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Robust Zebra-crossing Detection for Autonomous Land Vehicles and Driving Assistance Systems

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Abstract. Road scene understanding is critical for driving assistance systems and autonomous land vehicles. The main function of road scene understanding is robustly detecting useful visual objects existing in a road scene. A zebra crossing is a typical pedestrian crossing used in many countries around the world. When detecting a zebra crossing, an autonomous lane vehicle is normally required to automatically slow down its speed and to trigger a path-planning strategy for passing the zebra crossing. Also, most of driving assistance systems can send an early-warning signal to remind drivers to be more careful. This paper proposes a robust zebra-crossing detection algorithm for autonomous land vehicles and driving assistance systems. Firstly, an inverse perspective map is generated by utilizing camera calibration parameters to obtain a bird-eye view road image. Secondly, a course-to-fine detection process is applied to obtain a candidate zebra-crossing region and finally a true zebra-crossing region is recognized by combining appearance and shape features. Experiments on several kinds of real road videos which also include several challenge scenes demonstrate the effectiveness and efficiency of the proposed method.

Introduction

A zebra crossing is a typical road marker for pedestrian crossing used in many countries around the world. It consists of multiple white stripes, which are parallel to each other in a 3-D space. They intersect at a fixed point, called the vanishing point, when they are projected onto a 2-D image. A zebra crossing is an important perceptive object for Autonomous Land Vehicle (ALV) navigation systems and driver assistance systems (DAS) since it is crucial to identify crossing roads. For instance, zebra-crossing detection can help ALV to automatically slow down its speed and trigger a special planning strategy in a cross road, and it also can favor a DAS by sending an early-warning signal to remind drivers to be more careful to the pedestrians passing.

For zebra-crossing detection, research has been done for enhancing the safety and mobility of blind people while crossing a road [1-5]. In [1], a system called "cross-watch" is introduced; it can provide information about the location and orientation of crosswalks to a blind or visually impaired pedestrian holding a camera cell phone. In [5], a zebra-crossing detection approach is also designed for partially sighted people, which can tackle the ambiguity in distinguishing zebra crossings and stair-cases. However, these methods are only suitable for low-speed and rough detection. In [6], Adaboost is applied to detect strips of zebra crossing, a post-processing step is designed to group all strips to obtain final results. The method needs to employ large samples to train Adaboost classifier. Mohammad et.al. [15] use bipolar patterns to find candidate regions, the presence of a zebra crossing is inferred by analysis of structure and direction feature, including crossing width, bandwidth trends and so on. The method is further revised in [16] by introducing projection invariance recognition to adapt to various illuminations. Unfortunately, these methods are not specifically investigated for autonomous land vehicles and vehicle driving systems.

This paper proposes a robust zebra-crossing detection algorithm for autonomous land vehicle and driving assistance system. Firstly, inverse perspective map is created by utilizing camera calibration parameters to obtain a bird-eye view road image. Secondly, a course-to-fine detection process is applied to obtain candidate zebra-crossing region and finally true positives are recognized by extracting appearance and shape features. Experiments on real road image sequences which include many challenge scenes demonstrate the effectiveness and efficiency of the proposed method.

The Proposed approach

Our approach broadly consists of three stages: an incoming road image is transformed to an inverse perspective map (IPM), multiple candidate zebra-crossing regions are obtained in IPM based on morphologic filter and intensity projection. Finally, candidate zebra-crossing regions are further identified by a classifier to select true zebra-crossing. Below, we describe each stage in detail.

