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An Urban Lane Detection Method Based on Inverse Perspective Mapping

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Abstract. Lane markings can provide drivers significant warning instruction about current/ approaching road condition, in that case precise lane marking detection results are important assistance for safety issue in the driving assistance system (DAS). In this paper, we mainly focus on urban lane marking detection. We used sampling peaks from IPM image for lane markings' extraction and description. The proposed method is applied to various video images from black box, and is verified to be robust.

Keywords: DAS; Lane marking detection;

1 Introduction

In the DAS system, drivers require the perception of the environment in case of avoiding emergency circumstances on both highway and rural roads. Once the fundamental information of the road geometry is detected accurately, it will assist the driver a lot on assessing the possibility of the following driving behavior.

Firstly, the lane marking position can be used to localize lane boundaries in the given image and estimating the geometry of the road ahead, as well as the lateral position of the ego-vehicle on the road. Over the last two decades, a significant amount of research has been carried out in the area of road marking detection. This topic can be separated into lane detection and tracking. There are several useful technologies employed in lane detection that have achieved good results in terms of application requirements, which include RANSAC[1] or Hough Transform algorithm[2] for lane model description. Furthermore, essential tracking technologies like the Kalman and particle filter[3] are frequently utilized.

This paper based on a simple, fast, robust, and effective approach of taking a top view of the image, called the Inverse Perspective Mapping (IPM) [1]. To get the IPM of the input image, we assume a flat road, and use the camera intrinsic (focal length and optical center) and extrinsic (pitch angle, yaw angle, and height above ground) parameters to perform this transformation. Some following processing steps such as filtering and peaks extraction are applied on the IPM image to get the final lane detection result. We used a 1D Kalman filter to track the detection result.

The structure of this paper is described as follows: Section 2 presents the lane line detection and localization method which uses IPM and weighted point response

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histogram. In Section 3, we mainly show some detection results and describe brief approach of multiple lane detection. Finally, Section 4 gives concluding remarks and perspectives.

2 Lane Marking Detection

Lane detection in urban streets is especially a hard problem. Challenges include: parked and moving vehicles, bad quality lines, shadows cast from trees, buildings and other vehicles, sharper curves, irregular/strange lane shapes, emerging and merging lanes, sun glare, writings and other markings on the road (e.g. pedestrian crosswalks), different pavement materials, and different slopes[1].

It is known that lane lines only appear in the road region, and the road ROI(region of interest) is always needed in the first step. We use an adaptive ROI setting method[4]. The ROI is determined using the positional information of a vanishing point and line segments. The start bottom part of the ROI is acquired using the line segments distribution analysis. While the vanishing point is captured using the intersection points' clustering. The vanishing point and road ROI detection results are shown in Fig.1.a. Lanes we assumed are parallel for each other. And this information is usually lost in the original images due to the perspective effect. The resolution for near and further object is different in the original image. We here recover it using Inverse Perspective Mapping (IPM) which under a flat ground assumption transforms the image to a top view of the scene. IPM remaps pixels from the original image to the other image that has a different coordinate system. This remapping procedure can be done by a fast lookup table with distortion compensation [5]. Lane markings appear parallel in the IPM image. We turn color image into grayscale because any color information is not necessary in the IPM step.

a. road ROI and near/far region b. lane detection result c. world/ image plane

Fig.1. Image ROI setting and IPM

However IPM has an obvious disadvantage, since all objects are remapped, especially for some remote objects, their shapes are altered prominently. This problem can be ameliorated using different processing method in the road near and far region[6]. We simply assumed the 2/3 region from bottom as the near region. Lane lines in near region are more linear and clearer in presence, while far region contains more curved lines and lines become blurred. In our paper, we care about lane position rather than curvature. Since the lane markings are continuous in a considerable distance, the near region's lane markings shall be identical using the lane lines' model. In that case, we ignore the curved lines and only do the processing in the near region which is shown in Fig.1.a.

Assuming that the coordinates of the mounting position of the camera in the world coordinate system is (d,l,h), the camera calibrated parameters are as follows: γ represents the angle between the projection line of the optical axis at the z=0 plane and y axis; θ represents the deviation angle of the optical axis to the x=0 plane; $2\alpha\mu$ and $2\alpha\nu$ represent the field of view of the camera in the horizontal and vertical directions, respectively. R_w and R_h represent the video image's width and height. The world and image plane is shown in Fig.1.c. The real distance of the up part of IPM image in real world L_{max} is calculated using (1), the H_{up} and H_{down} is the start and end part of road ROI which is shown in Fig.1.a.

$$x(\mu,\nu) = h * \cot\left(\frac{2\alpha_\nu}{R_h - 1} * \nu - \alpha_\nu + \theta\right) * \sin\left(\frac{2\alpha_\mu}{R_w - 1} * \mu - \alpha_\mu + \gamma\right) + d \qquad (1)$$

$$L_{min} = x(R_w, H_{down}) - x(0, H_{down}) \qquad (2)$$

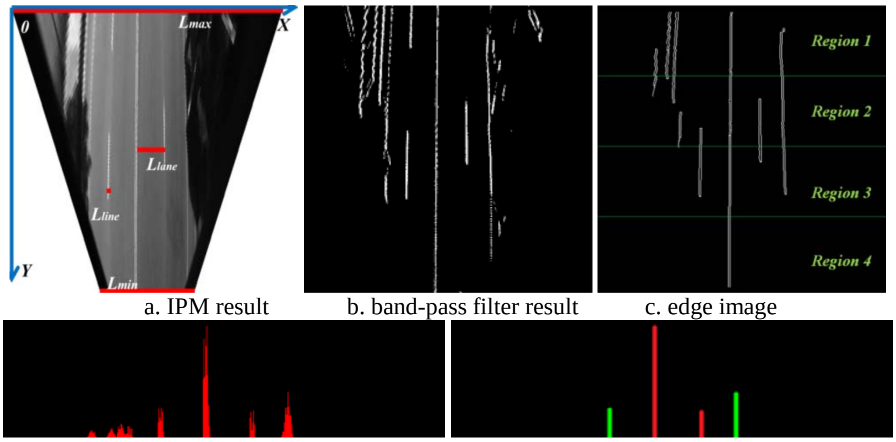
$$L_{max} = x(R_w, H_{up}) - x(0, H_{up}) \qquad (3)$$

