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Is approved by the final examining committee:

Stanley Chien
Chair

Lauren Christopher

Lingxi Li

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Approved by Major Professor(s): Stanley Chien

Approved by: Paul Salama 10/3/2015

Head of the Departmental Graduate Program Date

MODELING OF LOW ILLUMINANCE ROAD LIGHTING CONDITION USING ROAD TEMPORAL PROFILE

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of

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by

Libo Dong

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This work is dedicated to my parents who have given me all the support and love for achieving my goals in life.

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ABBREVIATIONS

HOG	Histogram of Oriented Gradient
SVM	Support Vector Machine
PAEB	Pedestrian Automatic Emergency Braking
ROI	Region of Interest
GPS	Global Positioning System
PSO	Particle Swarm Optimization

ABSTRACT

Dong, Libo M.S.E.C.E, Purdue University, December 2015. Modeling of Low Illuminance Road Lighting Condition using Road Temporal Profile. Major Professor: Stanley Chien.

Pedestrian Automatic Emergency Braking (PAEB) system for avoiding/mitigating pedestrian crashes have been equipped on some passenger vehicles. At present, there are many efforts for the development of common standard for the performance evaluation of PAEB. The Transportation Active Safety Institute (TASI) at Indiana University-Purdue University-Indianapolis has been studying the problems and addressing the concerns related to the establishment of such a standard with support from Toyota Collaborative Safety Research Center (CSRC). One of the important components in the PAEB evaluation is the development of standard testing facilities at night, in which 70% pedestrian crash social costs occurs [1]. The test facility should include representative low-illuminance environment to enable the examination of sensing and control functions of different PAEB systems. This thesis work focuses on modeling low-illuminance driving environment and describes an approach to reconstruct the lighting conditions. The goal of this research is to characterize and model light sources at a potential collision case at low-illuminance environment and determine possible recreation of such environment for PAEB evaluation. This research is conducted in five steps. The first step is to identify lighting components that appear frequently on a low-illuminance environment that affect the performance of the PAEB. The identified lighting components include ambient light, same side/opposite side light poles, opposite side car headlight. Next step is to collect all potential pedestrian collision cases at night with GPS coordinate information from TASI 110 CAR naturalistic driving study video database. Thirdly, since ambient lighting is relatively

random and lack of a certain pattern, ambient light intensity for each potential collision case is defined and processed as the average value of a region of interest on all video frames in this case. Fourth step is to classify interested light sources from the selected videos. The temporal profile method, which compressing region of interest in video data (x,y,t) to image data (x,y), is introduced to scan certain predefined region on the video. Due to the fact that light sources (except ambient light) impose distinct light patterns on the road, image patterns corresponding to specific light sources can be recognized and classified. All light sources obtained are stamped with GPS coordinates and time information which are provided in corresponding data files along with the video. Lastly, by grouping all light source information of each representative street category, representative light description of each street category can be generated. Such light description can be used for lighting construction of PAEB test facility.

1. INTRODUCTION

1.1 Motivation

Pedestrian Automatic Emergency Braking (PAEB) is an active safety system component that aims to avoid or mitigate the collision with pedestrians [2]. AEB is also called by difference names such as collision imminent braking (CIB), pre-crash braking systems (PCS), and others. Many automotive companies have been developing PAEB systems and have started to equip on their vehicles (e.g., Toyota Camry, Mercedes S550, and Volvo XC60) [3]. The performance of different PAEB systems varies greatly. Many research groups and government agencies are developing methodologies for the evaluation of PAEB systems [4]. At present, there was no publicly recognized evaluation standard for PAEB in low-illuminance condition yet. The Transportation Active Safety Institute (TASI) at Indiana University-Purdue University at Indianapolis has been conducting research related to the establishment of such a standard with the support from Toyota Collaborative Safety Research Center (CSRC). Many PAEB systems use mono or stereo cameras for pedestrian detection that is the key to the PAEB performance. One factor that may significantly affect the performance of the pedestrian detection is the low illuminance lighting condition since about 70% pedestrian crash social cost occurred at a low illuminance environment [1]. Due to there is no knowing existing scientific description of potential collision cases during low illuminance environment, a systematic way of categorized and summarized light sources in such environment is needed. Also, to define a testing standard for evaluating and comparing the PAEB systems, various lighting environments with specifications should be established.

1.2 Problem Statement

The purpose of this study is finding a technical specification for establishing the low illuminance test environment for camera based PAEB system evaluation. This specifications should consider major light sources that affect the operation performance of camera based PAEB systems, support different street types (such as local city street, major city street, city center, and rural road), and enable practical setup of PAEB test facility. The vehicle speed in testing is assumed from 10 to 50 miles per hour. Due to significant ambient light changes at dusk and dawn, dusk and dawn are not included.

1.3 Literature Survey

Previously, the development of lighting system for PCS System Testing is analyzed by Qiang Yi and Stanley Chien [5]. The approach of their work is using ANSI/IESNA RP-8-00 published by Illumination and Engineering Society of North America to establish a vehicle testing environment at night time. Sections 5 and 6 of the standard define the average illuminance level and light uniformity of the lighting requirement in US roadway lighting design. This approach is intrinsic, but could not describe real lighting characteristic in urban area that has denser population and higher probability of pedestrian collision.

In most of urban areas, especially in downtown, lighting components are random. Urban Planning tends to create an illuminance level higher than the national standard in big cities as well. Due to these reasons, a data source that contains real lighting information on the local area should be utilized as the input to the research so that the result will tend to resemble real environment.

From 2012 to 2013, TASI conducted 110 car one-year naturalistic driving study [8]. The purpose was to study pedestrian behaviors in various conditions. A CMOS camera with GPS and G-sensor was installed on each of the 110 vehicles to gather video of what the driver would see out of the front windshield. Each car collected video data for one year. The total size of the collected dash camera video exceeds 100 TB. Since this data source contains Indianapolis areas street view at night time and is fully labeled with potential collisions between vehicle and pedestrian, it is chosen to be the data source for this study.

1.4 General Approach

This research is conducted in four steps. The first step is to identify light sources that frequently appear in a low-illuminance environment and affect the performance of the PAEB. The second step is to collect all potential pedestrian collision cases at night with GPS coordinate information from TASI 110 CAR naturalistic driving study video database. The third step is to identify all light sources in the video. The last step is to generate the lighting parameters for different types of streets.

Light sources have to be defined since each light source may need its unique processing method. By carefully examine a large quantity of videos, it can be concluded that the major light sources that can affect the PCS system are (1) light poles, (2) opposite direction car headlight, (3) headlight of the opposite lane car according to the subjects car. Also, there is ambient lighting that is not explicitly lighting up the road or the environment, but rather available and affecting the pedestrian detection. Here we include building light and billboard light in the area as part of the ambient light. Ambient lighting defines the global environmental light intensity. Thus, it is a reasonable measure for evaluation of environment.

It is hard to detect different lighting components in the videos directly using pattern recognition. The light that are emitted from every lighting components is impossible to calculate in the video. Types of light sources are also hard to be accurately defined. To detect and classify lighting components on the video, a compression algorithm is needed to compress video data without sacrificing features to classify light sources. In here, to focus on the detecting and classification of lighting components on the video, Temporal Profile is used as a way to preserve features that various light sources generated and to be classified later. To be more specific, the temporal profile method is used to detect and classify all interested lighting components by processing the shape of the light emitted on the road. The Temporal Profile is introduced to scan the road on the video. Since Temporal Profile is an algorithm which generated image of the road by overlapping road region on the car dash camera video as time elapse, it will includes the unique light pattern on the road for different lighting components which can be classified latter. All lighting components classified are stamped with GPS coordinates and time that are provided in the corresponding data file along with the video.

Ambient lighting is relatively random, and lack of a certain pattern. Ambient light intensity for each potential collision case is defined as the average value of a region of interest of all video frames. The ambient light in different types of streets are treated the same except in city center where the building and billboard lights contribute to the ambient light significantly.

Non-ambient light sources are extracted by recognizing them in a road temporal profile. The recognition process is accompanied by the stamping of the corresponding GPS information thus a lighting components map can be generated. The lighting components map is a map that overlaid the lighting components with their location on a Google Maps. After processing the video generated Temporal Profile and obtained locations of the light sources, clustering is needed to surrender redundant information for PEAB testing purpose. To generate testing scenarios that are more focused on the potential collision cases, only the light sources that are within a certain range of a potential collision case will be considered in the clustering. The clustering should provide a result that applies to the testing purpose.

Once the light sources are identified in all potential collision cases on the same street type, they are classified into different lighting configurations to produce the light parameter of each representative street category. Such light description can be used for lighting construction of PAEB test facility.

2. BACKGROUND

This chapter will provide a literature review of the background information that is related to this thesis. Firstly, the technical methods that solve specific problems described later in the paper are briefly introduced. Previous work related to this thesis topic will be discussed to illustrate its applicability and limitations. Last but not least, TASI 110 Car Naturalistic driving data is introduced as the resource of this research. The structure and information will be reviewed in this chapter to explain how the data is utilized.

2.1 Technical Background

This section will provide a brief review of the pattern recognition, optimization, and compression algorithms that were used in this thesis.

2.1.1 Histogram of Oriented Gradient (HOG)

HOG is a widely used feature descriptor that can describe the shape and the relative intensity of the object within the region of interest (ROI) [6]. For this paper, MATLAB command extractHOGFeatures() is used to carry out the HOG by sampling an ROI on the image, firstly the ROI is separated into blocks with user defined size. Secondly one will calculate the magnitude of the gradient of the block by performing 2D convolution with a Laplace Operator [7] from both X and Y directions on the block. The Gradient direction is then calculated by the ratio of the convolution result in both X and Y directions [8].

$$\mathbf{G} = \sqrt{\mathbf{G_x} + \mathbf{G_y}} \tag{2.1}$$

$$\mathbf{\Theta} = arctan(\mathbf{G_x} + \mathbf{G_y}) \tag{2.2}$$

These results are then histogrammed into eight directions and normalized. By generating this histogram for each block, one can create an eight element vector consists of histogram results of 8 directions. HOG is especially useful in encoding shapes in ROI because the gradient of the image is a relative value, thus remain steady for consistent value. HOG will maximize the performance in the recognition of the pattern. In MATLAB 2015, function extractHOGFeatures() uses block size, and a number of bins to define the operation of the function. A block is the smallest unit in the HOG algorithm, which can be represented as a red square in Fig. 2.1. A block contains m by m pixels, which is shown as green cells inside the red blocks. A block will produce gradients by 2D convolving Laplace Operator. After convolving with 2D Laplace Operator, directions of the gradient are produced for each pixel as the arrows inside the green blocks in Fig. 2.2. These directions of gradients are then histogrammed to form the graph on the left of Fig. 2.2. In Fig. 2.2, the Height of the blue bar indicates the count of the direction of gradients that fall into the bin for one block. Each arrow is corresponding to the blue bar above. Normally eight bins are defined when histogram the direction of gradients from 0 to 360 degrees. And the count of each bin is the result of the HOG feature extraction, which is shown in the left part of Fig. 2.2. Multiple HOG feature vectors, which consist of the count of the bins for the red block, are produced for each red block in the image for this process. Finally, these vectors are concatenated into one final vector for all blocks in the image as the feature of the image.

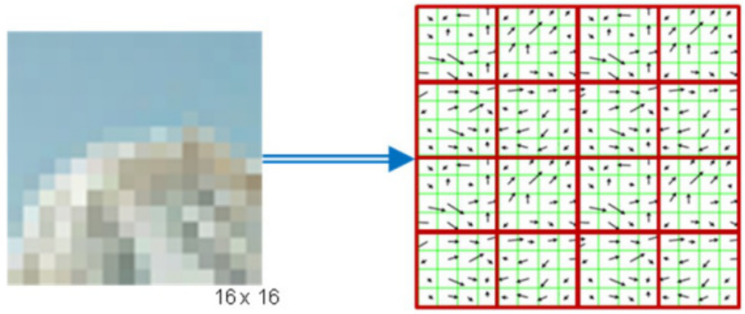


Fig. 2.1.: Image to 16 Blocks

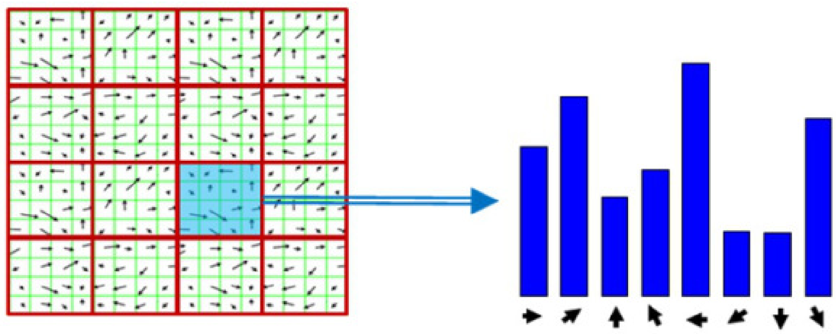


Fig. 2.2.: 16 Blocks to Bins of Gradients

2.1.2 Particle Swarm Optimization (PSO)

PSO is a cost-efficient method to find a solution to the optimization problem of a non-linear system, especially when the accuracy of the solution is not strictly required [9], [10]. PSO starts with an initial randomly generated n particle point in the domain of the function, and each particle in the population is assigned with a velocity vector. The point on the trace of the particle is evaluated, and each particle updates its best-so-far-position when the current position is better [11]. This is called personal best. Using all personal best, one can construct the global best. If the global best converged to certain error range, the process is complete. In here the x, y is calculated by using PSO. A variation of PSO named gbest algorithm is used by incorporating given constant real parameters: inertial constant ω, cognitive constant c_1 and social constant c_2 [9]. A detailed gbest algorithm is described in algorithm 1.

Algorithm 1 PSO gbest Algorithm

1. Set k = 0. For i = 1, , d, generate initial random positions $x_i^{(k)}$, velocities $v_i^{(k)}$, and set $p_i^{(k)} = x_i^{(k)}$. Set $g^{(k)} = \arg\min_{x \in x_1^{(k)}, x_2^{(k)}, \ldots, x_d^{(k)} f(x)}$, where $f(x)$ is the object function.

2. For i = 1, , d, generate random n-vectors $r_i^{(k)}$ and $s_i^{(k)}$ with components uniformly sampled in the interval (0,1), and set
$v_i^{(k+1)} = \omega \cdot v_i^{(k+1)} + c_1 \cdot r_i^{(k)} \cdot (p_i^{(k)} - x_i^{(k)}) + c_2 \cdot s_i^{(k)} \cdot (g^((k)) - x_i^{(k)}$
$x_i^{(k+1)} = x_i^{(k)} + v_i^{(k+1)}$

3. For i = 1, , d, if $f(x_i^{(k+1)}) < f(p_i^{(k)})$,then set $p_i^{(k+1)} = x_i^{(k+1)}$; else, set $p_i^{(k+1)} = p_i^{(k)}$

4. If there exists $i \in 1, , d$ such that $f(x_i^{(k+1)}) < f(g_i^{(k)})$, then set $g_i^{(k+1)}) = x_i^{(k+1)})$; else, set $g_i^{(k+1)} = g_i^{(k)}$.

5. If the stopping criterion satisfied, then stop.

6. Set k = k + 1, go to step 2

2.1.3 Supported Vector Machine (SVM)

The pattern recognition of light sources used SVM as a classifier [12]. SVM is a supervised machine-learning algorithm that find a hyper-plane that separating different classes at maximum margin when provided input of training set of $(x_1, y_1), (x_2, y_2)....(x_n, y_n)$ [13]. The training set defined as values $x_1, x_2, ..., x_n \in \mathbf{R}^p$, where p is the dimension of the data set, and labels corresponding to each data defined as $y_1, y_2, ..., y_n$. Such hyper-plane, which used as a system, is later utilized to predict the labeling of the testing sets. This paper used a simple variation of SVM called a linear SVM classifier. Linear SVM will only predict if the testing set is true or false.

