Vehicle Lane Position Estimation with Camera Vision using Bounded Polynomial Interpolated Lines

Christopher Rose, *Auburn University*
David M. Bevly, *Auburn University*

BIOGRAPHY

Christopher Rose was born in Huntsville, Alabama. He is a member of the GPS and Vehicle Dynamics Lab at Auburn University. His current activities focus on video processing applications and sensor fusion in ground vehicles. He received his B.S. in Electrical Engineering at Auburn University in 2007.

David M. Bevly received his B.S. from Texas A&M University in 1995, M.S. from Massachusetts Institute of Technology in 1997, and Ph.D. from Stanford University in 2001 in mechanical engineering. He joined the faculty of the Department of Mechanical Engineering at Auburn University in 2001 as an assistant professor. Dr. Bevly's research interests include control systems, sensor fusion, GPS, state estimation, and parameter identification. His research focuses on vehicle dynamics as well as modeling and control of vehicle systems. Additionally, Dr. Bevly has developed algorithms for navigation and control of off-road vehicles and methods for identifying critical vehicle parameters using GPS and inertial sensors.

ABSTRACT

Applications of camera vision, such as lane departure warning systems, are limited by the quality of the frame image and the information contained within each frame. One common feature extraction technique in image processing is the use of the Hough transform, which can be used to extract lines from an image. The detected lane marking lines are used in the interpolation of a 2nd order polynomial to estimate the shape of the lane marking's curve in the image. However, blurry frames, additional road markings on the ground, and adverse weather conditions can ruin detection of these valid lane lines.

To eliminate erroneous lines, a technique has been employed which bounds the previously detected 2nd order polynomial with two other polynomials that are equidistant from the original polynomial. These bounding curves employ similar characteristics as the original curve; therefore, the valid lane marking should be detected within the bounded area given smooth transitions between each frame. The effects of erroneous lines within this bounded area can be reduced by employing a Kalman filter on the coefficients of the 2nd order polynomial. The filter also allows for smooth transitions between curved and straight roads. The measurement of the position within the lane is carried out by determining the number of pixels from the center of the image and the estimated lane marking. This measurement value can then be converted to its real world equivalent and used to estimate the position of the vehicle within the lane.

This technique is verified by comparing lateral distance measurements from RTK GPS measurements and the measurements from a camera. Results will show that this method performs well on straight roads but fails to perform well on curves.

INTRODUCTION

The force of two cars colliding head on is much greater than that of a car hitting a stationary object. When two cars collide in this manner due to a lane departure, this additional force is catastrophic on the car and on the occupants within. Lane departures account for nearly 50% of all fatalities on the road [16]. With systems such as the technique presented in this paper in place to reduce lane departures, fatalities in vehicular collisions may significantly decrease.

Camera vision has already been implemented in lane departure warning (LDW) systems in commercial vehicles. These systems detect when the vehicle has left a lane and emit a warning for the driver. One such system, by Lee and others [12], incorporates perception-net to determine the lateral offset and time to lane crossing (TLC), which warns the driver when a lane departure is or may soon take place. A fuzzy evolutionary algorithm was used by Kim and Oh [10] to determine the lateral offset and TLC using a selected hazard level for lane departure warning. Another LDW system, by Jung and Kelber [8], used a linear-parabolic model to create a lane departure warning system using lateral offset based on the near field and far field. For the near field close to the camera's position in a forward looking camera, a linear function was used to capture the straight appearance of the road close to the car. For the far field, a parabolic model was used to model the curves of the road ahead. In their following paper [7], Jung and Kelber used their system with the linear-parabolic model to compute the lateral offset without camera parameters. Hsiao and others [6] avoided the use of the Hough transform and instead relied on peak and edge finding, edge connection, line-segment combination, and lane boundary selection for their LDW system. In [5], optical flow was used to achieve lane recognition under adverse weather conditions. Feng [4] used an improved Hough transform to obtain the road edge in a binary image, followed by establishment of an area of interest based on the prediction result of a Kalman filter. In [14], an extended Kalman filter was used to model the lane markings to search within a specified area in the image so that far lane boundaries are searched with a smaller area than closer lane boundaries, thus reducing the impact of noise.

