Predictive Lane Boundary-Detection in Roads with Non-Uniform Surface Illumination

A thesis presented to
the faculty of
the Russ College of Engineering and Technology of Ohio University

In partial fulfillment
of the requirements for the degree
Master of Science

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May 2013

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This thesis titled
Predictive Lane Boundary-Detection in Roads with Non-Uniform Surface Illumination

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Predictive Lane Boundary-Detection in Roads with Non-Uniform Surface Illumination

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This research work presents a method for the detection of road lane markers which is least affected by non-uniform surface illumination (shadow) and road shapes. The algorithm processes an image by two different approaches namely Gradient Spectrum Matching (GSM) and Principal Component Analysis (PCA), and selects the most optimal point on each horizontal scan line using the Least Square (LS) error criterion. The Fourier transform over the local window at each lane markers produces local characteristics features which are used to distinguish the lane markers as left and right. The PCA is employed to determine the direction of the lane markers within the local window with respect to direction of motion. The Auto Regressive Moving Average (ARMA) model based Yule-Walker regression is deployed to predict the direction of lane markers. The transformation from RGB (Red, Green, Blue) to HSV (Hue, Saturation, Value) color space has enabled the system to overcome the effect of non-uniform illumination. The accuracy and precision of the proposed mode are presented and compared with method existing in the literature.
DEDICATION

To my parents, who have worked hard to bring me where I am today.

Particularly, my father Gopi Nath Parajuli, who has inspired, and motivated me to
achieve higher and higher with persistence.
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CHAPTER 1: INTRODUCTION

1.1 Intelligent Transportation Systems

There has been a growing interest in Intelligent Transportation Systems (ITS) over the past few decades. This has drawn attention from researchers all around the world. The increase in number of vehicle crashes and fatalities everyday [1] has motivated the concern for safety which led to the inception of ITS for safer and reliable transportation.

The prime objective of ITS is to improve safety and efficiency of transportation by utilizing advanced computer, communication and surveillance technologies [2]. The techniques developed for the safety aspect of ITS range from semi-autonomous to autonomous systems, and from Collision Warning Systems (CWS) to Collision Avoidance Systems (CAS). Most of the technological developments to date are focused on Advanced Driver Assistance Systems (ADAS) [3], [18] such as Forward Collision Warning (FCW), Auto-parking, Lane Departure Warning, Vehicle/Pedestrian Detection, Pedestrian Collision Warning, Adaptive Cruise Control (ACC) etc. The DARPA Grand Challenge 2004 [4], DARPA Grand Challenge 2005 [4], and DARPA Urban Challenge 2007 [5] were the autonomous vehicles’ competition that displayed self-governing capabilities to perform basic and difficult maneuvers while driving in different environments. The “Google car” is another example of a smart car that can make smart decisions on its own [6].
Most of the techniques developed for the safety aspect of ITS focus on driver assistance systems, which work to continuously and accurately model the environment around the vehicle. Included in this environment description should be vehicle detection, tracking of lanes, stationary objects and pedestrians [7], [8]. One such important aspect of ITS is lane detection and tracking. There are various lane detection and tracking algorithms in the literature [9]-[17]. Herein, we focus on the vision based lane detection in roads with non-uniform surface illumination.

Lane boundary detection has long been an important area of research for people in ITS. Lane detection refers to the detection of white lane markers present on the roads, highways, and freeways. Lane detection makes the driver aware of the lane boundaries between which the vehicle is supposed to travel and helps in keeping the vehicle within its own lane. Lane keeping is particularly important in highways and freeways where a number of vehicles travel at high speed, and even a slight lateral displacement of a vehicle may cause collision with an adjacent vehicle. Such collisions are very severe at high speeds and cause many fatalities and serious injuries to human beings every year [1]. These types of collisions are common in freeways where a slight distraction on the part of the driver can lead to a crash scenario.

However, the presence of lane detection and tracking systems can either generate a warning and make a driver aware of any unintended lane change, or automatically take necessary control measures to prevent the deviation from the lane. Moreover, these lane detection systems are necessary for autonomous vehicles to safely navigate their way through the lanes. In some cases, these lanes are not clearly visible due to various
environmental conditions such as rain, shadow, fog, and snow. There are currently a large number of algorithms in the literature [9], [10], [12]-[18] which can effectively and efficiently detect lane boundaries in normal weather conditions. These methods, however, are not guaranteed to work on inclement environment conditions of variable illumination conditions. Also, the presence of shadow and non-uniform road surface makes the task of lane detection difficult and erroneous. Herein, we propose a method that can detect the lane boundaries in roads with non-uniform surface illumination.