To find the maximum margin using a linear SVM classifier with only 2 classes, one can assume that the data set with label is linearly separable and for all x_n. They are either true or false. The discriminate function can be expressed as $g(y) = c \cdot y$. A linear system c such that $c \in \mathbf{R}^{(n+1)}$ is solved so that a testing data point y_i is labeled true if $c \cdot y > 0$, false if $c \cdot y < 0$. For a given hyper-plane, we denote y_1 and (y_2) the closest points to the hyper plane among the positive and negative, respectively. By geometry the distance from the two points to the hyper-plane is $\frac{g(y_1)}{||c||}$ and $\frac{g(y_2)}{||c||}$. The margin is defined as the region between these two points. In SVM, the hyper-plane is chosen so that the margin is maximized, i.e. maximize $\frac{1}{||c||}$, which is equivalent to minimizing $||c||$. This leads to the following optimization problem:

$$\arg\min_{(c,b)} \frac{1}{2} \cdot ||c||^2 \tag{2.3}$$

subject to,

$$w_i \cdot (c \cdot y_i + b) \geq 1 \tag{2.4}$$

for i = 1,2,...,n

In here, multiple optimization algorithms can be utilized in solving linear system c. In Matlab R2015, the command svmtrain() in cooperated three algorithms: Quadratic Programming, Sequential Minimal Optimization, and Least Square [14], [15]. After optimization, the linear system c is the linear SVM that is trained. It will produce positive/negative labels based on the input testing sets.

2.1.4 Hough Transform

The Hough Transformation is a feature extraction method [16], [17]. The purpose of this method is to find the location of lines in images. For this paper, MATLAB command hough() is used to carry out the Hough Transform. Before finding locations of lines in images, edge detection is often used as a pre-processor to Hough Transform. For the edge detection, a canny edge detection (edge() command in Matlab) is used to extract the edges of the image. The result of the canny edge detected image is a binary image. Position of edges of the original image is shown as one in the binary image, and other positions are 0. This binary image is used to calculate gradient direction. By using Sobel operator, the binary image is convolved with three by three Sobel kernel to calculate the gradient. For each pixel in the binary image, by using Sobel operator [18], the gradient magnitude can be calculated as:

$$\mathbf{G} = \sqrt{\mathbf{G_x} + \mathbf{G_y}} \tag{2.5}$$

and the gradient direction is:

$$\boldsymbol{\Theta} = arctan(\mathbf{G_x} + \mathbf{G_y}) \tag{2.6}$$

The gradient direction $\boldsymbol{\Theta}$, magnitude $\mathbf{G}$, along with its corresponding pixels location(x, y), construct a line. This line has a point on (x, y), has a slope of θ and has a length of $\mathbf{G}$. These lines are the input to the Hough Transform.

In hough Transform, the goal is to find a point in image:

$$\bar{x}, \bar{y} \tag{2.7}$$

and a straight line,

$$y_i = ax_i + b \tag{2.8}$$

such that there are many lines pass through this point $(\bar{x}, \bar{y})$ and for these lines, they have to satisfy the equation $y_i = ax_i + b$ for some parameters $\bar{a}, \bar{b}$ [19].

Equation $y_i = ax_i + b$ can be easily written as $b = -x_i a + y + i$. And now we can consider x_i and y_i as parameters and a,b as variables. Thus, a transformation from (x,y) space to (a,b) space is possible as shown in Fig. 2.3. With multiple lines that passes through the point $(\bar{x}, \bar{y})$, lines in (a,b) space will create a intersection. The place where the lines intersect in (a,b) space forms a cluster of crossing.

To find one line that could represent the lines in the cluster best, the (a,b) space of lines is divided into cells with size c by c. The number of times a line intersects a

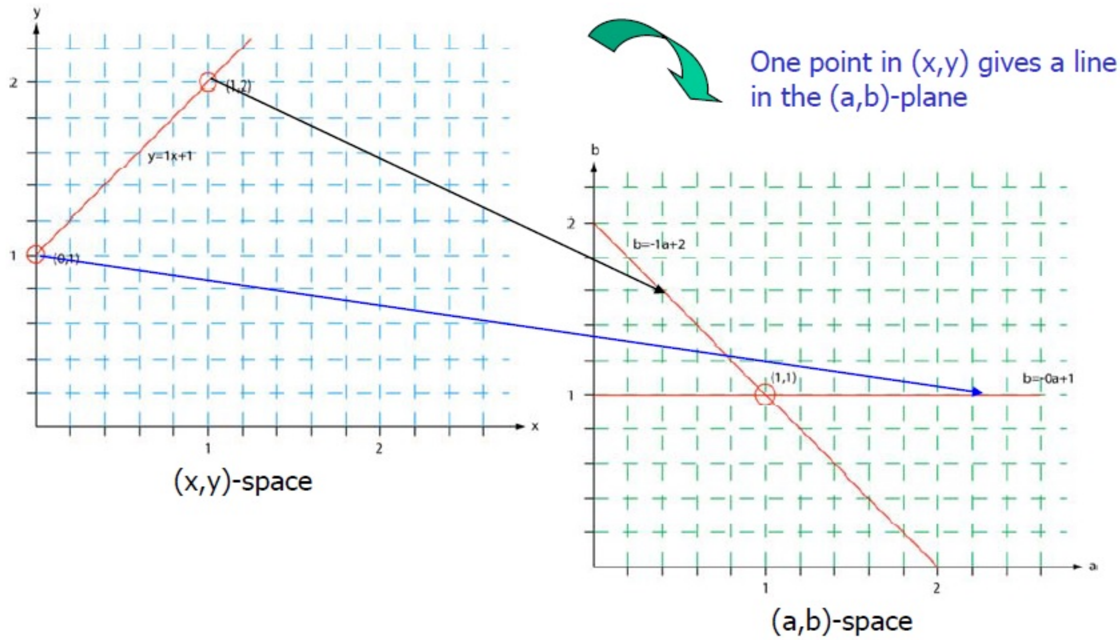


Fig. 2.3.: Example of Hough Transformation

given cell is calculated. The cell with most lines in (a,b) space, which mean the cell got more "vote" [20], is used to extract the parameter of the line that could represent the lines in the cluster. One line in the cluster that have the shortest distance to the center of the cluster is used to represent all other lines. Also, by finding all clusters in the ab space, multiple line's parameters are recorded as the result of the Hough Transform. Thus, the lines in the binary image are found and so as the corresponding original image.

Algorithm 2 Hough Transform Algorithm

1. Edge Detection on the input image and quantize to obtain a binary image.

2. Using Sobel Operator to obtain the gradient directionθ, magnitude$\mathbf{G}$, along with its corresponding pixels location(x, y).

3. Transfer gradient lines in (x,y) space to (a,b) space.

4. Quantize the parameter space (a b), that is divide it into cells Quantize the parameter space (a,b), that is, divide it into cells. This quantized space is often referred to as the accumulator cells.

5. Count the number of times a line intersects a given cell.

6. Cells receiving a maximum number of votes are assumed to correspond to lines in (x,y) space.

2.1.5 Temporal Profile

Construction of Temporal Profile

Temporal profiling is an algorithm that compresses video information to an image by selecting a region of interest in the video and overlaps the region to form an image file [21], [22].

Horizon detection is preformed each time before the generation of the temporal profile to avoid placing the region of interest on the hood of the car or the sky when dash camera is falsely installed. The input of the horizon detection algorithm and the temporal profile is the 5 minutes videos from the TASI 110 Car Database. For each 5 minutes video, the horizon of the video is calculated. Based on the horizon of the video, the region of interest will be placed 200 pixels below the horizon. This ensures the region of interest to be on the road.

The X axis of the image of the temporal profile is time and the other axis is the overlapped region from frames of the video file that is extracted. The video is sampled 60 lines per second by using the interlaced frame of the input video.

Fig. 2.4.: Example of Temporal file region

In Fig. 2.4, the red area is the region of interest. It is cropped from frames of the video, turn 90 degrees counter clockwise, and overlapped half the height of the region of the interest to obtain the road profile. For example, as shown in Fig. 2.5 the video frame is on the left part and the temporal profile result is in the left part. The red ROI area is copied from the frame of the video, turned 90 degrees and placed on the temporal profile as shown in red and blue. The second ROI from the second frame is placed on the first ROI on the temporal profile with half of it overlapped on the first RIO, as shown in blue and green. The blue area is the overlapped region, constructed by averaging two ROI region's RGB value. This overlap ensures a smooth temporal profile, which is easier for later process [23].

The height of the red region is defined as 50 pixels since the region should be sufficiently tall to sample high-frequency information in the road, but not too tall to filter out the information during overlapping.

By generating a temporal profile, the x-axis is the time axis from t_0 second to the end of the time. If the frame rate of a video with resolution m by n has a frame rate of l frames per second, then the converted temporal profile of 1 second video will be $m \times l \times p \times 2$ pixels in width and n pixels in height if the sampling rate is p frames per second using the interlacing frame of the video with overlapping [24].

Due to the fact that the dash camera is aiming at a relatively low position of the hood of the car, the generated profile is high in resolution in the road and low in resolution towards the diminishing point. Certain transformation can be utilized to generate a profile that is resembled the road that is viewed from a helicopter. However, since the major task is to classify certain pattern on the temporal profile, the spatial resolution difference can be neglected due to the major task is to classify.

The low-speed vehicle will most likely do large maneuver as well, which will create a dramatic change of the temporal profile. Also during day time the temporal profile is affected by more complex light sources. Due to these factors low speed (below 10 miles per hour) and daytime (including dawn and sunset) videos are excluded from the modeling of the low illuminance environment.

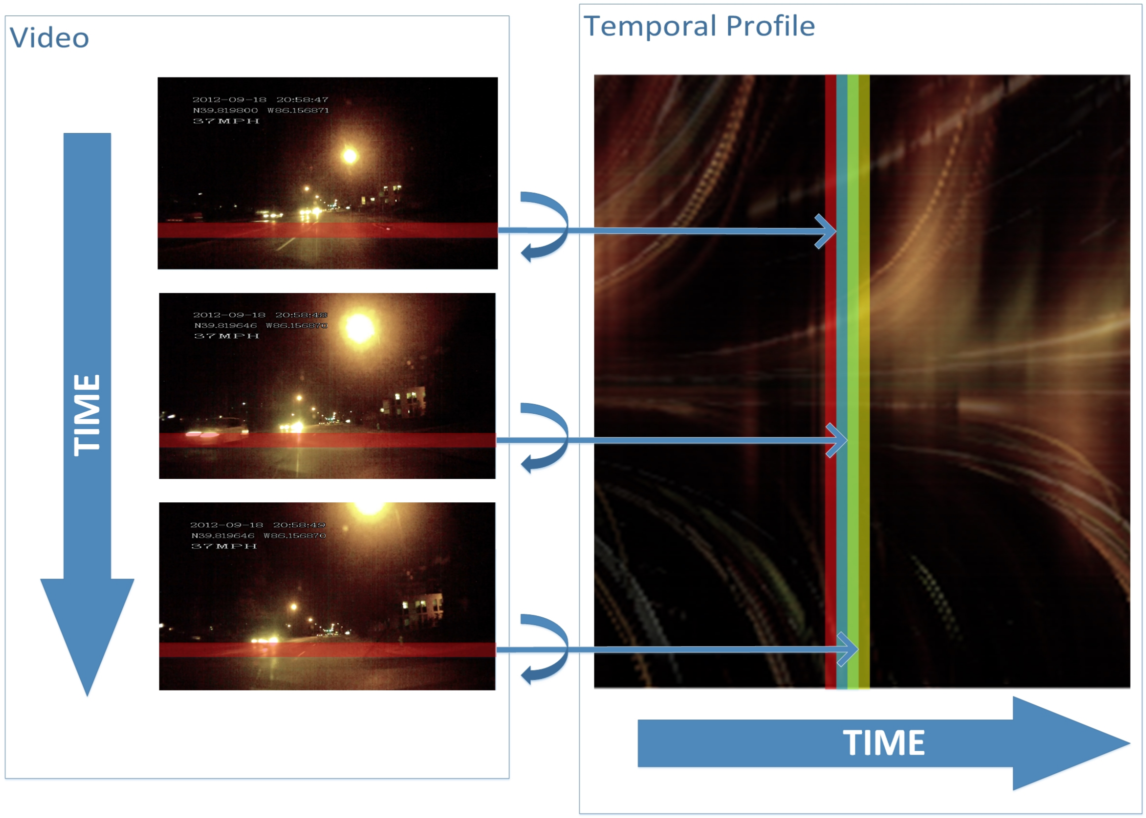


Fig. 2.5.: Construction of Temporal Profile

Temporal Profile in Low Illuminance Environment

The Temporal Profile is comparatively efficient when applied to the investigation of lighting model in low illuminance environments. Firstly, the dark environments suppress light infraction/diffraction during daytime. Thus, the environment is lighting up entirely by artificial light source, which makes patterns in the temporal profile especially unique for classification. Secondly, by focusing on road area of the video, one can extract the most out of a lighting environments feature using minimum input. Since recognizing lighting source directly in the video impose a heavy computational and recognition difficulties, using road temporal profile is the best approach [25].

In Fig. 2.6, an increase in the y-axis is right to the left side of the region described from the video frame in Fig. 2.4. An increase in the x-axis is an elapsing time in the

Fig. 2.6.: Example of Temporal Profile on Low Illuminance Environment

video. Since the camera is at the center of the right edge of the figure and only see the vertical line where the camera is located. The time axis of the profile is horizontal, and the vertical axis indicates the horizontal viewing angle through the camera frame.

2.2 Previous Work

This section reviews the previous work related to the set-up of the lighting environment during a PAEB testing, and TASI 110 Car Naturalistic Driving Data Base.

2.2.1 Lighting System Development for Pedestrian PAEB Testing

Previous work on the creation of the low-illuminance testing environment is majorly based on the municipal urban planning guideline [5]. This guideline provides general road lighting infrastructure requirements. Mostly used national standard of the United States roadway lighting design is ANSI/IESNA RP-8-00, which defines the standard for the uniformity of the light and the average illuminance level. However, road lighting conditions often do not match the requirement specified by the standard, especially in urban areas, due to more light sources are installed based on people's needs. Thus, the approach to calculating illuminance from the urban planning requirement may not be accurate. Although this study is not an extension of this approach, this paper will follow the idea that the light sources are a dynamic component of the environment and thus should be quantized. The definition of light sources has been extended from light poles only to including car head light and ambient light. This model will cover major light sources on the road and provide a more realistic analysis of the lighting on the road for vision-based PAEB testing.

2.2.2 TASI 110 Car Naturalistic Driving Data

From the year 2012 to 2013, TASI equipped 110 cars with systems capable of recording naturalistic driving data in the greater Indianapolis area [26]. The purpose was to study pedestrian behaviors in various conditions. A CMOS camera with GPS and G-sensor was installed on each vehicle to gather video of what the driver would see out of the front windshield. Each car collected video data for one year. The total size of the collected dash camera video is about 100 TB. The pedestrians on the video were extracted and categorized from this data.

