points P_k and P_{k-1} are in red color. The points Q_k and Q_{k-1} are in green color. Q_k , P_k belong to the same contour C_k in the image I_k and their associates respectively must also be belonged to the same contour C_{k-1} in the image I_{k-1}.

For each edge point in image I_{k-1} we look for its associate one, if it exists, the image I_k. The association technique consists of finding for each edge curve C^i_{k-1} in the set S_{k-1} its corresponding edge curve C^j_k in the set S_k , if it exists. Let $Ass(C^i_{k-1}) = \{ae_n\}_{n=1,..,Ni}$ be the set of edge points ae_n, belonging to the image I_k , which represent the associates of the edge points of the edge curve C^i_{k-1}. N_i is the number of associations found for the edge curve C^i_{k-1}. If M_i represents the number of edge points in C^i_{k-1}, $N_i <= M_i$ because there are edge points in image I_{k-1} for which there is no associate in image I_k . If there is no error in the association process, all the edge points belonging to the set $Ass(C^i_{k-1})$ should belong to one edge curve, which is the corresponding curve to $C^i_{k-1.}$

Unluckily, during the process of the association we found some mistakes. Therefore, the edge point's ae_m may belong to different curves in S_k. We find the match of C^i_{k-1} by looking for the curve C^j_k, which contains the maximum number of edge points in Ass (C^i_{k-1}). We apply the same method to all the edge curves in S_{k-1} to find their corresponding ones in S_k .

2.2.2. The edges moment computation

In the previous part we saw how to calculate the association that will allow us to find each one of the contours at time t_0 and his associate at time t_1, and we will reinforce this association by the use of the technique WTA which was used in the sparse match process [27]. This technique allows us to avoid erroneous calculations in the association.

After the calculation of the association and to avoid any ambiguity concerning the shape of the contours at time t0 and t1; that is to say; we can find the edge curve C^i_{k-1} and his associate C^i_k have not the same form. This is why we are going to add the imperial moment in checking the shape of the contours to achieve good results.

The moment computation gives us some rudimentary characteristics of a contour that can be used to compare two contours in the consecutive frames. However, the moments resulting from that computation are not the best parameters for such comparisons in most practical cases. In particular, one would often like to use normalized moments (so that objects of the same shape but dissimilar sizes give similar values). Similarly, the simple moments of the previous section depend on the coordinate system chosen, which means that objects are not matched correctly if they are rotated [30].

Assuming that the edges of a road obstacle at time t_0 remain unchangeable at time t1, so we get the following formula:

$$\begin{cases} M\left(C_{k-1}^{i}\right) = M'\left(C_{k}^{i}\right) \\ Ass\left(C_{k-1}^{i}\right) = Ass\left(C_{k}^{i}\right) \end{cases} \qquad (1)$$

$M\left(C_{k-1}^{i}\right) = \{m_u\}_{u=1,..,7}$ / values of moments for the edge curve C^i_{k-1}

$M'(C_k^i)$= $\{m'_u\}_{u=1,..,7}$ values of moments for the edge curve C^i_k.

And $Ass(C_{k-1}^i)$=$Ass(C_k^i)$.

From the previous formula (1), the correct associating of each edge between the two images I_{k-1} and I_K at time t_0 and t_1 is obtained. Assuming that the general shape of an obstacle remains unchangeable. That is to say, the edges of the S_{k-1} scene and their associates in the S_k scene (their correspondents) have the same geometric shape.

The edges of the same road obstacle in the two moments are similar. From this information and to know the edges of the same road obstacle we will calculate the displacement of each edge from the previous formula (1).

Let Dep(C_k^i) =(d_x,d_y) be the displacement value of the edges C^i_{k-1} in the scene S_k.

The movement of the object consists of the movement of its own edges. From this assumption all the edges of the same obstacle have the same value of displacement in both directions of abscissa x and y. (see Figure 2)

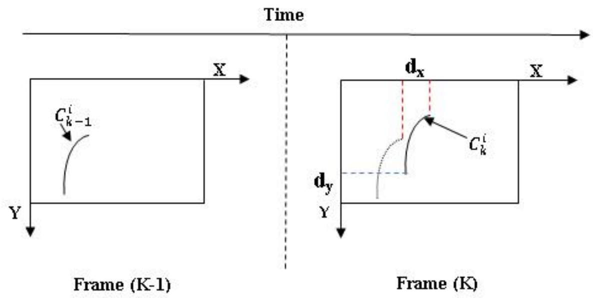


Figure 2: I_{k-1} and I_k represent the displacement value of the edges C^i_{k-1} in the scene S_k.