A. Inverse perspective Mapping

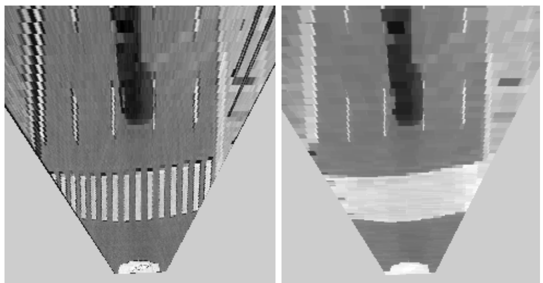
We first eliminate the perspective effect incurring in the captured road images to get the bird's eye view of the road [6-7], namely, inverse perspective mapping (IPM), in this process, all incoming images are remapped to a new image according to camera calibration parameters. The operation will make the following processing simpler than processing in the captured road image. Let $M=(x,y.z)^T$ denote by a point in the 3-D real world, and $m=(u,v)^T$ denote by the corresponding point of R in image coordinate due to the perspective effect. Let $\widetilde{M}=(x,y.z,1)^T$ and $\widetilde{m}=(u,v,1)^T$ denote by the homogeneous coordinate of M and m. Here we assume the road is flat and the road plane is in the plane $Z=0$, $\widetilde{M}$ is simplified as $\widetilde{M}=(x,y,1)^T$. Then we can obtain a 3×3 matrix H which can describe the relation of $\widetilde{M}$ and $\widetilde{m}$ is describe as follows:

$$s\cdot\widetilde{m}=H\cdot\widetilde{M} \tag{1}$$

Where s is a non-zero scale factor. $H=A[r_1\ r_2\ \mathrm{t}]$, which is a 3×3 matrix, the calculation of matrix H depends on the internal calibration parameter A and external calibration parameters r_1, r_2, t. The concrete formulation please refer to [8,9]. Now, the inverse perspective mapping can be realized by Eq. 1. Fig. 1 shows a result image of the Inverse perspective transformation. In the IPM image, a pixel represents 5cm×5cm (cm represents centimeter) region in world coordination. We set the width and height of an IPM image is both 500 pixels, which means that detection range in 3-D real world is -12.5m to 12.5m in X direction and 0 to 25m in Y direction, here m represents meter. It should be noted that there exist an invalid region in the two side of IMP image, which has can find corresponding points in captured image, we use gray color to represent this region (see Fig. 1). In the following, we use mask technique to avoid processing in the region. We can enlarge the width and height of an IPM image if we need to detect farther object, however, calibration error influences the accuracy of an IPM image approximately severe if we create a larger IPM image.

a b

Figure 1. Inverse perspective mapping. (a)Captured road image, (b) IPM image of (a)



a b

Figure 2. Horizontal morphological close operation. (a) An IPM image, (b) Result image of horizontal morphological close operation with(a).

An advantage of using IPM is that strips of zebra-crossing are parallel in IPM image which is easy to be detected. Another advantage is that some measure information can be utilized to recognize zebra-crossing. Usually, the size of zebra-crossing is standard, in China, the width of white strip is 45cm, the length is 500cm or 600cm, and the gap between two white neighborhood strips is 60cm. These measurements correspond to fixed number of pixels in IPM, which can be well used to remove most false positives.

B. Candidate Zebra-crossing Detection

Morphological close operation is applied to the IPM to make the stripes of zebra-crossing joint together. This can enhance the intensity of the zebra region with respect to other regions. Eq. 2 shows the formation of Morphological close operation, f is IPM image, b is 1×12 line-type structure cell, as introduced in section 2.1, 12 pixel represents 60cm. $\oplus$ and Θ represent dilation operation and erosion operation respectively, f' is smoothed image. Then horizontal projection (row direction) is applied to accumulate the intensity of pixels in each row using Eq. 3, here $f'(x, y)$ represents the intensity of pixel at position (x, y), the projection result is a 1D array P. Fig. 2 shows the curve of array P. Gaussian filter is further exploited to smooth P by using Eq. 4, the Gaussian function is shown in Eq. 5, which follows distribution parameter $N(u_1, \sigma_1^2)$, and $u_1 = 0, \sigma_1^2 = 4$ is a suitable parameter setting.