Raw data from camera

The raw data from camera contains two types of files. The first type is the video file. The videos resolution is 1280 x 720 with a frame rate of 30 per second. Each video is 5 minutes long. The second type of file is .dat file, which records the UTC time, GPS coordinates, and speed information when GPS signal is available at the rate of once per second. Each .dat file records 5 minutes long of information. One 5 minutes video has a corresponding 5 minutes .dat file. The first line of data in.dat file is aligned to the first frame of the video. By using this corresponding format between videos and .dat files, each frame of the video can be linked to its GPS coordinates, UTC time and speed information. The format of the .dat log file is shown in Table 2.1.

Table 2.1.: Example of input log file

Index	**Message**				
1	[S]	33	100	867	
2	[S]	33	100	865	
3	[G]	2/28/2012 16:21	N39.811451	W86.159936	6
4	[S]	18	100	885	
5	[S]	18	100	867	
6	[S]	18	100	867	
7	[S]	18	100	885	
8	[S]	33	100	885	
9	[S]	18	100	867	
10	[S]	18	100	885	
11	[S]	18	118	885	
12	[S]	18	100	867	
13	[S]	18	100	867	
14	[G]	2/28/2012 16:21	N39.811478	W86.159925	7
15	[S]	18	100	885	
16	[S]	18	118	885	
17	[S]	18	118	885	

In Table 2.1, the first column defines the data type of the corresponding row. [S] Implies that the row is related to acceleration to X, Y, Z axis, which is updated every 1/10 of a second. [G] Implies the row contain UTC time, coordinates information and the speed information, which updated every second.

2.2.3 Labeling of the Video

The 5 minutes videos contains pedestrians, along with corresponding .dat file, are then further divided into smaller video clips and manually labeled according to recorded vehicle, pedestrian, and environment feature. These labels provide the movement, the speed of the pedestrian, detailed scene description, and the response of the driver to the pedestrian. Also, the GUI can label the environmental feature of the video such as dawn, sunrise, daytime or nighttime. The GUI interface used to label video is displayed in Fig. 2.7.

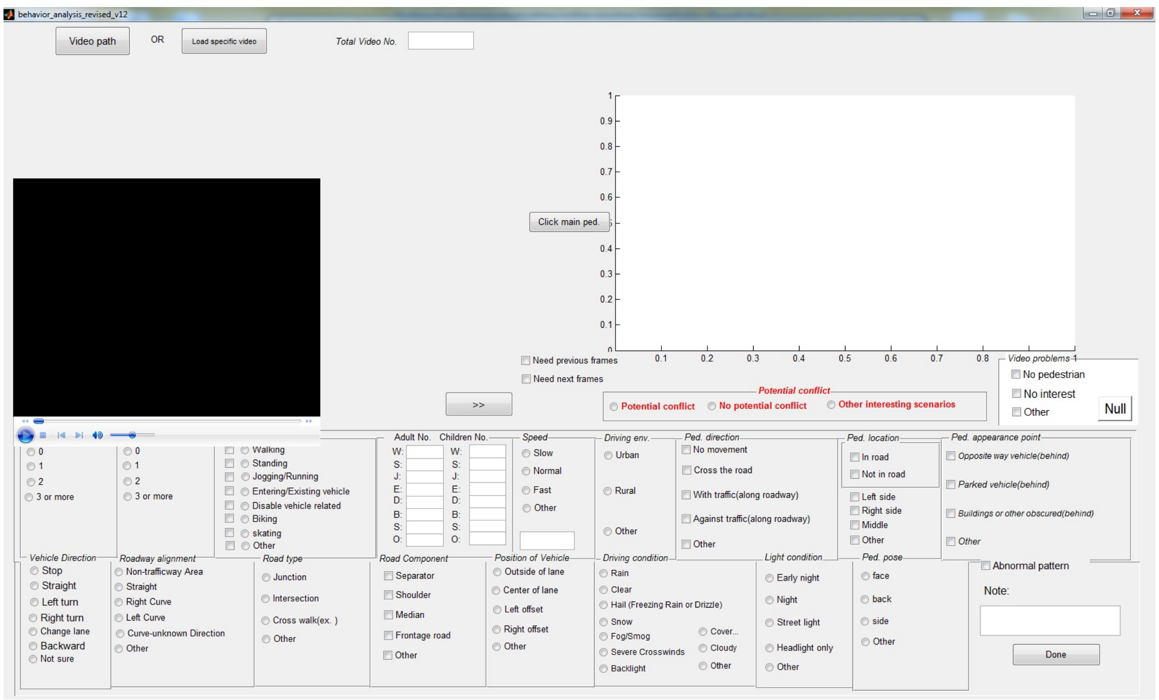


Fig. 2.7.: GUI Labeling Tool

One of the important information in all of the labels is if there is a potential collision. Potential collision case between a pedestrian and a moving vehicle is defined as a collision is inevitable if the pedestrian and the vehicle keep current speed and trajectory. To obtain potential collision cases, Kai Yang and Eliza Du [27] used an extreme learning algorithm to recognize pedestrian in a lot of videos. The recognized pedestrian in the video is then cropped from 5 minutes video into short time clips and manually labeled by using GUI in Fig. 2.7. The users of the GUI can efficiently label whether if certain video contain a potential case by scroll back and forth the video. This location information is then converted into an Excel sheet. The output of this GUI labeling for this study are all TASI 110 Car Naturalistic Driving Database and its corresponding .dat file, which is around 100 TB. In this database, all 5 minutes video is labeled with dawn, sun rise, day and night time so that night time videos can be retrieved.

2.2.4 Identify Location of Potential Collision Cases

By using the GUI, there is a total of more that 60000 potential collision cases in all 100 TB 5 minutes videos that were identified in the TASI 110 Naturalistic Driving Database. These potential collision cases were also labeled as dawn, sunrise, day and night time. In these 60000 cases, more than 600003729 potential collision cases labeled night time were identified. From the 5 min video clips. The GPS coordinates of each these 3729 collision cases were also obtained manually entered. The locations of some of all these 3729 potential collision cases within Indianapolis is plotted in Fig. 2.8.

It can be shown that in the plot, the distribution of the potential collision cases within Indianapolis is mostly at the city center area. This is due to a potential collision is more likely to happen in areas with a denser population. However, this assumption could be biased due to reason it is possible that the participated vehicles involved in TASI 110 Car Database is more active in the downtown area. This result, which is derived directly from the TASI 110 Car Database, is used as an input in later chapters.

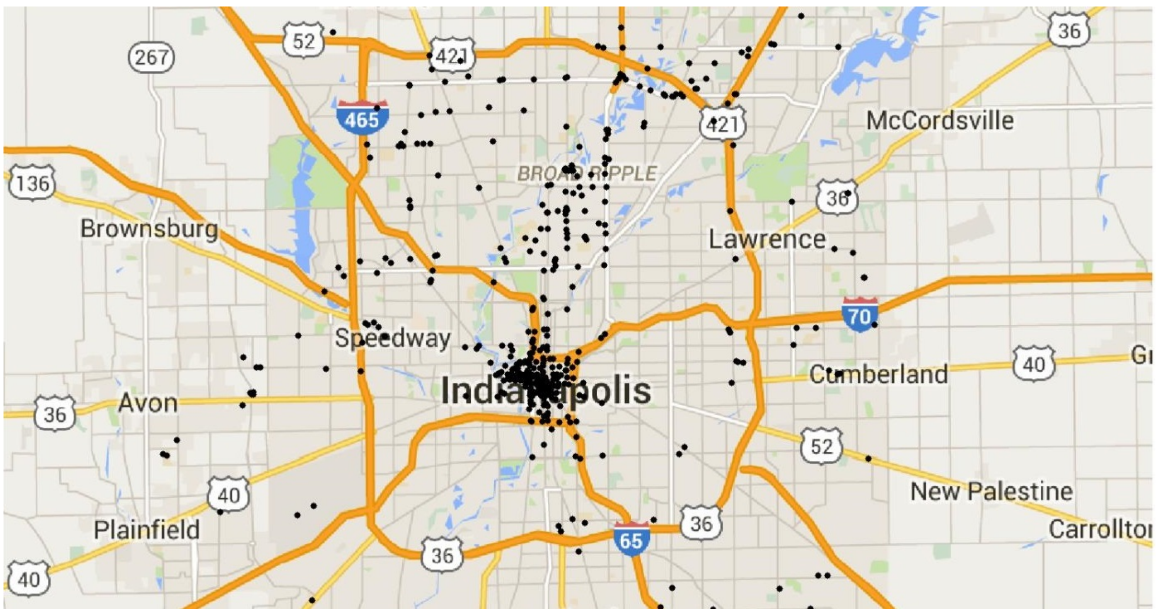


Fig. 2.8.: Potential Collision Cases Distribution of Downtown Indianapolis Area (Black Dot: Location of a potential collision Case)

3. PREDICTION OF LIGHT SOURCES BASED ON ROAD TEMPORAL PROFILE

The recognition and prediction of the light sources plays an important role in this study. In this chapter, the process of prediction of light sources by using temporal profile is introduced. The main idea of the prediction is to identify major components of the lighting and quantify their location and intensity. Different processing procedure is developed to recognize these components.

Three types of direct light sources that affect the PAEB performance are studied. They are light poles, car headlight and ambient light. Light poles and car headlight can be recognized on the temporal profile and will follow the same processing procedure. The ambient light are obtained from the averaging RGB pixel value of an region of interest on the horizon of the video.

To identify each light source, a pre-processing procedure, and a Linear SVM classifier were established. This process takes all 5 minutes video with corresponding .dat file in TASI 110 Car Database as input and produces excel files of the GPS coordinates of the three light sources. In this process, multiple techniques are used to distinguish three different patterns and suppress noises in an image. Before using linear SVM classifier to classify three light source samples, training sets have to be obtained to train linear SVM classifier. To obtain the training sets, 10 of 5 minutes videos were used to generate temporal profile with the correct horizon. Running Windows took samples of 3 light sources on different parts of the temporal profile. One can easily identify if the pattern on the temporal profile belongs to one of the three light sources or not. Thus, these samples are manually labeled as true or false based on the original video. Samples labeled as one of these three light sources will then be shape masked differently, thresholded, and extract HOG feature. These HOG features will be used to build up a training sets for 3 SVMs corresponding to 3 light sources. After obtained the SVMs for three light sources and trained, these linear SVM classifier will be used to predict samples by following the same procedure as generating the training set. These SVMs are used to predict temporal profiles of all 5 minutes video in the database.

Also, ambient light is introduced in this chapter as a value that is related to the luminance of background in the video. Ambient light will be calculated based on averaging RGB value of an area on the horizon of the video and stamped with GPS coordinates as well.

The input to this prediction process is all TASI 110 Car Naturalistic Driving Database videos and corresponding .dat files that are labeled as night time.

3.1 Modeling Lighting Components

To modeling lighting components, temporal profile generated from a low illuminance road is carefully examined to determine what is the major components of lighting that affect the PEAB performance. By reviewing the videos and the corresponding generated temporal profile, assumptions can be made for what kind of lighting components affect the low illuminance environment the most. In low illuminance environment, the lighting components can vary significantly in a different part of the city. The three most significant lighting components that affect the road lighting environment is declared as opposite/same side light poles, opposite side head lights, and ambient light. Subject's car headlight is neglected since it is a constant offset to the video. In here, opposite/same side light pole, opposite side head light have specific light sources, so these three components are called three light sources in later chapters. Since the temporal profile is generated from a specific region on the road, only these three light sources affecting road will be processed when using temporal file. Ambient light will be analyzed and quantized independently in later sections due to its randomness in location and intensity. In a typical suburban/urban area, the first three light sources are investigated. When these three light sources appear on the video, unique patterns can be generated on the corresponding temporal profile. In Fig. 3.1, light source 1 is the light pole from the opposite side of the road of the subject car. Light source 2 is the headlight of cars that on the opposite side of the street. Light source 3 is the light pole from the same lane side of the street as the subject car.

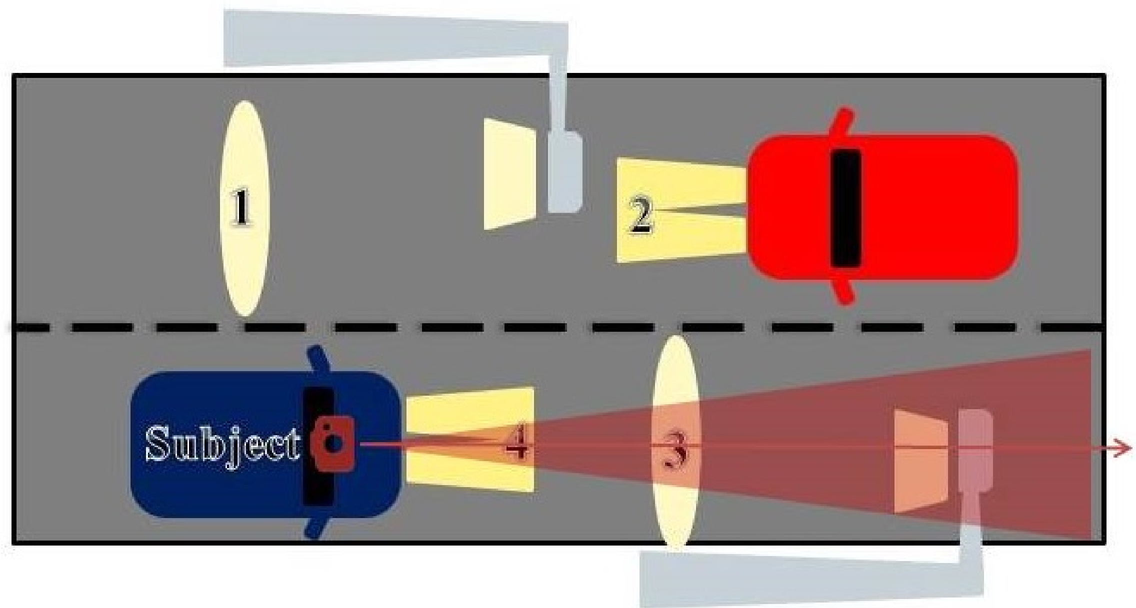
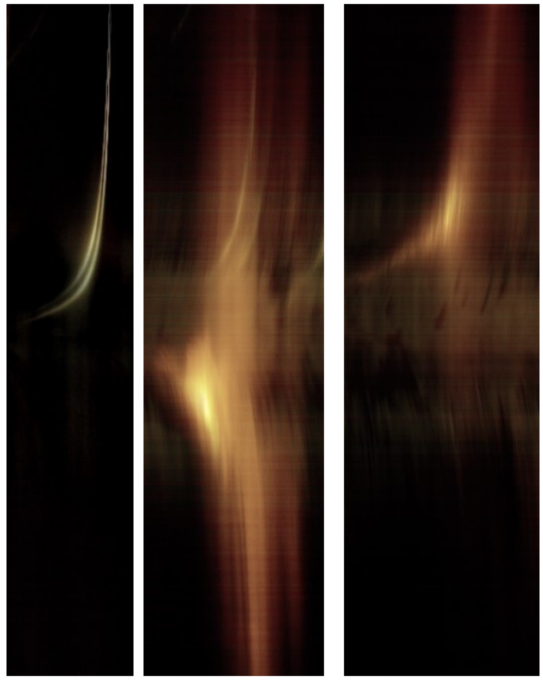


Fig. 3.1.: Demonstration of 3 types of light sources in low illuminance environment (1: opposite-side light pole, 2: opposite-side car headlight, 3: same-side light pole)

To clearly illustrate the three light sources, a demonstration is shown in Fig. 3.2 to present the relative location of the three light sources in a typical low illuminance environment on the road. These demonstrations of 3 light sources are generated by browsing video and selecting a period of video such that only one of the light source presents. This will ensure that the temporal profile showed only one light source at a time.