Three dimensional road modeling has become a popular method to reduce the errors associated with lane detection in image space. The clothoid is an often used model for three-dimensional reconstruction due to its linearly changing arc length. Dickmanns and Mysliwetz [3] used the clothoid parameters to recognize horizontal and vertical road parameters in a recursive manner. Khosla [9] used two contiguous clothoid segments with different geometries but with continuous curvature across each clothoid, which gives a closed form parametric expression for the model. However, Swartz [13] argues that the clothoid model for the road is unsuitable for sensor fusion due to the "sloshing" affect of the estimated values between the clothoid parameters.

Knowledge of the lane geometry in front of the vehicle gives information to the driver or autonomous system, such as the distance within the lane, whether or not a turn is located ahead, the road structure ahead for mapping, or map matching to identify the current location of the vehicle. However, camera systems have limitations due to non ideal visual conditions. Additional road markings on the ground, such as that of a crosswalk, turn arrow, or merged lane, can introduce rogue lines into the image and shift the estimated lines beyond that of the actual lane marking. Phantom lines detected from the Hough transform that are not readily apparent in the image itself can arise unexpectedly. Dashed lane markings of the center road can reduce its detection rate and lead to gaps in the measurement data for that lane marking. Sensor fusion with other lane detection systems, such as Light Detection and Ranging (LiDAR) [2], can ensure a more robust system [1].

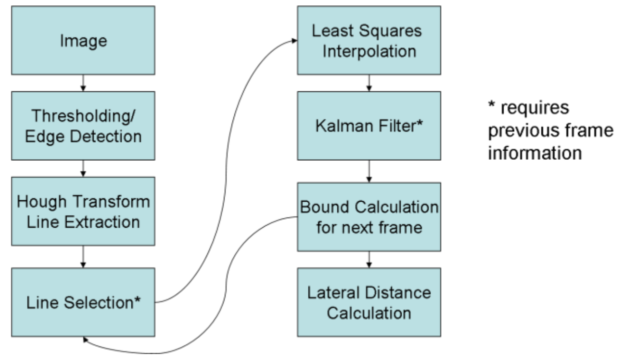

Figure 1: Overview of algorithm

The algorithm presented in this paper employs several of the ideas found in [3] through [14] but avoids the clothoid model from [3], [9], and [13]. Two polynomial functions are used in the models for the left and right lanes in image space after extraction with the Hough transform. Bounding polynomials are used to select valid candidate lines for the model. With the polynomial model, the distance at a particular point in the road ahead can be used to estimate the position within the lane based on the equations of the estimated lane. A summary of the algorithm presented in this paper is shown in Fig. 1.

The bounding polynomials reduce the effect of erroneous lines at far distances from the current estimated line. Due to the necessity of nearby line detections, the detected lines from the lane markings must not be far from the last estimated lane curve in the image. Assuming smooth driving and a relatively high frame rate, the distance between the last estimated lane curve and the new estimated lane curve should not increase significantly. This technique also allows for the detection of road shape in the lane ahead, which can be useful for navigation of autonomous vehicles, anticipation of future driver actions, or verification of the location of the vehicle with maps. This technique does not currently extend beyond image space and requires no other information other than the information from the frame image and the calibration for the lateral distance measurement.

LANE LINE EXTRACTION

Information from the road is limited to a grayscale image. Each pixel in a grayscale image has a value ranging from 0 (black) to 255 (white). Video processing on this image results in the extraction of the shape of the lane ahead. To determine the road shape, the lines from the lanes must be extracted. Thresholding is used on the grayscale image to extract the features in the image that are the color image equivalent of yellow and white, which are common colors of road markings for lanes. This process eliminates unwanted features in the image, such as grass, asphalt irregularities, and objects on the side of the road. Then, Canny edge detection reveals the edges of the extracted features in the image, such as the sides of the lane. The Hough transform can then be used to extract lines from images, as seen in Fig. 2. One advantage to using the Hough transform is that the extracted line can be discontinuous. Objects on the side of the road, such as dead animals or tree branches, and the occasional break in a road marking can still result in a detected line. Once a line has been extracted, its slope and location on the image can be used to determine whether it is a left lane marking, right lane marking, or not a lane marking at all.

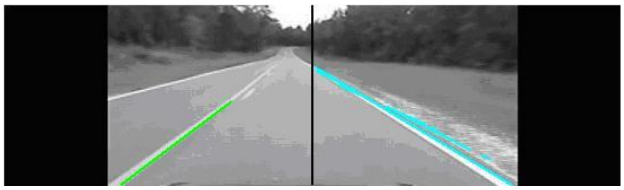

Figure 2: Lane lines extracted from the Hough transform

LANE DETERMINATION

Each lane in the image captured from the camera is modeled as a 2nd order polynomial. To determine the coefficients of the polynomial, least squares interpolation, shown in Eqs. (1)-(4), is used to estimate the shape of the lane in the image.

