ROBUST LANE MARKING DETECTION USING BOUNDARY-BASED INVERSE PERSPECTIVE MAPPING

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ABSTRACT

Road detection, which brings a visual perceptive ability to vehicles, is essential to build driver assistance systems. To help detect lane markings in challenging scenarios, one-time calibration of inverse perspective mapping (IPM) parameters is employed to build a bird's eye view of the road image. We propose an automatic IPM method based on road boundaries called BIRD (**B**oundary-based **I**PM for **R**oad **D**etection), avoiding common problems of fixed IPM. Furthermore, integrating top-down and bottom-up attention, an illumination-robust lane marking detection approach using BIRD is proposed.

***Index Terms*—** road detection, lane detection, Inverse Perspective Mapping

1. INTRODUCTION

Road detection technology is an essential part of the intelligent vehicle perception which may save human lives and reduce economic losses. While traditional safety facilities can only reduce injuries, automotive active safety technology makes the car capable of detecting and avoiding accidents proactively. One of the key techniques of active safety is environment perception, which aims to obtain environmental information surrounding the vehicle by analyzing data collected by sensors. Since the most important task of driving is following road, road detection plays a key role in environment perception and is of great significance for traffic safety. Lane markings are main clues for structured road following since they delineate traffic lanes. The structured road detection task is generally defined as locating lane markings from road images captured by an on-board camera.

After description of the meaning of road detection and its specific task, this paragraph focuses on its implementation. General object detection can be handled from two perspectives: bottom-up or top-down. The bottom-up approach is feature-based since it first extracts image features, then uses them to match high level model parameters. By contrast, top-down approach, which is model-based, uses predefined models to match low level features. Lane marking detection can also be divided into feature-based [1–3] and model-based [4–7] methods. Focusing on high-level features, model-based methods are more robust against noise, but the finite predefined models they used cannot match various road shapes accurately(e.g. the predefined geometrical model proposed in [4] contains only thirteen curvatures). On the contrary, feature-based methods are not sensitive to the road shape but are sensitive to noise. Due to the variability of road scene, it is difficult to find a robust feature extraction algorithm to filter out all noise. Common detection algorithms based on color [8], edges [9], brightness [10,11], orientation [2] or their combinations [1,12] cannot handle critical shadow cases since bright area surrounded by shadows also have these features.

Integrating top-down and bottom-up attention, this paper proposes an anti-shadow lane marking detection framework. We noticed that the road boundary information is often ignored since the detection target of most structured road detection algorithms is limited to lane markings. Meanwhile, there are lots of road boundary detection algorithms which can be used to extract road boundary information in the field of unstructured road detection. To help detect lane markings in challenging scenarios, we first extract road boundary information to build a road geometrical model, then detect the lane markings using a novel inverse perspective mapping technique called BIRD.

The remainder of paper is organized as follows. In Sect. 2, the related work is described, followed by the implementation of proposed approach in Sect. 3. We discuss the experimental results of our proposed approach in Sect. 4 and conclusions are drawn in Sect. 5.

2. RELATED WORK

2.1. Feature-Based Methods

Feature extraction is the key of feature-based detection method. Most existing methods use brightness feature to segment road images. Assuming that lane markings have brighter

This project was supported by Shenzhen Peacock Plan (20130408-183003656), and by Science and Technology Planning Project of Guangdong Province, China (No. 2014B090910001).

intensity than their surroundings, brightness-based lane marking detection searches low-high-low intensity pattern along image rows [13]. The general formula of brightness-based feature extraction can be summarized as follows [14]:

$$I(x, y) - \overline{I}(x, y) > T \tag{1}$$

Where T is the threshold used to segment, $I(x, y)$ is the gray value of a pixel of raw image locating row x, column y and $\overline{I}(y)$ is the corresponding pixel of filtered image. A good filtering process should smooth out the lane markings without making significant change to other parts. After a simple subtraction of corresponding pixels, the greater the difference, the more likely it is to be a pixel of lane marking.

When filter operation is not applied (or consider filter template is matrix of all zeros), Formula 1 represents a global threshold segmentation, which is applicable to uniform illumination cases (e.g. night scene). According to different filtering (such as mean filtering, median filtering, etc.) employed, Formula 1 can represent various kinds of local thresholding based extraction algorithms (e.g. *LT, MLT, PLT* [14]).