The unique pattern generated from all 3 light sources on temporal profile is due to the physical location of the camera and the light source. By comparing Fig. 3.2(b) and Fig. 3.2(c), one can see that the light pole pattern at opposite lane and same side



(a) (b) (c)

Fig. 3.2.: Modeling of 3 Types Of Light Sources in Low Illuminance Environment: (a) Opposite Lane car Headlight, (b) Same Side Lane Light Pole, (c) Opposite Side Lane Light Pole

lane is not vertically flipped. This is because the center axis of the camera, which shown as a line point out of the camera on the subject car in Fig. 3.1, is not on the center of the road. This mismatch will shift the pattern of the light sources up thus the same side lane light pole pattern is shift towards the middle of the temporal profile. However, this shift is small on the temporal profile and does not affect the performance of the process.

For opposite/same side light poles, the emitted light from the light pole should resemble an L-shaped 2D Gaussian distribution on the road. For opposite side headlight, the motion of emitted light from the opposite lane car is L-shaped in the video. Light sources to show an L shape on the temporal profile. This is due to the temporal profile samples more pixels on the closer views and fewer pixels on the further views.

So the pattern of the light pole and the headlight is distorted according to speed into an L-shape as shown in Fig. 3.2. Since the temporal profile overlaps the region on the video by turning the cropped region 90 degrees clockwise and place them in the y-axis (elapse of time) as shown in Fig. 2.5. The same side light pole shape appeared in both upper and lower half of the temporal profile as shown in Fig. 3.2(b). The opposite side light pole and car headlight only appear on the upper half of the temporal profile as shown in Fig. 3.2(c).

Since same side headlight, which is the subject's car's headlight, is consistent in the video, this light source is neglected. Also, there are more light sources that could significantly alter the temporal profile in this model such as tail light. However, these light sources are neglected in the model since theyThese light sources do not affecting the performance of the PEAB system. Thus, these light sources are neglected in the model as well.

3.2 Processing Procedure to prediction 3 Light Sources

To predict light sources on the video, a batch process is developed. This batch process load video and its corresponding .bat file, generate temporal profile from the video, predict light sources from the video, and record the predicted light sources location.

Before using linear SVM classifier to predict a patterns true or false, manually created training sets with true and false label have to be utilized to train the SVM first. To obtain a training set. A pre-processing procedure is established.to create HOG features corresponding to opposite/same lane light pole and opposite lane car headlight. These HOG features are training sets for three different linear SVM classifier corresponding to these light sources. Three SVMs are created based on these training sets.

After obtaining the SVM, the batch process starts. firstly, the horizon of all 5 minutes video is calculated so the road area on the video can be found. Secondly, the temporal profile is generated 100 pixels below the detected horizon for all input 5 minutes video from TASI Naturalistic Driving Database. On the generated temporal profile, Running Windows samples these light sources on different parts of the profile with different window sizes. Samples will then be shape masked, thresholded, and HOG feature extracted from different light sources. Three linear SVM classifier will predict the HOG feature for three different light sources. This prediction result along with its GPS coordinates are recorded.

3.2.1 Horizon Detection

Since the installation of the dash camera is unspecified in TASI 110 Car Driving Database, the lens of the camera tends to aim higher or lower than the horizon line of the road. This mis-installation resulted in video clips cover mostly the sky, or cover mostly the hood of the vehicle, which makes the determination of temporal profile ROI extremely hard to cover the road area of the video. To generate an accurate temporal profile, a correct horizon line, which can be derived from the diminishing point of the frames of the video, has to be proposed before generating temporal profile. A general solution for finding the diminishing point of the dash camera video is to determine the lines on the pavement. Since lines on the pavement are all aiming to the diminishing point on video frame, the intersection of all the lines on the pavements on the video frame will determine the diminishing point [28]. However, lines on the pavement is hard to extract due to low-illuminance. A method is proposed to recreate the lines on the pavement by averaging all the frames of the 5 minutes video. Averaged frame means produces a single video frame representing an average of a series of frames on a pixel by pixel basis. Each pixel in this resulting frame is the average RGB value of the pixel at the same position of the corresponding pixels from a series of frames.

Since the 5 minutes video is recorded in low illuminance environment, lines on roads at low illuminance environment are low in contrast thus unable to provide edges. Averaging the entire 5 minutes clip is based on the assumption that with the averaging of the overlapping of the higher and lower illuminance objects, the averaging of frames of the video will eventually create a new frame that have lines to determine diminishing point.

A horizon detection method is developed in here using Hough Transform with additional processes. The averaged frame is the input to this process to find lines pointing to the horizon. We assume that the diminishing point will only exist around the center area of the whole frame since the installation of the dash camera will not be too mis-aligned. Center area of the frame is defined as a square area of pixels which is 764 by 774 and extracted from the center of 1280 by 860 averaged frame. After the center area is cropped, Edge detection and Hough Transform is performed on the center area. The threshold of the Hough Transform is set to a minimum such that some noise will be extracted. An example averaged clip is shown in Fig. 3.3. In this figure, the green lines on the averaged frame of the video are Hough Transform Lines. In these Hough Transformation Lines, lines under 15 pixels are eliminated to suppress noises. It can be observed that in Fig. 3.3, Hough Transform of the center area of the averaged frame generate lines converge towards the diminishing point.

After obtaining the Hough Transform on the center part of the averaged frame, an optimization problem is constructed such that a point that has minimal distance to all Hough Transform lines is defined as the diminishing point. It is known that the equation for a point-slope form of the line is:

$$y - y_n = k_n \cdot (x - x_n) \tag{3.1}$$

Where y_n and x_n are one point on the line and the k_n is the slope of the line.

The green lines, which exceeds a predefined length, are used to generate the horizon. The green line is described in the point-slope form in the calculation. One point on the line with coordinate is x_n, y_n and the slope of the green line is k_n.

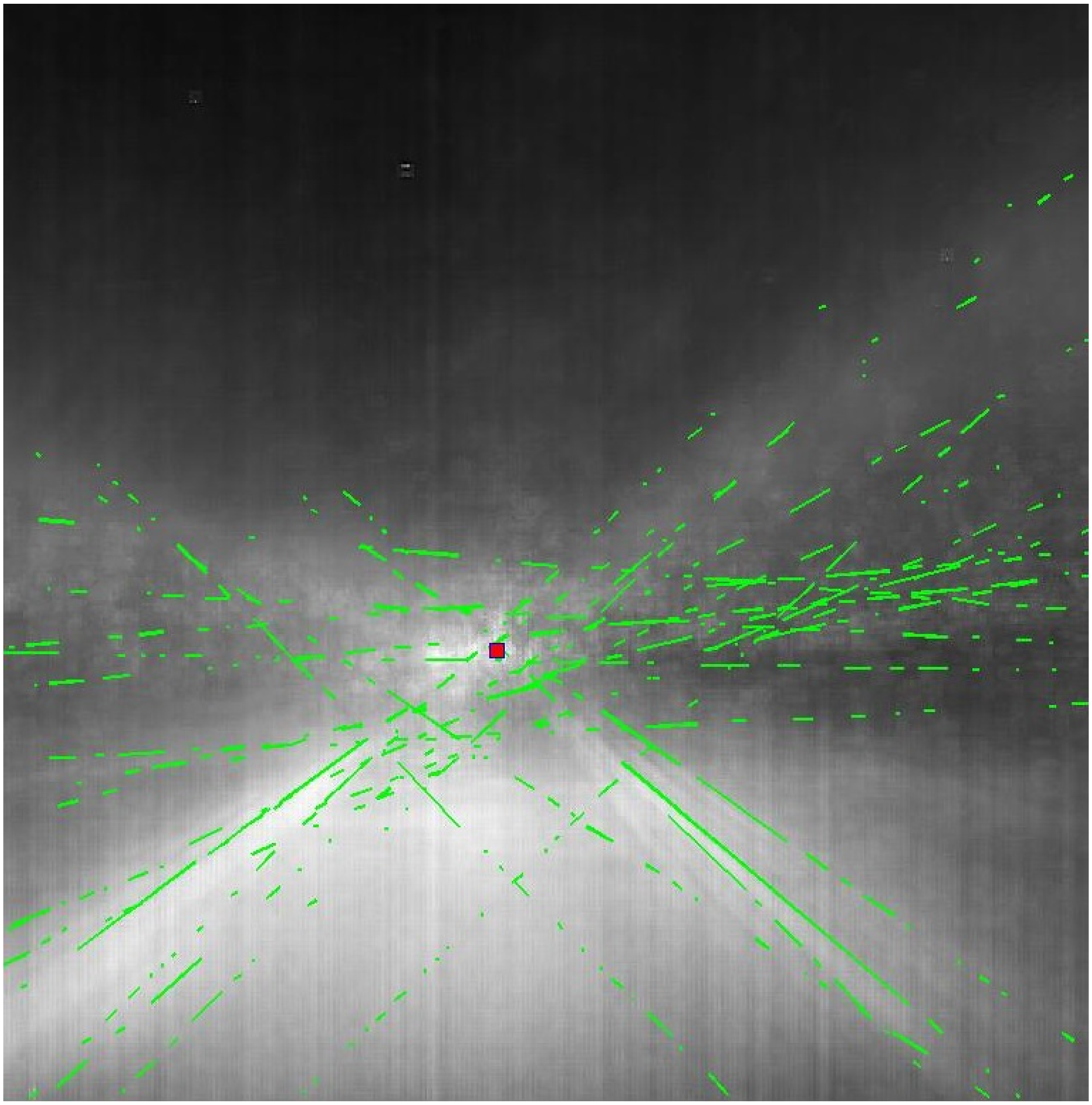


Fig. 3.3.: Example of Hough Transform Lines

The optimization problem formulated in here is finding a point that has the minimum distance to multiple lines in point slop form, For each line there is an associated weight depending on the length of the line. This optimization can be described as the equation below:

$$\arg\min_{(x,y)} \sum_i l_i \frac{|x + k_n y + (k_n x_n - y_n)|}{\sqrt{1 + k_n^2}} \tag{3.2}$$

Where x, y is the point that minimize the sum of weighted distance from itself to all lines defined by the point-slope equation. This optimization can be solved by using PSO gbest algorithm that has a low computational cost. For the PSO gbest algorithm, inertial constant ω is set to 20, cognitive constant c_1 and social constant c_2 is set to 5. Setting a large inertial constant(ω) to the algorithm will converge the result faster, but will be hard to converge to an accurate result. Also, a large cognitive(c_1) and social(c_2) constant will tend to be affected by the personal and global best more. These parameters are ideal since an accurate location for horizon detection is not required as long as the result is within certain tolerance. For the beginning of the algorithm, initial positions $x_i^{(k)}$ are randomly generated in the 764 by 774 center area and velocities $v_i^{(k)}$ are uniformly and randomly generated from 0 to 1. These uniform initial positions and velocities will ensure a random start point of the particles on the image, thus the result will converge faster. With these inputs and parameters, the PSO gbest algorithm generates the most likely diminishing point.

Since the object function in equation 3.2 is a 2D convex function, the PSO's result will surely converge to the global minimum. The result of the diminishing point for the example in Fig. 3.3 is represented as a red square in the middle of the frame. Then y-axis of the diminishing point is used as the horizon location of the 5 minutes video.

3.2.2 Temporal Profile

After the horizon is detected, the temporal profile ROI is set as 50 pixels in height and is 200 pixels below the horizon to ensure the region is covering the road surface in the video. The region at the start time of the video is then cropped and pasted to the temporal profile by turning the region 90 degrees counter clockwise. The second frame of the same region is then turned and placed to the right of the frame but overlapping half of the height of the region, which equals to 25 pixels. The frame rate of the input video with resolution 1280 by 860 is 30 frames per second. The generated temporal profile of 5 minutes video will be 30(frame rate) x 50(ROI height) / 2(overlap) x 5(Minutes) x 60 (Seconds/Minutes)= 22500 pixels in width and 1280 pixels in height if the sampling rate is 30 frames per second using the frame of the video with 50% overlapping. Overlapping is defined as average the RGB values for overlapped pixels to generate a new pixels value. Overlapping ensure a smoothed temporal profile.

3.2.3 Running Windows

The running window is half the height of the temporal profile to sample only upper part or lower part of the temporal profile, which corresponding to left or right part of the road. In Fig. 3.2(b), although the same side light pole create a temporal pattern that covers the entire height of the temporal file, we only need the lower half of the pattern since the lower half possess enough feature for prediction. The upper part of the image is neglected.

For upper and lower part of the profile, running windows are placed on the left most of the temporal profile and moving along with certain overlap to sample all pixels within the window on the profile. Two different window sizes are used. The light pole window is applied to both upper and lower part of the temporal profile. The car headlight window is applied to only the upper part of the temporal profile since opposite lane car headlight only exists in the opposite lane.

The light pole window, which is 240 in pixel width due to that most of the time that the light source pass through is 240 pixels / 60 pixels per second = 4 seconds.

The headlight window has a width of 120 pixels instead of 240 pixels. Since the subject car passes a steady light pole in 4 seconds, opposite lane car and subject car have a relative speed of twice the speed of the subject car. Considering double of the speeds when 2 cars at opposite direction, the headlight window will be half in the width of the light pole window, which is 120 pixels. These running windows sweep through the entire temporal profile to sample the temporal profile and generate images for shape mask.

3.2.4 Shape Mask

Fig. 3.4 shows the shape of different light sources in the temporal profile. It can be concluded that the contours of these three different light sources are distinctive. The headlights of a vehicle in opposite direction show a clear curve with short width on the temporal profile due to relatively high speed and high intensity in pixel values and low diffraction. The light pole has a low-intensity pixel value and a longer width on the temporal profile since it emits relatively smooth light distribution on the road. Subjects car headlight illustrates a Gaussian distribution since it is not time invariant and relatively steady to the camera..The training and detection of Subjects car headlight are neglected and treated as an offset in training and prediction of other light sources. Shape masks are used to eliminate noises and extract interested light sources on the temporal profile.

The shapes of the masks are determined by experiment on different temporal profiles to ensure maximally that headlight of opposite cars and light poles are captured in all vehicle speed range, but avoid overlap of 2 consecutive headlights. Consecutive headlights pattern means two headlight pattern that are very close. Due to the relative speed of the subject car to the opposite lane car, the opposite lane car's headlight can be very close in temporal profile. The shape mask should separate the headlight patterns that are close so that they can be predicted as two patterns instead of 1.