The objectives of this thesis can be summarized as follows:

- To develop a robust algorithm for accurate and precise detection of lane markers of various shapes under non-uniform road surface illumination.
- To investigate the performance of our algorithm with the recent methods in the literature.

1.2 Contributions of the Research

The contribution of this research work is twofold. One aspect introduces the gradient spectra features (local image descriptors) and Gradient Spectrum Matching (GSM) function [25]. The other aspect is improvement in the accuracy of the lane detection by using the information fusion of the results obtained from GSM and PCA method. The proposed method yielded true detection rate of approximately 96 % over a public databases of images in [26]. This result is better than that obtained in [17], [22], [24].
CHAPTER 2: LITERATURE REVIEW

2.1 Literature Survey

The problem of accurate detection and localization of lane boundaries or lane markers is well investigated area in the field of ITS. Currently, a large number of computer vision based techniques are present in the literature for the detection and tracking of lane markings. These vision based algorithm can be classified in one of the two groups i) template based, and ii) feature based. A brief summary of various lane detection methods present in the literature are presented in [28], [29].

The template based lane detection algorithm has a predefined set of lane models or templates for representing the road lanes. These algorithms typically preprocess the image and extracts parameter to find the best model for the lane markings in the image from the predefined set of templates [12]-[14]. In [17], Yue et al. used the cubic B-spline to model the lane boundaries where the problem of detecting two sides of a road was reduced to the task of detecting midline of the road. It also presented Canny Hough Estimation of Vanishing Points (CHEVP) algorithm for locating the initial points and locating the vanishing point. The algorithm performs particularly well in detecting both the straight and curved segments of the road in various illumination conditions and even in presence of shadow along the edges of the road. However, it still detects false points in presence artifacts such as large shadow of tree trunks, poles, and buildings [27], [22]. In, [14]-[16], [18], a deformable template was used to match the road lanes. These methods give good result in detection of roads segments of various shapes during normal environmental condition. Applications of this template based methods, however, are
limited to structured road environments and cannot perform well when weather and road surface conditions changes because only a finite number of templates can be generated to model a particular road scene.

Wang et al. [24] proposed a method for lane detection and tracking which combines parabolic model and the Hough transform to detect both the straight and curved segments of the road. The method follows the traditional approach using Prewitt edge operator followed by threshold to obtain a binary edge detected image. Then, the Hough transform is used for initial boundary detection followed by fitting of parabolic for lane boundary detection and tracking. As discussed in the result section of [24], the presence of large shadow leads to incorrect results, however.

Lipski, in [19] formulated a data fusion based algorithm (input from multiple cameras) and employed RANSAC (RANdom SAmple Consensus) algorithm to generate lane models using the feature points from the multiple cameras. While the method is robust and computationally efficient, it can be used in real time operations at low vehicle speed only. Also the presence of vehicles and other obstacles on the road, leads to the detection of large number of false lane points.

The feature based lane detection algorithms [9]-[11] involves processing of image features such as edges, and gradient. In [9], [10] a method is presented for the detection of road lane markings which uses edge detection and Hough transform. These methods perform accurately for a given environment where the illumination is fixed but the performance degrades rapidly when the illumination changes and a new suitable intensity threshold is required to remove the unwanted edges. Borka et al. presented a method [11],
based upon edge detection, Hough transform, and temporal characteristics for the purpose of real time lane detection during night-time. However, this method is heavily affected by shadow and illumination condition and is limited for straight road segments. Additionally, these methods have experienced difficulties when choosing a suitable intensity threshold to remove the unwanted edges without degrading the true road lane marker edge points. Lane finding in AAnother domAin (LANA) [16], obtains information about the intensity and direction of the edges by using frequency domain features. Again, good performance of both methods in varying illumination conditions and over a wide variety of road shapes will be a critical issue to examine. The author in [20], obtained the vanishing point of the road segment by computing the major direction of the gradient within the local window and the detection of lane markings was performed using the local gradient direction. However the directions obtained from gradients within the local window may not converge all the time and the presence of vehicles on the lane markings results in detection of false points. Therefore, convergence to a fixed point is not necessary and this method is prone to image artifacts and other occlusions.

