



Development of an Innovative Prototype Lane Departure Warning System

Final Report

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16. Abstract (Limit: 250 words) Development of various techniques such as lane departure warning (LDW) systems can improve traffic safety significantly. An LDW system should be able to detect when the driver is in danger of departing the road and then trigger an alarm to warn the driver early enough to take corrective action. This report presents the development of a new prototype LDW system. It is mainly an image-based approach to find the vehicle's lateral characteristics and then uses that information to establish an operation algorithm to determine whether a warning signal should be issued based on the status of the vehicle deviating from its heading lane. The system developed takes a mixed approach by integrating the Lucas-Kanade (L-K) optical flow and the Hough transform-based lane detection methods in its implementation. The L-K point tracking is used when the lane boundaries cannot be detected, while the lane detection technique is used when they become available. Even though both techniques are used in the system, only one method is activated at any given time because each technique has its own advantages and also disadvantages. The developed LDW system was road tested on I-35, US-53, Rice Lake Road, Martin Road, and Jean Duluth Road. Overall, the system operates correctly as expected, with a false alarm occurring only roughly 1.18% of the operation time. This report presents the system implementation together with findings. Factors that could affect the system performance are also discussed.			
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Executive Summary

Roadway departure fatalities including run-off-the-road (ROR) and head-on fatalities are a serious problem in this country. The use of rumble strips on roads has proven to be an effective means of providing drivers lane departure warning (LDW). However, rumble strips require an infrastructure and do not exist on a majority of roadways. Development of various techniques such as LDW systems can improve traffic safety significantly. An effective LDW system should be able to detect when the driver is in danger of departing the road and then trigger an alarm to warn the driver early enough to take corrective action. General working principle of camera-based LDW systems is to track lane markers on the road to see if the vehicle is straying outside the lane. But there is no guarantee that the lane markers will always be present on the road. Various environmental factors such as rain and heat might wear out the lane markers and the presence of snow on the road might also affect the visibility of road markers. Therefore, it is highly desirable to develop a system that can not only make use of lane markers when they are available, but can also work when lane markers become invisible for a short period of time. This report presents the development of an image-based LDW system that integrates two techniques, the Lucas-Kanade (L-K) optical flow method and the Hough transform-based lane detection method, into its operation and implementation algorithm to determine the vehicle's lateral status and then issue a warning to the driver, if necessary. L-K optical flow point tracking is used when the lane boundaries cannot be detected, while the lane detection technique, via the Gaussian filtering/smoothing and the Hough transform, is used when the lane markers become available. The front-view images captured by an in-vehicle camera were converted to their corresponding top-view images via a homography. Based on these top-view images, the L-K optical flow is then used to track points (i.e., the Harris "corners") from frame to frame to find the vehicle's heading angle and thus its lateral position by evaluating the relationship between these tracked features. The lane detection method looks for the lane markers painted on each side of the road and if available, the system calculates the distance to it and compares that to a past value to determine where the vehicle is in the lane and in which direction it's headed.

In this report, we present our developed system, which includes the lane detection method, signal flow block diagrams, operation algorithm, and hardware implementation of an alarm warning mechanism. Even though both the L-K optical flow and lane detection techniques are integrated into this system, only one method is activated at any given time because each technique has its own advantages and disadvantages. In the system developed, we tried to limit the amount that the L-K method is used because it is slow computationally and has proven to be less reliable in the majority of cases than the lane detection method. We conducted road tests to check the accuracy of our LDW system in issuing a warning sound when the deviation of the vehicle from the center of its lane exceeds a threshold. The test sites surrounding the Duluth area included Interstate I-35, US-53, Rice Lake Road, Martin Road, and Jean Duluth Road. These roads varied in speed limit, curvature, amount of traffic, number of lanes, and road construction, which gives a richer diversity in the data. The road test results and findings are presented in this report. Overall, the system operates correctly as expected with a false alarm occurring only roughly 1.18% of the operation time. Factors that could affect the system performance are also discussed.

Chapter 1. Introduction

Roadway departure fatalities including run-off-the-road (ROR) and head-on fatalities are a serious problem in this country. According to the National Motor Vehicle Crash Causation Survey (NMVCCS) data [1], ROR crashes contribute to a large portion of fatalities and serious injuries to motor vehicle occupants and over 95% of the critical reasons for single-vehicle ROR crashes were driver-related. The category of the critical reasons attributed to 27.7% driver performance errors (e.g., poor directional control, overcompensation), followed by 25.4% driver decision errors (e.g., too fast for curve/conditions), 22.5% critical non-performance errors such as sleeping, physical impairment and 19.8% driver recognition errors (e.g., internal and external distractions). Moreover, statistics data indicated that 70% of ROR fatalities occur on rural highways and about 90% occur on two-lane roads [2]. The most common approach to prevent single vehicle lane departure is the use of rumble strips [3, 4] on road shoulders. Actually, the use of rumble strips on roads has proven to be an effective means of providing drivers departure warning [5]. But rumble strips require an infrastructure and are not available on all roadways. Furthermore, rumble strips presents a difficult issue of where to establish the rumble-strip distance threshold (see the headline news: “Rumble Strips Unpopular in Other Minnesota Counties, Too”, “Roadsides Rumbles Cause a Grumble”, *Duluth News Tribune*, September 12, 2010; “County Vows to Reduce Rumble”, *Duluth News Tribune*, September 29, 2010). Development of various techniques such as lane departure warning (LDW) systems can improve traffic safety significantly. LDW systems are one of the most desired attributes in the vehicle safety system. This is due to the fact that they play a crucial role in preventing drivers from unintentional lane crossing and avoiding potential road mishaps.

