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Stereo Vision-Based Road Obstacles Detection and Tracking

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Abstract

This paper presents a fast road obstacle detection system based on stereo vision. The algorithm contains three main components: road detection, obstacle detection and vehicle tracking. The road detection is achieved by using a small rectangular shape at bottom center of disparity image to extract the disparities of the road. The roadsides are located by using morphological processing and Hough transform. In the obstacle detection process, the objects can be easily located by the segmentation process. The vehicle tracking is achieved by the discrete Kalman filter. 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; road detection; obstacle tracking; Kalman filter.

1. Introduction

Advanced driver-assistance systems intend to understand the environment of the vehicle contributing to traffic safety. 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. In the field of stereo vision-based road obstacle detection, a number of hypotheses are frequently made about the environment in order to facilitate the process.In this paper, we focus on vision-based road obstacle detection. That is, detecting the free road surface ahead of the vehicle using an stereo-camera. STEREO matching is used in many applications, like obstacle detection, 3D-reconstruction, autonomous vehicles and augmented reality [11,12]. 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.

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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 problem of monocular vision method is that it cannot get estimate global 3-D information and is always based on strong constraints. As we know, none of monocular vision systems achieves practical application in rough outdoor terrain. Unlike a monocular vision system, multi-camera systems obtain the three dimensional (3D) positions of obstacles by matching two images with relatively low sensor cost, but the accuracy and precision fall short compared with other range sensors. Stereovision-based distance measurement gives relatively good accuracy for objects within a short distant range, but this method has poor accuracy for objects in the long distant range due to the matching. ambiguity, quantization errors, and in accurate parameters of the camera model [18,19,20,21,22,23]. 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 summary, there are two points of improvement about the above methods. One is the at ground plane assumption, which is not always available in outdoor unstructured environment and hence become a potential limitation. Even the V-disparity image-based methods, which had good results for obstacle detection, however, their results are also found on the above assumption. This paper describes a new detection and tracking obstacles approach based on stereo vision. This approach is composed of extracting the interest road area, extracting possible obstacle from disparity image and tracking these obstacles by using the discrete Kalman filter to estimate their positions in the next frame. Our System can extract the road obstacles by using the depth disparity image.

This approach provides a good and robust representation of the geometric con-tent of road scenes and it can detect and locate the road obstacles. The remainder of the paper is organized as follows: After reviewing the introduction, the road detection method based on depth disparity image will be introduced in Section 1. The improved obstacles detection method is given in Section 2. Then in section 3 the tracking process is explained and some experimental results will be shown in Section 4 to demonstrate the advantages of our system. Finally, conclusions and discussions of this study will be given.

2. Road detection : interest Road Area

In this section, we concentrate on vision-based road detection. That is, detecting the free road surface ahead of the Systems advanced driver assistance. Road detection is an important task within the context of autonomous driving. Other-wise, it is an invaluable background segmentation stage for other functionalities such as vehicle [28] and pedestrian [29] detection. The knowledge of the free road surface reduces the image region to search for objects (vehicles, pedestrians, and infrastructure elements).

To determine the free road surface and to reduce false detection, we propose to use a technique based on the road disparity variation. Moreover, we aim to use road shape information which is presented by the slope of the geometry road and Hough transform. For the depth disparity image, we used the algorithm developed by Shawn

Lankton [30]. That is based on the Compute pixel disparity by comparing shifted versions of images. A summary of processing steps of the proposed method is given in Fig. 1.

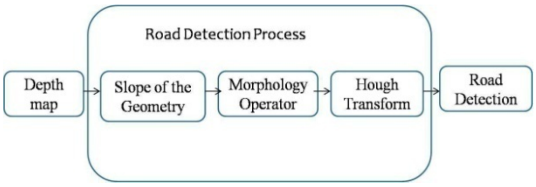

Figure 1: Scheme of the proposed algorithm

2.1. Slope of the geometry road

We propose to use a simple rectangular shape R should be assumed at the bottom center of this image as shown in Fig. 2(left). The selection of the rectangular shape position is located directly in the road in front of the driver system. The only constraint for size of this rectangular shape is the width 3 height. This constraint, we allow us to gain maximum points of the road to treat them. The slope of the geometry road is calculated as follows:

- For each row of the R, the most dominant disparity is chosen as a disparity of this row.
- The repetition number of the dominant disparity determined before change is considering as slope value.

The important role of the slope is allows us to guess the value of disparity road in the disparity map to perform road binary image Fig. 2(right). In the next step, we aim to localize the roadsides of the road to achieve the road triangle that includes all our objects of interest (road and obstacles).

