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Monocular Vision-Based Lane Detection Using Segmented Regions from Edge Information

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Abstract – For autonomous navigation of a mobile robot in outdoor environments, the information on the lane markers on the road is useful for localization, path planning, and other navigation techniques of a mobile robot. To detect the lane markers, this paper proposes the segmentation based on the Canny edge and the inverse perspective mapping (IPM). The experimental results show that the proposed scheme successfully works in real outdoor environments.

Keywords – Mobile robot, lane detection, Canny edge, IPM, outdoor.

1. Introduction

Research about lane detection was started in order to decrease the loss by car accident. The lane detection technique, one of the driver-assistant technologies, has been widely applied to the auto industries. It can be used not only for the car navigation assistance, but also for the mobile robotics. Especially in case of navigation in the urban environment, lane markers provide useful information for unmanned vehicles. For example, if the mobile robot has road map data including the lane markers, the robot can correct its pose by matching the observed lane information to the map. Also, the robot can plan the optimal paths based on the corrected pose.

There are several methods that have been proposed for the lane marker detection using road image data from a vision sensor. One of the most basic methods to detect the lane marker is the Hough transform [1]. Compared to other methods, the Hough transform based lane detection algorithm is simple since it consists of only two steps; edge extraction and Hough transform. But if the number of pixels of straight lines on the pixel domain is large at the process of drawing the trajectories of each pixel on the parameter domain, computational load increases dramatically.

Histogram information of the road image was also used for the lane marker detection [2]. To extract the lane marker, the algorithm forms a horizontal bend and scans the entire image from the bottom to the top of the image. At each stage of the scan, it makes a histogram of the bend and extracts the pixels having higher intensity than the threshold value. Though this method requires less computational load, not enough considerations to the nearby environment may lead to detection failure of the lane markers.

Meanwhile, Wang *et al.* proposed to use the B-snake algorithm for the lane marker detection [3]. This algorithm can robustly extract lane features from various kinds of road environment. However, complicated recursive calculations of the snake model-based algorithm makes real-time operation difficult.

To overcome the problems of existing lane marker detection schemes, we propose to use inverse the perspective mapping (IPM) [4] and segmentation technique based on the Canny edge detection. First, the original image is filtered by the adaptive thresholding method. Then this filtered image is transformed into the top-view image and segmented by contours extracted by the Canny edge detector. After the segmentation, adjacent pixels are clustered to become a single object. Finally, the objects corresponding to the lane marker are extracted. The proposed method is robust to illumination changes and show accurate detection with relatively good real-time performance.

This paper is organized as follows. Section 2 gives the result of the IPM method and its implementations. Section 3 introduces the segmentation, labeling, feature extraction methods in detail, and shows the experimental results of the proposed method. Finally, conclusions are drawn in section 4.

2. Inverse Perspective Mapping (IPM)

The inverse perspective mapping (IPM) for lane marker detection is useful to eliminate the perspective effect of the original image. The IPM is a technique which remaps each pixel of the original image to a different position and generates another 2 dimensional pixel array. By applying the IPM to the original image, the lane features become vertical and parallel. Therefore, the IPM scheme is widely adopted by other researches concerned with the lane marker detection.

In this paper, the IPM method is applied to the thresholding and segmentation process. The IPM is based on the flat road hypothesis which agrees with the fact that most urban roads are flat and the lane markers on the roads are parallel to each other. Figure 1 and the following equations represent the geometrical relationship of IPM.