Each line from the Hough transform consists of its two endpoints and midpoint, shown in Fig. 3. With these three points, a single line can be used for the interpolation of the left or right lane marking.

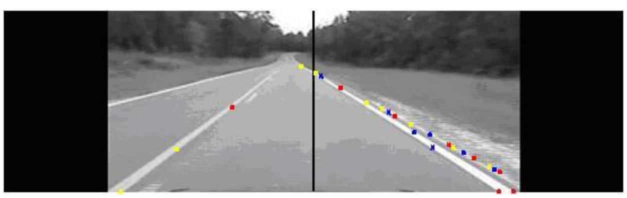

Figure 3: Endpoints and midpoints of the extracted lines

Additional lines for each lane marking create an over-determined system with multiple points for each lane marking, as seen in Fig. 3, and the interpolation gives the least squares estimate of all available data points, shown in Fig. 4.

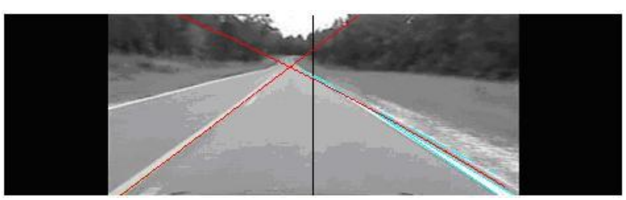

Figure 4: Least squares interpolated polynomial

Least squares interpolation consists of:

$$\beta = (f' f)^{-1} f' y \tag{1}$$

where

$$f = \begin{bmatrix} 1 & x_1 & x_1^{\,2} \\ 1 & x_2 & x_2^{\,2} \\ \vdots & \vdots & \vdots \\ 1 & x_{n-1} & x_{n-1}^{\,2} \\ 1 & x_n & x_n^{\,2} \end{bmatrix} \tag{2}$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{n-1} \\ y_n \end{bmatrix} \tag{3}$$

$$\beta = [c \quad b \quad a] \tag{4}$$

for

$$y_{est} = a x_{est}^{\,2} + b x_{est} + c \tag{5}$$

Since Canny edge detection extracts both sides of a single lane marking, the least squares polynomial interpolation results in the estimated lane at a position directly down the center of the lane, as seen in Fig. 5. This position at the center of the lane reduces error in the estimation of the lane, since even divergences from the center of the lane marking can still result in estimation within the lane marking itself.

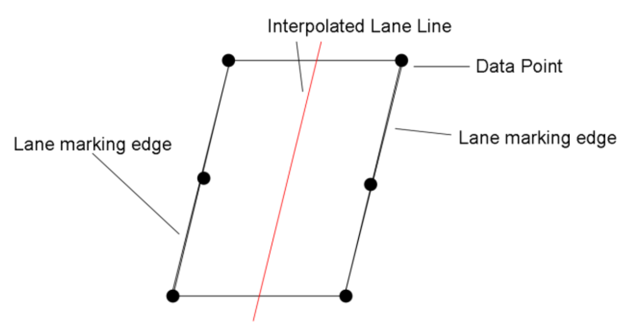

Figure 5: Lane marking diagram of interpolation result with two detected edges of the lane

LANE POSITION ESTIMATION

Erroneous lane lines extracted from the Hough transform can result in an erroneous model of the lane shape in the image. These lines can be brought about by objects on the side of the road or asphalt color discoloration. To reduce the impact of these erroneous lines, a three state Kalman filter is used to slow the convergence of the lane marking model on the current frame's measured lane. The coefficients of the 2nd order polynomial model make up the states of the filter. Since the erroneous lines are generally only present for a limited number of frames, sudden swings in the estimated model of the lane marking due to these erroneous lines are reduced. Lines that are extracted from the actual lane stay consistent over the course of many frames, which allows the coefficients to converge on the actual position of the lane.

