POLAR RANDOMIZED HOUGH TRANSFORM FOR LANE DETECTION USING LOOSE CONSTRAINTS OF PARALLEL LINES

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ABSTRACT

In this paper, we propose a new methodology for detecting lane markers that exploits the parallel nature of lane boundaries on the road. First, the input image is pre-processed and filtered to detect lane marker features. Then, using a new technique called Polar Randomized Hough Transform that is introduced in this paper, lines are fitted through the detected features and the orientation of each line is evaluated. By finding near parallel lines separated by a constraint specified distance, false signalling caused by artifacts in the image is greatly reduced. The proposed system was tested using a real world driving videos and showed good results despite the presence of neighboring vehicles, shadows, and irregularities on the road surface.

Index Terms— Lane detection;Parallel line detection;Polar Randomized Hough Transform

1. INTRODUCTION

Camera based lane detection is an important area of automotive research and development. Lane detection can be described as a problem of detecting painted white or yellow markings on the road surface with little to no prior knowledge of the road geometry. Generally, it is a core component for many applications like lane change assistance, lane departure warning and blind spot monitoring to name a few. Lane detection is commonly performed with the help of a monocular camera that is mounted under the rear-view mirror and looks at the road ahead. Images captured by the camera system are then interpreted to extract meaningful information such as lane marker positions and boundaries.

Over the years, a variety of techniques have been introduced to extract lane markers from the road. Variations of the classical Hough Transform are still among the most popular and commonly used methods [1, 2]. The Randomized Hough Transform (RHT) [3] which is a quicker and a more memory efficient counterpart of the classical Hough Transform has also been also been used for lane detection [4, 5]. The use of 1D template matching and searching for Dark-Light-Dark (DLD) transitions has also been shown in [6, 7]. A comprehensive literature review found in [8] summarizes most of the prominent lane detection techniques used today. However, most techniques existing today still face difficulty to produce accurate results in the presence of shadows and similar artifacts in the image. The novelty of our method is the evaluation of "parallelness" of the detected features. This is done by fitting lines through the detected features and checking the conformity of these lines to certain constraints. The detection of parallel lines using the Hough transform was first introduced in [9]. However, this technique is primitive and expected to show poor results if the stringent constraints are not met. A more recent parallel line detector using an HMM is shown in [10]. Unfortunately, this technique is used to find parallel lines in a ruled document in which lines are far more structured and abundant as opposed to extracted lines on the road surface.

In this paper, we present a new technique that takes into account the parallel nature of lane boundaries to detect lane markers on the roadways of common urban environments. In addition, a new line fitting method called Polar Randomized Hough Transform is also presented. Following the introduction, the core components consisting of Pre-Processing, Filtering, Polar Randomized Hough Transform, and Parallel Line Detection are explained. Then, the performance of the system is assessed on real world videos recorded at different times of the day under various conditions. Finally, the conclusion and planned improvements are discussed.

2. METHODOLOGY

2.1. Pre-Processing

In a camera image, lane markings appear as lines that decrease in thickness and converge near the horizon. This can be seen on the left in Fig. 1. Consequently, feature extraction can become difficult since the line features change as a function of distance from the camera due to the effects of perspective.

As a result, the camera acquired images first undergo a geometric transformation known as Inverse Perspective Mapping (IPM) to remove the effects of perspective from the image [11]. With IPM, the captured images are transformed to appear as a birds-eye view with lane markers now appearing as nearly parallel lines. In addition, the thickness of these lines remain constant in the IPM image as shown on the right in Fig. 1. Pre-processing is concluded by converting the IPM image from RGB to grayscale.

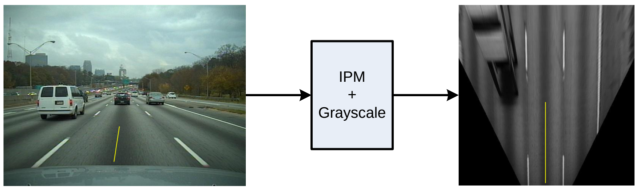

Fig. 1: Pre-processing stage with road center shown in yellow.

