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A real-time lane marking localization, tracking and communication system

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ABSTRACT

In this paper, we present an in-vehicle computing system capable of localizing lane markings and communicating them to drivers. To the best of our knowledge, this is the first system that combines the Maximally Stable Extremal Region (MSER) technique with the Hough transform to detect and recognize lane markings (i.e., lines and pictograms). Our system begins by localizing the region of interest using the MSER technique. A three-stage refinement computing algorithm is then introduced to enhance the results of MSER and to filter out undesirable information such as trees and vehicles. To achieve the requirements of real-time systems, the Progressive Probabilistic Hough Transform (PPHT) is used in the detection stage to detect line markings. Next, the recognition of the color and the form of line markings is performed; this it is based on the results of the application of the MSER to left and right line markings. The recognition of High-Occupancy Vehicle pictograms is performed using a new algorithm, based on the results of MSER regions. In the tracking stage, Kalman filter is used to track both ends of each detected line marking. Several experiments are conducted to show the efficiency of our system.

1. Introduction

Lane marking localization and tracking is an important component of in-vehicle computing systems. Lane marking localization and tracking systems have attracted an extensive amount of interest from both academia and the automobile industry. Many architectural and commercial systems have been proposed in the literature, for example [1–3]. Lane marking recognition systems, conversely, have received surprisingly little attention. Lane marking such as lines and pictograms, are important tools for communicating regulations and guidelines in order to keep vehicles in the correct lanes.

In this paper, we present a real-time lane marking localization and communication system able to detect, recognize and track pavement markings. To the best of our knowledge, this is the first system that combines Maximally Stable Extremal Region (MSER) with Hough transform to detect and recognize lane markings. Not only does our architecture take advantage of the MSER features of road images, it also refines MSER regions so that MSER fits better with Hough transform. In this paper, lane markings and pavement markings are used interchangeably to designate line and pictogram markings. Line markings are used to indicate a well-defined category of lane markings, i.e., solid or dashed lines that are yellow or white. On the other hand, pictogram markings mean ideograms which convey messages as understandable graphics to drivers, for example High-Occupancy Vehicle (HOV) lanes, or as pictures.

Our system consists of the following stages: preprocessing, detection, recognition, and tracking using Kalman Filter. This framework is distinguished from our predecessors by the following: (1) The computation of the detection stage is carried out using texture information, which is generated by MSER. In contrast to traditional computing methods, MSER feeds more effective and stable lane marking information to Hough transform by exclusively recognizing stable extremal regions. A three-stage refinement algorithm is then introduced to enhance the results of MSER and to filter out undesirable information such as trees and vehicles. We begin by computing the Minimum Bounding Rectangle (MBR) of all MSER regions. We then use a heuristic based on the dimensions of MBRs to filter out non-line-marking blobs. Finally, we use a scanning method to localize lane marking edges. (2) To achieve the requirements of real-time systems, the Progressive Probabilistic Hough Transform (PPHT) is used in the detection stage. Compared to Hough transform, which returns the parameters ρ and θ, PPHT returns two end-points of the detected line-markings. (3) The recognition of line markings is performed in HSV color space to better distinguish between white and yellow colors; it is based on the result of the application of MSER to left and right markings. The recognition of HOV signs is based on the results of MSER regions. We develop an algorithm that

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filters out unwanted objects and retains HOV signs. (4) We have used Kalman filter in the tracking stage to track both ends of each detected line-marking instead of tracking the parameters (ρ, θ) of Hough transform as done in many research papers, e.g., [4]. The main reason of using Kalman filter to track both ends of each detected line-marking is that it has much lower computational requirements, which fits perfectly with the real-time constraints of our system.

Our paper is structured as follows. In Section 2, we summarize and reference the related works for our research. In Section 3, we describe the preprocessing stage used by our System. We then refine in Section 4 the results of the last stage using our refinement procedure. Next, we present in Section 5 the detection algorithm adopted by our system. Then, in Sections 6 and 7 we described the recognition strategy and the tracking filter used by our system. Several experiments are conducted in Section 8, and we conclude our paper and present our future work in Section 9.

2. Related work

To detect and track pavement markings, most lane detection and tracking systems adopt the following architecture: preprocessing, detection, and tracking [5–7]. In this section, we review some important papers regarding these stages.