Sivaraman and Trivedi in [21], presented a method for lane detection and tracking using vehicle localization where lane detection is performed by using steerable filters, lanes are tracked by Kalman filters and vehicle tracking is done using condensation particle filtering. They mainly focused on lane tracking in high density traffic scenes and it is likely that it cannot perform well in low traffic conditions where there no vehicle is ahead of the host vehicle. Also it is a well-known fact that the Kalman filter is computationally expensive than Yule-Walker predictor [30], [34]. These problems are
addressed and a method is presented for lane detection and tracking irrespective of the presence or absence of on-road vehicles. We employ principal PCA to determine the direction of the lane markers within the local window selected on the lane markers. Further, the ARMA (Auto Regressive Moving Average) model based Yule-Walker regression successfully predicts the direction of lane markers with a high degree of accuracy [30], [34].

Fan et al. in [22], proposed a new method for lane detection and tracking which uses the angle component of the gradient to compute the Edge Distribution Function (EDF), Hough transform and bi-directional sliding window. The Bi-directional sliding window is applied along the image from bottom to top, and EDF is computed. The authors computed the rate of successful detection of their results with that of other methods present in the literature. Their results yielded 94% successful rate which surpassed previous detection results. However, it is doubtful to conclude that the proposed method will work well on other images with extreme weather conditions like rain, snow and varying road geometry with heavy shadow effect.

The authors in [23], have put forward a method to perform High Dynamic Range (HDR) lane detection and tracking system that is robust in varying conditions of illumination. Kou et al. in [23], begins with obtaining HDR image by merging three images with varying exposure rates from a single camera. Then, the HDR image is processed to detect lane boundaries whose accuracy would not be affected by lightning conditions. The authors assert that the computation time achieved by their method is 65 ms, which is better than that of others and can be used for real time applications.
However, no information has been provided on the number of images used for the testing and calculating the computational time which is presented as 65 ms. The method can be robust and computationally efficient over a varying condition of lighting but most of the detection results presented were only straight road line segments. Therefore, there is a need of a method that works on varying illumination conditions as well as for straight and curved segment of the road.

2.2 Analysis of the Limitations of Current Methods

The different algorithms present in the literature [17]-[24] are designed for favourable weather conditions. These methods perform well in favourable weather; however, they are not guaranteed to perform effectively in presence of shadow and non-uniform road surface illumination conditions [25], [27]. The study presented in this study focuses on development of robust and accurate techniques for lane detection in presence of non-uniform road surface illumination.
CHAPTER 3: METHODOLOGY

The algorithm begins with extraction of individual frames of the video and processing each single image frame to detect the lane markers or lane boundaries. The first step is the conversion of the RGB image into a grayscale one. The grayscale image is fed into the gradient spectrum method [25] which extracts the vertical edges of the image to remove the effect of shadow which is generally horizontal. The first few points detected by the GSM method are used to initialize the subroutine of principal component analysis (PCA) [32]. After the initialization of PCA subroutine, the PCA method works to compute the direction of lane and follows the lane markings along the road. The PCA subroutine works in the spatial space by computing major direction (principal component) of the grayscale image within the local window placed on the lane markings. This process continues all along the lane markings and the next lane points on the next horizontal line is computed.

The horizontal scan line begins at a pre-specified point which is about the $\frac{3}{4}$th length of image from top. The distance between the successive scan lines is a constant which is equal to five pixel points. The horizontal scan line continues until the end of the image is reached. The top level functional block diagram is shown below in Figure 1. This method works directly on the grayscale image, gradient of the image and does not require a suitable intensity threshold to convert the gray scale image into a binary image and is thus less prone to illumination condition.
3.1 Gradient Spectrum Matching Method

The method uses the novel frequency domain features of the lane markings and the gradient spectrum matching function as outlined in [25]. This method consists of
several subsections like feature extraction, spectrum matching plot generation and processing, maxima points discrimination, and linear prediction and correction.