2.2. Roadsides detection

The road binary image is then processed for object of interest segmentation. Firstly, a quick morphology is applied on the road binary image to improve the subtraction result. A sequence of erode and dilate operation are involve in the morphology where the effect is to remove smaller detected regions usually due to noise and to enlarge the areas of object of interests and to close any holes within them. In the next step, the boundary points are extracted from the binary image. These contour points are transformed to Hough coordinate to find the extreme lines of the road (Fig. 3).

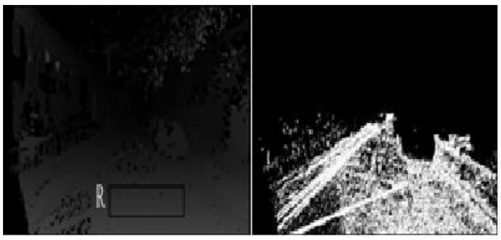

Figure 2: (left) Disparity map image and (right) road binary Image

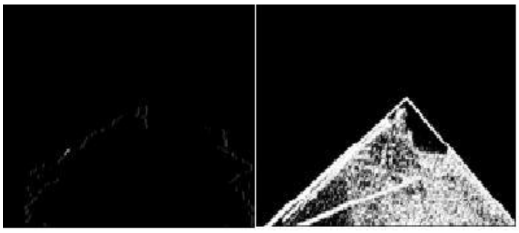

Figure 3: (left) Boundary point image and (right) road triangle image

3. Road detection : interest Road Area

The next objective of this algorithm is the extraction of ROIs. After obtaining the road triangle image that includes all objects of interest. The obstacle detection process will be carried out in the road triangle; a segmentation operation is applied to the road triangle image to retrieve all objects located on the road. The Segmentation process consists in grouping the points detected which does not belong to the road that corresponds to the same ROI. This phase is usually completed by considering two consecutive points as belonging to the same obstacle if they are closer. We then applied a connected component analysis on the image to segment the object of interests on the image. Connected component analysis locates separated regions in the binary image and labels them as different objects. The aspect ratio of the horizontal and vertical sides of the potential object is computed to imply that an obstacle is detected. We select the objects that have the ratio between height and width satisfied 20 pixels. The candidates that satisfied the constraint are selected and passed to the next evaluation. From the connected component analysis results, ROIs extraction is done by drawing the bounding box around the every object of interests The next step is to separate the objects found in the ROIs. To perform this task, we must return to the disparity depth image, seeking in this ROI the most significant disparities and choosing disparity peaks that have a higher frequency. The dominant disparities are estimated within the ROI to extract only the pixels corresponding to the obstacle. The dominant disparities are extracted by the disparity histogram, which is calculated by disparity distribution within the ROI. Dominant disparities consist of disparities that have a higher frequency. The obstacles separation process is described below (Fig. 4).

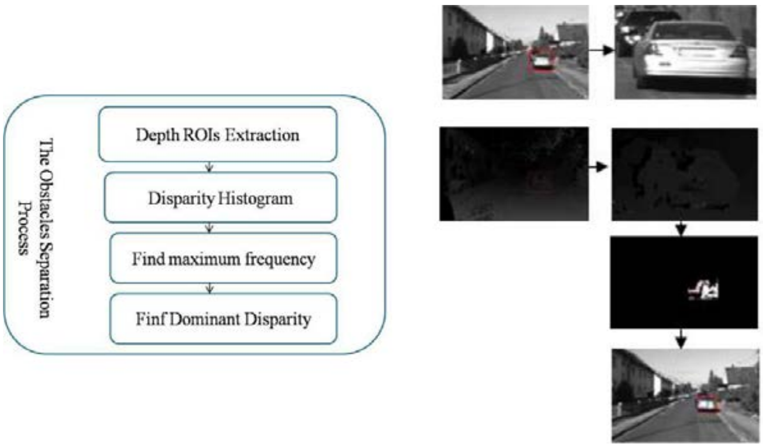

Figure 4: The obstacles Separation Process

We applied a technique described previously, to extract the road based on the variation of disparity ie: how the row of disparity value will be changed and this number we can easily know the points that belong to the road. Otherwise, in methods based on V-disparity, the extraction of the road from v-disparity image is difficult if the map is not well calculated and also the appearance of noise [11,27]. All that, adversely affect the detection of pixels belonging to the road in the v-disparity image and give a precise road profile.

One of strong points of our system as it allows us to detect obstacles road easily though there are overlapped obstacles. Otherwise in other systems based on v-disparity it is difficult to determine the width of the obstacles, as in the work that is based on this technique, the height is known from the v-disparity image and the width they used u-disparity [11]. The disadvantage of the u-disparity is that several objects that overlap it are difficult to determine the width of each one of them.

