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Robust Lane Detection using Two-stage Feature Extraction with Curve Fitting

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ABSTRACT

With the increase in the number of vehicles, many intelligent systems have been developed to help drivers to drive safely. Lane detection is a crucial element of any driver assistance system. At present, researchers working on lane detection are confronted with several major challenges, such as attaining robustness to inconsistencies in lighting and background clutter. To address these issues in this work, we propose a method named Lane Detection with Two-stage Feature Extraction (LDTFE) to detect lanes, whereby each lane has two boundaries. To enhance robustness, we take lane boundary as collection of small line segments. In our approach, we apply a modified HT (Hough Transform) to extract small line segments of the lane contour, which are then divided into clusters by using the DBSCAN (Density Based Spatial Clustering of Applications with Noise) clustering algorithm. Then, we can identify the lanes by curve fitting. The experimental results demonstrate that our modified HT works better for LDTFE than LSD (Line Segment Detector). Through extensive experiments, we demonstrate the outstanding performance of our method on the challenging dataset of road images compared with state-of-the-art lane-detection methods.

1. Introduction

In the modern society, transportation has become a vital part of daily life. As a consequence, over the past few decades, the number of vehicles in the world has increased exponentially. One negative aspect of this growth is the traffic accidents that take many lives everyday. Fatigue and ineptness are the major causes of these mishaps. Many Intelligent Transportation Systems (ITSs), such as Advanced Driver Assistance Systems (ADASs), have been developed to ensure road safety. ITS is an active research area, including tasks like obstacle detection, lane departure warning and collision prevention.

The lane is a very important part of carriageways and highways as many traffic rules for controlling and guiding drivers and reducing traffic conflicts are based on the lane. Therefore, lane detection plays a vital role in improving the performance of ITS. It can be used in a lane alarming system to warn drivers that their cars may deviate from the lane. Moreover, it can also be applied in automated driving systems. In [1], a stereo vision-based hardware and software architecture named GOLD is proposed to increase road safety.

The objective of lane detection is to separate lane markings from background clutter and to locate their exact position by employing special hardware devices or machine vision based techniques. In this work, we focus on vision-based approaches as they are cheaper in cost but can yield high detection accuracy. The lane detection algorithm should be capable of adapting to the natural outdoor surroundings, including inconsistencies in lighting, background clutter and lane occlusion.

According to [2], there are two types of approaches used for lane detection: the feature-based methods and the model-based methods. The feature-based methods are usually applied to localize the lanes in the road images by extracting low-level features. On the other hand, the model-based methods use several geometrical elements to describe the lanes, including parabolic curves, hyperbola and straight lines. Feature-based methods require a dataset containing several thousand images of the roads with well-painted and prominent lane markings that are subsequently converted to features. Moreover, these methods may suffer from noise. To avoid these issues, we opt for a model-based method. In the literature, several model-based lane detection methods are present.

We propose a novel and robust method named LDTFE to locate the lane position for an assortment of outdoor environments. First,

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we obtain a set of points by our proposed two-stage feature extraction. Then, we will identify final lanes using curve fitting. Our major contributions via this work are (1) we consider a lane boundary as a collection of small line segments, which can be detected more robustly against inconsistencies in lighting, weather, background clutter and lane occlusion with our proposed two-stage feature extraction; (2) we propose a modified version of Hough Transform (HT) [3] for detecting small line segments, which is capable of detecting small line segments located on a straight line or a line having small curvatures, thus providing robustness against noise; (3) we efficiently cluster the detected small line segments located on the lane boundaries by using the DBSCAN (Density Based Spatial Clustering of Applications with Noise) clustering method [4], and obtain cluster features to provide a set of points for curve fitting.

The remaining sections of this paper are organized as follows. Section 2 surveys the existing literature in this area. Section 3 presents the overview of our method. In Section 4, we describe our proposed two-stage feature extraction (includes small line segment detection and small line segment clustering). In Section 5, we describe the process of identifying the final lanes. In Section 6, the experimental results with analysis are presented. Lastly, deductions are given in Section 7.

2. Related work

Many model-based algorithms for lane detection have been proposed recently. There are four major phases in the model-based procedure: lane feature extraction, noise reduction, model fitting, and lane generation. It is important to mention that usually noise reduction is crucial for these phases, as any phase with large noise can degrade the final result irreversibly. After the phase of model fitting, sets of lane candidates are generated with a lot of false negatives. So the lane generation phase strives to handle these failure detections in an appropriate way.

