Improved Lane Detection for Unmanned Ground Vehicle Navigation

Seok Beom Kim, Joo Hyun Kim, Bumkyoo Choi, and Jungchul Lee

Department of Mechanical Engineering, Sogang University, South Korea

Abstract. Fast and efficient lane detection is prerequisite for unmanned vehicle navigation. For lane detection, previous works mostly used algorithms based on edge detection. Our approach uses the Hough transform and Inverse perspective transform (IPT) via morphological vision processing and filtering and then extracts lanes to construct a local map. The suggested algorithm improves the processing time by using partially extracted lanes and enhances the detection efficiency by separating noises resulting from external light sources. In addition, camera vision images are reconstructed onto the local map using the IPT method to control unmanned vechicles.

Keywords: Hough Transform, Inverse Perspective Transform, Lane Dectection, Morphology, Unmanned Ground Vehicle

1 Introduction

Recently, smart technologies draw continuing attention with the help of advanced informational technology. As such technologies are adapted to automobiles, active research activities on unmanned autonomous navigation are ongoing to aid and replace human perceptions. For unmanned ground vehicle applications, a vision system is one of the key components. Since a vision system detects lanes using a series of image data through an algorithm, the vision recognition algorithm needs to be improved to deal with lanes including more complicated morphologies.

Various methods have been used for lane detection. Most frequently used methods are to detect edges between roads and lanes [1], to use the perspective mapping [2], to use the Hough Transform [3], and to use the Kalman Filter [4].

In this paper, we construct an improved lane detection system which generates a localized map using the Hough transform and Inverse perspective transform (IPT). Depending on the morphology of lanes, a variety of image filters and operators are employed in the Hue-Saturation-Value (HSV) color space based on human color perception.

2 Methodology

2.1 Camera Setup

To detect lanes using charge-coupled device (CCD) cameras, installation position and angle are key parameters for a local map generation around the unmanned ground vehicle. Therefore, optimized setup parameters are required based on the region of interest (ROI). The optimized position and tilt angle of our CCD camera are 1.55 m from ground and 12.5 °downward (see Fig. 1). After installation, camera angle of view is 43.6028°x61.9275° (vertical(V) x horizontal (H)) and the ROI is 20 m x 10 m (VxH). With 0.25 m step on the predefined ROI, total 3200 bits (80x40) are used to describe the localized map.

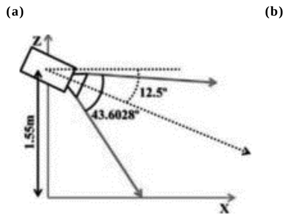

Fig. 1. (a) Camera setup parameters (b) 2D Boolean array with 3200 bits (80(V)x40(H)) in the ROI.

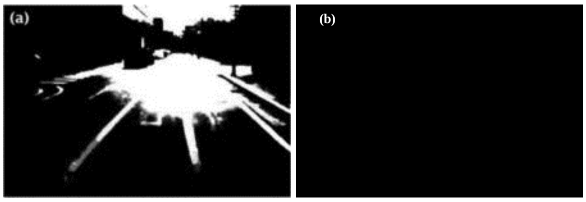

Fig. 2. (a) A road image showing light spreading phenomenon with contrast image processing (b) A processed image showing the difference between background and original image after fixing light spreading phenomenon.

2.2 Pre-processing

During lane detection using a vision system, different local properties in an identical image may exist due to uncontrollable factors such as the intensity of external light sources and shadowing from neighboring obstacles. As a result, noises are inevitably introduced and the quality of lane detection becomes degraded. To compensate such uncontrollable environmental factors, a pre-processing step is necessary. For example, the camera image of lanes on a bright day contains more light spreading than one on a cloudy day (see Fig. 2(a)). Due to the similar color level of light spreading to that of white lanes, light spreading prevent lane detection and edge extraction. To compensate the local light spreading, a parallel processing using morphology is necessary since the morphology is efficiently used to clarify an object by separating image components such as boundaries and structures within an image. The background of an image is expanded to extract the overall background, then the same structuring element is dilated to reconstruct the background of which size is identical to the original image. Using the difference between one image with the Hue channel removed and another image processed morphologically, background, lanes, and other neighboring objects are successfully extracted (see Fig. 2(b)). With different to Fig. 2(a), the exceptionally bright area can be removed.

To emphasize bright lanes, each pixel is processed from 1 to 255(= 2^8-1) with high speed using a lookup table pre-stored in our algorithm. Once lanes are extracted, filtering is required to suppress noises on the image. To this end, the Median filter is employed and the highlight convolution is used to extract edges.

2.3 Lane Detection

Since there are various types of lanes in real roads, points recognized as parts of lanes from edges of the pre-processed image are extracted using the Hough transform in the form of *p=x* cos *0+y* sin *0* , where *p* and *0* are the distance and angle from the origin, respectively, to perform an abstract line fitting for the tracking purpose. Lanes from the Hough transform are ones in the camera coordinate having the perspective in the camera image. Therefore, they are transformed into lanes on roads in bird's-eye view using the **IPT** and camera setup parameters.