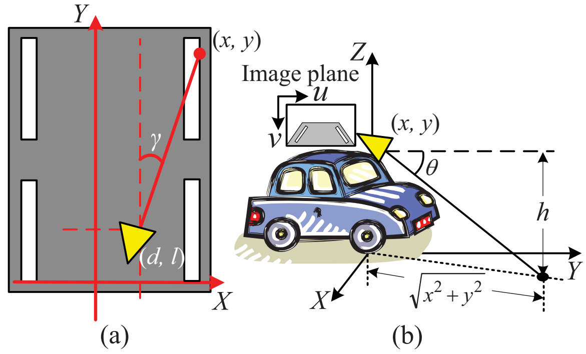


Fig. 1. Geomatric model of IPM: (a) top view geometry of IPM, and (b) side view geometry of IPM.

$$u(x,y,0)=\frac{\arctan\left[\dfrac{h\sin\left\{\arctan\left(\dfrac{x-d}{y-l}\right)\right\}}{x-d}\right]-(\gamma-\alpha)}{\dfrac{2\alpha}{n-1}} \quad (1)$$

$$v(x,y,0)=\frac{\arctan\left(\dfrac{x-d}{y-l}\right)-(\theta-\alpha)}{\dfrac{2\alpha}{m-1}} \quad (2)$$

$$\gamma=\tan^{-1}\left(\frac{x}{y}\right)$$
$$\theta=\tan^{-1}\left(\frac{h}{\sqrt{x^2+y^2}}\right) \quad (3)$$

where γ is the angle between the projection of the optical axis on the flat plane(i.e., $z=0$), θ is the angle between the optical axis and the horizon, α is the camera angular aperture, and $n\times m$ is the resolution of the image. The camera is placed at the point (d, l, h) of the world coordinate system $W=\{x, y, z\}$. Meanwhile, the world coordinate of each pixel in the image plane $I=\{u, v\}$ is (x, y, 0). The IPM scheme in this paper is detailed in [4].
In this paper, only the subregion which corresponds to the road area was considered to reduce the computational burden as shown in Fig. 2(a). Then, it was remapped to build a new image by the IPM which projects 3D space into the 2D image plane mathematically as represented in Fig. 2(b).

Fig. 2. Results of IPM: (a) original Image, and (b) top view of the original image transformed by IPM.

3. Segmentation and Line Feature Extraction

3.1 Thresholding and Segmentation

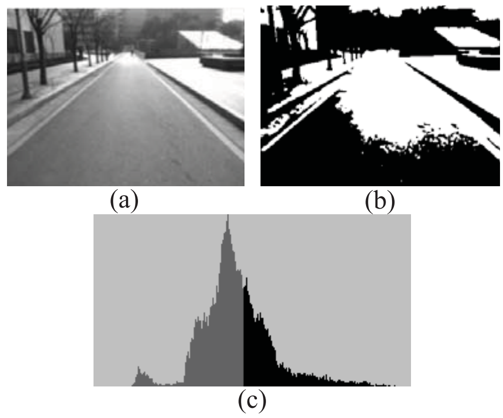


Fig. 3. Thresholding result: (a) grey scale image, (b) thresholded image, and (c) histogram of (a)

The original image taken from the camera is converted into grey scale image as represented in Fig. 3(a). After the conversion, the image is filtered by the adaptive thresholding method using the histogram information. The detail of this process is as follows. First, the histogram of the grey scale image is obtained from its pixel intensity as depicted in Fig. 3(c). Then, the threshold value which determines the ratio of pixels with higher intensity to pixels with lower intensity is calculated. This ratio is empirically set to 0.6 to extract 60 percent of pixels in the image. After selecting the threshold value, every pixel whose intensity is higher than the threshold value is extracted to make a binary image as shown in Fig. 3(b). This binary image is transformed into the top-view image by the IPM scheme.