4. Road obstacle tracking with Kalman filter

Kalman filtering is a recursive procedure for optimal estimation of the state of a dynamic system, on the basis of noisy measurements and an uncertain model of the system dynamics. A Kalman filter is used in the tracking to predict the locations of objects in the future video frames. The advantages of including the Kalman filter in the tracking process are:

- It gives the estimated position of a moving feature point in the next frame.
- Estimate the uncertainty of the estimation, i.e. the degree of confidence of finding the feature in the next frame in a region around the predicted point.
- It reduces the search area for re-detecting an object and therefore shortens the processing time.

The motion of the observed scene is usually continuous, being then possible to make prediction on the motion of the image points, at any instant, based on their previous trajectories. Then object visual tracking can be approached as a problem of state estimation of a dynamic system motion. The process and the measurement models of a linear discrete-time system can be defined by the following equations [31][32]:

Where X_k and Z_k are the state and measurement vectors at time step k. F_k and H_k are the transition and measurement matrices. W_k and V_k are the process and measurement noise.

The variables that are integrated into the Kalman filter are the bounding box of the detected vehicle in the image plane which presented by four parameters (see Fig. 5).

The determination of these variables is given in previous sections. The integration of these variables into the Kalman filter has resulted in the following state and measurement vectors:

$$\mathbf{X_k = [x\ y\ h\ w\ vx\ vy]^T}$$

$$\mathbf{Z_k = [x\ y\ h\ w]^T}$$

As a new frame of the image sequence is acquired and processed at each instant $t_k = t_0 + k$, with k = 0; 1; 2...and delta is a certain sampling time between frames.

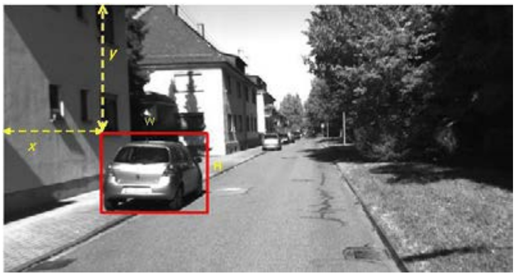

Figure 5: Figure shows the parameters used in the Kalman lter. They are the coordinates of the objects top left point (x,y) and the size (width (w) and height (h)) of the object.

$$F_k = \begin{bmatrix} 1 & 0 & 0 & 0 & \Delta_t & 0 \\ 0 & 1 & 0 & 0 & 0 & \Delta_t \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad H_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

Figure 6

The a priori estimate of the Kalman filter suggests the location and size of the region where the object could possibly appear in the following video frame.

This information is utilized by the tracking function to reduce the search space for re-detecting an object. Once the re-detection is completed, the new measurement data will be given to the system. The a posteriori estimate is then calculated and used as the best estimate for the object's location and size.

5. Results and Analyses

5.1. Road obstacles evaluation

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 30 ms. First, we used the Vision Benchmark Suite stereo images available from [33]. The images had a size of 1226x376 pixels.

Table1 shows the processing time of the road obstacle detection, the overall average processing time for one frame is 30ms.

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

	Average processing time (ms)
road detection	10
obstacle detection	12
Separation process	8
Total	30

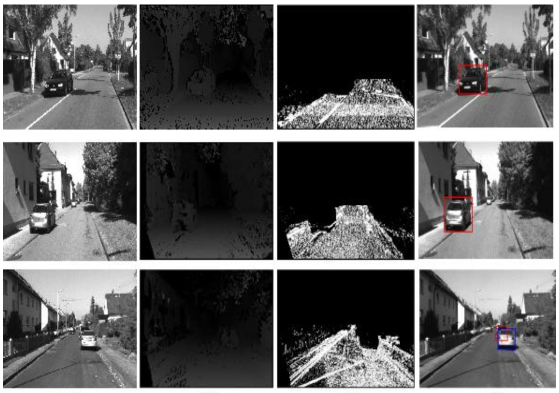

Figure 7: Results of the proposed algorithm: (a) Real images, (b) disparity map. (c) Road segmentation Image, (d) Bounding boxes around obstacles.

The results of the proposed obstacle detection approach are depicted in Fig. 6. The detection rate is high, and our approach proves to be reliable and be able to detect most road obstacles in road environments. The Fig. 6 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 effectiveldescribe the road obstaclesThis experiments result describes a fast, accurate and robust method for detecting the road obstacles by using stereo-vision. The detection process is based on the construction of road (through a Slope of the geometry road and Hough transform) and the obstacles segmentation. This process provides all the information that is required in order to rapidly detect and robustly estimate the road obstacles. Furthermore, if there are objects which are overlapped, it is easy to separate them by using the obstacles separation process, which presents a powerful point to improve the efficiency of our approach.

5.2. Tracking results for the test sequences

In this section we present tracking results over the whole test sequence. The Discrete Time Kalman Filter is used to estimate the position of the obtained obstacles (ROIs) in the next frame. Fig. 7- 9 shows some representative tracking results. The bounding box superimposed on the original frame shows the final detection results.

