

ROBUST LANE DETECTION AND TRACKING WITH RANSAC AND KALMAN FILTER

Amol A. Borkar, Monson H. Hayes III

Center for Signal and Image Processing (CSIP)
Georgia Institute of Technology
Atlanta, GA
{amol,mhh3}@gatech.edu

Mark T. Smith

Institut för Tillämpad Informationsteknik
Kungliga Tekniska Högskolan
Stockholm, Sweden
msmith@kth.se

ABSTRACT

In a previous paper, a simple approach to lane detection using the Hough transform and iterated matched filters was described [1]. This paper extends this work by incorporating an inverse perspective mapping to create a bird's-eye view of the road, applying random sample consensus to help eliminate outliers due to noise and artifacts in the road, and a Kalman filter to help smooth the output of the lane tracker.

Index Terms— Lane detection, Hough transform, Kalman filter.

1. INTRODUCTION

Driver safety on the highways has been an area of interest for many years. With the development of fast, cheap, low-power, and sophisticated electronics, automobiles with sensors, electronics, and warning systems are beginning to appear on the market.

One of the interesting areas of research and development is collision avoidance. An important component for effective collision avoidance is lane detection. The ability to detect sudden or unexpected lane changes when there is traffic in the lane a driver is moving into could help a driver to avoid collisions. Effective monitoring of the position of a car within a lane could be used to help avert a collision due to driver distractions, fatigue, or driving under the influence of a controlled substance. There are obvious difficulties and challenges in designing collision avoidance systems, and some of the challenges fall outside the realm of engineering and involve complicated issues related to law and liability.

In this paper, we address some of the image processing challenges in designing a lane detection system. It is organized as follows. After a brief survey of some previous research, we then describe the various components of the system. These include image enhancement using temporal blurring, inverse projective mapping to create a bird's-eye view of the road, a Hough transform for detecting candidate lane markers, a random sample consensus algorithm to help deal with outliers in the image, and tracking of the lane parameters using a Kalman filter. Then, we briefly describe the hardware

that was used to collect data, and then show the performance of the lane tracking system. It is shown that this system exhibits considerable improvement in performance compared to a system using only the Hough transform and matched filtering that was previously described [1].

2. PRIOR RESEARCH

Numerous techniques for vision-based lane detection have been developed in an attempt to robustly detect lanes. In the extraction of features for lane detection, one of the most commonly used approaches is to apply an edge detector to the data [2, 3]. With this approach, a Canny edge detector is typically used to generate a binary edge map. From the binary edge map, the classical Hough transform is then used to extract a set of lines as candidates for the lane markers. While this approach shows good results in general, the detected lanes are often skewed due to surface irregularities or navigational text markers on the road. Color segmentation to extract lane markers is another approach that is often used [4, 5]. Unfortunately, color segmentation is sensitive to ambient light and requires additional processing to avoid undesirable effects.

The majority of the approaches used for lane detection operate directly on the images that are captured by the camera without any geometrical correction or change in camera perspective [1, 2, 4, 6]. Although dealing with images from the camera perspective allows access to raw data values, defining the properties of the features of interest may be complicated. For example, a forward-looking camera will capture images that have lane markers that are not parallel and have line widths that vary as a function of the distance from the camera. These variations often necessitate processing each row of a captured image in a different manner.

Many of the systems described above perform well under certain driving conditions and often require that a certain set of assumptions are valid. Some of these assumptions include the presence of strong lane marker contrast and roads devoid of artifacts such as cracks, arrows, or similar markers. Unfortunately, these assumptions do not hold in many high traffic urban streets and highways.

This paper describes the combination of several image enhancement and filtering methods that yield substantially improved results.

3. METHODOLOGY

This paper extends the layered lane detection approach in [1] by (1) using an inverse perspective mapping, (2) applying a random sample consensus to help eliminate outliers, and (3) using a Kalman filter for prediction and smoothing. In the following sections, the various components of our lane detection system are described.

3.1. Image Enhancement

The captured color images undergo a grayscale transformation and temporal blurring by averaging $N = 3$ successive frames. This smoothing helps connect dashed lane markers to form a near continuous line [1].