$$f' = (f \oplus b)\Theta b \tag{2}$$

$$P(y) = \frac{1}{N(y)} \sum_{x=1}^{W} f'(x, y) \tag{3}$$

$$P' = P * G \tag{4}$$

$$G = e^{-\frac{(x-u_1)^2}{\sqrt{2\pi\sigma_1^2}}} \tag{5}$$

We select an adaptive threshold T_0 to segment the 1D projection array, T_0 can be calculated adaptively use Eq. 6 - Eq. 8, Then we sequentially test each consecutive run-length which the value larger than T_0, and further analyze the corresponding region R of each run-length, if R satisfies following two conditions, it can be a candidate zebra-crossing region. One is standard deviation of the region should be larger than a minimum threshold T_1 (we set $T_1 = 10$), the other is that the height of the region should fall in the range of 80 to 140 pixels, which equals to the range from 400cm to 700cm in 3-D world coordination, since the size of zebra-crossing is a standard size.

$$u_2 = \frac{1}{H} \sum_{y=1}^{H} P'_y \tag{6}$$

$$\sigma_2 = \sqrt{\frac{1}{H-1} \sum_{y=1}^{H} (P'_y - u_2)^2} \tag{7}$$

$$T_0 = u + \sigma \tag{8}$$

Base on above processing, many unrelated regions have been removed, although, candidate zebra-crossing regions still include some false alarm regions, these false alarm regions will be identified effectively in the following stage.

C. Zebra-crossing recognition

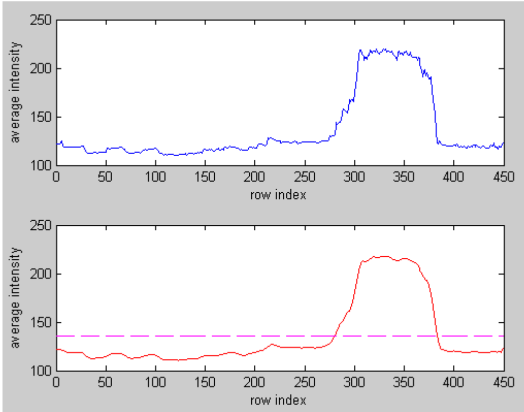


Figure 3. Projection curve of horizontal intensity. The bottom red curve is the smoothed curve of the top one.

Object recognition is a fundamental problem in computer vision and has been a major focus of research activities. Zebra-crossing region contains a serial of parallel straight line segments and period intensity change exists in the direction of the perpendicular line of these parallel straight line segments. In this section, we present a zebra-crossing recognition method based on combinations of line segment and appearance features, combination of the two features has been demonstrated robust in many object detection and recognition problems [10]. Firstly, we use LSD method [11] to detect line segments. LSD is a linear time line segment detector with a control number of false detection, once parameters are set, it requires no parameter turning while achieves a good performance. Fig. 4(b) shows result of straight line segments detection in Fig. 4(a).

Secondly, we find parallel straight line segments from these line segments which satisfy three conditions:

(1) The direction of these line segments should be vertical or approximately vertical in IPM, since the strips of zebra-crossing are along to the road direction;