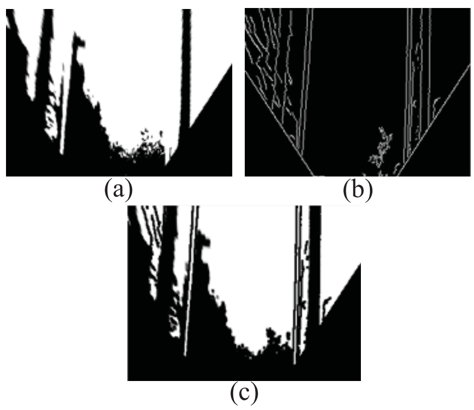


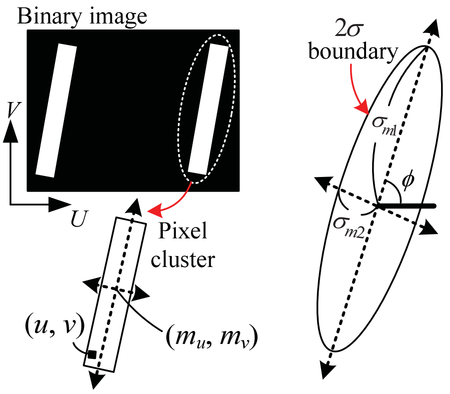
Fig. 4.Segmentation result: (a) IPM transformation result of the thresholded image, (b) contours extracted by canny edge detector and (c) final result.

The next step is to perform segmentation of the thresholded image. To exclude unnecessary pixels which do not correspond to the lane marker feature, the binary image generated by the thresholding process needs segmentation. The segmentation process requires the contour information of the road image. In this stage, the Canny edge detector is used to extract contours from the top-view image transformed by the IPM. The segmentation result can be attained by dividing the binary image based on the contour information as shown in Fig. 4. To achieve a clearer segmentation result, the regions with high intensity are eroded by the morphological operation.

3.2 Lane Feature Extraction

By the segmentation process, the lane markers become more distinctive. To robustly extract the lane markers, only the long-shaped regions are considered. The whole procedure is explained below.

First, clustering of adjacent pixels is required. The clustering process is performed by the grassfire algorithm [5] in order to handle the clustered pixels as a single object. Then we need the geometrical information of the clusters; in this paper, the mean point, direction, and the length of both minor and major axes [6].



(a) (b)

Fig. 5. Geometric information of lane marker: (a) real lane marker in binary image, (b) lane marker feature transformed into 2σ boundary.

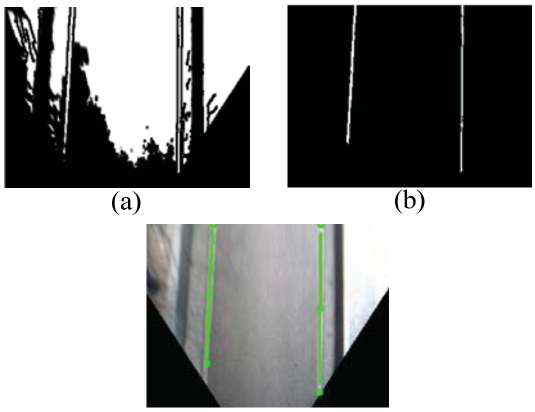
To find out the geometrical information of a cluster, the average and variation are calculated from the distribution of the pixels. Then the lengths σ_{m1} and σ_{m2} of the major and minor axes and the rotation angle ϕ of the major axis are obtained as follows:

$$\mathrm{cov}(u,v)=\begin{bmatrix} \mathrm{E}[(u-m_u)^2] & \mathrm{E}[(u-m_u)(v-m_v)] \\ \mathrm{E}[(v-m_v)(u-m_u)] & \mathrm{E}[(v-m_v)^2] \end{bmatrix} \quad (3)$$

where cov(u,v) is the covariance matrix of the distribution of the pixels belonging to the cluster, and (m_u, m_v) is the average point of the distribution. Equation (3) can be given by

$$\mathrm{cov}(u,v)=M^T\begin{bmatrix} \sigma_{m1}^2 & 0 \\ 0 & \sigma_{m2}^2 \end{bmatrix}M,\ M=\begin{bmatrix} \cos\phi & -\sin\phi \\ \sin\phi & \cos\phi \end{bmatrix} \quad (4)$$

where M is the matrix that rotates the object by ϕ. Consequently, σ_{m1}, σ_{m2}, and ϕ can be induced by following formulas.