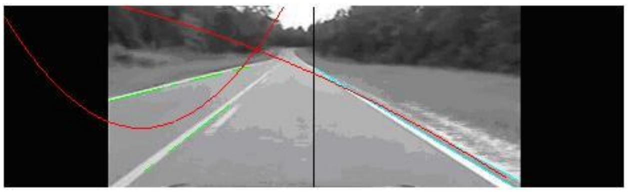

Figure 6: Erroneous left lines from the Hough transform and the resulting interpolated polynomial

Tree lines, other road markings, and lightly colored asphalt are a few of the sources of the erroneous lines, as seen in Fig. 6. Preferably, these sources of erroneous lines would be ignored completely. Assuming smooth lane markings, the estimated lane position for the current frame should be close to the previous frame's lane position, as shown in Fig. 7. As such, the lines from the Hough transform that are close to the previous frame's estimated lane marking are likely to be the lane marking of the current frame. Polynomial curves which act as bounds for valid lane lines can ignore erroneous lines. These curves, set to a certain distance from both sides of the last estimated lane marking, should yield lane lines that are close to the previous frame's estimated lane. This method allows the model to track the transition between straight roadways and curved roads.

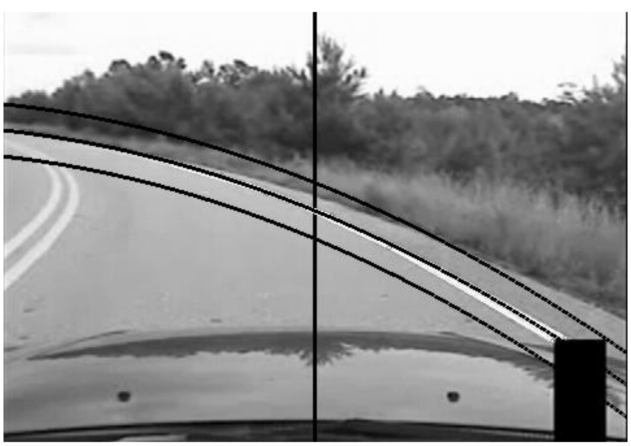

Figure 7: Interpolated polynomial with bounds for the right lane marking

Each polynomial bounding curve consists of three points found by sampling three selected points, x_{est} and y_{est}, on the estimated lane curve and by employing Eqs. (6) through (9) to determine the three new points on either the left bounding curve or right bounding curve for each lane marking. For the bounding polynomial to the right of the estimated lane curve, the following equations, Eqs. (6) and (7), are used:

$$x_{rightbound} = x_{est} + r\cos(\tan^{-1}((\frac{dx}{dy})_{est}) - \frac{\pi}{2}) \qquad (6)$$

$$y_{rightbound} = y_{est} + r\sin(\tan^{-1}((\frac{dy}{dx})_{est}) - \frac{\pi}{2}) \qquad (7)$$

For the bounding polynomial to the left of the estimated lane curve, the equations, Eqs. (8) and (9), are as follows:

$$x_{leftbound} = x_{est} + r\cos(\tan^{-1}((\frac{dy}{dx})_{est}) + \frac{\pi}{2}) \qquad (8)$$

$$y_{leftbound} = y_{est} + r\sin(\tan^{-1}((\frac{dy}{dx})_{est}) + \frac{\pi}{2}) \qquad (9)$$

These equations use the slope at each specified x_{est} and y_{est} to determine the angle at which the bounding polynomial curve will be perpendicular to the estimated lane curve point. A new point is then found at this angle at a distance, r, away from the estimated lane curve. With three new points, polynomial interpolation can once again be employed to determine the coefficients of either the left or right bounding curves. The erroneous lines at a far distance from the last estimated lane curve are ignored, as shown in Fig. 8.

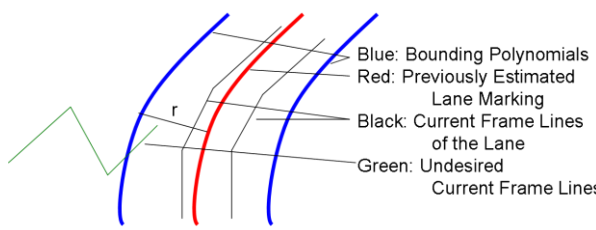

Figure 8: Left lane marking estimation with bounding polynomials

LATERAL DISTANCE ESTIMATION

Assuming the camera is positioned at the center axis of the vehicle, the distance from the center of the vehicle to the estimated lane curve can be determined. This distance in pixels can be converted to real distances with the conversion factor n. As seen in Fig. 9, the lane width is 3.3274 meters. With the knowledge of the number of pixels, 204 pixels, in the image that make up the width of the lane, the conversion factor can be determined using Eq. (10):

$$n = \frac{l}{p} = \frac{3.3274m}{204} = .0163m \quad (10)$$

where l = actual distance, p = number of pixels, and n = conversion factor.