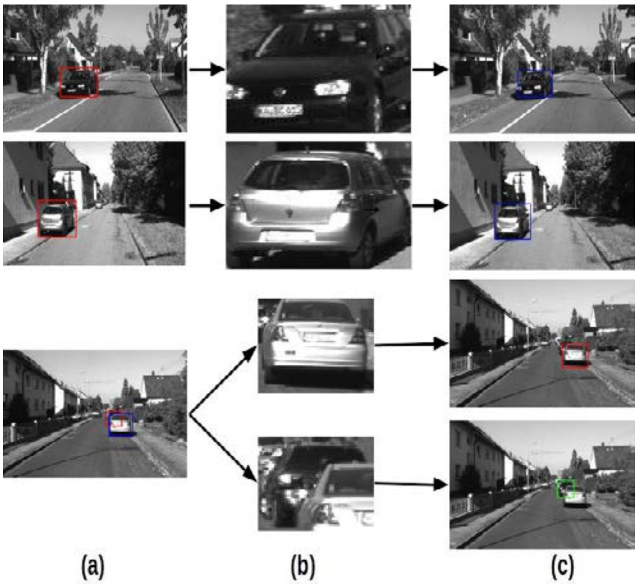

Figure 8: Global tracking results: Figures a) image obstacle at instant t, b) template ROI image, c) image obstacle at instant t+1.

At the Fig. 9, the blue line represents the measured values while the red line is for the values of the Kalman filter's estimates. It can be seen that there are some random fluctuations in the measured values. This is mainly caused by the error in the road obstacles detection process.

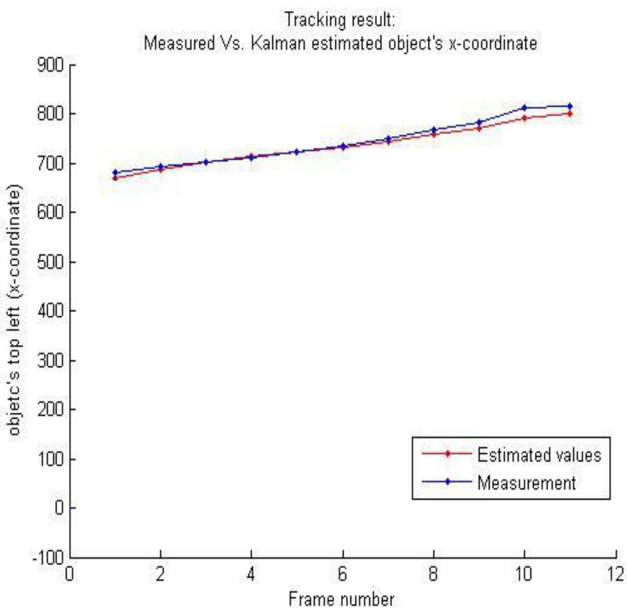

Figure 9: Tracking result for an overtaking road object: The measured and the Kalman's estimated values for the road object's x-coordinate.

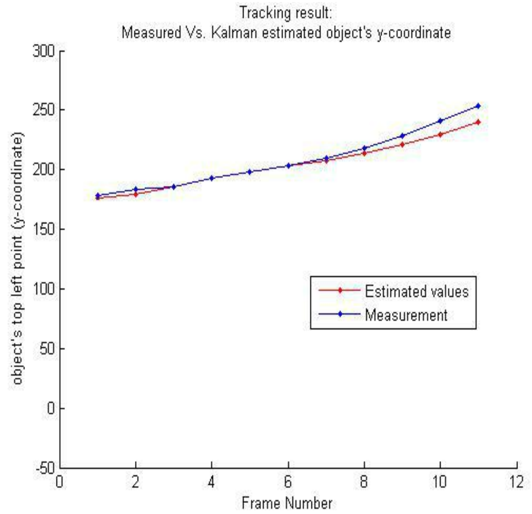

Figure 10: Tracking result for an overtaking road object: The measured and the Kalman's estimated values for the road object's y-coordinate.

6. Conclusion

In this paper, we have developed an algorithm that detects and tracks road obstacles; our algorithm is proposed to detect and to track road obstacles using stereo images which are obtained from cameras installed at a moving vehicle and discrete Kalman filter. The proposed obstacle detection algorithm can be used for the development of driver assistance system and autonomous vehicle systems. Firstly, the road obstacle detection process will be carried out to segment the road by using a slope of the geometry road to extract road disparities. Secondly, the obstacle detection process used to retrieve all objects found it in the road. Then the Kalman filter is used for tracking these objects. The obtained results are perfect and satisfactory. Among the limits of our approach is that the road obstacle is not defined in the validation phase of the obstacles detected. That's why we want to apply the obstacle validation phase to differentiate between vehicles and pedestrians tree ... we will consider using the adabor filter to obtain a perfect detection of vehicles.

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