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Real-time illumination invariant lane detection for lane departure warning system

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ABSTRACT

Lane detection is an important element in improving driving safety. In this paper, we propose a real-time and illumination invariant lane detection method for lane departure warning system. The proposed method works well in various illumination conditions such as in bad weather conditions and at night time. It includes three major components: First, we detect a vanishing point based on a voting map and define an adaptive region of interest (ROI) to reduce computational complexity. Second, we utilize the distinct property of lane colors to achieve illumination invariant lane marker candidate detection. Finally, we find the main lane using a clustering method from the lane marker candidates. In case of lane departure situation, our system sends driver alarm signal. Experimental results show satisfactory performance with an average detection rate of 93% under various illumination conditions. Moreover, the overall process takes only 33 ms per frame.

1. Introduction

Lane detection is an interesting and important research area for intelligent vehicle technologies because the number of car accident victims has increased annually with the growing number of vehicles on the road. Many accidents are caused by a lack of awareness about driving conditions due to driver carelessness or visual interference. Consequently, advanced driver assistance systems (ADAS) are regarded as an important technology to reduce the frequency of such accidents, and lane detection and tracking are considered to be basic modules for ADAS. ADAS uses a variety of sensors such as vision, scanning laser radar, radar, and global positioning system (GPS) devices. The research focuses on a vision-based application because vision sensors are cheaper than other sensors, and the performance of lane detection is superior (Youchun & Rongben, 2001). Vision-based methods such as inverse perspective mapping, particle filters, and Hough transforms (Graovac & Goma, 2012; Mccall & Trivedi, 2006; Southhall & Taylor, 2001) have been proposed for lane departure warning systems (LDWS) and lane keeping systems (LKS); however, they exhibit high computational complexities and unsatisfactory performances under various illumination conditions.

In this paper, we propose an illumination invariant lane detection algorithm which works well in various illumination conditions such as in bad weather conditions and at night time. It also works in real-time by reducing computational complexities to cope with rapidly changing traffic conditions. The main contributions of this paper can be summarized as follows:

- Robustness under various illumination conditions: We analyzed the invariance property of lanes under various illumination conditions, and used it to detect lanes. The proposed method also works well even under outdoor environment which diversely changes depending on the weather conditions and time.
- Low computational complexity: The proposed method defines an adaptive region of interest (ROI) by detecting a vanishing point and it creates a binary lane candidate image to reduce the computational complexity.

We tested our proposed lane detection algorithm for various experimental datasets to verify its performance. This study includes simulation results for datasets of 10236 frames from DIML-dataset1 (vehicular camera), DIML-dataset2 (smart phone camera), Caltech and SLD-2011 datasets.

This paper is organized as follows: Section 2 briefly reviews related works on lane detection systems. Section 3 describes a proposed lane detection system. Section 4 shows the details of the

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experimental environment and results. Finally, Section 5 provides the conclusion including further research suggestions.

2. Related works

Various studies have been done to detect and extract lanes using vision sensors. Most lane detection methods use the following three steps: The first one typically uses basic features such as edge, gradient and intensity (Borkar, Hayes, & Smith, 2012; Kong, Audibert, & Ponce, 2010; Wang, Lin, & Chen, 2010). Edges are one of the most significant features because lanes create strong edges on the road. In other words, large gradients exist between the road and lane due to the difference in their intensities. For example, edges of driving input image are extracted by canny edge detector (Canny, 1986). The Hough transform (Southhall & Taylor, 2001) is then used to find straight line in the edge image which could be road lane. In addition, the modified Hough transform methods have been proposed for much quicker and enhanced memory efficiency (Kuk, An, Ki, & Cho, 2010; Leandro & Manuel, 2008). However, methods based on edge and Hough transform have many problems in detecting curved lanes, sensitivity in various illumination conditions, artifact and road patterns (Hsiao, Yeh, Huang, & Fu, 2006; Sotelo, Rodriguez, Magdalena, Bergasa, & Boquete, 2004). Gradient-enhancing conversion method was proposed to detect lane boundaries under various illumination conditions (Yoo, Yang, & Sohn, 2013). However, it does not work well in extremely different multi-illumination conditions such as water reflection in heavy rainfall at night because they assume that one scene does not include multiple illuminations.

The second method uses geometric information (David, Jose, Pablo, & Mateo, 2012). The geometric coordinate of camera and road lane have parameters that predict the detection of lanes (David et al., 2012). These parameters are used for Kalman and particle filters (Graovac & Goma, 2012). A new method using dynamic homography matrix estimation has been introduced recently for lane detection (Kang, Lee, Hur, & Seo, 2014). They showed good lane detection performance since parameters include the actual geometric information. However, it is not easy to define geometric information because the camera shakes and road environment frequently changes.