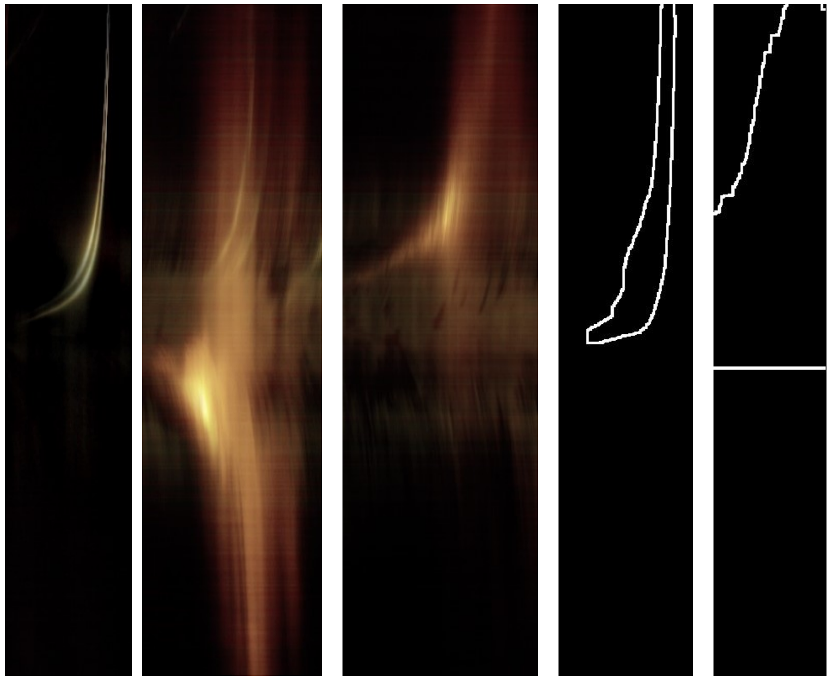
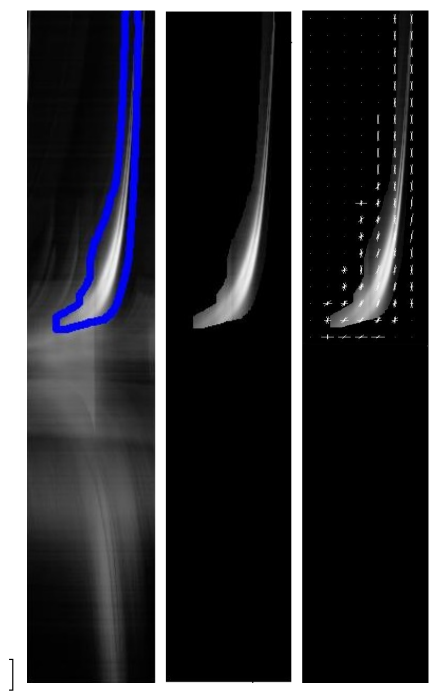

(a) (b) (c) (d) (e)

Fig. 3.4.: Shape mask(From left to right: (a)opposite-side car headlight, (b)same side light pole, (c)opposite side light pole, (e)head light mask

Fig. 3.4(d) and Fig. 3.4(e) shows the shape mask of different light sources. Shape mask Fig. 3.4(d) is the mask of opposite car head light shown in Fig. 3.4(a). Shape mask Fig. 3.4(e) is the mask for the same side and opposite side light pole as shown in Fig. 3.4(b) and vertically flipped Fig. 3.4(c).

3.2.5 HOG Feature Extraction

A window that is generated by running window and masked by shape mask described in the earlier section is feature extracted by HOG. The masked off image is not square shaped, and HOG need its block to be square to apply image filter. So, the masked off image is then filled with 0 as shown in Fig. 3.5(b). In Fig. 3.5(b), the masked off opposite lane car headlight is irregularly shaped, so the pixel value for the masked off region is filled with 0, which is the black area on the image surrounding the opposite lane car headlight. The HOG feature is extracted with 32 by 32 pixels as a block and each block uses eight bins for the histogram. In MATLAB 2015, function "extractHOGFeatures()" used the configuration above as default to provide HOG feature of the image.



(a) (b) (c)

Fig. 3.5.: HOG Feature Extraction Process (From left to right: (a)desired Opposite-side car headlight feature with shape mask, (b) masked window, (c)visualization of HOG on masked window

3.2.6 Thresholding (opposite/same side light pole only)

Since the light source patterns (as shown on Fig. 3.2) can interfere each other by appearing at the same time. Also, the intensity of opposite-side car headlight is much higher than that of light from light poles; thresholding is utilized to filter out opposite-side car headlight. During the pattern recognition, the upper part of the temporal profile has opposite side light poles. The lower part of the image only have same side light pole, which means no interfere will occur. So the thresholding will not be applied to the processing of the same side light pole.

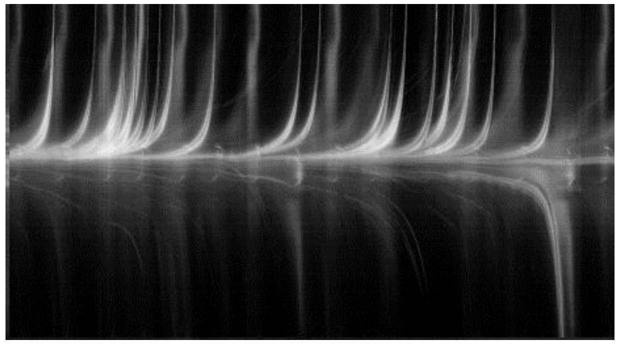
In here a threshold is produced by finding the middle point of the gap between two peaks of the histogram of intensity on the temporal file where headlight and light pole pattern coexist. One can assume that the higher intensity peak on the temporal profile is the opposite-side car headlight since it is brighter on temporal profile. And the lower intensity peak is the opposite side light pole one since it is darker. If it is impossible to find the peak, which means the intensity of headlights or light pole is low, a predefined threshold will be used.

For training set generation and prediction, when processing opposite lane car headlight, the pixel value is changed to 0 if it is lower than the threshold. When processing opposite lane light pole, If a pixel value is higher than the threshold it is changed to 0. This will ensure information from other light sources is deleted.

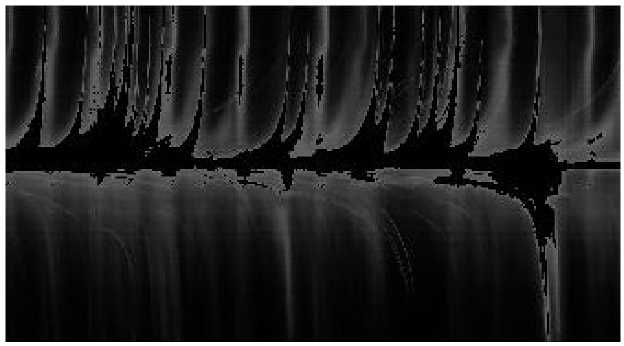
3.2.7 Training Sets Generation

The training set is used in here to train the SVM to generate a hyper-plane to maximize the margin between the positive samples and negative samples of the three light sources.

A total of 10 temporal profiles were generated from 10 clips of 5 minutes video in the database with night time label since training sets are hard to create manually. These ten temporal profiles are used to extract training sets. These ten temporal files are selected from the database to cover complex light sources such as high-intensity



(a) Before Thresholding.



(b) After Thresholding.

Fig. 3.6.: Example of Before/After Thresholding

neon lights or too many turning of the subject car. The selection is based on a maximal coverage of various situations that temporal profile recorded to improved classification capabilities.

For these ten temporal files, each is then cropped twice by two different running windows and two different shape masks. For same side light poles, the lower half part of the profile, which is corresponding to the same side of the lane to the subject car, is thresholded and cropped from left to right with running window length of 240 pixels and width of 640 pixels. The middle point of the running window moves 30 pixels to the right each time to cropping a new running window thus each cropped running window has 210-pixel overlap. Finally, light pole shape mask is used to further mask of irrelevant pixels. Since the light pole pattern is wider comparing to the headlights, a larger overlap is used in here to reduce computational cost. 30 pixels is the overlap set for the running window in here to save computational cost. There will not be consecutive light poles in the same side of the lane within 1 second on video, which is normally 20 meter at the vehicle speed of 40mph. For opposite headlights, the upper half part of the profile is cropped from left to right with running window length of 120 pixels. The middle point of the running window move 10 pixels to the right each time to crop a new running window thus each cropped running window has 10 pixel overlap. Finally, headlight shape mask is used to further mask of irrelevant pixels. Since the headlight has a small width in temporal profile, overlap of the sample is set to be small in order to prevent miss detection. For opposite side light poles, processing procedure is as same as same side light pole expect that the light pole mask is mirrored since light pole profile from opposite direction lane and subject cars lane is mirrored as well. These generated images is then manually inspected and labeled true or false based on the ground true of the video information. Any generated images with overlapped true label are re-centered to avoid miss-detection. This situation is most likely to occur for opposite light pole due to the fact that the same side and opposite side light pole is generally evenly distributed for the requirement of the municipal construction. But opposite side car headlight can occur more than 3 times within a second since multiple vehicles can pass the subject car at high speed.

The generated images are further inspected to minimize human error. In Fig.3.7, a simple GUI that is used to generate training set is displayed. The left part of the GUI is the temporal profile of the 5-minute clip, which the blue line will indicate the current sample location related to the while profile. In the right side of the GUI is the sample running window of the temporal profile. The upper part of the GUI is the display of the 5 minutes video frames. Due to the reason that it is hard to precept pattern directly in temporal profile, visual verification of the ground truth is presented during training to ensure a correct training set.

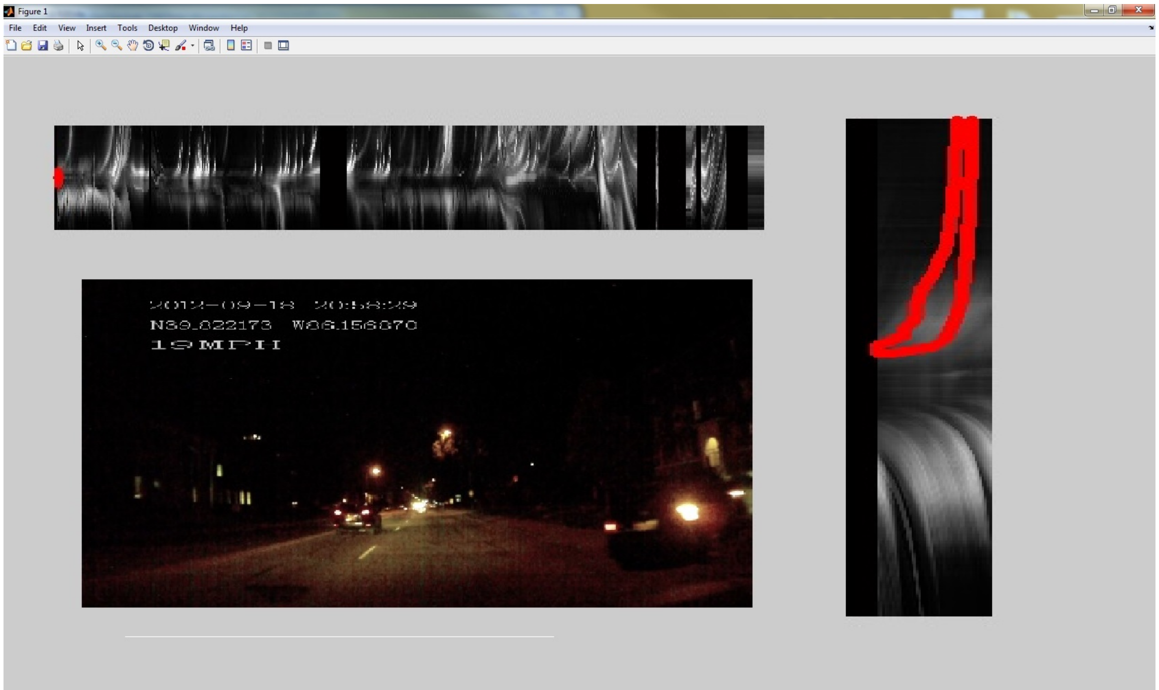


Fig. 3.7.: Training set GUI

3.2.8 Support Vector Machine (SVM)

The pattern recognition of light sources from the temporal profile generated from 5 minutes video uses linear SVM classifier. Linear SVM classifier is a supervised machine-learning algorithm that when provided input of training set of (x_1, y_1), (x_2, y_2) ....(x_n, y_n), the linear SVM classifier will find a hyperplane that separating different class at maximum distance. Such hyper-plane, used as a system, is later utilized to predict the labeling of the testing sets. For the simplicity of the recognition process, a linear kernel is used in SVM. All manually labeled HOG descriptor value in training set is the input to the training of the linear SVM classifier.

The training maximizes the margin between true and false labels. Since each light source pattern is classified independently and uses a linear classifier SVM, the prediction of the vector generated from HOG is either true or false. There are three SVM classifiers designated for opposite side light pole, same side light pole and opposite sidecar headlight independently. Each SVM is independently trained and used in the prediction. And three different types sample will be predicted by three different SVM.

3.3 Results of Classification

This section will present the performance and the result of the classifier formulated above. The performance of the classifier is presented as confusion matrices instead of the Receiver operating characteristic curve since the parameter that can be changed in the processing procedure is fixed and determined. A demonstration of the classification result will be presented on Google Map as a layer. These results are generated by the pre-processor and classifier, along with the corresponding .dat file. All 5 minutes raw data from the TASI 110 Car Naturalistic Driving Data Base is processed with results generated. This information will be display in this section.

3.3.1 Performance of Classifier

A total of 10 temporal files, other than the training set were generated from the all of the 5 minutes video labeled as night time in TASI 110 car Naturalistic Driving Data Base. These ten temporal profiles are chosen as testing sets. For the same reason in generating training sets, temporal profiles are hard to label manually thus ten temporal profiles are used.

These ten testing sets, manually labeled from 10 temporal profiles, are utilized in verifying the performance of the prediction process. A confusion matrix is used to illustrate the performance of the three classifiers in table 3.1, table 3.2 and table 3.3. In the table, the rate of correct prediction is defined as:

$$RateofCorrectPrediction = \frac{SamplesCorrectlyPredicted}{AllSamplesPredicted} \tag{3.3}$$

Table 3.1.: Confusion Matrix of Classification - Opposite Side Lane Car Headlight

	Actual Class	
	Opposite lane Car Headlight Positive 142 Samples	Opposite lane Car Headlight Negative 4868 Samples
Classified as Positive	138	33
Classified as Negative	8	4835
Rate of Correct Prediction	80.70%	99.83%

Table 3.2.: Confusion Matrix of prediction - Opposite Side Lane Light Pole

	Actual Class	
	Opposite lane light pole Positive 192 Samples	Opposite lane light pole Negative 3914 Samples
Classified as Negative	137	167
Classified as Positive	55	3767
Rate of Correct Prediction	71.35%	95.75%

Table 3.3.: Confusion Matrix of prediction - Same Side Lane Light pole

	Actual Class	
	Same lane light pole Positive 142 Samples	Same lane light pole Negative 4085 Samples
Classified as Positive	109	29
Classified as Negative	33	3896
Rate of Correct Prediction	76.98%	95.40%

It can be illustrated that the true case of opposite and same side light poles have the lowest Rate of Correct Prediction comparing to opposite lane car headlight. They interfere with each other in the temporal profile. Thus, it is hard to extract exact feature or to be predicted. The true case prediction of the opposite side headlight is higher than the other two light sources. This can also result from its relatively unique HOG feature during the extraction.

All false case rate of correct prediction is better comparing to the true case due to there are more false cases than the true cases in training sets. This will move the margin of the hyperplane in SVM that separate the true and false cases towards the true cases. When using a running window, there are more false cases generated since on the video, the three light sources still rarely appear at night. By using TASI 110 Car Naturalistic Database, all 5 minutes raw videos and corresponding .dat files were processed. The .dat files provided GPS coordinates to the light sources identified by the pre-processor and the SVM classifier. The GPS coordinates are ”stamped” with the classified three light sources and displayed in Google Map.

