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Video Analysis to Detect and Track Road Ahead for Safety

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Abstract: ***Detecting the road area and ego-lane ahead of a vehicle is central to modern driver assistance systems. While lane-detection on well-marked roads is already available in modern vehicles, finding the boundaries of unmarked or weakly marked roads and lanes as they appear in inner-city and rural environments remains an unsolved problem due to the high variability in scene layout and illumination conditions, amongst others. While recent years have witnessed great interest in this subject, to date no commonly agreed upon benchmark exists, rendering a fair comparison amongst methods difficult. In this paper, we introduce a novel open-access dataset and benchmark for road area and ego-lane . detection. Autonomous vehicles (AV)" are not a new concept. They have been proposed for the longterm goal of having vehicles driving autonomously in an unknown environment for the purpose of human safety, convenience, and ease of life; both in civilian and military applications. In day-to-day life, humans take such navigational capabilities for granted. The human brain achieves all this simultaneously using mostly the sense of vision. That being one of the strong motivation behind vision based control, it is also desirable to use computer vision systems to achieve low cost, low maintenance autonomous vehicle navigation. Proposed is a vision solution based on accumulator based parametric transforms to detect navigable regions in the urban environment. The novel accumulator voting scheme is called \Parametric Transform for Lanes (PTL)," which enables detection of multiple lanes and variations of lanes such as exits and intersections possible concurrently. Other than being robust to shadows, invariant to color, width and texture of the road, this PTL is based on a control-motivated philosophy. Thus, this dissertation proposes a novel total image-based control solution to the autonomous vehicle control problem, called \Predictive Control in Image Plane (PCIP)." PTL and PCIP together inherently support control for multiple operations; such as lane following, lane changing, turning at intersections, etc.***

Keyword: Road,traffic,vision, cmarea,lane parameters,parametric transform

1. Introduction

Autonomous Navigation is new concept. This to give an idea: \Car that drives itself gets closer to reality," \Automobile Control Research Opens Door To New Safety Features," \Let the Car do the Driving," \MULE Autonomous Navigation Vehicle By Lockheed Martin," and \General Dynamics Robotic Systems Completes Successful Autonomous Navigation System Critical Design Review.

Therefore there is no doubt that it does not seem far from reality and everybody in the engineering world has an idea of what it is and its potential impact on society. With this thought in mind, we begin to talk about \Autonomous Vehicles (AVs)" and their brief history in this chapter, followed by the motivation, importance and potential of the research work presented in this dissertation. Detection of the road, lane or any navigable region in the scene can be classi_ed as one of the feature detection and classi_cation problems in the computer vision [33].

Therefore, it is important to know the important features to be detected for example, road boundaries, color of the road, texture of the road, etc. The output of the road detection system is thus dependent on the type of feature detector as well as the accuracy and e_ciency of the same. Based on this, there are three main approaches to the road detection in literature.

1. Feature Learning: With this approach the vision system is extensively trained for road and non-road regions using a neural network or other machine learning technique [55, 63]. Some of the examples use a combination of features such as texture, color, luminance and coordinates of the image pixel to classify road and non-road regions [62, 17]. Sha et al. [62] faced issues with sunny and shadowed roads.

2. Methodology

Introduction to PTL

Parametric Transform for Lanes (PTL): Detecting multiple and varying instances of the same object, object being road/lane here, suggested an accumulation based framework. Thus the dissertation designed and implemented \Parametric Transform for Lanes (PTL)."

2.1 Problem Formulation

The problem is broken down into following sub-parts and executed in that order:
1) Determine the type of lane parameters needed to calculate the correct immediate vehicle controls to keep the vehicle in its lane.
2) Detect the lanes and the lane parameters from the scene image.
3) Use the lane parameters to calculate the local controls for the vehicle. The _rst task is done o_ine as a part of studying the requirement for a vehicle control. The later two tasks are part of the algorithm design running real-time on the vehicle to control it.

2.1.1 Camera Configuration

To derive the camera projection matrix and the transformation from ground plane to image plane, first a simple 3-D projection case is considered in Figure 2.1. x is the projection of point X on the image plane. Let,

O: Location of the camera and the center of the world coordinate system.

f: focal length of the camera.

(Xw; Yw;Zw; 1): The homogeneous world co-ordinate system at O.