The last one uses lane color information. Vision-based methods usually convert RGB to HSI or custom color spaces because RGB color space is difficult to express the lane color information (Chin & Lin, 2005; Sun, Tsai, & Chan, 2006). In these alternate color spaces, the luminance and chrominance components of a pixel are separately modeled. As a result, the effects of shadows and various illumination conditions in color components can be greatly reduced. However, since these approaches operate at a pixel level, they are very sensitive to street lights or similar illumination sources. It is difficult to detect lanes in various environments such as road patterns and illumination conditions. Moreover, real-time processing is required to prevent accidents in an environment of fast driving. However, existing methods still have high computational complexities and unsatisfactory performances under various illumination conditions. We propose a new system which is fast and powerful in various illumination conditions without geometry information such as characteristics of the device and road environment.

3. Proposed method

Fig. 1 illustrates the overall process of the proposed system. Our proposed lane detection algorithm consists of 3 stages such as a vanishing point detection stage,a lane marker detection stage, and a lane clustering and fitting stage. First of all, we detect a vanishing point using a voting map to establish an adaptive ROI, which reduces the computational complexity at the vanishing point detection stage. Then, we obtain a binary lane image from the white and yellow lanes since typical road images include these lanes, and they retain their own properties of colors under various illumination conditions at the lane marker detection stage. Third, we detect main lanes using a clustering and fitting method in the binary lane image at the lane clustering and fitting stage. Finally, Our system determines that the lane departure situation based on finding main lane at the lane departure warning stage.

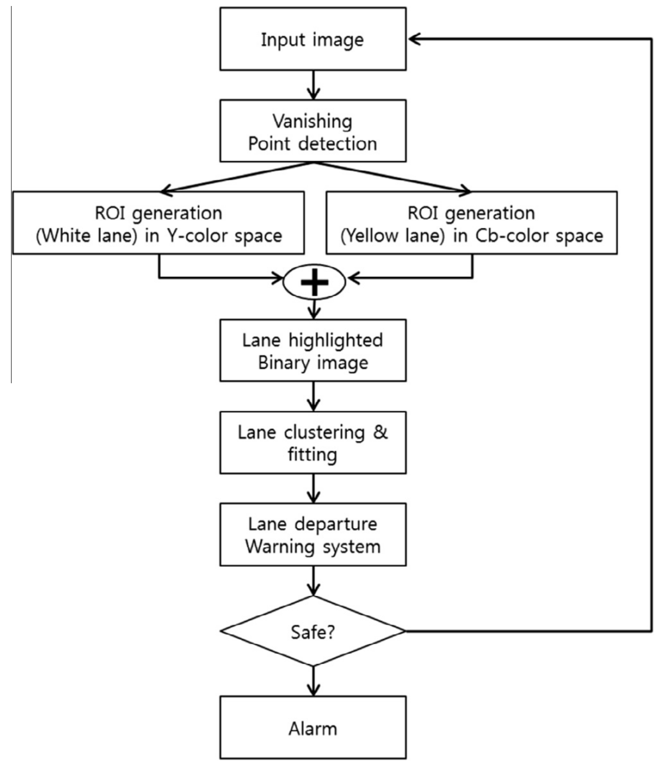

Fig. 1. Flowchart of the proposed lane detection algorithm.

3.1. Vanishing point detection stage

Lanes generally exist at the bottom half of a captured image while regions including the sky and landmarks appear at the top half (Foedisch & Takeuchi, 2004; Glaser, Mammar, & Sentouh, 2010). Thus, it is reasonable to consider only the bottom half of the image to extract the lane markings. However, the bottom half of the image may not be sufficient for lane detection because the features of those lane markings may be unclear and easily affected by illumination changes, shadows, and occlusions. Establishing an adaptive ROI using a vanishing point effectively reduces the computational complexity. In this paper, the vanishing point is detected as follows: First, edge detection preserves the structural properties important and significantly reduces the amount of data. Among the edge detection algorithms, we use the canny edge detector since it is robust to noise. In addition, we extract line components using Hough transform to use straight properties of lane. We detect line components using a canny edge detector and Hough transform as shown in Fig. 2(c) and (d). Second, we calculate the intersection point of the detected lines. Then, we generate a voting map which is cumulative line component sets. We counted the number of intersection points in voting map as shown in Fig. 2(e) and (f). Finally, we find the center point of the most voted area, which is defined as a vanishing point; it is denoted with a