2.2. Filtering & Thresholding

The transformed image is then filtered using Normalized Cross Correlation (NCC) [12] with a template that resembles a common lane marker on the road. NCC with the template is tuned to find areas in the IPM grayscale image that correspond to lane markings represented by white or yellow near vertical lines of a predefined thickness. The dimensions of the template are specified by the Federal Highway Administration (FHA) and shown on the left in Fig. 2 [13]. The filtered image is then thresholded with a static value ($\tau = 0.5$) to locate the areas of high similarity to the template. Using this information, the grayscale IPM image is modified where only the pixels and their values mapping to the regions above the threshold from the filtered image are preserved while the remaining pixels are set to zero as shown in the middle of Fig. 3. Finally, the modified grayscale IPM image is converted to a binary image by applying a threshold equivalent to the 97.5^{th} percentile of the preserved pixel values. Since NCC normalizes the pixel values under the template, it often detects artifacts as well. This can be seen on the left in Fig. 3; however, the use of the 97.5^{th} percentile helps remove these artifacts and mostly preserves lane markings as shown on the right in Fig. 3.

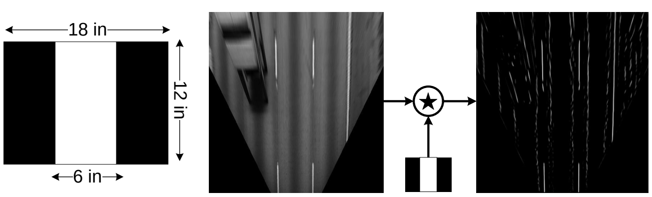

Fig. 2: Template and the Normalized Cross Correlation Process.

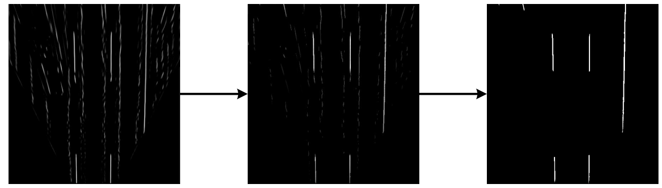

Fig. 3: Left: NCC coefficients. Middle: Modified grayscale IPM image. Right: Binary image after 97.5^{th} percentile threshold.

2.3. Polar Randomized Hough Transform

The next step is to find a collection of straight lines in the binary image using the Randomized Hough Transform (RHT). The Randomized Hough Transform operates iteratively by randomly sampling a set of points to compute a single location in the Hough space that is incremented [3]. To elaborate, in each iteration of the RHT, two non-zero pixels at (x_1, y_1) and (x_2, y_2) are randomly selected without replacement from the binary image. Since two pixels are trivially collinear, the parameters of the line on which they lie can be determined by solving the system of equations below:

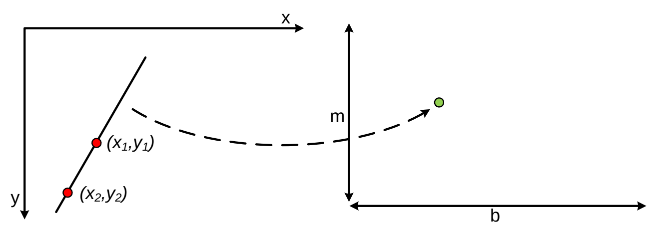

Fig. 4: Randomized Hough Transform.

$$y_1 = mx_1 + b \tag{1}$$

$$y_2 = mx_2 + b \tag{2}$$

where m represents the slope and b represents the y-intercept of the line. The recovered parameters are then used to increment the accumulator cell at (m, b) in the Hough space. The underlying idea of the RHT is illustrated in Fig. 4 with the two randomly selected non-zero pixels shown in red and the computed accumulator cell in the Hough space shown in green. The RHT takes advantage of the fact that a straight line can be fully realized using two points, there by avoiding the exhaustive computation used in the classical HT and providing a speed improvement. However, the RHT has a major shortcoming. Since the RHT recovers parameters using the slope-intercept form, it faces difficulty when the two points lie on a near vertical line as the slope approaches +/-∞. Therefore, to handle this difficulty, the Polar Randomized Hough Transform is introduced.