As the image plane is located at Zw = f in the world coordinate system, let the coordinates of the point x in the world coordinate system be (xc; yc; f). Therefore, the relationship between camera and the world co-ordinates system is given by x = fXw/Zw and y = fYw/Zw Therefore, Eq. 2.1.

$$\begin{bmatrix} x \\ y \\ f \end{bmatrix} = \frac{f}{Z_w} \begin{bmatrix} X_w \\ Y_w \\ Z_w \end{bmatrix} \qquad (2.1)$$

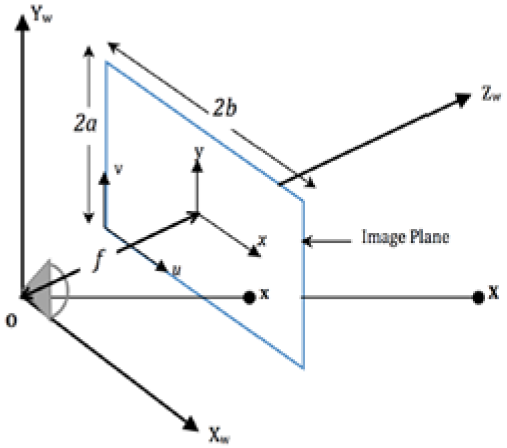


Figure 2.1: Camera Projection Matrix

This can be written as a linear mapping between homogeneous coordinates. (Eq. 2.2).

$$\begin{bmatrix} x \\ y \\ f \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & f & 0 \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} \qquad (2.2)$$

(u; v; 1) is the homogeneous image co-ordinate system in pixels. ku, kv are the image resolution in pixel/meter in u and v direction respectively i.e. k u and kv are the pixel spacing on the focal plane of the camera. 2a and 2b are height and width of the image in pixels. Therefore, b=f, a=f is the pixel/meter resolution on the focal image plane. Thus, u and v are the pixel numbers with respect to the left bottom corner of the image corresponding to the x and y distances on the focal plane. Therefore, Eq. 2.3

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} k_u & 0 & b/f \\ 0 & k_v & a/f \\ 0 & 0 & 1/f \end{bmatrix} \begin{bmatrix} x \\ y \\ f \end{bmatrix} \qquad (2.3)$$

Therefore, we can derive Eq. 2.4 depicting the relation between the pixel co-ordinates (u; v; 1) and the world coordinate system (Xw; Yw;Zw).

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} k_u & 0 & b/f \\ 0 & k_v & a/f \\ 0 & 0 & 1/f \end{bmatrix} \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & f & 0 \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix}$$

$$\therefore \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} fk_u & 0 & b & 0 \\ 0 & fk_v & a & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} \qquad (2.4)$$

Figure 2.2: shows the camera con_guration on a vehicle with respect to the ground plane. Where, f { Focal length of the camera.

{ Tilt angle of the mounted camera with respect to the line of horizon.

H { Height of the camera from the ground plane.

Because of the camera tilt, the new ground plane homogeneous co-ordinate system (X; Y;Z; 1)

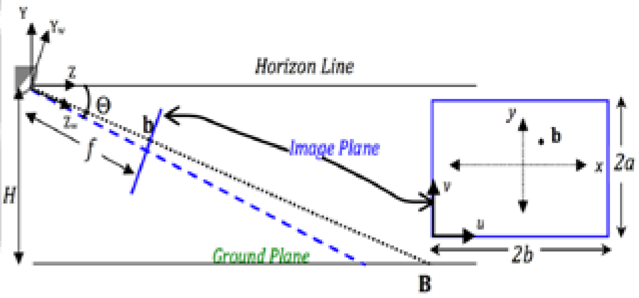


Figure 2.2: Vehicle Camera Configuration

The camera is tilted down an angle _, corresponding to a negative rotation about the positive X-axis, therefore, the R and T are given by Eq. 2.6

$$\begin{bmatrix} R & T \\ 0^T & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos(-\Theta) & -\sin(-\Theta) & 0 \\ 0 & \sin(-\Theta) & \cos(-\Theta) & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\Theta & \sin\Theta & 0 \\ 0 & -\sin\Theta & \cos\Theta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad (2.6)$$

Considering a point B on the ground plane with the ground co-ordinates [X;H;Z; 1] as shown in Figure 2.2. Therefore, the image plane co-ordinates of the corresponding point b are given by Eq. 2.7.

$$\begin{bmatrix} x \\ y \\ f \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & f & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\Theta & \sin\Theta & 0 \\ 0 & -\sin\Theta & \cos\Theta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ -H \\ Z \\ 1 \end{bmatrix}$$

$$\therefore \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & f & 0 \end{bmatrix} \begin{bmatrix} X \\ -H\cos\Theta + Z\sin\Theta \\ H\sin\Theta + Z\cos\Theta \\ 1 \end{bmatrix}$$

$$\therefore \begin{bmatrix} x \\ y \\ f \end{bmatrix} = \begin{bmatrix} fX \\ f(-H\cos\Theta + Z\sin\Theta) \\ f(H\sin\Theta + Z\cos\Theta) \end{bmatrix} \qquad (2.7)$$

and the image plane pixel coordinates, given camera mounting con_guration and assuming that the ground is at.

$$x = f\left(\frac{X}{Z\cos\Theta + H\sin\Theta}\right), u = fk_u\left(\frac{X}{Z\cos\Theta + H\sin\Theta}\right) + b \qquad (2.12)$$

$$y = f\left(\frac{Z\sin\Theta - H\cos\Theta}{Z\cos\Theta + H\sin\Theta}\right), v = fk_v\left(\frac{Z\sin\Theta - H\cos\Theta}{Z\cos\Theta + H\sin\Theta}\right) + a \qquad (2.13)$$

The problem is formulated keeping multiple presence of road and ease of control of the vehicle in mind. Figure 2.3 is a typical urban scene. In the perspective transform, road boundaries Looking at it intuitively, for driving correctly on the road shown, we would have to be aware of three parameters approximately. These parameters will be quantied in the next section.