Pre-processing. The purpose of this stage is to enhance input frames in order to increase the likelihood of the successful delivery of areas with useful information to subsequent stages [6]. In other words, it allows the extraction of the region of interest (ROI) that contains pavement markings, in order to reduce the computational cost. To get the ROI, three main approaches are used: vanishing point detection, perspective analysis and projective model, and sub-sampling. Vanishing point detection technique is used to determine the ROI in many papers, such as in [2,8,9]. However, this has some strict limitations related to the vanishing points in the image, i.e., straight lanes with constant vanishing points. The second approach, i.e., perspective analysis and projective model, is based on the fact that parallel lane markings in the real world plane intersect at a vanishing point in the image plane. Usually, by analyzing the perspective effect, the detection range can be focused on a certain area, which can be ROI. With a reasonable projection applied between the image plane, the real world plane and the camera plane, the ROI can be extracted. For instance, RALPH (Rapidly Adapting Lateral Position Handler [10]) constructed a very basic projection model to obtain ROI. In [11], a projection model is constructed based on a 2D lane geometric model, which also helps estimate lane model parameters and lane model matching for the refinement stage. Sub-sampling is the third approach used to determine the ROI, as performed in [12,13], in which a predefined or adaptive percentage of the image can be used to determine the size of ROI.

After the generation of ROI, inverse perspective mapping (IPM) is usually deployed on the extracted area. IPM is used to transform an image from a real world plane to a birds-eye-view in order to obtain the desired line candidates straight and parallel, (e.g., [6,14–16]). Moreover, unwanted regions are removed because the remapped image focuses only on the road surface. Segmentation techniques are also used to enhance edges of lane markings and remove excess undesirable blobs. To prepare images for the detection stage, segmentation is used to extract certain features from the input image. Color [17], blobs [18] and edge [19] are three main features which are considered for lane detection segmentation.

Detection. After preprocessing, detection is used to extract lane markings from the ROI using feature extraction methods and refinement approaches. Three main feature extraction approaches are found in the literature: edge-based methods, color-based methods and hybrid (edge and color) methods.

Edge-based methods: The Hough transform is the most commonly technique used to detect lines [19]. However, two drawbacks are reported: high false positive rate and computational complexity [20]. To cope with the high false positive rate, probabilistic Hough transform [17,19] and adaptive random Hough transform [6,7] are employed. Apart from Hough transform and its variants, another edge-based method based on Steerable filter is applied in many research papers such as in [5,16,21,22]. This method yields good results when road markings are clearly painted and consistently smooth. However, Steerable filter does not adapt to heavy traffic where the orientation of lane markings are not always dominant in all directions.

Color-based methods: Unlike edge-based methods, color-based methods are not widely used by researchers, because they are influenced by lightning. The authors in [23] use a color-based method in the HIS color space by computing the cylindrical distribution of color features.

Hybrid methods: Color and shape information has been used to overcome the drawbacks of color-based and edge-based methods. These types of techniques usually combine width, length, and location of lines with gray levels and brightness values of pixels, which improves the extraction results [24].

Tracking. To facilitate following of line markings over time, a tracking stage is usually incorporated. The aim of the tracking stage is the prediction of future line marking positions in the image, and the decrease of false detection. The most common trackers used in lane tracking systems are Kalman and Particle filters. The parameters of Hough transform have previously been tracked using variants of Kalman Filter, such as Extended Kalman Filter used in [25].

3. Pre-processing

Based on the detection scheme proposed in [26], a line marking localization, recognition and tracking system is proposed in this paper. Our system is composed of a pre-processing stage based on MSER computation (Section 3), a detection stage using an improved version of Hough transform (Progressive Probabilistic Hough Transform, outlined in Section 5), a recognition stage that identifies lines and pictogram markings (Section 6) using computational geometry, and a tracking stage using Kalman filter (Section 7).

The purpose of the pre-processing stage is to generate a binarized picture, which contains the desired line information while effectively reducing unwanted information. To the best of our knowledge, the most common method for solving the above problem is to use segmentation based on edge and area information. The key in selecting suitable segmentation methods for line marking detection is to retain line marking pixels while weakening unwanted pixels. Many different masks (e.g., Canny, Sobel or Prewitt) are used to be convolved with gray images. Only a few of them use blob-extraction-based methods (e.g., MSER) to extract desired pixels (e.g. [26]). To select the best segmentation method, comparative experiments have been conducted in [26], focusing on MSER segmentation and edge segmentation.

3.1. Edge-based segmentation

Edge-based segmentation is usually performed on the ROI in gray scale to enhance edges and to obtain pixels that belong to the desired lane markings. Region of interest is always mandatory for edge-based segmentation. Different methods have been used to extract the ROI from the target frame, as performed in [3]. In fact, input images contain lane markings and some unwanted objects such as electrical poles, pedestrians, trees and cars. In order to reduce undesirable objects which might affect the system results, the detection area should be focused only on the road surface.