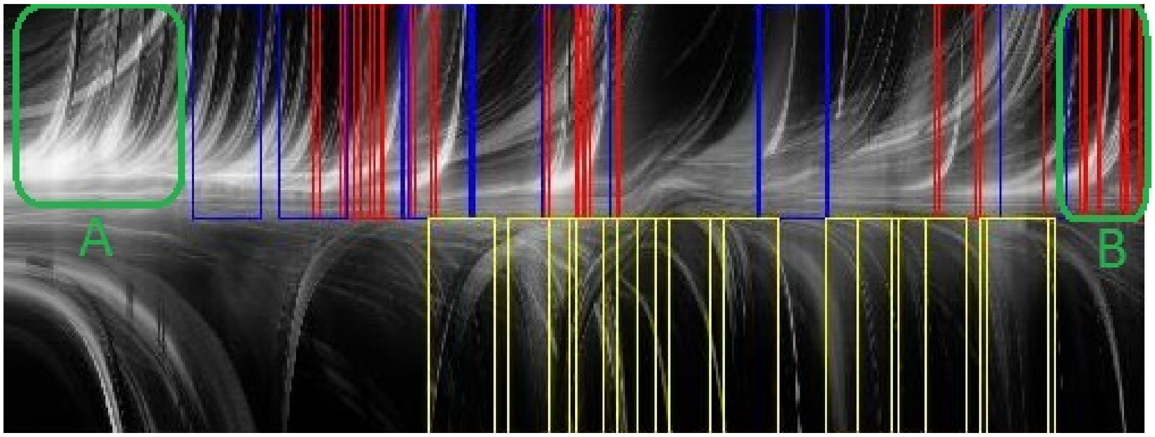


Fig. 3.8.: Example of Classification Results on Temporal Profile (Blue: opposite-side light pole, Red: opposite-side car light, Yellow: same-side light pole)

By observe the example classification result in Fig. 3.8, typical errors of prediction can be observed. It can be observed that for prediction result in Fig. 3.8 green circle A. The pattern of the opposite side car headlight is missed in prediction when the car tail light in front of the subject car obstruct the ROI of the temporal profile. In green circle B, the running windows area too close thus two opposite lane car headlight are labeled 3 times.

3.4 Display of Classification Result

After obtaining the prediction result of the light sources and the corresponding GPS coordinates in the .dat file, a google map is generated and displayed in Fig. 3.9. This result is then overlaid on the Google Map in Matlab. It provides a clear distribution of the 3 light sources as defined in the model. Since the prediction result is large, only the central area of the Indianapolis city is displayed. In Fig. 3.9, Red Dots indicate opposite light pole, blue dots indicate opposite car and yellow dots represent same side light poles.

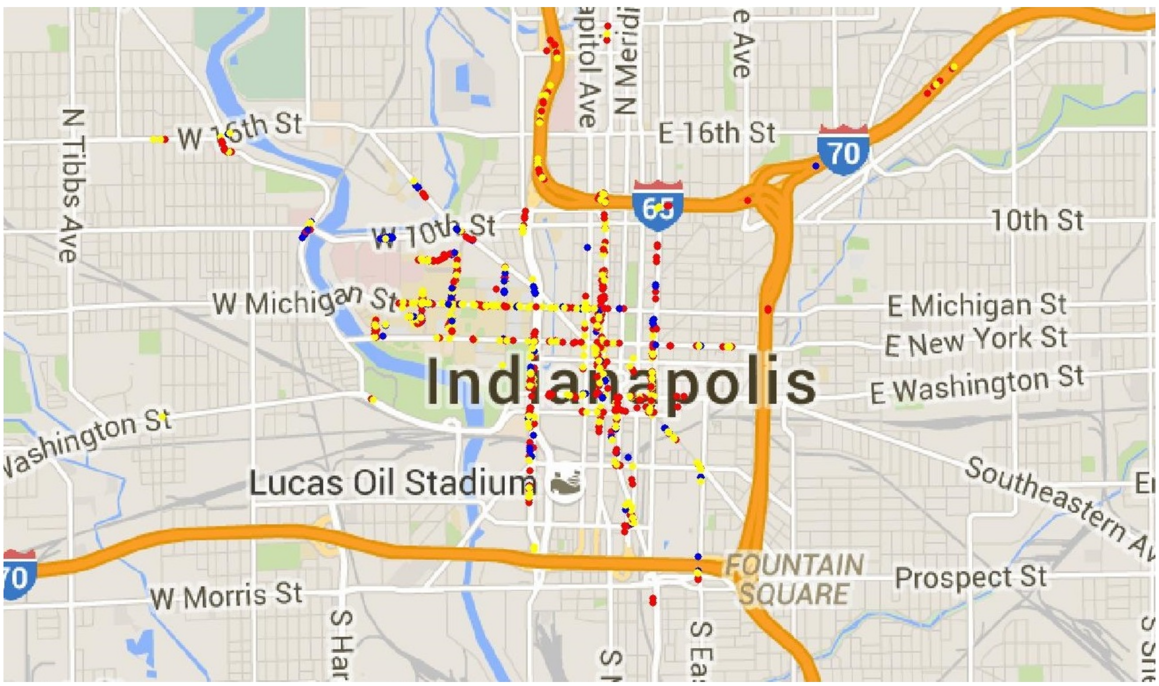


Fig. 3.9.: Display of prediction Result (Red Dot: Opposite light pole, Blue Dot: Opposite car, Yellow Dot: same side light pole)

By reviewing Fig. 3.9, one can study the distribution of the three light sources. Firstly, It can be perceived that the opposite light pole and same side light pole has a relatively uniform spacing between others and resemble the normal spacing of the light poles in an urban area. Secondly, the downtown area has most of the traffic at night time. Thirdly, there are areas that have no light sources. It is unknown if it is due to lack of information or no light source in the area. This problem will be taken into consideration later.

3.5 Ambient Lighting of Potential Collision Cases

Ambient light is a unique light source comparing to other three light sources studied above. This section proposed different methods for analyzing and quantizes the ambient light information from the 5 min video clips in TASI 110 Car Naturalistic Driving Database. The idea of the process is to average RGB value of a certain area that is on the horizon line of the video. By using the experience when viewing the video, a pedestrian that travels at horizon when the background is lit up will create a non-idea environment for the driver or the PAEB system to recognize pedestrians. Thus, the ambient light around the horizon line is a critical component to affect the performance of the PAEB system, and it is processed independently.

3.5.1 Processing Procedure

Ambient light is defined as the light that affects all area in the video comparing to a specific location. It is difficult to specifically define or recreate the ambient light due to the fact that the ambient light is highly random on the background of the frame. Intensity of ambient light can be affected by 2 types of light sources that is not in the 3 light source classifier model: far away light sources, such as moonlight, and short distance light sources, such as light from buildings, red light signal and neon signs. The first type of light sources are transmitted to the camera as parallel projections, which the location of the light source on the camera is invariant when the subject car travels. Since most of far away light sources have minimal impact on the camera, this type of light source can be neglected. The second type of light sources are transmitted at a short distance with perspective projections. They appear in random on the video and their locations varies when subject car travels. the short distance light source affect the background light. In order to focus on the perspective projection type of the light source, the ROI to be analyzed should be place on the horizon instead of the sky area.

The ambient light that affect the PAEB operation is in the horizon region (shown in red) in Fig. 3.10. A method for calculating the ambient light intensity in RGB value for this region is introduced. This averaged RGB value is used as the ambient light intensity for that area. The method is to generate averaged RGB value corresponding to the ambient light region in the video clip. In order to determine the horizon on the video for the region, the horizon detection algorithm described previously in this chapter is used.

The height of the ambient light region is determined by the area that the short distance light affect the contour of the pedestrian most. But the ambient light region should not cover any road surface in the video or sky area(parallel projection such as moonlight) since it is already modeled by 3 light sources in road temporal profile.

To best approximate ambient light, the average RGB of the ambient light region on the horizon of 5 minutes video is calculated every 5 seconds. In here the ambient light intensity is defined as the RGB value that averages RGB values of all the pixels in the ambient light region. This region is 1280 x 600 pixels in size with 300 pixels overlap that covers the whole vertical axis. In the end, the ambient light is stamped with GPS coordinates. The ambient light processing results of all video clips are the sequential average of the RGB value of the ambient light area of the input videos. These averaged RGB values are then stamped with corresponding GPS coordinate by using the .dat file in the database.

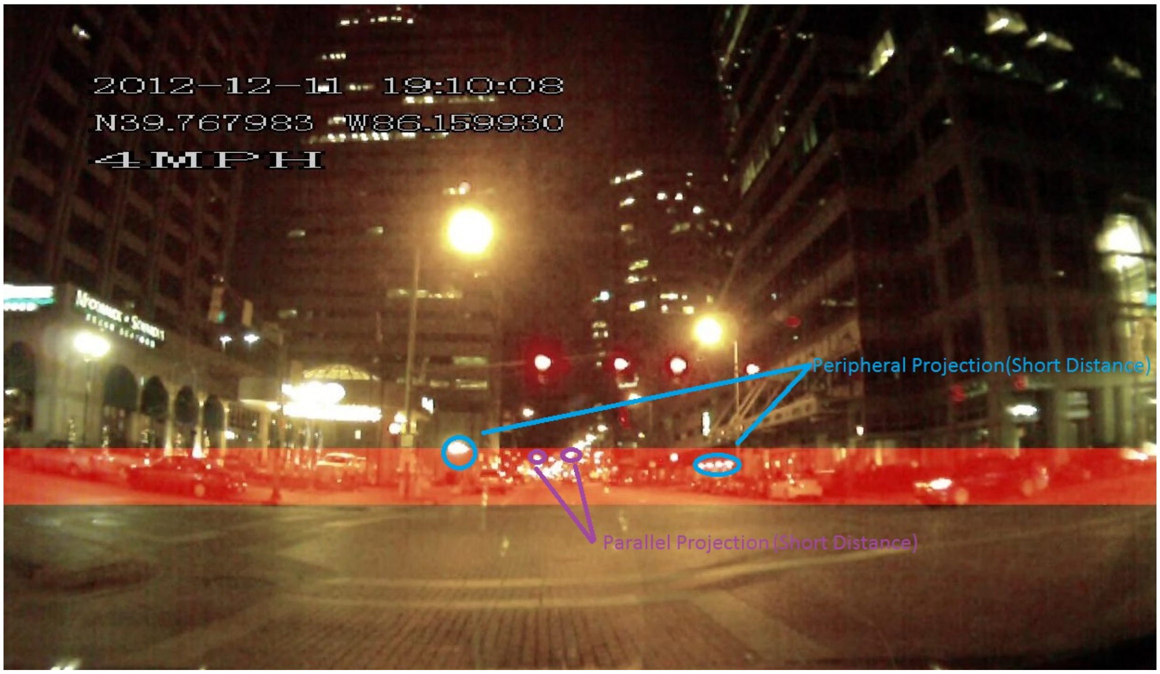


Fig. 3.10.: Ambient Light Region

In Fig. 2.4, we can see the temporal file ROI is defined as 200 pixels below the horizon, and the ambient light region is on the horizon. So the three light resources in earlier chapters will not affect the calculation of the ambient light. Since opposite/same lane headlight/light pole will only affect the road area of the video, ambient light did not calculate the light information twice. Instead, it only focuses on the area around the possible pedestrian position in the video. Since the ambient light defines the background of the pedestrian, it affects the AEB system significantly, and it is a valuable parameter during testing.

3.5.2 Processing Result

The ambient light intensity values of all potential pedestrian crash points at night are displayed on Google Map with the averaged RGB value as face color of the square block and GPS coordinates as the locations of the square block. The color in each square block represents the averaged RGB color of the ambient light region in that location.

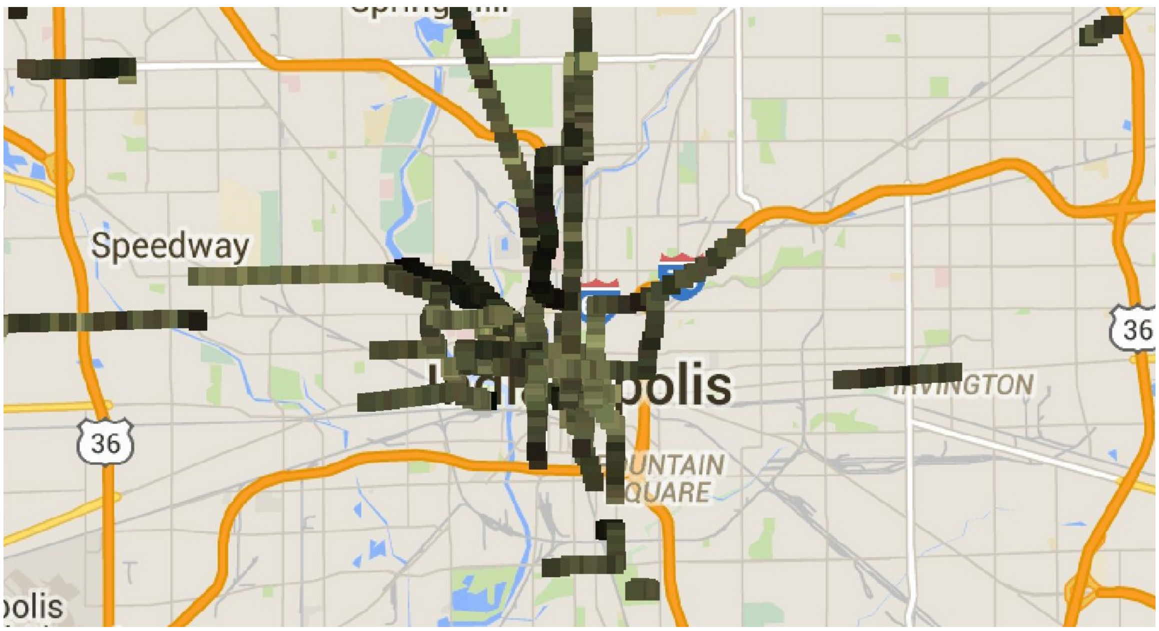


Fig. 3.11.: Ambient Lighting Intensity of downtown Indianapolis Area

It can be seen that the area in the center of the map has higher ambient light intensity comparing to other areas. Also, data points are denser in downtown area. In Fig. 2.8, it can also be seen that the potential collision cases have a denser distribution in downtown area. Due to these reasons, PAEB system may experience difficulties in pedestrian detection and recognition in downtown areas since not only the environment of the driving but also the pedestrian will be harder for PAEB to detect and react in time.

4. TESTING ENVIRONMENT GENERATION

Since the final goal for this study is to generate testing environment for PEAB testing, a method to mining data from current light components result and potential collision cases location result for generating a testing environment should be developed. Since the creation of a different testing environment for PAEB testing is both time consuming and costly, certain grouping technique has to be utilized to find the similarities of the potential collision cases. In here, grouping is defined as gathering a set of objects in a manner that objects in the same group are have shared qualities and characteristics. In this chapter, a grouping method is introduced to incorporate potential collision locations, light sources locations, and ambient light information together to generate lighting parameters for PEAB system testing site environment setup. In this process, the input is the ambient light value and 3 predicted light sources with GPS location (results from chapter 3) and the GPS location of 3729 potential collision cases at night time.

4.1 Objective of Grouping

To generate the lighting parameters for PEAB test facilities in dark lit condition, a generalized environment of a typical pedestrian collision case should be reviewed first. First the most important lighting components will be determined since it represents the most of the characteristic of the potential collision cases. This lighting component will be the primary parameter to group the result. Since the number of light poles along the road affects the performance of the PEAB System the most by changing the illuminance of on the road, light poles are used as the major components to grouping. Also, according to [5], there are two types of light pole arrangements. The first one is called dark lit local road such that all light poles on the same side of the road. The second one is called dark lit major road such that light poles on both sides of the road. The first type is usually used on local roads and the second type are usually used in major roads which require higher light level and more uniform lighting. Based on the study, one of the task for the grouping procedure is to categorized roads recorded in the TASI 110 Car Naturalistic Driving Database into dark major road and dark local road based on the location of the light pole. Generally speaking, in the urban area, both sides of the road will have light poles to provide adequate illuminance at least comply with the national standard. If both sides of the road have light poles, the road will be brighter. In small streets or the residential area, the light poles will be alternating, or only one side of the road will have light poles. These areas will be less lit up compare to areas with two light poles. In some side streets and rural area, there is no light pole at all, these areas are the darkest area. The categorization of these three areas is based on if there is light poles on both sides, only one side, or no light pole available. This categorization is simple and useful, and will be used in categorizing the road lighting condition.