Similar to the RHT, Polar RHT also operates iteratively and uses a random sample of points. At first, two non-zero pixels $\mathbf{P}_1$ and $\mathbf{P}_2$ are randomly selected. The location of each pixel is written in vector notation as shown below:

$$\mathbf{P}^T = [x\ y] \tag{3}$$

Consider the origin $\mathbf{O}$ at the top left of the image. The projection of the origin $\mathbf{P}_o$ on the line formed by $\mathbf{P}_1$ and $\mathbf{P}_2$ is computed as

$$c = \frac{(\mathbf{O} - \mathbf{P}_1)^T \cdot (\mathbf{P}_2 - \mathbf{P}_1)}{\|\mathbf{P}_2 - \mathbf{P}_1\|} \tag{4}$$

$$\mathbf{P}_o = \mathbf{P}_1 + c \cdot (\mathbf{P}_2 - \mathbf{P}_1) \tag{5}$$

The norm of $\mathbf{OP}_o$ represents the orthogonal distance of the line from the origin which is the same as ρ in the normal form of a line equation

$$\rho = \|\mathbf{OP}_o\| \tag{6}$$

Similarly, the angle between the x-axis and $\mathbf{OP}_o$ represents θ and is calculated as

$$\theta = \arctan(\mathbf{P}_o) \tag{7}$$

Using Eq. (6) - (7), the accumulator cell at (ρ, θ) in the Hough space is incremented. On the next iteration, another pair of points is randomly selected and Eq. (4) - (7) are repeated.

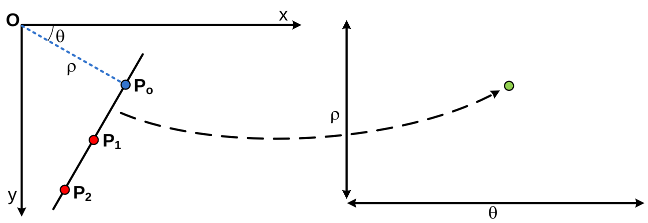

Fig. 5: Polar Randomized Hough Transform.

The concept of the Polar Randomized Hough Transform is illustrated in Fig. 5 with the two randomly selected pixels shown in red, the projection of the origin shown in blue, and the computed accumulator cell in the Hough space shown in green. The Polar Randomized Hough Transform has the benefits of both classical and Randomized Hough Transform. By using polar descriptors (ρ, θ), a line can be extracted and described without much restriction on its orientation like in the classical approach. And, with random sampling of points, the speed benefit of the Randomized Hough Transform is also attained. A similar Polar RHT method is shown in [5]; however, the intermediate computation of slope-intercept parameters is avoided. Using Polar RHT introduced in this paper, the 10 best fitting lines in the binary image are located.

2.4. Constraint based Parallel Line Detection

The 10 best fitting lines in the binary image correspond to the 10 highest scoring co-ordinates or peaks in (ρ, θ) space. This idea is diagrammatically shown in Fig. 6 with each peak shown in red and labeled $P_{1,2\ldots}$. To determine if two lines are parallel, the relationship between their corresponding peaks needs to be determined. By definition, parallel lines are non-intersecting; as a result, peaks with identical θ values could be paired. Ideally, lane boundaries also run parallel on most roadways; however, due to imperfections in the captured image, camera lens, variations in lane marker placement, they may not appear parallel. As a result, the constraint on requiring identical θ values can be "loosened" by allowing some tolerance. This tolerance is shown as a pale blue window in Fig. 6 portraying that peaks with similar θ values can be paired. The Federal Highway Administration (FHA) states that lane boundaries are on average spaced approximately 12ft apart [13]. This width is computed in pixel units using the IPM transformation and serves as a distance constraint δ. Again, by allowing some tolerance on δ as well, bounds are placed on the minimum and maximum distance between two peaks to be considered as a lane boundary pair.