Note that all these methods need to address the problem of perspective effects. Since the pixel width of a lane marking becomes smaller from near to far, filter template should adjust the size among different rows. A simple approach is to let the size of filter template decrease linearly from the bottom row to upper, reaching zero at a predefined horizon row [10].

As both sides of a lane marking is road surface, this symmetry feature can be used (e.g. assuming the gray value difference between road pixels on each side is little [15]) to introduce more robust feature extraction methods. Let s_x be the lane marking width at row x, Formula 2 represents an extended form of Formula 1 taking symmetry into account. Related algorithms are symmetrical local threshold (*SLT*) [10] and extension of *SLT* [1].

$$I(x, y) - \overline{I}(x, y \pm s_x/2) > T \tag{2}$$

There are many problems of feature-based methods. First, we need to define pixel width of lane marker for each image row to solve the perspective problem. Second, calculating threshold adapting to a variety of road scenes is still a problem. Finally, since the local feature extraction does not use the road geometric information, it is difficult for feature-based detection methods to handle the situation of a road full of shadows.

2.2. Model-Based Methods

The model-based methods utilize the information of high-level model to constraint underlying pixel features, having a relatively higher noise immunity than feature-based methods. Road can be simplified to a plane enclosed by two parallel boundary, above which are several road marks which are parallel to boundaries and split the road surface into lanes. Based on this assumption, if we can get the relationship between image coordinates and world coordinates, a top view image can be obtained through inverse perspective mapping (IPM). Coordinate transformation matrix is usually calculated by camera calibration, so most IPM-based methods need off-road calibration [6, 7, 15–17]. In addition, fixed calibration parameters may generate dislocation when encountering road slope variations or slight rotation [18].

Automatic top view transformation is introduced to tackle the problem of one-time calibration. Some [18,19] obtain calibration parameters based on vanishing point estimation while others [5] extract homography matrix for coordinate transformation based on the lane marking detection. The problem is that the detection of lane markings or vanishing point is difficult in shadowy road, which will be addressed in this paper.

3. OUR APPROACH

Our approach is mainly divided into two stages: road boundary modeling (Sect.3.1) and lane marking detection (Sect.3.2). The former detects road boundaries from raw image and then fits it to a geometric model. The latter uses the road boundary model previously built to locate lane markings.

3.1. Bottom-Up Road Boundary Modeling

3.1.1. Road Feature Extraction

There are many road feature extraction methods in the unstructured road detection area. In order to reduce the interference of shadows, color-based method is widely used. For example, Hue component of HSV Color Space is used in [3] to extract road features. However, the Hue component is unstable in shadow cases (cf. Fig. 1). An illumination-robust feature called S' (cf. Equation 3) is proposed in our earlier work [20]. We use S' instead of Hue to extract road boundary features.

$$S' = \frac{max(R, G, B) - B}{max(R, G, B)} \tag{3}$$

Fig. 1. Raw image of a shadowy road (left) and its H (middle), S' (right) components.

3.1.2. Road Boundary Detection and Model Fitting

In the binarization step, a single threshold segmentation is applied to S' feature image. First, the upper 1/4 of image which is mainly covered by sky is removed. The remaining image is then divided into left and right halves and the two regions' adaptive threshold is calculated through Otsu's method independently, intending to handle uneven illumination cases. Finally, connected component analysis is employed to remove small isolated areas which are probably noise.

After binarization, we use the two-pass-scan method [20] to extract boundary points. The first bottom-up scan of binary image selects the non-zero pixel first encountered as candidate points, then the second middle-side scan selects the first encountered candidate points in both sides for each row as boundary points.

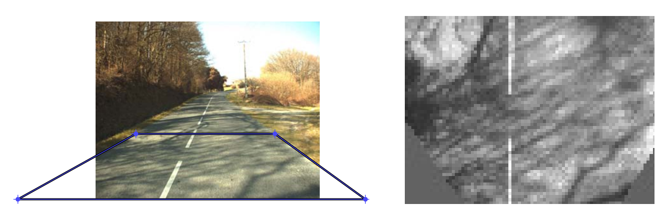
The final step of road boundary detection is boundary model fitting. Straight line model is used to facilitate following process. Hough Transform is employed to fit two straight lines which represent left and right boundaries. The results are shown in Fig. 2.