Generally, there are two kinds of features for the lane detection task, i.e. colors [5–7] and edges [8–11]. As lane markings are painted in bright white or yellow on the road (obviously different in color from other parts of the road), it makes sense to consider the color feature for lane detection. Sun et al. [5] propose a method named HSILMD (HSI color model based Lane-Marking Detection), which makes use of the HSI color space. In [7], the authors propose a method for extracting lane-mark colors designed in a way that is not affected by illumination changes and the proportion of space that vehicles on the road occupy. However, most color models are sensitive to the varying illumination. Hence edge based features promise more robustness against changing light conditions. There are many conventional approaches based on edge features. In [8], a modified Canny detector with low threshold from Inverse Perspective Mapping (IPM) is applied to extract edge points. Wang et al. [9] propose a novel approach for the lane feature extraction, which is based on the observation that upon zooming into the discontinuities in the lane markings, the lane markings move on the same straight line that they are on, while other objects don't possess this characteristic. Wang et al. [10] propose a novel method to detect the edges by dividing the original image into horizontal strips, and then using contextual information for detecting the vanishing point of the lanes. In addition, Wang and Lin [12,13] propose a reconfigurable model for recognizing objects.

For model fitting, the lane is represented by using a mathematical model and then the model parameters are estimated. HT is a common approach to detect straight lines in a single binary image. In [14], a linear model based on the randomized HT is employed to detect the lanes, which is faster and more thrifty in internal storage as compared with the traditional HT. Yoo et al. [15] present a piecewise linear model based on HT. HT also has been employed in some non-linear models. For instance, a parabolic model is applied to describe the representation of the lane [16], which brings HT into play for detecting the initial lane boundary. In order to improve the representation of lanes, several deformable models [2,17–19] have been exploited to fit feature points. Wang et al. [2] suggest a novel spline-based lane model, which makes use of the cubic B-spline to fit the middle line of two sides of the lane. In their approach, two sides of the lane are assumed to be parallel. Eidehall and Gustafsson [17] present an innovative approach based on an approximation clothoid curve to estimate the road shape automatically. A hyperbola-pair model of lane boundary is introduced in [19], which detects the lane as two parallel hyperbolas. A lane detection approach based on a combination of Catmull–Rom spline with the extended Kalman filter tracking is proposed in [20], which exploits the robustness and stability of the extended Kalman filter. In [21], a lane detection algorithm is given, which utilizes gabor filters and a lane geometrical model consisting of four parameters (starting position, lane's original orientation, lane's width and lane's curvature). The work in [22] proposes lane-mark extraction by analyzing the boundaries of Regions Of Interest (ROIs) in the images and dividing the boundary images into sub-images to calculate the local edge-orientation of each block and remove bad edges. This is followed by multi-adaptive thresholding and curve fitting. Wu et al. [23] use the fan-scanning method to derive the lane-boundary information, and also exploit the angular relationships of the boundaries.

3. Overview of the LDTFE

We formulate the research problem with the lane model shown in Fig. 1. In the ideal case, the two boundary lines of a lane should be parallel. We consider that the middle line of a lane is represented by a curve line. A novel approach named LDTFE (Lane Detection with Two-stage Feature Extraction) is proposed for detecting this curve line.

In LDTFE, lane boundaries is considered as a collection of small line segments. As shown in Fig. 1, S is denoted as the set of small line segments and P stands for the set of midpoints of each small line segment in S. The curve line can be described by the function defined in the following equation:

$$f(\vec{\alpha}, x) = \alpha_0 + \alpha_1 x + \cdots + \alpha_k x^k \tag{1}$$

where $\vec{\alpha} = (\alpha_0, \alpha_1, \ldots, \alpha_k)$ can be estimated by using the least-squares method as shown in Eqs. (2) and (3):

$$\min \frac{1}{2} \sum_{i=1}^{n} (y_i - f(\vec{\alpha}, x_i))^2 \tag{2}$$

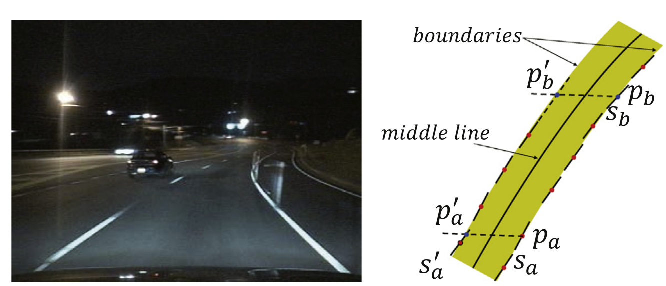

Fig. 1. A road image in night and our model for lane detection.

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