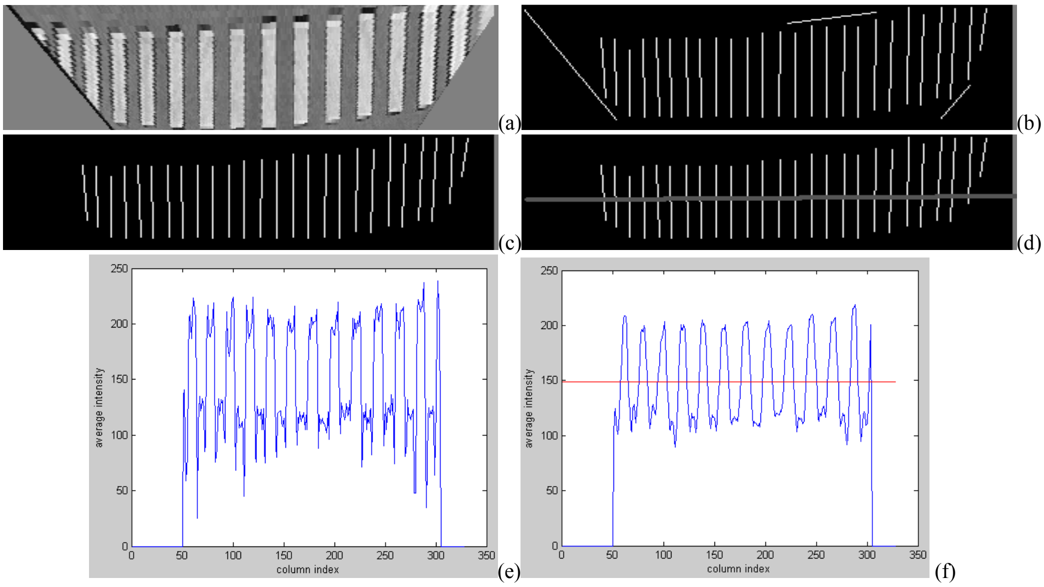


Figure 4. Zebra-crossing recognition

(2) The distances of any two neighboring straight line segments should be approximately the same, this is effective to distinguish other road markings, such as turning markings shown in Fig. 5. The

width and gap of turning markings are usually uneven comparing with zebra-crossings, an example is shown in Fig. 3;

(3) For any pair of line segments, they should largely overlap in the vertical direction of IPM. We apply multi-RANSAC method [12] by involving the above conditions to select parallel line segments. Fig. 4(c) show detection results of parallel line segments. It is noted that if there is no parallel line segments being found, the region is classified as a non-zebra-crossing region, our approach will continue to process next candidate zebra-crossing region as described in section B.

In the following, we further apply intensity feature to recognize zebra-crossing. It is clearly that there exits alternative intensity variation in the direction of perpendicular line of parallel straight line segments, if these line segments are generated from a zebra-crossing region. Fig. 4(e) shows the projection curve of intensity along the gray line in Fig. 4(d), Fig. 4(f) is a smooth result of the projection curve in Fig. 4(e).we can use this intensity feature to recognize zebra-crossings. In order to exploit the characteristic, horizontal Haar-like feature (See Fig. 6(a)) is applied. Haar-like feature [13] is developed by Viola and Jones, A Haar-like feature considers relations of neighboring rectangular region at a detection window in specific location and scale, sums up the pixel intensities in each region and computers the difference between these sums as a simple feature of an image. Haar-like feature usually includes two or more blocks and generates over-complete set of 2D Haar functions to encode local appearance of structures. Haar-like features at any scale and any position can be rapidly evaluated using integral images to obtain real time performance. Here, we use several lines with a fixed interval to split the parallel line segments just like Fig. 6(b) to generate multiple rectangle blocks. Then we use local binary pattern (LBP)[14] as feature to represent zebra-crossing feature.

For each sub-block, we calculate LBP value using the mean intensities of the block and its eight neighborhood blocks. And an LBP histogram is aggregated for the candidate region. In practice, the LBP histogram has high concurrency in the bin 11011101 (221) and 00100010 (34). So we calculate the ratio of the sum of concurrency of bin 221 and 34 to the sum of the whole histogram, and use the ratio as a confidence measure to recognize the zebra-crossing.

$$p = \frac{h_{221} + h_{34}}{\sum_{i=0}^{255} h_i} \tag{9}$$

$$R = \begin{cases} 1 & \mathrm{p > T} \\ 0 & \mathrm{else} \end{cases} \tag{10}$$

If a candidate region does not satisfy the three criteria, the zebra region may be occluded by vehicles or pedestrians.

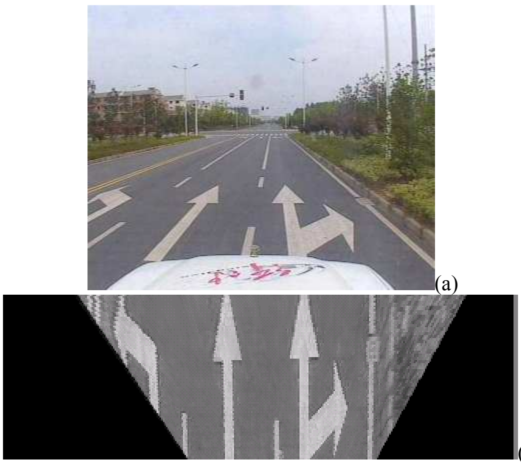


Figure 5. Road scene including turning marker. (a) Original road image, (b) turning marker region of IPM of (a).