Also, the potential collision locations need to be considered. In PEAB testing, a lighting setup that imitates the lighting of a potential collision case are more realistic for testing. Due to this reason, only lighting sources and ambient light information near the potential collision location should be considered. Lighting sources and ambient light information not around the potential collision cases will be neglected since they are not related to the testing.

Car headlight in opposite lane greatly affects the performance of the PEAB system since the diffraction of the light changes the contour of the pedestrian, causing a hard time for object recognition. At night time, car headlights are relatively infrequent, so it does not affect PEAB as much as light poles. The car headlight will be counted around the potential collision location after the light poles are grouped into different categories. After that, the car headlight will be averaged according to the categories of the light pole. The averaged car headlight count will present the averaged traffic that passes the subject car into that category. This information will help to determine the performance of the PEAB at direct headlight situation. Ambient light is crucial to describe the background lighting of the horizon area that pedestrian likely to appear. In grouping, the ambient light around a potential collision case will be averaged to represent the background light. It is averaged again according to road types.

In here, no light pole cases are defined as no light pole on either opposite side or same side of the road for a certain distance to the coordinates of the potential collision case. One light pole (dark local) case is defined as that there is a light pole on either opposite side or same side, but not on both side of the road for a certain distance to the coordinates of the potential collision case. Two light poles (Dark Major) case is defined as that there are light poles on both sides of the road for a certain distance to the coordinates of the potential collision case. The center of the Indianapolis downtown is chosen as the special area to perform downtown grouping. In here the downtown urban area is defined within the red rectangular area in Google Map in Fig. 4.1 along with ambient lighting intensity information. This region and other areas will be grouping as 2 separated cases. So there will be two grouping operated in 2 mutually exclusive areas(Urban and Non-Urban Area).

The grouping process has four steps: The first step is to find the ambient light and three light sources around a certain distance to all the potential collision cases. The second step is to average the ambient light and three light sources for each location. Third is to categorize potential collision cases into no light pole, dark local and dark major cases. The forth step is to average the ambient light and three light sources associated with each potential collision cases again with all other potential collision cases within the same category. The result of the grouping will be the twice averaged ambient light information, averaged headlight count associated with no light pole/one side light pole/two side light poles category.

In here, a radius of 30 meters is defined as the Area of interest around each potential collision cases, ambient lighting and light sources outside the radius will be deemed as no use to the case. Also, due to the reason that the downtown areas have high averaged RGB value in ambient light, it should be treated separately to avoid average out this location which has a higher intensity in ambient light.

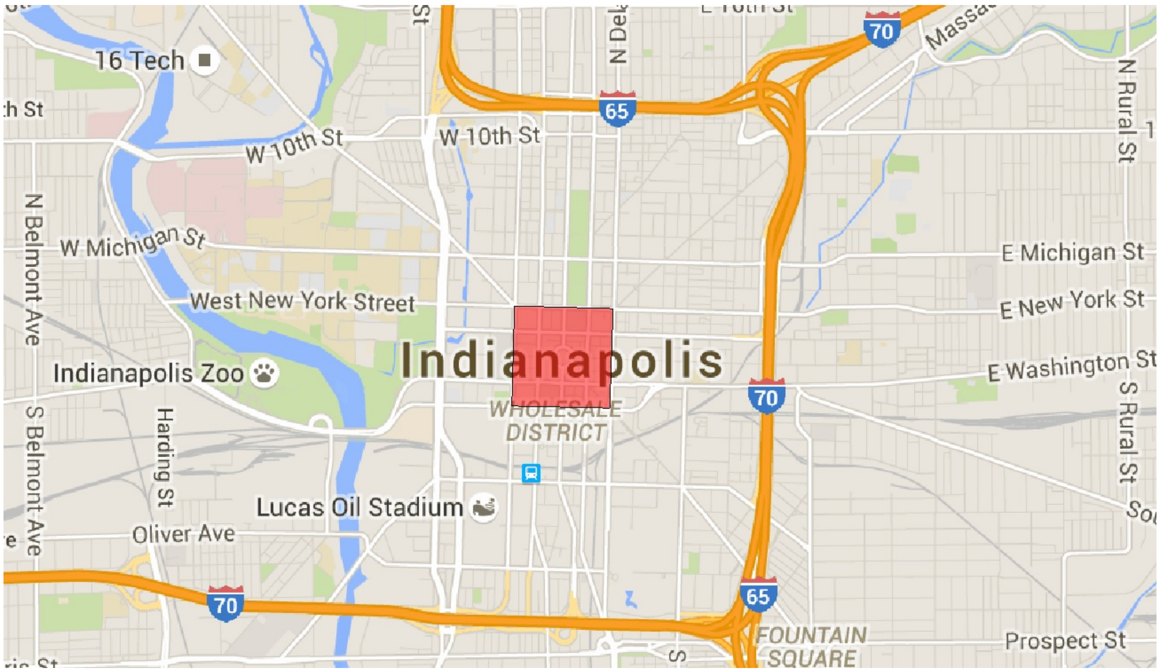


Fig. 4.1.: Ambient light in Downtown Region

4.2 Important Issues to be Considered in the Grouping Process

There are several issues that should be considered before grouping since the three light sources result is overlapped in some areas. Issues that will be taken into consideration of the grouping process are listed below.

The area around potential collision cases and the classification results of light sources location can be exclusive in a specific area on the map. It means a potential collision area may or may not have result for light sources location, but it is not able to predict if the area has no light sources or TASI 100 Car Database has not covered such area. For example, there are roads without light poles or car headlight, which can be interpreted as no light pole or car headlight on that road or the database has no video recorded on that road. Also, popular roads can be recorded multiple times on different videos, and GPS coordinates can also be inaccurate because the dash cameras inaccuracy. As a solution, for an potential collision area that contain multiple .dat file and video from multiple cars passed by, the length of the driving path from the .dat and video file is used as a weight to weighted average the car head light count in such potential collision case. The weight in here is defined as the traveled path length of the car inside the potential collision area. For example, if car A has 5 data points with GPS coordinates inside the potential collision area and car B has 15 data points, then the light sources generated from car A will count as 25% of the final light source result, and light source result from car B will count as 75%. For ambient light information, since the number of samples are generated as same as the path driven by the car with the dash camera, all the ambient light value inside the potential collision area will be averaged as same weight.

4.3 Process of Grouping

In here this procedure is used to realize the data mining procedure described:

Begin of Grouping.

1. Loading a potential collision location in the downtown urban area and define a circular area of interest with a radius of 30 meters.

2. Determine if the area were in the night time TASI 110 Car Naturalistic Driving Database. Potential collision locations not recorded in the database are categorized as no information and thus not count into grouping.

3. For all opposite car headlight and same/opposite lane light pole observed by different videos inside the potential collision area, calculate the weighted averaged opposite car headlight count.

4. For all ambient light intensity value observed by different car dash cams inside the potential collision radius, calculate averaged ambient light.

5. Determine averaged opposite car headlight count for no light pole/one light pole/two light poles by averaging all head light count, and ambient light falls into each category.

6. Iterate the process for all potential collision location in downtown area.

7. Grouping again in non-downtown area.

End of Grouping.

To illustrate the potential collision area, Fig. 4.1 is used to show that the radius around the potential collision cases and the light information within. Ambient light is not shown in this figure.

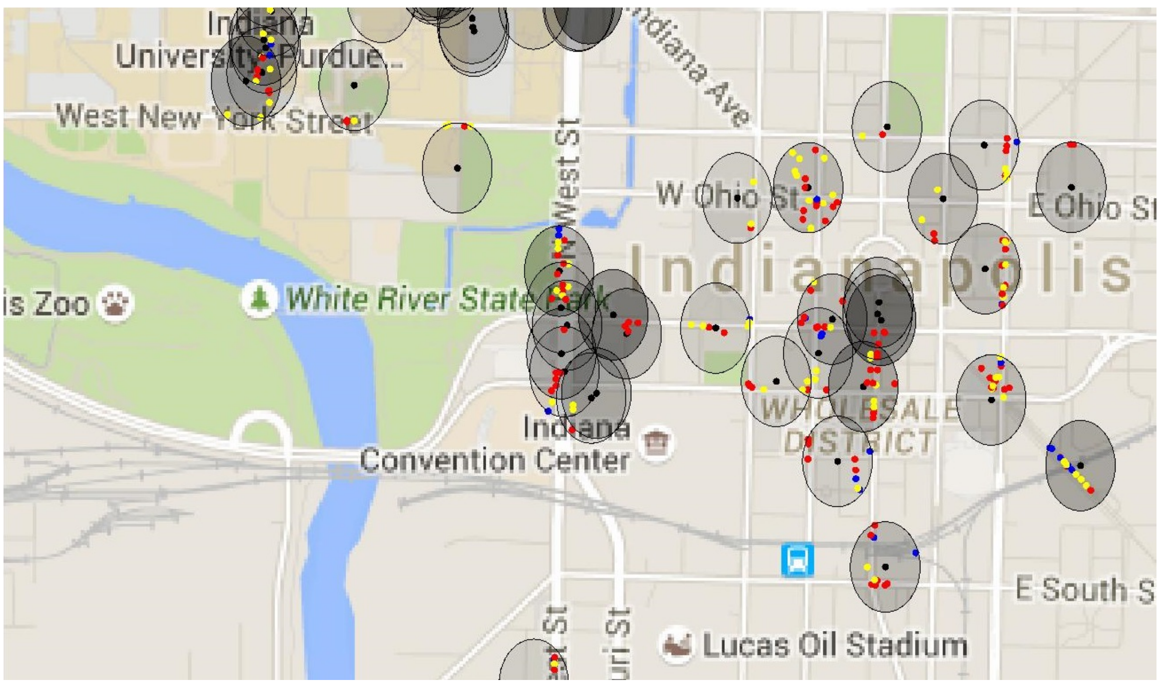


Fig. 4.2.: An Illustration of Clustered Data on Google Maps (Black Circle and Dot: Potential Collision Environment, Red Dot: Opposite Side Lane light pole, Blue Dot: Opposite side Lane car Headlight, Yellow Dot: Same Side Lane Light Pole)

4.4 Grouping Process Result

With the grouping procedure, the two regions are averaged based on the configuration of the light pole.The clustering result can be presented in the table 4.1 and table 4.2. In here HSV is used instead of RGB to emphasize the illuminance of the ambient lighting intensity. HSV represent the Hue, Saturation and Value of a color. HSV Value is the last number of HSV result, which represent the value of the color. Since the Hue and Saturation of color are not relevant in this process, only the Value in HSV is used for illuminance recreation.

Table 4.1.: Urban Test Scenario

Light Pole Configuration	Case No. (Percentage)	Opposite Lane Car Headlight	HSV value of Ambient Light
Dark Lit Major	50 (86.2%)	0.3850	$[0.0794, 0.1118, 87.4400]$
Dark Lit Local	8 (13.8%)	No vehicle	$[0.0356, 0.0807, 96.4400]$
No Light Pole	0 (0%)	N/A	N/A

In Table 4.1, one can find that the opposite lane has averaged 0.3850 cars at 30 meters radius around the potential collision location in downtown. However, there is no vehicle at opposite lane when potential collision cases only have one side of the light pole, possibly due to traffic is minimal that the video do not catch any opposite lane car. Also, there are no potential collision cases that have no light pole within the radius. Also, the Dark-Lit Local case has a higher HSV Value comparing to Dark-Lit Major case in Urban Scenario, possibly due to that the Dark-Lit Local in Urban area is mostly back allies small corners.

Table 4.2.: Non-Urban Test Scenario

Light Pole Configuration	Case No. (Percentage)	Opposite Lane Car Headlight	HSV value of Ambient Light
Dark Lit Major	376 (69.6%)	0.4689	$[0.1667, 0.1129, 70.8900]$
Dark Lit Local	88 (16.2%)	0.6064	$[0.0982, 0.2226, 62.7400]$
No Light Pole	76 (14.0%)	0.3092	$[0.1422, 0.3119, 44.2800]$

In Table 4.2, one can find that the Dark Lit Major Road (light poles on both sides of the road) has more traffic comparing to Dark Lit local road (light poles on one side of the road) and No Light Pole, possibly due to most of the area in the TASI 110 Naturalistic Driving Database belongs to the dark local category. Also, the value of the HSV space decreases when light pole number decreases.

It can be seen that ambient light intensity has significantly increased when more light poles appear. This can be explained by the social correlation of the light pole count and the ambient light intensity in an area. Since if more light pole presents, the area could be more populated, which means there will be more windows or neon signs on the ambient light region of the video. Thus, the ambient light intensity will be higher.

4.5 Generation of Lighting Environment Specifications

Since the purpose of this study is to generate a testing environment for PEAB testing, a final step is to transform grouped data around potential collision cases into genetic lighting parameters for a testing site. In here there are three types of lighting environment generated, which are Dark-Lit Major, Dark-Lit Local, and Dark-Unlit (No Light Pole). These three types of lighting categories are different in terms of location and count of light poles and ambient light. The spacing and the output luminance of the light poles can be determined based on the research done in [5]. However, for ambient light, it is hard to define directly accurate lumen parameters, such as location and watt of light sources on a testing site. Firstly there is no direct way to recreate location and luminance information from the ambient light value. Ambient light is an average value generated from video background data. The actual physical luminance recorded on video cannot be directly translated to luminance without aperture information at that location. Secondly, the luminance is also affected by the efficiency of light bulbs and defusing property of the lighting apparatus, so it is not just the number of lights and the bulb wattage. Due to these reasons, to generate generic light parameters for testing site lighting description, a lighting set up on the intermediate testing site need to be created to match the grouped ambient light result obtained. Then the lighting requirement can be measured in device independent scientific parameter. This enables the test results to be used in test environment set up anywhere. This intermediate testing site can link the grouped result and a genetic parameter without direct calculation. By matching the ambient light value with the grouped value, one can simply add additional background lights on the testing track that facing the test vehicle. These background lights should have adjustable power outputs. An additional measurement is then needed with lumen meter at a set distance facing the background lights on this intermediate testing site to create genetic lighting parameter. By measuring this intermediate testing site, one can obtain the lumen value, and thus create a genetic parameter for ambient light.

Also, it should be noticed that when the testing vehicle drives towards the background lights, the lumen value perceived will change due to that the background light sources is getting closer to the subject car. The intensity of light observed from a constant light source decrease as the square of the distance from the light source. This is the inverse square law of light intensity. This can be expressed as:

$$\frac{I_1}{I_2} = \frac{(D_2)^2}{(D_1)^2} \tag{4.1}$$

Where I_1 and I_2 is the illuminance seen from 2 distances d1 and d2 away from the light source. This phenomenon should be considered in lighting set up in a test environment. When a car drives with dash camera on the road, ambient light intensity changes with its distance to the car. Fig. 4.3 and Fig. **??** shows two histograms of the percentage of change of ambient light intensity. Fig. 4.3 shows urban area and Fig. 4.4 shows non-urban area. This change of ambient intensity is defined as the difference of the RGB value of the first frames ROI and last frames ROI. The ambient light use 6-second segments from the 5 minutes video in the TASI 110 Car naturalistic Database.