3.1.1 Feature Extraction

The vertical edges $G(m,n)$ of an image $I(m,n)$ is obtained by 2D discrete convolution [31] of the image $I(m,n)$ with the mask $h(m,n)$ as shown in eqn. 1.

$$G(m,n) = I(m,n) * h(m,n) \quad (1)$$

where $h(m,n)$ is a impulse response for vertical edge detection [31] given as

$$h(m,n) = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}. \quad (2)$$

Figure 2: RGB image to vertical edge conversion and sample points.
For the purpose of extracting the lane marking features, a 15x15 sized window is selected and placed on the lane markings at points s1, s2, s3, s4, and s5 as shown in Figure 2, and Figure 3. The points s1, s2, s3, s4, and s5 are selected at random along the lane markings in the vertical edge of the image. In spatial domain, the points within these five 15x15 local window s1, s2, s3, s4, and s5 are placed in five different matrices m1, m2, m3, m4 and m5, respectively. The FT (Fourier Transform) of these five matrices m1, m2, m3, m4, and m5 is computed (Figure 3) and the mean value of the magnitude of the FT’s is also obtained (eqn. 5). This mean value of the magnitude of FT is represented as \( L_{spectra} \) [25] which is the characteristic feature or characteristic spectrum of the lane markings. A pictorial representation for generating the characteristic spectrum for the point s1 with coordinates \((n_1,n_2)\) as in Figure 5 and represented from eqn.3 through eqn. 5.

\[
m1 = G(n_1 + k, n_2 + l) \quad (3)
\]

\[
p = mag(FT\{m1\}) = mag(FT\{G(n_1 + k, n_2 + l)\}) \quad (4)
\]

\[
L_{spectra} = \frac{1}{5} \sum_{i=1}^{5} mag(FT\{mi\}) \quad (5)
\]

The size of the local window was selected as 15x15 after an extensive experimentation on a large number of images from the database in [26]. It was found that the window size of 15x15 produced the most consistent and accurate representation of the lane markers that is invariant to rotation, translation, and scaling [25].
Table 1: Selection of local window dimension.

<table>
<thead>
<tr>
<th>Window Dimension</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>5x5</td>
<td>Varying results in different images</td>
</tr>
<tr>
<td>7x7</td>
<td>Varying results in different images</td>
</tr>
<tr>
<td>11x11</td>
<td>Varying results in different images</td>
</tr>
<tr>
<td>13x13</td>
<td>Varying results in different images</td>
</tr>
<tr>
<td>15x15</td>
<td>Most invariant to translation, rotation and scaling</td>
</tr>
</tbody>
</table>

*Figure 3: Gradient of an image with vertical edges and sample points.*
3.1.2 Gradient Spectrum Match Function

The gradient spectrum match function is a function that precisely locates the lane marking points along the horizontal scan line. The precisely localized points are the points along the horizontal scan line which best matches the characteristic spectra,
The working principle of this function is described in detail in [25]. At each point on the horizontal scan line we generate the characteristic spectrum as described in section 3.1.1 above. Then, the generated spectrum at each point on the horizontal scan line is correlated with the characteristic spectra $L_{spectra}$ and highest value of correlation $R(0,0)$ is used. Mathematically, the steps are represented as in eqn. 6 to eqn. 9. Let $G(n_1,n_2)$ be the gradient of the image containing vertical edges which is the result of eqn. 1.

\[ G(n_1,n_2) \text{, } n_1, n_2 \text{ are discrete variables in the range} \]
\[ 1 \leq n_1 \leq R , 1 \leq n_2 \leq C \quad (6) \]

The 15x15 local window is placed at each point on the horizontal scan line (see Figure 6) and the values of image $G(n_1,n_2)$ within the local window are represented by the matrix $\mathbf{M}$ as given in eqn. 7. The row component of the image $G(n_1,n_2)$, row $n_1$, is constant and column, $n_2$ varies along the scan line from 1 to $C$ ($1 \leq n_2 \leq C$).

\[ \mathbf{M} = G(n_1 + k, n_2 + l) \quad (7) \]
\[ \forall \quad -7 \leq k \leq 7 , -7 \leq l \leq 7 \]
\[ P = \text{mag}(\text{FT}[\mathbf{M}]) = \text{mag}(\text{FT}[G(n_1 + k, n_2 + l)]) \quad (8) \]

The 2D matrix $P = \text{mag}(\text{FT}[\mathbf{M}])$ is calculated for each point along the horizontal scan line. Then the matrix $P$ generated at each point is correlated with the
$L_{spectra}$ (characteristic) and the maximum value of correlation, $R(0,0)$ is obtained and stored for each point. This maximum correlation value \([31]\) $R(0,0)$ is computed through element wise multiplication of $P$ as represented in eqn. 9 for each point along the horizontal scan line (refer to Figure 3) and stored in the variable $S_m(n_2)$ where $n_2 = 1, 2, \ldots, C$. The normalized plot of $S_m$ for all the values of $n_2$ along the horizontal scan line is called Spectrum matching plot (Figure 6).

$$R(0,0) = \sum_{i=-7}^{i=7} \sum_{j=-7}^{j=7} L_{spectra}(i,j) \cdot P(i,j)$$  

(9)

$$S_m(n_2) = R(0,0)$$  

(10)

where $n_2 = 1, 2, 3, \ldots, C.$
Figure 6: Spectrum matching (Sm) plot and the filtered version with maxima points.