Fig. 2. Road boundary modeling. Left: segmentation result. Middle: extracted boundary points. Right: detected road bounderies.

3.2. Top-Down Lane Marking Detection

3.2.1. Boundary-based IPM for Road Detection (BIRD)

For IPM-based lane marking detection methods, feature extraction can be performed before [11,15,21] or after [6,16,17] IPM. For road image with heavy noise, it is more efficient to apply strong feature extraction from an IPM image utilizing geometrical information than to filter noise in the IPM image after weak feature extraction. In this paper, we carry out IPM first.



(a) Trapezoidal area of road surface (b) Bird's view image

Fig. 3. Example of proposed automative IPM method.

We choose a trapezoidal area with two pairs of border points in the same row as vertex and convert it to a fixed-size top view image, as shown in Fig. 3. Using the obtained homography matrix which reflects coordinate relations, more road surface pixels can be mapped to world coordinate, as is shown in Fig. 4. It can be seen that the BIRD method can handle a variety of challenging road scenes, such as light reflections and cast shadows.

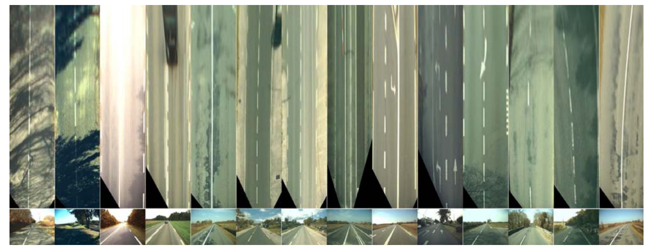


Fig. 4. More examples of BIRD method.

3.2.2. Lane marking Positioning

Road boundaries and lane markings in the near field of road can be simplified to straight line segments. As in Fig. 5, the trapezoid $ABCD$ represents the area we selected previously. The two lateral sides AD and BC, which denote road boundaries, together with PQ which represents lane markings converge at one point O since they are parallel to each other in the world space.

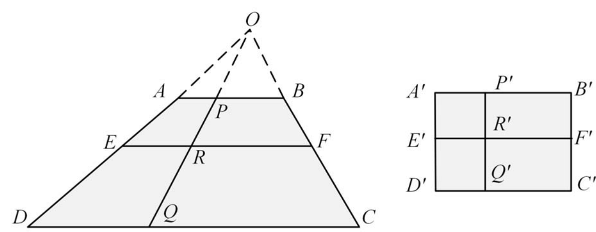


Fig. 5. Relationship between raw image and top view image

$$\because \frac{\overline{AP}}{\overline{ER}} = \frac{\overline{OP}}{\overline{OR}} = \frac{\overline{PB}}{\overline{RF}} = \frac{\overline{AB}}{\overline{EF}} \qquad \therefore \frac{\overline{AP}}{\overline{AB}} = \frac{\overline{ER}}{\overline{EF}} = r \quad (4)$$

According to previous derivation, the lane markings in each row are distributed with a fixed percentage r. This property holds after perspective transformation (Equation 5). Since road boundaries are aligned in bird's eye view, the lane markings are also aligned, which greatly facilitates the subsequent feature extraction. When the column where lane markings are aligned is found in an IPM image, we can calculate r and then locate road mark pixel of each row by Equation 7.

$$\frac{\overline{AP}}{\overline{AB}} = \frac{\overline{A'P'}}{\overline{A'B'}} = r \quad (5)$$

$$\because r = \frac{\overline{ER}}{\overline{EF}} = \frac{x_R - x_E}{x_F - x_E} \quad (6)$$

$$\therefore x_R = (1-r) \times x_E + r \times x_F \quad (7)$$

The last problem to be solved is to find the column where the lane marking pixels are aligned. First, we filter the top view image using filter template shown in Fig. 7. After that, the filtered image is binarized by simple fixed-threshold image segmentation. Connected component analysis is then employed to remove small isolated regions (cf. Fig. 6). Finally, the column with maximum value of the sum of non-zero pixels is considered as the location of lane markings. The detection result is shown in Fig. 8.