(a) (b)

(c)

Fig. 6. Extraction of lane features from segmented binary image: (a) segmentation result, (b) extraction of long-shaped clusteres, and (c) detected lane features.

$$a=E[(u-m)^2],b=E[(u-m)(u-m)], \quad c=E[(v-m)^2] \quad (5)$$

$$\phi=\frac{1}{2}\tan^{-1}\left(\frac{2b}{a-c}\right) \quad (6)$$

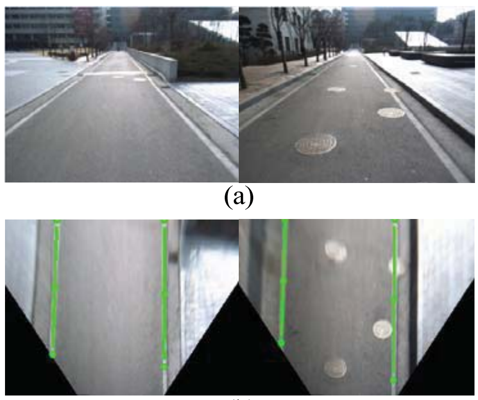
$$\sigma_{m1}=\sqrt{a+b\tan\phi},\sigma_{m2}=\sqrt{c-b\tan\phi} \quad (7)$$

Finally, the long-shaped regions corresponding to the lane markers are determined according to the ratio of σ_{m1} to σ_{m2}.

$$R=\frac{\sigma_{m1}}{\sigma_{m2}}(\sigma_{m1}>\sigma_{m2}) \quad (8)$$

A cluster whose ratio is larger than a threshold (e.g., 20) is extracted as a lane feature. Figure 6 shows the result of lane feature extraction based on the proposed algorithm.

3.3 Experimental Results



(a)

(b)

Fig. 7. Result of lane feature extraction: (a) original images and (b) IPM images with extracted lane features.

A series of experiments were conducted using a mobile robot equipped with a well-calibrated monocular camera.

The time required for the whole procedure was up to 30 msec on the quad core CPU operating at 3 GHz.

Figure7(a) is the input images of the road while Fig. 7(b) is the IPM images of the feature extraction results. Figure 7(b) proves that the proposed method works well even though the lane features are contaminated by unexpected condition change such as shadows casted or obstacles placed on the lane markers. As shown in the right side of Fig. 7(b), lane features were stabely extracted although the lane feature is disturbed by the manhole covers.

4. Conclusion

For the successful extraction of lane features in outdoor environments, the features were clearly separated from the binary image by using the adaptive thresholding method and the calculation of major and minor axes of each cluster. In spite of illumination changes and noise, adaptive thresholding and Canny edge detector enabled to achieve stable feature extraction from real road images. The lane feature information from the proposed algorithm can be applied to other applications such as localization and path planning for outdoor navigation.

However, the proposed lane detection algorithm has a limitation: it may provide inaccurate results for the curved lane markers, since the current lane detection algorithm is based on the assumption that lane markers on the roads are straight. Therefore, our future work will focus on the detection of both curved and straight line features.

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References

[1] H.-J. Kwon and J.-H. Yi, “An Efficient Lane Detection Algorithm Based on Hough Transform and Quadratic Curve Fitting,” The Transactions of The Korea Information Processing Society, Vol. 6, No. 5, pp. 100-112, 1999.

[2] J. P. Gonzalez and U. Orguner, “Lane Detection Using Histogram-based Segmentation and Detection Tree,” Proc. of IEEE Intelligent Transportation Systems, pp. 346-351, 2000.

[3] Y. Wang, E. K. Teoh, and D. Shen, “Lane Detection and Tracking Using B-Snake,” Image and Vision Computing, Vol. 22, pp. 269-280, 2000.

[4] M. Bertozzi, A. Broggi, and A. Fascioli, “Stereo inverse perspective mapping: theory and applications,” Image and Vision Computing, Vol.16, pp. 585-590, 1998.

[5] Pitas. I, Digital image processing algorithms, Prentice-Hall, 1993.

[6] S. Y. Hwang and J. B. Song, “Monocular Vision and Odometry-Based SLAM Using Position and Orientation of Ceiling Lamps,” Journal of Institute of Control, Robotics and Systems, Vol.17, No.2, pp. 164-170, 2011.