The Figure 6 represents Spectrum matching plot which contains maximum correlation values generated by sliding local window along the horizontal scan line on the gradient image (refer to eqn. 9 and eqn. 10). The moving average filtered spectrum matching plot with green points representing maxima points is shown in Figure 6.
3.1.3 Spectrum Match (S_m) Plot Processing and Maxima Points Discrimination

The spectrum matching plot (S_m) is filtered by a low pass filter (Moving Average filter of order 20) [30], [31], and the local maxima points on the plot are found using the algorithm described in [33]. The spectrum matching plot (S_m) is threshold by a suitable value 0.3 to remove the processing of insignificant maxima points that are below the threshold. The choice of the threshold is not critical. The detected local maxima points are further classified in one of the two classes, namely left line class (C_L), and right line class (C_R). The details of the S_m plot processing and maxima points discrimination algorithm is described in [25], [33].

Figure 7: Horizontal scan lines on a gradient image.
The Figure 8 shows the spectrum matching plot for the three scan lines depicted in Figure 7. The maxima points are represented by green dots on Figure 8 and the median line by yellow (in Figure 7) and red line (Figure 8). The distance between the scan lines is set to 50 pixels in the Figure 7 for the purpose of simplifying the visualization process. The distance between the scan lines in the actual algorithm is set to 5.

![Image](image.png)

*Figure 8*: Sm plots with green dots representing maxima points.

### 3.1.4 Linear Prediction and Correction

After the initial processing of first five scan line, the right and left lane points on the adjacent horizontal line are predicted using a simple linear extrapolation model. The displacement between the first five points is calculated taking two points at a time. The mean displacement is computed from the lane points of the preceding 5 horizontal scan lines. The lane point on the next horizontal scan line is estimated \( \hat{g}(n) \) by adding the
mean displacement to the computed lane marking point on the current scan line $g(n)$. If the actual lane points (obtained from section 3.1.3) are far away from the estimated point then the estimated point is chosen as the actual and the computed actual point is discarded. The details of the steps for the linear prediction and error correction are described in the author’s previous work [25].

3.2. Principal Component Analysis (PCA) Method

The task of detection of road lane markers is accomplished, in parallel, by the use of principal component analysis method [32]. The PCA subroutine works in the spatial space by computing major direction (eigen Vector) of the grayscale image within the local window placed on the lane markings. The PCA based lane detection method requires initial information about the localization of right, and left lane points for initialization. This initial information of lane points is provided by the GSM method. The first three left and right lane points on the horizontal scan line detected by the GSM is provided as initial points to the PCA method. After the initialization process, the PCA method is independent of the GSM method and both these methods work in parallel and independent of each other. The local window’s major axis orientation (eigen vector) determines the direction of the road lane markers and is updated to the next scan line along the direction of previous eigen vectors. The next scan line is at a distance of five pixel points from the current scan line.
Figure 9: Schematic representation of the two lane road with lane markers, local window and line markers unit directional vector.

Consider the diagram of Figure 9. The horizontal scan line intersects the left and right lane markers at points L, and R, respectively. The initial points L and R are the ones provided by the GSM method based on the best match of the locally generated spectra with the characteristic spectrum as explained in section 3.1. These horizontal scan lines also provide initial three direction vectors $\hat{e}(n)$ corresponding to the strongest lane marker direction for applying the 2nd order yule-walker equation for prediction. The local windows’ major axis orientation is computed at points L, and R on the horizontal scan line. The lane points on the next scan line are calculated in the direction of the window’s major axis orientation from the preceding scan lines. In other words, the lane markers direction from current scan line generates the lane markers points on the next scan line. The local window’s major axis orientation (eigen vector) determines the direction of the
road lane markers and updated to the next scan line. This process continues along the line markers until the lane markers are obstructed by some objects (outliers). The progressive lane markings points are drawn on the horizontal scan line based on the PCA major axis orientation changes.