1) Center of the lane: Lateral position of the center of the lane to follow with respect to the position of the vehicle
2) Lane angle: Angle/Curvature of the immediate part of the lane with respect to the vehicle orientation.
3) Lane width: This is for safety such that to make sure lane is wide enough for the vehicle to travel and have an estimate of the distance from the curbs/lane edges etc.

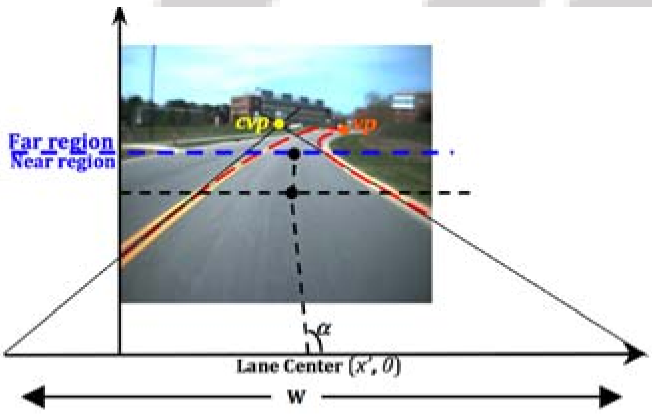


Figure 2.3: A typical urban scene

2.2 Basic Principle of the PTL Design

This is based on the same principle as the hough transform [29], which was used to detect straight line segments using an accumulator and later, extended to detect parametric shapes like circles and ellipses and thus got the name as Parametric Transforms. The basic philosophy is evidence accumulation in terms of the parameter set representing the object/shape to be detected uniquely.

The multi-lane detection algorithm explained here is designed to obtain the following threelane parameters for every lane in the scene: lane center at the bottom of the scene (x0), the angle that the lane forms with the x-axis (_) and lane width W. Figure 2.4 is used for describing the Coordinate system used, showing the possibility that two lanes are visible in the image. The left lane is parametrized for explanation purpose

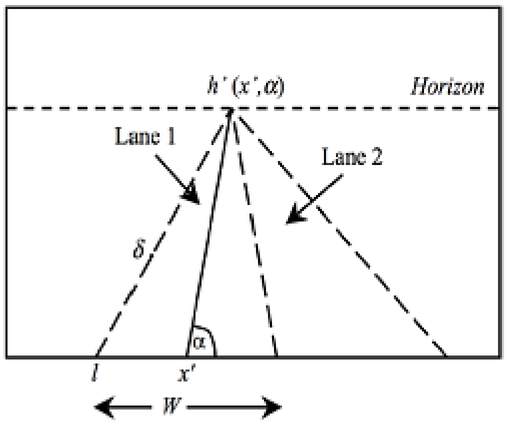


Figure 2.4: Coordinate system used, showing the possibility that two lanes are visible in the image. The left lane is parametrized for explanation purpose method. The _gure shows presence of two lanes in the image. Dotted lines represent the edges of the lanes. The left lane is parametrized for the purpose of explanation. In this discussion, it is assumed that the \bottom" row or row 0, is at the bottom of the image, unlike many image

3. Results and Discussion

The algorithm in this work is designed to detect multiple lanes simultaneously in the form of multiple peaks in an accumulator. This is similar to any parametric transform where multiple instances of the object and their parameters can be detected simultaneously using accumulator voting. The algorithm is tested on real road images (See Figure 2.11). Some of them are from the previous lane detection literature, see Figure 2.10 and Figure 2.11. The red dots predict the direction of vehicle motion as well as the future position of the vehicle. Red solid lines are the approximately predicted locations of the road boundaries in the \near region" extended up to the horizon. It is observed that irrespective of the lighting conditions, horizon location on the

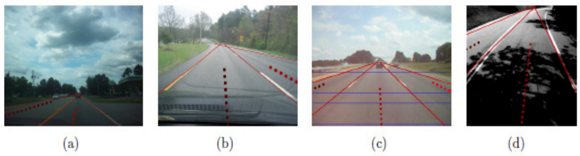


Figure 2.11: Concurrent multi-lane detection results. Original road image in 2.11(d) is taken from [78]