Distance from the center of the vehicle, x_{cam}, to the left and right lanes can be achieved with the general form of the quadratic formula in Eqs. (11) and (12).

$$d_{right} = n\left(\frac{-b+\sqrt{4ay+b^2-4ac}}{2a} - x_{cam}\right) \quad (11)$$

$$d_{left} = n\left(x_{cam} - \frac{-b-\sqrt{4ay+b^2-4ac}}{2a}\right) \quad (12)$$

where a, b, and c are the coefficients of the estimated polynomial model, y is the row in the image at which the measurement should take place, n is the conversion factor, and x_{cam} is the center of the image.

Figure 9: Conversion factor calibration

With this calibration method, the assumption is made that every pixel on the image represents the same width in actual distances. Also, the current measurement is actually measuring the location of the car with respect to the road ahead of it rather than its current location. Due to delay in the camera and computation time, the affect of the lateral measurement in front of the camera might be reduced.

EXPERIMENTAL RESULTS

Truth data was acquired with differential GPS measurements at the National Center for Asphalt Technology (NCAT) Test Track of Auburn University [1]. Lane markings when present on the track were surveyed using differential GPS on the outer lane marking and middle lane marking. These lane markings were nonexistent in some areas, faint in others, and diverged from their normal path when the road branched to other parts of the NCAT track. Also, the asphalt on the track differed at various intervals due to other work being done at the NCAT track. As such, the track was not an ideal track for lane detection. Once the survey of the track was complete, the car was driven around the track to simultaneously acquire RTK GPS coordinates and frame grabs from the camera. In this test run, a Hyundai Sonata was equipped with a forward-looking camera that was mounted on a conventional roof rack. The conversion factor, n, can be found in Eq. (10).

Fig. 10 shows the lateral distance measurement from the GPS measurements and the camera measurements. The two areas where the two measurements diverge are the turns, which are problematic for this algorithm. Additionally, several regions are shown where no camera measurement was reported. These areas were either regions on the track where no lane was actually present or where the lane was not detected by the camera. No lane marking was present on the track in some areas due to wear from use or from diverging lines from branching roads to other parts of the NCAT facility. Additionally, the dashed middle lane was not detected consistently, so an assumption about the width of the lane was necessary to determine the lateral distance from the center of the lane required by the RTK truth measurements.

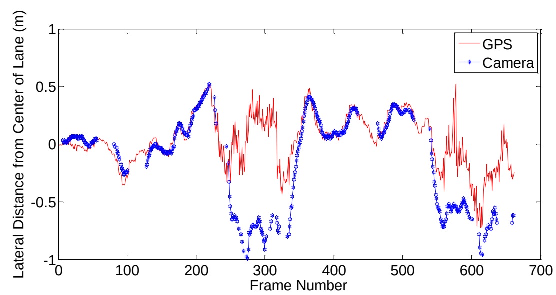

Figure 10: Lateral distance from center over entire run for camera (starred blue) and GPS (solid red)

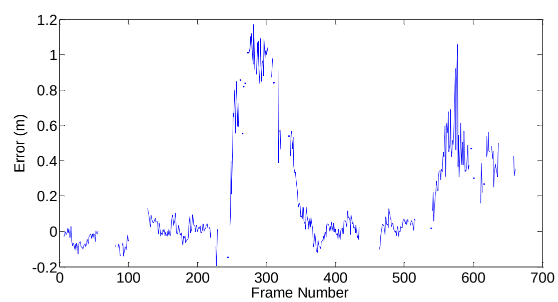

Figure 11: Error for entire run

Fig. 12 shows the lateral distance measured for camera and GPS where the frames for a lane that were undetected by the camera were ignored. Fig. 13 shows the error between the GPS and camera measurements. The standard deviation of this error between these two measurements was 0.3037 meters, and the average error was 0.20068 meters.