As lane marking has a natural Dark-Light-Dark(DLD) transition principle, a band-pass filter [7] which performs a convolution using a top-hat-shape kernel is utilized in the lane markings' extraction step. This filtering method is relatively robust to illumination changing and can be easily accelerated using the cumulative function. After IPM all lane lines are remapped to be parallel, so the length of the top-hat filter kernel has a consistent value. We test the relationship between the video resolution and the road width in a regular Korea and USA road environment. And the kernel's width W_{kernel} is shown in (4). The W_{IPM} is width of the IPM image (we use a value of 500). L_{line} is the lane line's length in real world. We get the band-pass filtered image by slicing the filter kernel line by line.

$$W_{kernel} = 2 * W_{IPM} * L_{line} / L_{max} \qquad (4)$$

Top-hat kernel is sensitive to these DLD features. Even though most lane lines belong to this group, other noises also have a high response of such filter. As is shown in Fig.2.b, some shadows and remote objects turn to be foreground features. In order to achieve these objectives, a noise removing strategy is indispensable. If we only care about the near region, the appropriate lane lines have some common characteristics. First, they turn to some approximately linear connected components after band-pass filtering. On the other hand, these components can't be too big or too small according to the lane markings nature showing. Third, their main direction is roughly vertical. Based on these pre-knowledge, we combine morphology and contour filter for this noise removing task. In the morphology step, we use the opening processing (first erosion then dilation), the morphology kernel that we use is a perpendicular rectangle. Since lane lines which we need to protect is within the same orientation of the kernel. This step can remove some punctate and horizontal noises.

Appropriate edges in the grayscale images are extracted using Canny algorithm which is known to be one of the best edge detection algorithms so far as it produces edges that are one pixel wide. Contour filter is realized on the edge image. We calculate the lengths of all contours of the detected edges and keep edges whose lengths are over 50 pixels in order to remove wispy details. The envelope ellipse of every contour is generated, and the main orientation of the envelope is analyzed for angle filtering. We remove contours whose slopes are smaller than 11.4(dip angle 85). The output edge of lane position's preprocessing is shown in Fig.2.c.



a. IPM result b. band-pass filter result c. edge image

d. points histogram e. peak analysis result

Fig.2. Lane marking detection

A pixel distribution histogram based method is then applied using such an edge image. In [1], the author used the point distribution histogram which cluster the points number col by col, and points in the upper/lower part shows the same response. Nevertheless, in IPM image, the more close to the bottom the less remapped processing pixels have. Less operated and clearer pixels are also more trustable in the lane position detection system. Based on that, we use the weighted region collection in this step. As is shown in Fig.2.c, we separate the whole image into 4 parts. We give a score of 4 for each foreground pixel in the lowest region, the score has a decreasing in position upward, which means in region1, every foreground pixel only have a score of 1. This part is one of the weighted sampling sections in this paper.

We then calculate pixels response and sum them row-by-row, the histogram of points distribution is shown in Fig.2.d. Next step is peak collection. A peak is the local maximum response in a neighborhood range. Peaks' analysis and collection work is related with the purpose of lane detection. If only the ego lane is needed, we only output the two main peaks which are most close to the center position. Here we need to pay attention to the interval of these peaks result. Since the IPM processing can show up the width relationship between the world and the image coordinate. Any pair of peak which interval is over/less 20% of the real distance of the lanes shall be removed for reducing the noise influences.

Tracking is also an important part in the lane position detection. A good tracking algorithm can make the result more smooth and robust. Since the result of the lane position is only the X-coordinate in the IPM image, we applied a simple 1D Kalman filter for each lane in our paper. Kalman filtering allows a linearized version of the system dynamics to be incorporated in order to generate optimal estimates under the assumption noise. Lane marking tracking can provide improved results in noisy situations and generate useful metrics for lane detection in the next frame.
The peaks analysis results are then applied using inverse IPM transformation. The final lane position detection results are shown in Fig.1.b. More detection results are shown in Fig.3 to demonstrate that our method is insensitive to many complex conditions.

3 Experiment Results

For lane detection, more detection results in different situations are shown in Fig.3. We've tested over 1072 frames image in different situations. The total lane detection ratio is 96.7%. In case of using the near region IPM and adaptive weighted sampling method, our system is robust for some intricate situations such as shadow covered/ non-clear road marking painted/ other objects influenced/ partial-curved etc. If we missed tracking for over 10 frames the warning system will work and lane markings are shown in red color like Fig.3.i. Working on different road markings of urban roads, our vision based approach to detect lanes shows promising results.

a. normal urban road b. shadow-coverd road c. road marking painted road

d. crossroad region e. weakly painted lane marking f. weakly painted lane marking

g. shadow-coverd road h. partial painted marking i. missed tracking

Fig.3. Lane marking detection results

4 Conclusion

In this paper, we approached a robust lane detection method based on inverse perspective mapping. After inverse perspective mapping processing, following steps such as filtering and peaks extraction are applied on the IPM image to get the final detection results. We used Kalman filter to track the lane detection results. Results showed that our method worked robustly on different urban roads.

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