There are cases where two obstacles are even moving so the symmetry technique will help us to differentiate between the edges of the two obstacles.

2.2.3. ymmetry detection

In general, symmetry is based on the shape of an obstacle. In our case road obstacles like vehicles or pedestrians have a vertical symmetry [31].

The road obstacle Detection algorithm is based on the following considerations: a vehicle and pedestrians are generally symmetric, characterized by a rectangular bounding box which satisfies specific aspect ratio constraints, this aspect ratio is fixed before a lot of experience in our method in our case we fixed it at (w:20,L:20) pixels. First an area of interest is identified on the basis of road position in the previous section. This area is searched for possible vertical symmetries; just vertical symmetries are considered. Once the width and position of the symmetrical area have been detected, a new search begins, aimed at the detection of the two bottom corners of a rectangular bounding box.

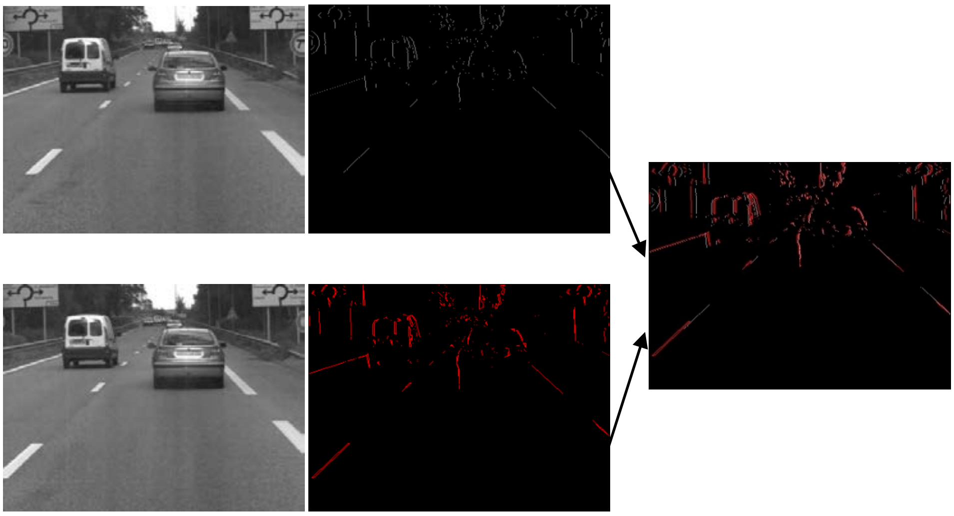
3. Results and Analyses

To evaluate the performance of the proposed obstacle detection system, tests were carried out under different images. The system including a hardware used for the experiments is a HP Intel(R) Core(TM) i5 running under Linux Ubuntu is able to process approximately 10ms. First, the images had a size of 512x512 pixels are used.

Table1 shows the processing time of the road obstacle detection, the overall average processing time for one frame is 10ms.

Table 1: Processing time of the road obstacle detection approach.

	Average processing time (ms)
Association calculation	3
Moment calculation	4
Symmetry process	3
Total	10



(a) (b) (c)

Figure 3: Results of the proposed algorithm: (a) Real images at the instant t0 and t1, (b) edges detection. (c) Association image.

The results of the proposed obstacle detection approach are depicted in Figures 3, 4 and 5. The detection rate is high, and our approach proves to be reliable and be able to detect most road obstacles in road environments. The Figures 3, 4 and 5 shows some representative detection results. The bounding box superimposed on the original images shows the final detection results. From these results, we can see that the bounding box on the image can effectively describe the road obstacles.