3.2.1 Principal Component Analysis

The Principal Component Analysis (PCA) is a well-known method in the field of computer vision and image processing [32]. It has been used in various applications such as face recognition, dimensionality reduction, data mining, intrusion detection, and biomedical applications [31], [32]. We use the same notion of PCA to determine the direction of road lane markers by computing the local window’s major axis orientation. The process begins with calculation of the mean vector, and covariance matrix. The last step is the computation of eigen vector (major axis orientation) from the covariance matrix.

3.2.1.1. Local window size

The size of the local window was selected as 15x15 after an extensive experimentation on a large number of images from the database in [26]. It was found that the local window size of 15x15 produced the most consistent and accurate representation of the lane markers’ direction (major axis orientation) from the PCA.
Table 2: Optimum size for local window.

<table>
<thead>
<tr>
<th>Size</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>5x5</td>
<td>Varying results</td>
</tr>
<tr>
<td>7x7</td>
<td>Varying results</td>
</tr>
<tr>
<td>11x11</td>
<td>Varying results</td>
</tr>
<tr>
<td>13x13</td>
<td>Varying results in different images</td>
</tr>
<tr>
<td>15x15</td>
<td>Most invariant to translation, rotation and scaling</td>
</tr>
<tr>
<td>17x17</td>
<td>Varying results</td>
</tr>
</tbody>
</table>

3.2.1.2 Calculation of mean vector

In Figure 9, the horizontal scan line intersects the left lane marker at point L. Let the co-ordinates of the image $G$ at point L be $(n_1, n_2)$ where $n_1$ is the row number and $n_1$ is the column number of the image. The 15x15 local window is placed such that the center of the window is at $(n_1, n_2)$. If $A$ is the matrix containing the pixel points within the local window then we have,

$$A = G(n_1 + k, n_2 + l)$$

$$\forall \ -7 \leq k \leq 7, -7 \leq l \leq 7;$$

where $k, l$ takes discrete values $-7, -6, ..., 0, ..., 6, 7$.

In matrix representation, the 15x15 matrix $A$ can be written as
The elements of matrix $A$ can be generalized as

$$a(i, j) = G(n_1 + i - 8, n_2 + j - 8)$$

where $i, j = 1, 2... 15$.

$G(n_1, n_2)$ is the center pixel on which the local window is placed (see Figure 10 below), and $n_1, n_2$ is the row number and column number of the center pixel, respectively.

*Figure 10: Local window direction on the lane markers along scan line.*
The mean vector ($\vec{u}$) for the matrix $A$ is computed by using the equation

$$\vec{u} = \frac{1}{\sum_i \sum_j a(i,j)} \sum_{i=1}^{15} \sum_{j=1}^{15} \vec{x} \cdot a(i,j)$$

(14)

where $\vec{x} = \begin{bmatrix} i \\ j \end{bmatrix}$ is the position vector.

3.2.1.3. Calculation of covariance matrix

The covariance matrix ($C$) for the matrix $A$ is computed as represented in eqn. 15.

$$C = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} = \frac{1}{\sum_i \sum_j a(i,j)} \sum_{i=1}^{15} \sum_{j=1}^{15} \vec{x} \cdot \vec{x}^T \cdot a(i,j) - \vec{u} \cdot \vec{u}^T$$

(15)

3.2.1.4. Calculation of eigen vector (principal component)

Let $\vec{e}$ be the eigen vectors of the matrix $C$ such that

$$(C - \lambda I) \cdot \vec{e} = 0$$

(16)

where $\lambda$ is the eigen value, and $I$ is the 2x2 identity matrix.

The eigen vectors $\vec{e}$ can be computed from the eqn. 17
$$C \cdot \vec{e} = \lambda \cdot \vec{e} \quad \text{(17)}$$

The eigen vector corresponding to the eigen value with maximum magnitude is the principal component or the local window’s major orientation which depicts the direction of the lane markings. The principal component vector is \( \vec{e} \) when

$$\lambda = \lambda_{\text{max}} = \max \{ \lambda_1, \lambda_2 \} \quad \text{(18)}$$

### 3.2.2 ARMA Model Yule-Walker Prediction

The horizontal scan line intersects with the lane markers (see Figure 9 and Figure 10) at points L, R on left, and right lane markers respectively. At each point L, and R on the horizontal scan line we perform the following process.