3.2. Inverse Perspective Mapping

The next step is to perform an inverse perspective mapping (IPM) on the images. This transformation is used to change the captured images from a camera perspective to a bird's-eye view as illustrated in Fig. 1. [7, 8, 9]. With this transforma-

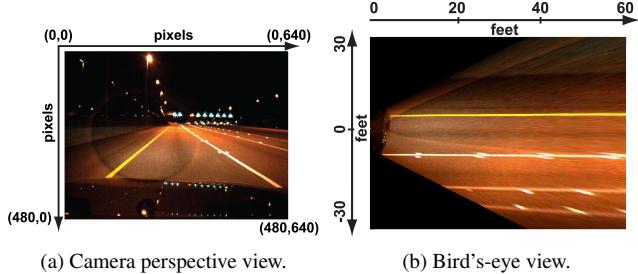


Fig. 1: Inverse perspective mapping transforms a camera perspective image into a bird's-eye view image.

tion, lane detection now becomes a problem of detecting a pair of parallel lines that are generally separated by a given, fixed distance. In addition, this transformation enables a mapping between pixels in the image plane to world co-ordinates (feet) as shown in Fig. 1b. The camera's intrinsic and extrinsic parameters are necessary to ensure an accurate transformation.

3.3. Lane Candidate Location Detection

Next, an adaptive threshold is applied to the IPM image to generate a binary image [1]. Each binary image is then split into two halves, each one presumably containing one lane marker. A low resolution Hough transform is then computed on the binary images and a set of $X = 10$ highest scoring

lines are found for each half image [1]. Each line is then sampled along its length at a specified distance as indicated by the red “+” indicator in each line in Fig. 2. To find the approxi-

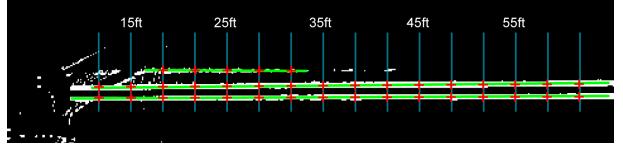


Fig. 2: Each green line represents a high scoring line of the Hough transform, and the + indicators show the locations where the line are to be sampled.

mate center of each line, a one-dimensional matched filter is applied at each sample point along each of the X lines. As described in [1], the matched filter is a Gaussian with a variance that is a function of the line width. Since the bird's-eye view created with the IPM produces lines of approximately constant width, a fixed variance Gaussian kernel may be used for the matched filter. After the matched filtering, the pixel with the largest correlation coefficient at each sample point is selected as best estimate of the center of the lane marker as shown by green “+” indicator in Fig. 3.

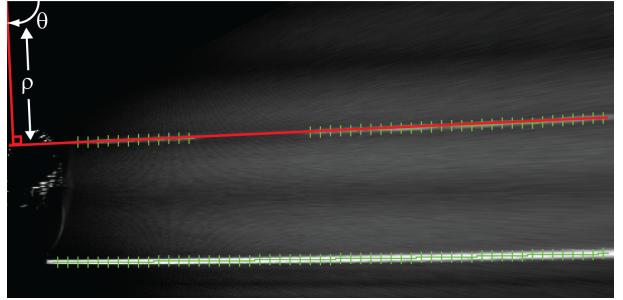


Fig. 3: Line fitted through one set of candidate points and parameterized with ρ and θ .

3.4. Outlier Elimination and Data Modeling

Once a candidate lane marker position is identified at each sample point for each candidate line, Random Sample Consensus (RANSAC) is applied to the data points. The generic RANSAC algorithm robustly fits a model through the most probable data set or inliers while rejecting outliers [10, 11]. Linear Least Squares Estimation (LSE) is then used to fit to a line on the inliers. Fig. 3 illustrates the parametrization of the fitted line in terms of ρ and θ . ρ is the perpendicular vector from the origin (top left corner pixel) to the line and θ is the angle of this vector with respect to the horizontal axis (generally is close to 90°).

3.5. Tracking

The parameters of each line is predicted using a Kalman filter. The state vector $x(n)$ and observation vector $y(n)$ are defined as

$$\mathbf{x}(n) = \mathbf{y}(n) = [\rho(n) \quad \dot{\rho}(n) \quad \theta(n) \quad \dot{\theta}(n)]^T \quad (1)$$

where ρ and θ define the line orientation and $\dot{\rho}$ and $\dot{\theta}$ are the derivatives of ρ and θ that are found by forming the difference in ρ and θ between the current and previous frame. The state transition matrix A is

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

and the matrix C in the measurement equation is identity. The independence between the variables in $x(n)$ and $y(n)$ allows creation of simple covariance matrices Q_w and Q_v . Q_w and Q_v represent the process and observation noise respectively [12]. The covariance matrices are defined as identity and multiplied with non-uniform weights along the diagonal, these weights correspond to the variances of the parameters in $x(n)$ and $y(n)$. The Kalman filter recursively predicts the parameters in the state vector from the previously available information [12, 13]. In the case of a lane markers not being detected, the matrix C is set to zero forcing the Kalman filter to rely purely on prediction.

Finally, the estimated line is mapped back to the camera perspective to portray the lane detection results.