First, the Otsu method is employed to make data recognized from the image computable binary arrays in pixel where lanes are clustered and only existing pixels are computed to reduce the calculation time. In the case of the Inverse perspective transform, geometrical parameters in Fig. 3 and Eqns. **(1)** and (2) are used to transform the camera image *(u, v)* into the real image *(x, y,* 0).

hx cos[(2v1 (x $_{resolution}$ *-1) -1) x* al1

***x(u,* v) =** **, _____** (1)

tan LO + *(2u/(x* $_{resaution}$ **- 1)-1) x** *a2] h x* sin *[(2v/(x* $_{„soha,0„}$ - 1) -1) **x al]**

y(u,v) = (2)

tan Le + *(2u/(x* $_{resoh,,„on}$ -1) -1) x *a2]*

where, *h* is the height from the ground and $X_{resolution}$ and v $_{resolution}$ are pixel resolutions in x and y coordinate, respectively.

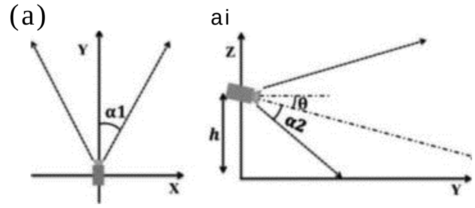

Fig. 3. Geometrical parameters for the Inverse perspective transform

3 Experiment

Experiments are performed on campus roads (Sogang University, Seoul, South Korea). Of note, maintenance condition of campus roads and luminance of lanes are not as good as regular traffic roads. While the camera installed on a 4-wheeled electric vehicle platform takes images (resolution : 320 x240) at 30 frames per second (fps), performance of the lane detection including the error rate and computing speed with the IPT employed are experimented. The flow chart of the algorithm used is shown in Fig. 4.

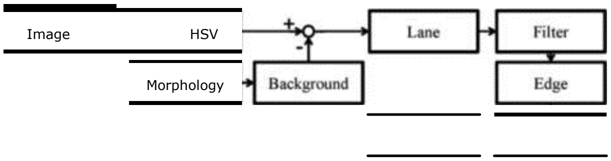

Fig. 4. A flow chart of the lane detection algorithm

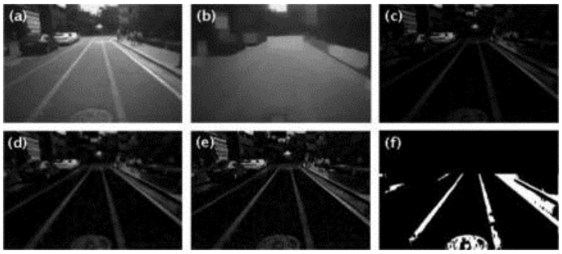

Fig. 5. (a) Original image (b) Background image processed with the morphological operators ("Erode" and "Dilate") (c) Image with the background eliminated (d) Image with the Median filter used (e) Image with the Highlight convolution (f) Binarized image with the ROI extracted.

Fig. 5(a) shows an original image of a road on campus. All lanes are well removed in the background image processed with the morphological operators shown in Fig. 5(b). Fig. 5(c) is obtained by taking the absolute difference between Fig. 5(a) and Fig. 5(b). Neighboring objects which are not included in the same background as lanes are well recognized without the light spreading phenomenon resulting from external light sources. In addition, we can confirm that most data are well preserved when images processed with filters are binarized from Fig. 5(f).

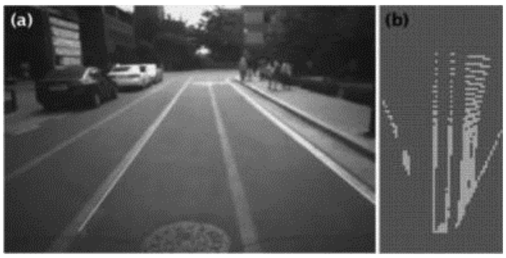

Fig. 6. (a) Detected lane with the Hough transform overlaid onto the original image (b) Local map 2D Boolean array

When our lane detection algorithm is applied based on such pre-processed images, results from the Hough transform show a good agreement with the direction of actual lanes if the ROI excludes the central blue guideline. Local mapping is performed to realize a path planning algorithm for autonomous navigation and results are shown in Fig. 6. The width of the lane extracted from the IPT is 2.6 m which agrees well with the real width of 2.7 within 3.7 % error. And the computing speed in our real-time imaging processing is 15.4 fps. The maximum speed of our 4-wheeled electric vehicle platform is 5.3 m/s so our lane detection algorithm would update road information every 0.34 m.

4 Conclusion

In this paper, points estimated as parts of lanes are extracted by image processing using various morphological operators and filters from HSV color channels for improved lane detection. The Hough transform and IPT are employed to construct a local map for unmanned autonomous navigation.

By introducing pre-processing, masking, and configuring the ROI, computing speed of the lane detection algorithm is improved to 15.4 fps. However, objects with similar color or morphological data and noises are recognized as lanes sometimes depending on light reflection. The algorithm needs to be further improved to address such issues.

Acknowledge

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