The first frame and last frames ROI is defined as the Ambient light ROI on the first frame and the last frame of the 6 seconds segment from the 3927 night 5-minutes videos. The x-axis is the percentage of change of the ambient light intensity and y-axis are counts of the percentage of change falls into the bin.

It can be seen here that the median value of the percentage of change for the urban area is at 35% and 20% for the non-urban area. For testing purpose, the percentage of change of ambient light intensity should not exceed this value. To realize a small change of ambient light intensity during testing, a moving platform is needed for moving the background light sources.

4.5.1 Approaches to find Background Light Illuminance

In real testing for PAEB system, light poles will be placed along the lane with configurations Dark lit Major Road, Dark lit Local Road and no light pole. The spacing of the light poles can follow the research done in [5]. For recreation of ambient light, light sources act as background lights can be placed on one end of the testing lane.

Fig. 4.5 describes a possible way to generate the ambient lighting specification in luminance for the dark lit major road and dark lit local road scenarios. Since the maximum speed, the testing vehicle is approximately at 40mph (18m/s). If a minimal

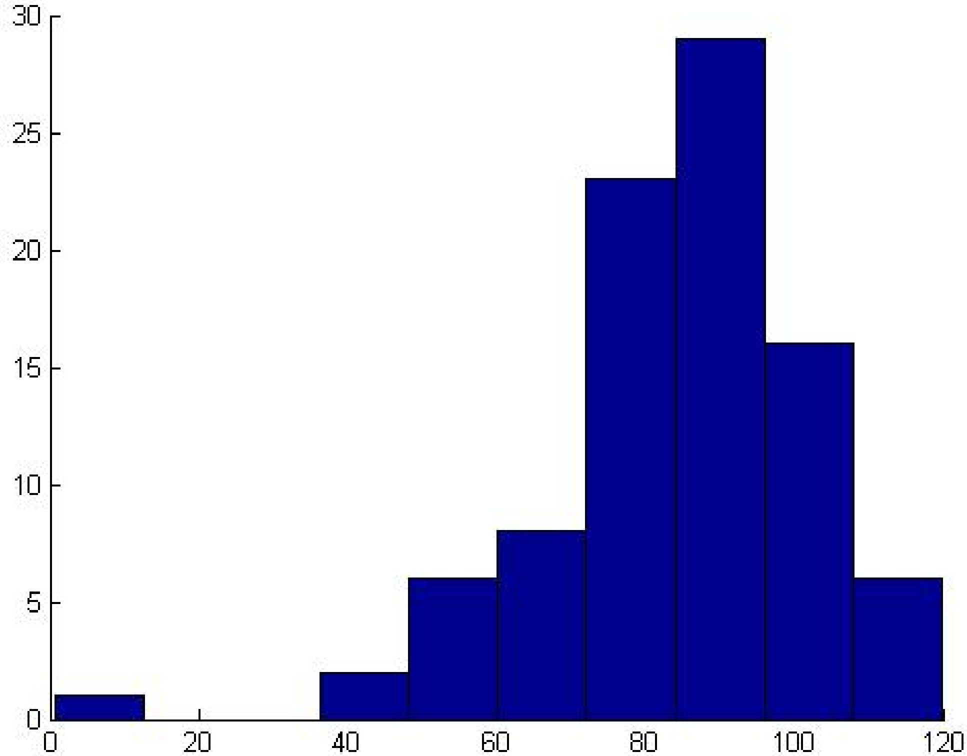


Fig. 4.3.: Histogram of Change of Ambient Light Intensity in Urban Area

of 3 seconds is needed for PEAB system to react before crashing, the minimal distance needed from the background lights to the testing vehicle is 18m/s x 3 = 54m. The background lights should be kept 54 meters away from the testing vehicle during testing.

The stronger the background light, the more likely the PAEB system will be failed, which resemble the potential collision cases in the downtown area. In order to generate the ambient light specified in the result of grouping in dark lit major and dark lit local road, we can set three background lights as shown as 3,4 and 5 that are aiming to the test vehicle on the background as shown in Fig. 4.5.

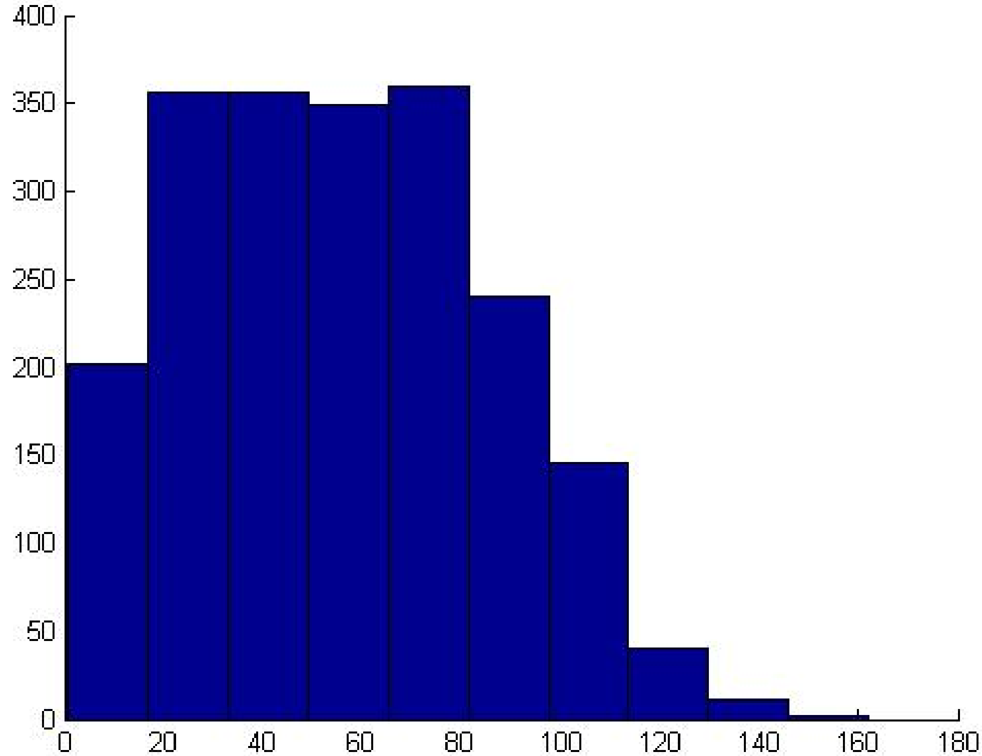


Fig. 4.4.: Histogram of Change of Ambient Light Intensity in Non-Urban Area

The luminance used as ambient lights at for Dark Lit Major/Local or No light pole at Urban/Non-Urban Environment can be determined in the following steps:

A. Select light poles setting for Dark Lit Major/Local or No light pole at Urban/Non-Urban Environment.

B. Setting up Intermediate Testing

B(1). One to N background lights is set up on the horizon of the test lane along with light poles with Dark Lit Major/Local or No light pole setting. These background lights can be evenly spaced crossing the testing lane.

B(2). Next, initial background lights are turned on, and the light intensity is measured by the dash camera. Measuring the intensity of these background lights means select a region of interest on the horizon of the frame of the video that has a

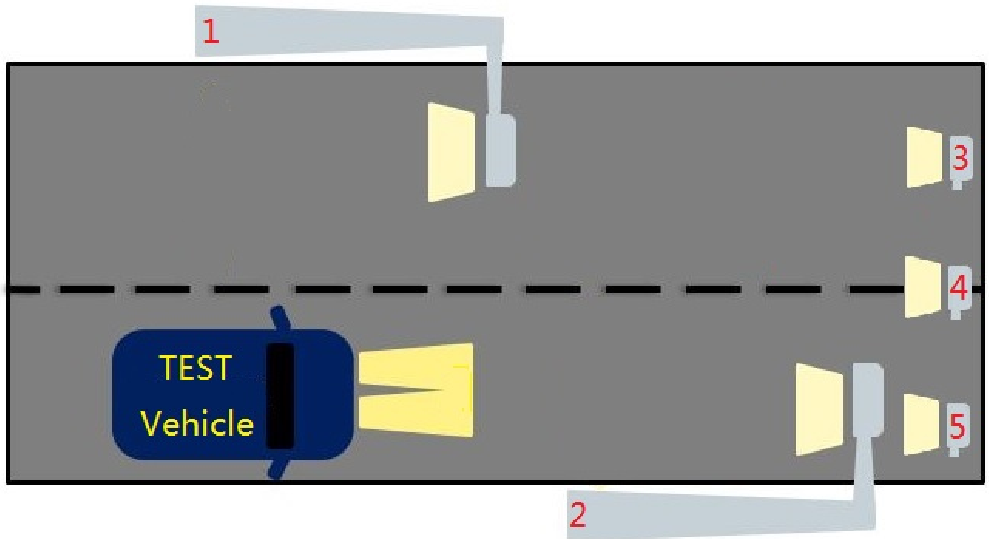


Fig. 4.5.: An Illustration of utilizing background lights in testing

height of 50 pixels, width of 1280 pixels and its middle point is on the horizon. This region of interest is the same as ambient light region described in Fig. 3.10. This area is approximately 15 meters across the road at 30 meters away from the front of the testing vehicle. The ambient light value for one to N lights are measured from the video.

To match the HSV value in table 4.1 and 4.2, the testing vehicle with the dash camera will be at 54 meters away from the background lights along the testing track. The number of the background lights that are turned on is increased or decreased. The testing vehicle in here should be equipped with a normal headlight. Since most of the vehicles in TASI 110 Car Naturalistic Driving Database are using normal headlight bulbs, the testing vehicle should match the headlight with cars on the database. This will ensure a matched headlight illuminance when matching HSV Value.

The dash camera will record a period of video facing the background light. This short period of video is used to generate an HSV value. The goal is to determine light settings that match intensity in table 4.1 and 4.2. The ambient light HSV value for the setting are measured from the video. Also, while video recording using a dash camera, a luminance meter is set at the same location as the dash camera facing directly to the background lights. The luminance meter reading is recorded.

C. Exhaust all Dark Lit Major/Local or No light pole with Urban/Non-urban Environment Scenarios.

To roughly estimate how many lights that is need in the testing, an experiment is done by setting multiple 500 watt Halogen background shop lights 30 meters in front of the testing vehicle. These shop lights are facing towards the testing vehicle. The testing vehicle is equipped with a dash camera. HSV Values are recorded each time when the number of background lights increases from one to four. The Result is shown in Fig. 4.6.

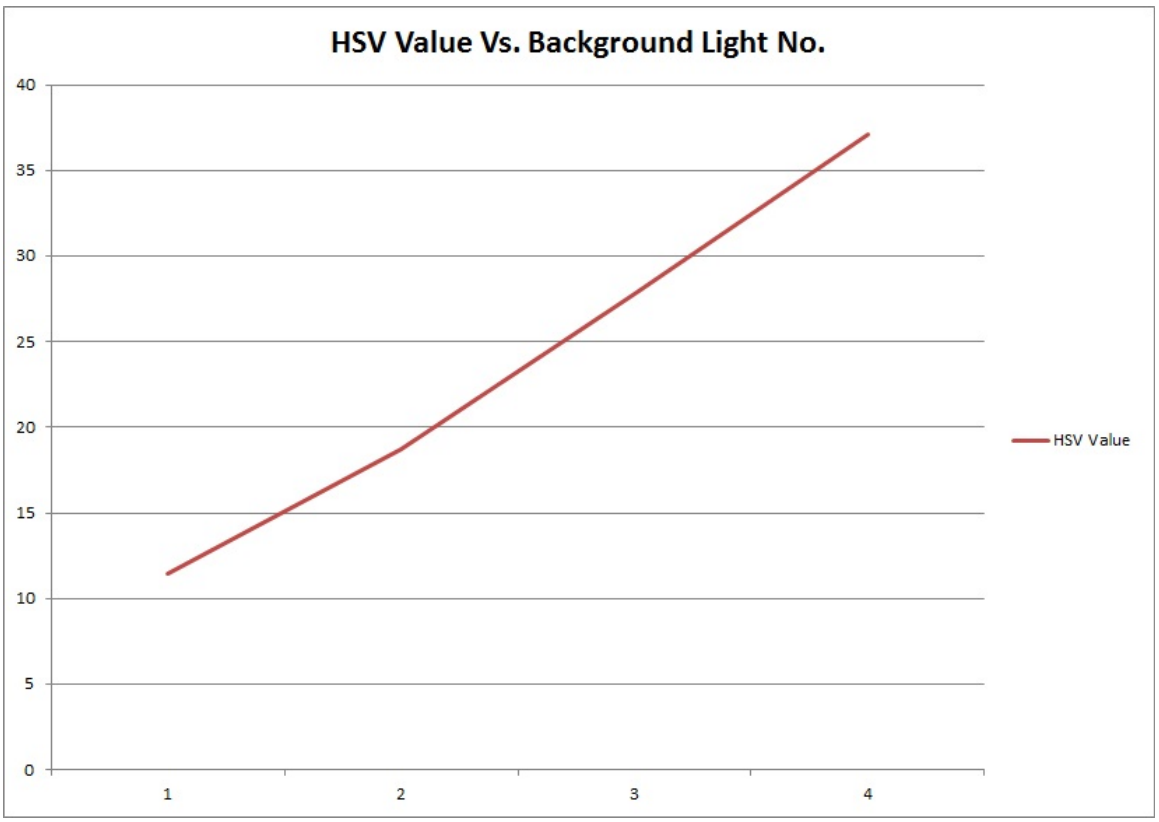


Fig. 4.6.: HSV Value Vs. Background Light No.

In here, we can estimate that if four 500 Watts Halogen lights are needed to generate an HSV Value of 37, then approximately 144 lights are needed at 54 meters distance to generate an HSV Value of 96.44 in Table 4.1 by using equation 4.1. This is the maximum number of Halogen lights needed for the testing.

When Utilizing this measured lumen result, one have to incorporate a moving platform to carry light source 3,4 and 5 in Fig. 4.5 to make sure the distance of the background lights and the testing vehicle are the same. When the testing vehicle starts to move, the moving platform has to keep the same distance to the testing vehicle so that the ambient light intensity is the same all the time.

5. SUMMARY

The modeling of the low illuminance environment can be achieved by incorporating temporal profile on pattern recognition. This model successfully proposed such modeling, provided reliable pattern recognition results.

These results can be used to generating testing scenario of Pedestrian Pre-Collision Systems. Since the standard of the testing scenario at low-illuminance condition is not defined, a reliable testing scenario is not created before. One can extract the distribution of the lighting from different of light sources. Using this model of lighting and the location types of potential collision cases abstracted in chapter 2, the lighting scenario of the location types can be imitated for PAEB testing.

By using the HSV Value result in Table 4.1 and Table 4.2 generated in Chapter 4 and following the recommended HSV Value matching procedure, one can recreate a lighting environment with Dark-Lit Major/Dark-Lit Local/Dark-Unlit configurations in Urban or Non-Urban scenario. Using these testing scenario will ensure that the testing site resembles a real road environment. Testing a vehicle with PEAB system in this environment will help to determine the true performance of the PEAB on board in real potential collision case.

Although this model proposed an approach to approximate real light sources presents on the real environments, there are still possible improvements to expand further for this model. This model may need more improvements on including additional modeling of the lighting sources into the model.

There are other light sources can be illustrated on the road such as obstructed light sources(tail light), which is due to improper installation of the dash camera. This will produce a non-ideal result of the temporal profile, create a pattern recognition result that is inaccurate. A dash camera aiming too high or low to the horizon are likely to have its region of the road in figure 2.1.1 obstructed by the vehicle ahead or have little to none information of the road. These obstructed scenes should be identified and neglected.

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REFERENCES

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