Therefore, we learn a part based model to identify the candidate region. This is mainly due to each sub-region of zebra-crossing is constituted by several white and black strips, which show strong self-similarity. So a model can be learned to do recognition.

We randomly sample rectangle sub-regions form zebra-crossing region, each region includes at least three while strips, and resize these sub-regions to 60×15 patches, and a linear SVM classifier is trained to recognize each sub-region. In order to train SVM properly, we collect 5000 sub zebra-crossing regions as positive samples, and randomly select 5000 regions form nature images as negative samples.

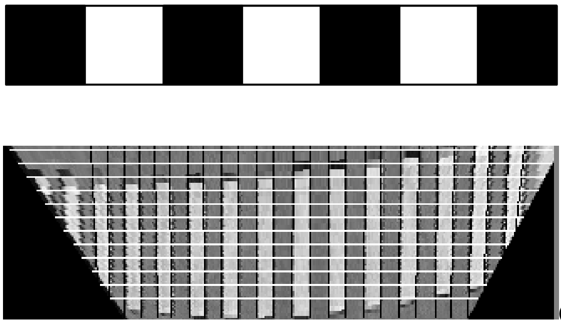


Figure 6. Recognition of sub-region of Zebra-crossing. (a) Horizontal Haar-like feature, (b) split blocks.

This recognition approach can effectively deal with occlusions caused by vehicles and pedestrians. Base on the recognition approach, we can further refine the zebra-crossing location result by combining all zebra-crossing sub-regions and calculate their maximum boundary rectangle.

Finally, the maximum boundary rectangle obtained from IPM is transformed to 2-D image coordinate using the inverse transformation of Eq.1.

Experiments

All the experimental data in this paper are captured by a WAT-1000 camera which is mounted in the front floor of our autonomous lane vehicle. The image resolution is 352 by 288. Some typical detection results are reported in Fig.7, here we use blue rectangle represents zebra-crossing region. The images in the first row show detection results of zebra-crossing with different distance. Detection results in different scenes of variant illumination and partial occlusion are shown in the second and the third row respectively.

We also test our algorithm quantitatively by construct an image dataset. The image dataset include different scene videos such as different illumination in morning, noon and afternoon, road reflection after raining, partially occluded by vehicles or pedestrian or dust. Our proposed method achieves good

Figure 7. Zebra-crossing detection results

TABLE 1
QUANTITATIVE RECOGNITION RESULT OF ZEBRA-CROSSING DETECTION

Sequence No	Description	Frame number	False Negative	False Positive	Accuracy rate
1	Morning	757	19	0	97.5%
2	Noon	1393	18	0	98.7%
3	Afternoon	960	14	14	97.1%
4	Partial occluded	378	3	3	98.4%
5	Reflection	298	2	2	98.7%

detection performance in all these scenes. The quantitative result is shown in Table 1. The average accuracy amounts to 98.9%. In our experiments, most of incorrect detections due to the distance is too far for the IPM to detect, and the original road markers are severely unclear or almost being occluded.

Finally, we test the average time cost of our method with all images of the dataset. Our method runs in a PC whose main configure are: CPU-AMD2.0, memory size-1G, and VC++6.0 develop environment is used. The average time cost of one frame is 57.24 ms, which shows that our proposed method is time efficient.

Conclusions

In the above, we have presented a zebra-crossing detection method that exploit very simple and generic shape primitives of line segments and intensity for ALV and DAS. The approach is based on IPM, and its robustness is enhanced by partly utilizing 3D prior information of zebra-crossing markers. In the future, we will combine traffic light and traffic sign recognition techniques with our zebra-crossing detection approach to achieve robust road scene understanding, for example, crossing road scene.

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