A lane departure warning system should be able to detect when the driver is in danger of departing the road and then trigger an alarm to warn the driver early enough to take corrective action. The LDW systems are mainly associated to lane departure warning system to detect lane markings and use this information to determine the vehicle’s position on the road. The simplest LDW systems make no assumptions other than the built-in threshold distance, provides no look-ahead or prediction and requires no vehicle state information. One of the alternatives for LDW systems is to use the “time-to-lane-crossing” (TLC), which is a measure of the time remaining before a vehicle on a given trajectory will departure the road [6]. TLC was first proposed as a metric to evaluate human factors issues in vehicle driving [7], where the TLC value represented the time predicted for a potential lane edge crossing. In [7], Hayward calculated TLC using simple particle dynamics where the vehicle lateral acceleration and velocity are used. Pomerleau calculated TLC by using a preview driver model and his approach includes a computer-vision system to estimate the vehicle’s position in the lane and provides an estimate of the instantaneous road curvature [8]. In another approach, LeBlanc *et. al.* implemented a TLC algorithm using a dynamic estimate of the effective steering gain to predict the vehicle path [9]. The vehicle path is compared to a computer-vision generated image of the upcoming road to predict potential lane crossings. In general, TLC provides more warning time than roadside rumble strips because warnings are triggered when a driver is predicted to be in danger. However, this prediction can be wrong because its calculation takes only into account vehicle’s trajectory not driver’s actions, and therefore, the number of false alarms is generally higher than roadside rumble strips. This could reduce the effectiveness and also driver confidence when using such a system. However, rumble strips require infrastructure and do not exist on a majority

of highways. In [10], Jung and Kelber proposed a lane departure warning system using lateral offset with a uncalibrated camera. Their method uses a linear-parabolic model to determine the lateral offset of the vehicle with respect to the center of the lane without needing information about camera parameters. Other forward looking, camera-based systems that use algorithms to interpret video images to estimate vehicle state and roadway alignment include AutoVue (Iteris's device), the Infiniti Lane Departure Prevention (LDP) system, the Volvo's and BMW's LDW systems, the Lexus LS 460 multi-mode Lane Keeping Assistant (LKA) system, etc. AutoVue is already being offered as a factory-installed option on Freightliner's Century and Argosy trucks. Automakers offering a lane departure warning system on some of their models include Audi, Infiniti, BMW, Cadillac, Volvo and Buick. The California PATH program has demonstrated the use of in-road magnetic markers and magnetometer-equipped vehicles for lane tracking [11]. Recently, Batavia proposed an extension to TLC and road side rumble strips idea by allowing the driver to drift beyond the lane boundary by adding a virtual lane boundary adjusted by a learning phase [5]. The comparison of LDW systems on real driving conditions was also reported in the literature (e.g., [12, 13]).

The main goal of this research is to develop an innovative vision-based LDW system. Vision-based systems offer a number of advantages including longer field of view, useful information extraction of surrounding environment. General working principle of camera-based systems is to track lane markers on the road to see if the vehicle is straying outside the lane. But there is no guarantee that the lane markers will always be present on the road. Various environmental factors such as rain and heat might wear out the lane markings. The presence of snow on the road might affect the visibility of road marking. Hence, a system is desired which makes use of lane marking when they are available, but can also work when lane markings become invisible for a short period of time. In this report, we describe our developed LDW system which takes a mixed approach by using the Lucas-Kanade (L-K) optical flow technique and the Hough transform-based lane detection technique. The optical flow point tracking is used when the lane markers (boundaries) cannot be found in images while the lane detection technique is used when the lane markers become available. In other words, an in-vehicle camera constantly captures images in real time for processing. In the meantime time, the LDW system checks whether the lane markers are available, if they are, then that information is used to determine the vehicle's lateral position; and if not, then the L-K optical flow technique is activated to find the vehicle's heading angle and thus, the vehicle's lateral position. Based on the vehicle's lateral characteristics, we then develop an operation algorithm which can issue a warning sound when the vehicle is in danger of deviating from its lane. Even though both the L-K optical flow and lane detection techniques are used in our system, only one method is activated at any given time because each technique has its own advantages and disadvantages.