i. At points L, R we place 15x15 local window and obtain the largest eigen-values (\( \lambda_L \) and \( \lambda_R \)) and unit eigen-vectors (\( \hat{\theta}_L \) and \( \hat{\theta}_R \)) from PCA, respectively. (see section 3.2.1)

ii. Representation of those vectors from PCA are in the form of

$$\hat{\theta}_L = |\hat{\theta}_L| \angle \theta_L \quad \text{(19)}$$

$$\hat{\theta}_R = |\hat{\theta}_R| \angle \theta_R \quad \text{(20)}$$

iii. Road lane’s prediction

The Yule-Walker equation of second degree is used to predict the lane direction. The overall block diagram of the prediction process is shown in Figure 11.
\[
\hat{\theta}_L(n+1) = \alpha_1 \theta_L(n) + \alpha_2 \theta_L(n-1) \quad (21)
\]
\[
\hat{\theta}_R(n+1) = \beta_1 \theta_R(n) + \beta_2 \theta_R(n-1) \quad (22)
\]
where \(\hat{\theta}_L, \hat{\theta}_R\) are the predicted road directions; \(\theta_L\) and \(\theta_R\) are the corrected directions, and \(\theta_L(n), \theta_R(n)\) are the actual calculated direction at time \(n\).

Here, \(\alpha_1, \alpha_2, \beta_2\), and \(\beta_2\) are the 2nd order ARMA coefficients calculated as described in [30], [34].

\[\text{Figure 11: Block diagram representation of ARMA model prediction.}\]

### 3.3 Information Fusion

The image sequence is processed in parallel by two different methods namely gradient spectrum matching (GSM) method, and Principal component analysis (PCA) method. The lane points detected by these two methods are plot on the original RGB image. The detected lane points are fed in the prediction module, thereby producing a cluster of points along the right and left lane markings. There are four points (one each from GSM, PCA and their predictions) on each side of each horizontal scan line. It is in the interest of the information fusion algorithm to choose the best left and right lane
marking points along each scan line from the four different available points. The information fusion is based upon the principle of Least Squares error criterion [32] which minimizes the error between the detected and the predicted points. The functional block diagram of the process is presented in Figure 12. The information fusion helps in improving the accuracy and precision of the lane detection algorithm.

The block diagram in Figure 12 clearly depicts the working principle of the information fusion process. Let $g_L(n)$ and $\widehat{g}_L(n)$ be the detected and predicted left lane marking points by the GSM method at $n^{th}$ horizontal scan line and $\xi_1(n)$ is the error between the detected and predicted points.

$$\xi_1(n) = g_L(n) - \widehat{g}_L(n) \tag{23}$$

Similarly, $p_L(n)$ and $\widehat{p}_L(n)$ be the detected and predicted left lane marking points by the PCA method at the $n^{th}$ horizontal scan line. The error between the PCA predicted and detected points is $\xi_2(n)$ represented as

$$\xi_2(n) = p_L(n) - \widehat{p}_L(n) \tag{24}$$
The least square error (LS) criterion is used to choose the left and right points along each horizontal line. This is represented in eqn. 25.

If $\xi_2(n)^2 < \xi_1(n)^2$ then

$$y_L(n) = \hat{p}_L(n)$$

else

$$y_L(n) = \hat{g}_L(n)$$

end

(25)

where $n$ is the $n^{th}$ scan line, starting from the bottom of the image; $n=1, 2, 3, \ldots, N$.

This process is applied to both for left and right lane points for each horizontal scan line, and the best lane point is stored in $y(n)$. It is important to note that $y(n)$ contains the column number of the optimum left and right points for the $n^{th}$ horizontal
scan line, while the row number at each point on the given horizontal scan line is constant and predefined. The choice of the optimum points leads to better accuracy and improved results for the lane detection. This can be seen below in Figure 13.

**Figure 13**: Results of the GSM method, PCA method and information fusion and the respective error curves on lane segments.
CHAPTER 4: RESULTS AND DISCUSSION

The method presented in this thesis is tested on the publicly available database of images in [26]. The GSM method, PCA method, and the information fusion algorithm were implemented in MATLAB 2008 and run successfully on a PC with a clock rate of 2.2 GHZ. This thesis is an extension of the author’s previous work [25] which contained results for only the GSM method. The algorithm presented here is tested on the publicly available database of image [26], and its performance is compared with methods existing in the literature.