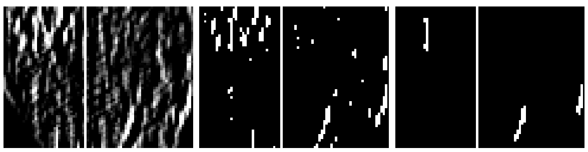


Fig. 6. Lane marking feature extraction. Left: filtered image. Middle: binarization. Right: small isolated regions removed.

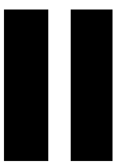


Fig. 7. Filter template used.

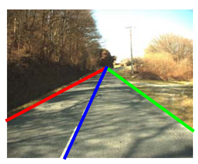


Fig. 8. Detection result.

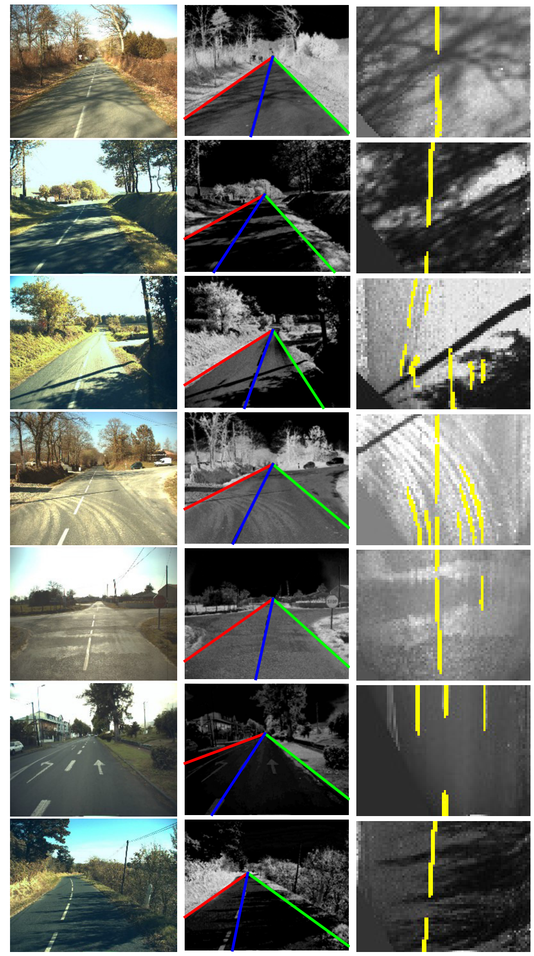


Fig. 9. Experimental results. Left: raw image. Middle: S' boundary feature image, detected boundaries and located lane markings. Right: near field road surface obtained by BIRD.

4. EXPERIMENTAL RESULTS

Performances of proposed approach are first evaluated on an online dataset called *ROMA*[1]. Many challenging scenarios (e.g. strong illumination, highly cluttered shadows, interference from other road marks and special road shapes) are selected to test the robustness of proposed approach, as shown in Fig. 9. The proposed approach is also tested on image sequences from *Santaigo Lanes Dataset*[2]. There is no error detection among 80 images of poor lane markings in straight road with many shadows. Experimental results are available online[3].

5. CONCLUSIONS AND FUTURE WORKS

The main contribution of this paper can be divided into two parts. The first part is BIRD, which provide an automatic bird's view of road image based on boundary information. Unlike traditional IPM method, BIRD does not need camera calibration and it is free from problems caused by fixed parameters. In addition, it provides a convenience for feature extraction since the lane marking pixels are aligned to column in top view image obtained through BIRD. The other part is the proposed lane marking detection approach, which provides a BIRD-based framework for challenging scenarios. We introduced road boundary detection techniques from unstructured road detection researches to help detect lane markings of structured road.

There are lots of work can be carried out further. First, more sophisticated methods can be applied to improve proposed detection framework, such as road boundary segmentation based on Machine Learning and boundary points fitting by RANSAC. Second, expansion can be done like multi-lane detection, far field road detection, curve line road modeling and lane tracking in a video. Last, the main problem to be solved is that the lane marking detection cannot be performed if road boundary detection fails and the performance of lane marking detection is limited by previous road modeling.

[1] http://www.lcpc.fr/english/products/image-databases/article/roma-road-markings-1817

[2] http://ral.ing.puc.cl/datasets/ldw

[3] http://github.com/baidut/openvehiclevision

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