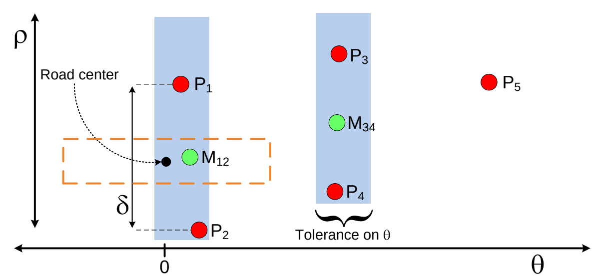

Fig. 6: Evaluating the peaks in the (ρ, θ) space.

In Fig. 6, the road center is mapped from the IPM image (yellow line in Fig. 1) to a point in the Hough space. A window shown as an orange dashed border is placed around the center point. To determine the ideal lane boundary pairs, the corresponding peaks (e.g. P_1, P_2) must observe both constraints and their midpoint (M_{12}) must lie within the window. By specifying a window around the road center, detection of parallel lines in irrelevant or isolated parts of the image can be avoided. For example, P_3 and P_4 observe both constraints; however, their midpoint (M_{34}) is outside the window of the road center suggesting that the parallel lines are located in isolated parts of the image. Aside from restricting the locations of the parallel lines, the rectangular shape of the window allows detected parallel lines to contain some rotation.

3. RESULTS

The proposed lane detection approach was tested on over 2000 frames from real world driving videos and showed good results. The videos used in testing contain variations in illumination, road surface, marker quality, shadow, and traffic to enumerate realistic conditions that one would encounter while driving. The vehicle travels near the center of the lane

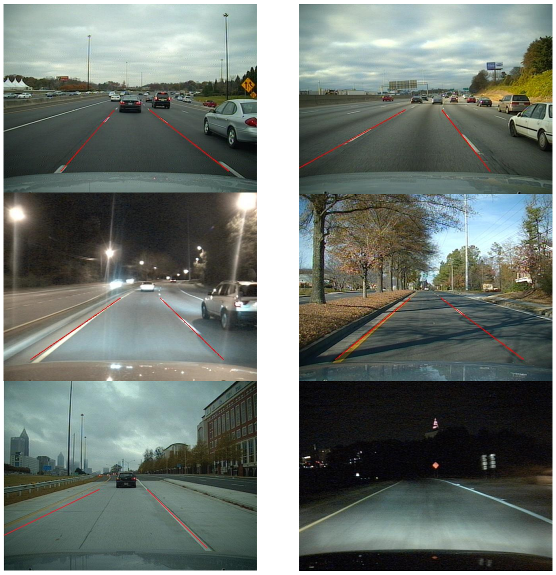

Fig. 7: A few lane detection results.

in most frames. Fig. 7 shows a few lane detection results. Lane detection algorithms tend to face difficulty when encountered with shadows, presence of neighboring vehicles, and surface irregularities to name a few. By exploiting the parallel nature of lane boundaries, false detections caused by many of these artifacts were greatly reduced. However, there were a few occasions where lane markers were missed or incorrectly detected. One example of these mistakes is shown on bottom left of Fig. 7 where our approach encountered lane markers that were worn out due to age making them difficult to detect. Similarly, lane markers went undetected near exit ramps of interstate highways. This is because the width between lane boundaries temporarily increases more than 12ft as can be seen on the bottom right in Fig. 7. Though it is primarily intended for usage on highways with gentle curves, the proposed lane detector also works well on many city roads.

4. CONCLUSION

A new methodology for detecting lane markings using the constraints of parallel lines is presented in this paper. In addition, a new yet simple technique for finding straight lines called the Polar Randomized Hough Transform is also introduced. The current implementation is designed in Matlab and operates at 2-3fps. The localization of lane boundaries and can be further improved by using piece-wise lines, iterated matched filtering and tracking. Detailed quantitative analysis and comparison to other systems will also be conducted.

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