4.1 Results of Lane Detection

The lane detected image result for GSM, and PCA methods as well as the fusion of these two will be presented turn by turn in this section. Some of the results of the detected points by GSM algorithm tested on images from the above database [26] are presented in Figure 14 and Figure 15.
Figure 14: Results for GSM method overlaid on the image gradient.
Figure 15: Some more results from GSM method.
The Figure 16 through Figure 23 shows the result of GSM, and PCA method along with the horizontal scan line on the top 1st and 2nd column as indicated. The top 3rd column is the result obtained after the information fusion from the two methods (PCA and GSM). The computed and predicted points (column no.) for left and right lane markings on each horizontal scan line (n) are shown in Figure 16 for both the PCA and GSM method. The error between the prediction and computed points is computed and shown in the Figure 16. The predicted points, corresponding to the minimum error among the PCA and GSM method is selected for each horizontal scan line and shown in 3rd column as final result.

Figure 16: Final image obtained after information fusion.
Figure 17: Final image obtained after information fusion.
Figure 18: Final image obtained after information fusion.
Figure 19: Results of fusion.
Figure 20: Results of fusion continued.
Figure 21: Results of fusion continued.
Figure 22: Results of fusion continued.
Figure 23: Results of fusion continued.
4.2 Analysis of Performance

The algorithm presented herein, is tested on the publicly available image databases [26]. The algorithm was tested on each of the 157 images present on the databases. The algorithm obtained successful detection rate of 96.1% while testing in a database of 157 images with successful detection on 151 images while average performance on 6 images. These results are better than those presented in [17], [22], [24], and [25].

The algorithms presented in [22], [25] uses same testing database [26] as used by this research work. In comparison to [25], this work is an extension of author’s work with the inclusion of PCA and information fusion scheme. The final results (Figure 16 - Figure 23) illuminates the differences in performance of GSM method [25] and the method presented here which uses the information fusion to correct the errors from the GSM and PCA methods. Clearly, this research work yields better performance than [25].

4.3 Improvements

The algorithm is robust with high detection accuracy in presence of shadow. However, the above algorithm has an important disadvantage. The above algorithm needs accurate points for the initialize the error correction and prediction scheme. It means that the first five lane points detected by horizontal scan line must be able to precisely locate the accurate lane markers. The presence of artifacts, heavy shadow in the initial scanning of the image (first five scan lines) will lead to detection of false points which may not be rectified by the error correction module. This problem can be corrected by two different techniques, i) temporal tracking, or ii) color transformation to remove heavy shadow.
4.3.1 Temporal Tracking

Temporal tracking refers to the use of results from previous image frames of the video can be used to compare with the current results. Since, the road lanes do not change abruptly between the video frames, the located lane points will be consistent with a few adjacent frames. Any large deviation from the results of preceding frames corresponds to error in detection. This will help to eliminate the effect due to vehicle occlusion in the adjacent lane.

4.3.2 Color Space Transformation

Another approach is to employ the transformation of color space from RGB to HSV (Hue Saturation Value) space. We will use the method described in [31] to change the color space from RGB to HSV. The transformation process is implemented in MatLab. The images in the database [26] are transformed from RGB to HSV color spaces and shown in Figure 24.
The Figure 24 above shows the color space transformation from RGB color space to HSV color space. The selected S-component in red box indicates the reduced effect of shadow.
CHAPTER 5: CONCLUSION AND FUTURE WORK

This thesis work has presented an algorithm for the detection of lane markings in the presence of artifacts like shadow, non-uniform illumination condition, diminishing or missing lane markers, and high dynamic range images. The use of information fusion to select the optimum lane points from the two methods namely GSM and PCA has contributed to obtain higher accuracy and precise localization of lane marking points. Further, the investigation of color space transformation from RGB to HSV has revealed that the effect of shadow is less on the S-component of the HSV color space. The experimental result obtained by testing the image database reveals the efficacy of the algorithm than those present in the literature.

The future work can be the integration of temporal tracking schemes to improve accuracy and precision. It would be of interest to apply this algorithm for detection of lane boundaries during heavy snowfall, unstructured roads and other inclement weather conditions.
REFERENCES


APPENDIX I: RESULTS EXTENDED

The results obtained for the images in the database [26] are presented in this section. The image in third column is the consequence of the information fusion process.