4. EXPERIMENTAL ANALYSIS

4.1. Hardware

The hardware used to test and evaluate this new lane detection system is built around an Intel based computer. A forward facing Firewire color camera is installed below the rear-view mirror so that it has a clear view of the road ahead. The Firewire allows video to be captured at VGA resolution and 30fps. Video from the camera is recorded onto hard disks.

4.2. Results

The lane detection algorithm was implemented in Matlab and requires approximately 0.8 seconds to process each frame. The results in Table 1 illustrate the performance of the proposed system when applied to over 10 hours of captured video. The results also show improvement in accuracy over the system developed in [1]. The lack of accessibility to implemented lane detection algorithms and turnkey software systems makes it impossible to compare results.

Table 1: Accuracy of the lane detection system

Road type	Traffic type	Average Detection Rate Per Minute					
		Current System			Previous System [1]		
		Correct	Incorrect	Misses	Correct	Incorrect	Misses
Isolated Highway	Light	99.08%	0.99%	0%	89.69%	5.31%	5.19%
	Moderate	98.34%	1.65%	0%	91.47%	6.65%	1.87%
Metro Highway	Light	98.37%	1.65%	0%	83.53%	8.89%	8.14%
	Moderate	96.34%	3.65%	0%	84.97%	10.33%	4.68%
City Streets	Variable	86.39%	12.71%	0.78%	76.55%	11.94%	11.95%

The captured videos contain scenes with a variety of traffic and illumination conditions that depict environments a driver might encounter [1]. Fig. 4 shows a few of instances of detected lane markers. The results are quantified in terms of detection rate per minute. This metric allows to normalize the results when data is captured using cameras with different frame rates.



Fig. 4: Successful lane detections in various environments.

Defining a ground truth for the data is extremely tedious; hence, it is commonly avoided. Consequently, detections are generally quantified based on visual inspection. Despite noisy measurements, the Kalman filter recursively estimates the dynamics of the state vector. Fig. 5 shows a comparison between the observed and predicted value of ρ .

A few instances of incorrect lane detections are also shown in Fig. 6. Fortunately in Fig. 6a, the Kalman filter is able to settle within a couple of milliseconds after passing the bump on the road. However, in Fig. 6b, the absence of lane markers due to road aging and wear leads to the detection and tracking of false signals such as cracks.

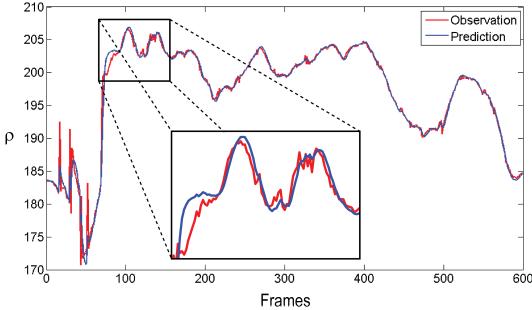


Fig. 5: Comparison between observed and predicted values of ρ over a range of frames. A blow up shows the Kalman filter smoothing the noisy measurements.

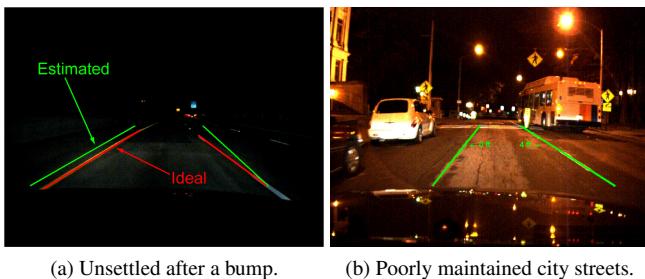


Fig. 6: Inaccurate lane detections in a few scenes.

5. CONCLUSIONS

The work presented in this paper is a significant improvement over the layered lane detection system presented in [1]. The addition of features such as (1) Inverse Perspective Mapping (IPM), (2) Random Sample Consensus (RANSAC), and (3) Kalman filtering has added to the novelty and extension over the previous system. IPM aids in simplifying the process of finding candidate lane markers, while RANSAC helps in rejecting outliers within the estimations. Finally, the Kalman filter ignores minor perturbations and keeps the lane marker sequence on its track.

The data set used to test the accuracy of the proposed system was recorded on Interstate highways and city streets in and around Atlanta, GA. Despite the variety in traffic conditions and road quality encountered, the proposed system still yielded good performance as reflected in Table 1.

6. FUTURE WORK

Lane Departure Warning (LDW) will be implemented in the future. It will leverage from the lane detection system's ability to accurately determine the distance to the lane markers as shown in Fig. 4. By analyzing the velocity and acceleration of lane marker movement, the driver can be notified of an upcoming lane change. Further investigation is needed to enable day time lane detection. In addition, the implemented algo-

rithms will be ported to C++ with the help of existing libraries like OpenCV and VXL to facilitate a real-time system.

7. REFERENCES

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