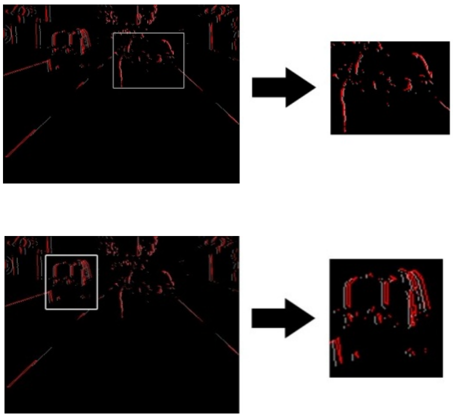


Figure 4: (left) Edges detection satisfied formula (1). (Right) bounding box detection

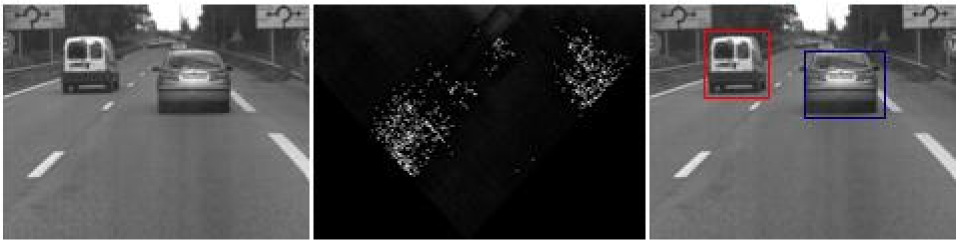


Figure 5: Symmetry detection; (left) initial image. (Center) symmetry map, (right) vehicle detection.

The following table summarizes some statistics concerning the different stages of our approach; first, we computed the possible contours found in the two frames of images at time t0 and t1. The number of contours of the first frame t0 is 197 and in the second is 180. After getting all the contours, the next step is the association between the two sets of contours in the two frames of images and of course the number of associated contours becomes lower than the initial value found by the canny operator. So our approach is able to find 170 associated contours between the two images. To reinforce the proposed approach we will add the imperial Moment factor to determine the good result. In this approach we have applied the imperial moment of the order 7 that is to say we have 7 level of comparison between the contours obviously in the combination with the association. We got 160 contours so a very high rate 94%. Table 2 justifies clearly the performance of our method.

Table 2: statistics for each stage of our approach

	Frame k-1	Frame k
Number of edges detected	197	180
Number of Association edges without the moment factor	170	
Number of Association edges with the moment factor (Formula 1)	160	

The following figure shows the moment values for the edges of two images at time t0 and t1. We performed a 7-level comparison to find the correct association values and to eliminate the false calculations found during the association process (figure 6).

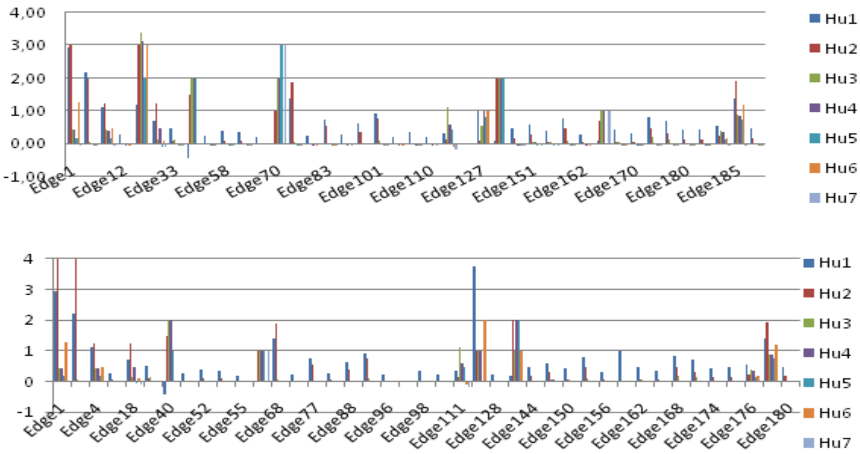


Figure 6: The moment values for edges of two images at t0 and t1 time.

4. Conclusion

In this paper, we have developed a real time method that detects road obstacles (vehicles, pedestrians); our algorithm is proposed to detect road obstacles by using consecutive images which are obtained from cameras installed at a moving vehicle. The proposed obstacle detection algorithm can be used for the development of driver assistance system and autonomous vehicle systems. Firstly, the edges detection process will be carried out to obtain all edges presented the obstacles. Secondly, the association technique used to retrieve all objects found it in the scene. Then the symmetry is used for obstacles validation. The obtained results are perfect and satisfactory. Among the limits of our approach is that the validation phase is not use it except the symmetry operator. That’s why we will to apply vehicle validation phase to differentiate between vehicles and pedestrians. we will consider using the adabor filter to obtain a perfect detection of vehicles.

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