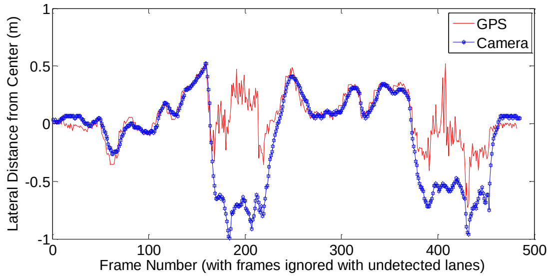

Figure 12: Lateral distance measured for camera (starred blue) and GPS (solid red) with ignored lanes

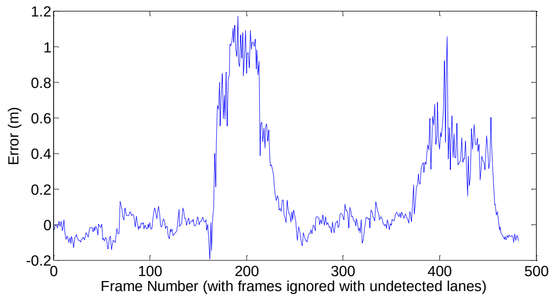

Figure 13: Error with undetected lane frames ignored

Since the accuracy of the camera measurements on the turns was low, a comparison between the camera and GPS measurements on the straight paths is important, shown in Fig. 14. The standard deviation of the error, shown in Fig. 15, on the straight road was .0586 meters, and the average error was 0.0461 meters.

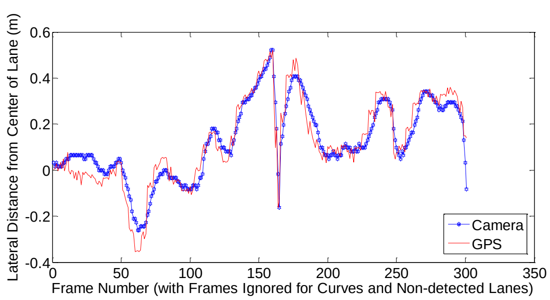

Figure 14: Lateral distance measured for straight roads for camera (starred blue) and GPS (solid red)

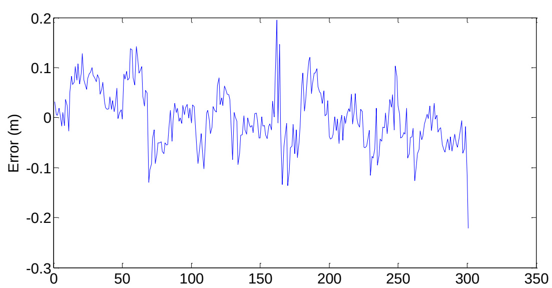

Figure 15: Error for straight roads with ignored frames with non-detected lanes

As seen in Fig. 15, this method performs well on the straight paths with solid lines. On curves, however, the method fails to return a measurement accurate enough for navigation within the lane. This failure could be due to the bank in the turns, the inaccurate assumption for the width of the lane in turns, or a failure to return a proper distance measurement of the present location of the lane since the camera is making its measurements on the road ahead. Note that the GPS measurements become noisier in the turns as well. Also, the dashed line at the center of the road failed to be detected consistently and could not be used as a measurement.

CONCLUSIONS AND FUTURE WORK

This paper presented a technique for extraction of lane shape in image space which uses bounding polynomials to ignore extraneous lines from line extraction of the Hough transform from other objects in the image. Additionally, a Kalman filter is employed on the coefficients of the polynomial lane model to reduce the effect of erroneous lines that are included within the region of the bounding polynomials. Experimental results show that this method performs well on straight roads, but in curves, the error is significantly higher. This error can be attributed to several factors. The assumption that the conversion factor is the same across all pixels in the image may fail in turns and on hills and troughs on the road. Measurement on the road ahead of the vehicle rather than the current location of the vehicle could lead to errors in measurement, especially on curves. Inaccurate assumptions of the lane width, such as where the lane widened as the road branched away from the track, could have also led to differences between the camera and GPS measurements. Finally, successful detection of the middle lane marking could have led to a more reliable lateral measurement.

Despite the knowledge of the road shape ahead of the vehicle, most of this information was not used in the determination of the lateral distance. Whether or not the road is in a curve can be determined using the curvature of the road shape, and the algorithm can be modified during curves to reduce the current curved road error. Also, 3-D reconstruction, such as that found in [3], [9], and [13], of the road in front of the vehicle can be used to help establish the location of the vehicle in curves by mapping the curve based on the road geometry.

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