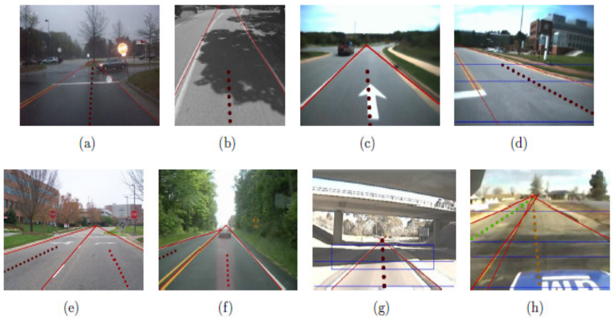
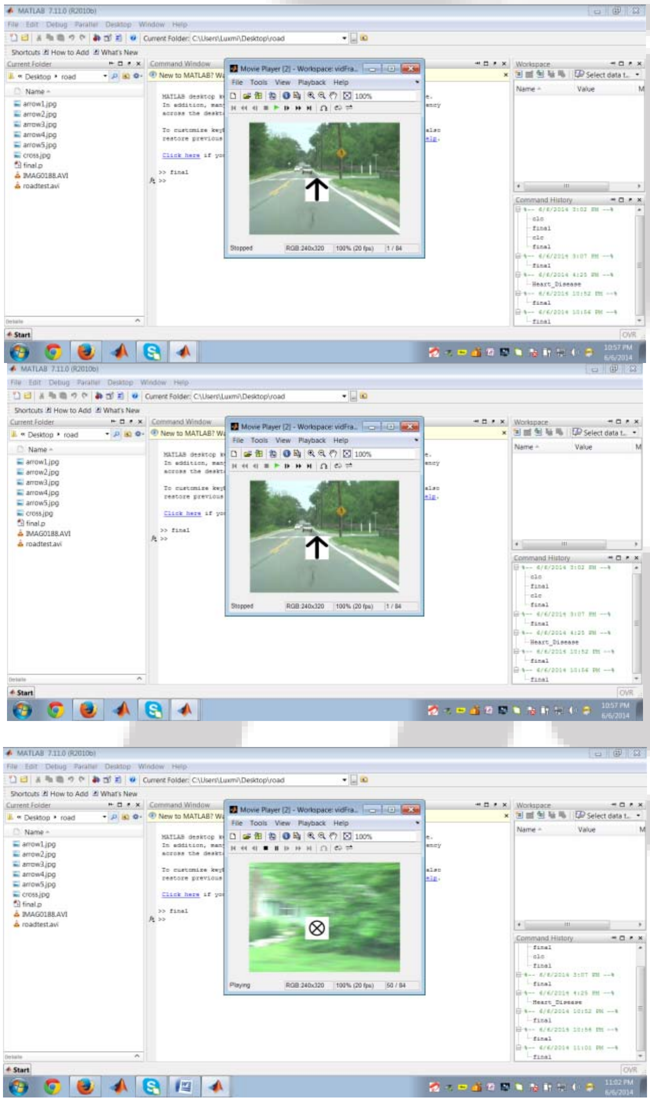


Figure 2.12: Some more results. Original road image in 2.12(b) is taken from [78]

Snapshots of Implementation



Road situation	stright	turn	Obstacle	OVAL
%Accuracy of Testing	76.1	73.8	77.3	72.5
% Success Rate	79.9	71.7	73.7	77.9
Accuracy Validation	65.2	64.3	65.3	67.3
% Error	10.1	8.3	6.3	12.1
Overall	77.06	76.6	78.76	75.9
Overall Detection Performance =75.08%				

4. Conclusion and Future Directions

The dissertation investigates and presents solution to AV control stability; especially, in scenarios containing varying curvature turns, vehicle speeds, and sampling rate. Each necessary control parameter { such as steering angle, rate of change of the steering angle and vehicle speed { is explained and integrated into a navigational system for AV motion control. The integrated navigational system consists of all of the important control parameters (which are determined concurrently) in order to achieve the desired vehicle control.

Through achieving the vehicle control in image plane coordinates (i.e. without transformation to ground plane coordinates) control complexity is reduced. This method, \Predictive Control in the Image Plane," of predictive control enables navigation on the desired path and increases the application space to multiple types of vehicles. The vehicle's control of its position within the lane boundaries demonstrated and evaluated using a 3D simulator (Blender). Stability of the control algorithm is then tested and demonstrated in multiple scenarios; such as slow sampling rate, high curvature, varying speeds using PCIP. PCIP is key to enabling the future of vision based autonomous navigation in military, civilian, and commercial applications. It is demonstrated below that the vehicle control parameters can be calculated from the image plane co-ordinates; thus the transformation to the ground plane co-ordinates is not necessary making the control more intuitive and easier to implement.

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