This report is organized as follows. Chapter 2 describes the lane detection technique used in our system implementation. An explanation of the image processing via the Gaussian filtering/smoothing and the Hough transformation is given. In Chapter 3, the L-K optical flow method is briefly mentioned before we describe our system implementation, which includes the integration of these two techniques, operation algorithm and hardware implementation of an alarm warning mechanism. Chapter 4 presents our road test results and findings. Factors that could affect the system performance are also discussed in this chapter. Finally, Chapter 5 gives the conclusion.

Chapter 2. Lane Detection via the Hough Transform

The LDW system we developed uses two techniques, i.e., the Lucas-Kanade (L-K) optical flow method [14, 15] and the Hough transform-based lane detection method [17-21]. The lane marker detection is based on the Gaussian filtering and smoothing of images via an in-vehicle camera and also the Hough transformation. In order to improve the overall system performance, heading angle and lane markers information (if available) are used and incorporated into the system implementation. The in-vehicle camera constantly takes images in real time for processing. In the meantime time, the LDW system will check whether the lane markers are available, if they are, then that information will be used to determine the vehicle's lateral position; and if not, then the optical flow point tracking technique will be used to fine the vehicle's heading angle and then based on that information to determine the vehicle's lateral position. In this chapter, we describe the lane marker detection we used in our system.

To improve the accuracy of the vehicle's lateral position, its "initial" lateral position needs to be reset as often as possible (please refer to Chapter 2 in [16]). This reset can be performed once the lane markers were detected. We used a Microsoft H5D LifeCam Cinema CMOS image sensor to capture front-view images in real time. These images are processed via the L-K optical flow technique as described in [16] to determine the vehicle's lateral position. In the meantime these images are also processed to check whether lane marker(s) (or boundaries) can be detected. The Hough transformation [17-21] is used in the lane marker detection, which forms a subset of our entire LDW system. The flow chart showing the procedure conducted to check the lane marker availability is given in Figure 2.1.

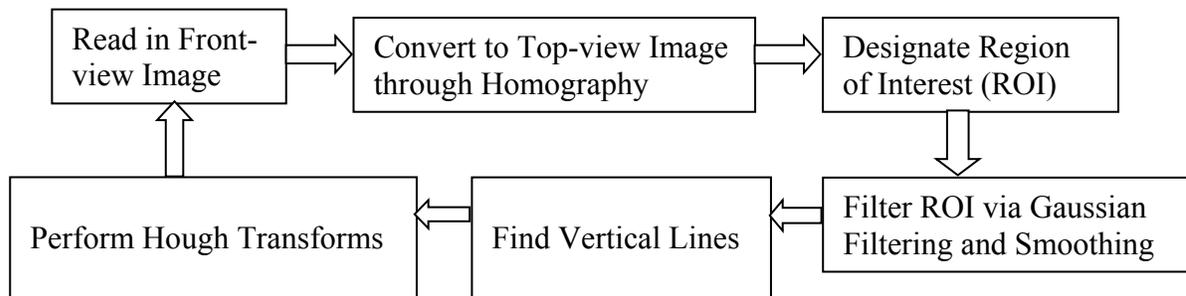


Figure 2.1: Flow chart implementation of the lane detection algorithm.

In order to explain the lane detection signal processing shown in Figure 2.1, we use a sample front-view image given in Figure 2.2 as an example. Figure 2.3 shows its corresponding top-view image after the homography transformation. Note that the conversion to top-view image in Figure 2.3 involves removing the perspective effect in the front-view image. That is, re-sample the incoming image and re-mapping each pixel in the captured image toward a different position and producing a new two-dimensional array of pixels. The resulting image represents a top view (or the bird's eye view) of the road region in front of the vehicle, as it was observed from a significant height.

To reduce real-time computation, a Region of Interest (ROI) instead of the whole region in a top-view image is chosen. For instance, for the top-view image shown in Figure 2.3, we choose its

ROI to be a rectangular box image, a 100 pixel \times 320 pixel sample of the image centered to be straight in front of the vehicle. This ROI image, as shown in Figure 2.4, starts right after the vehicle's hood on the bottom of Figure 2.3 and goes up to show about 10 feet in front of the vehicle. The ROI is chosen just wide enough to fit the width of a normal lane on a road or highway. Note that we use the ROI to greatly speed up the computations, allowing the computer program to run in real time. In addition, we don't have to worry about distortion effect caused by converting to its top-view image since distortions (the so-called "fisheye effect") only arise around the edges of the original image.

In filtering the ROI, it first converted from a color image to a grey scale image, this is done by using the Gaussian smoothing in the vertical direction and the derivative of Gaussian smoothing in the horizontal direction. This picks out vertical areas where there are large changes in the contrast. And the smoothing takes the average of neighboring pixels and set them to that value and this helps eliminate noise and imperfections in the image. The derivative of the Gaussian conducted in the x -direction (i.e., the horizontal direction) will only let regions where the grey scale values of the pixels have a large amount of change between them. The filtered as contrasted to the unfiltered ROI is shown in Figure 2.5.



Figure 2.2: A snapshot of a front-view image using the Microsoft H5D camera.

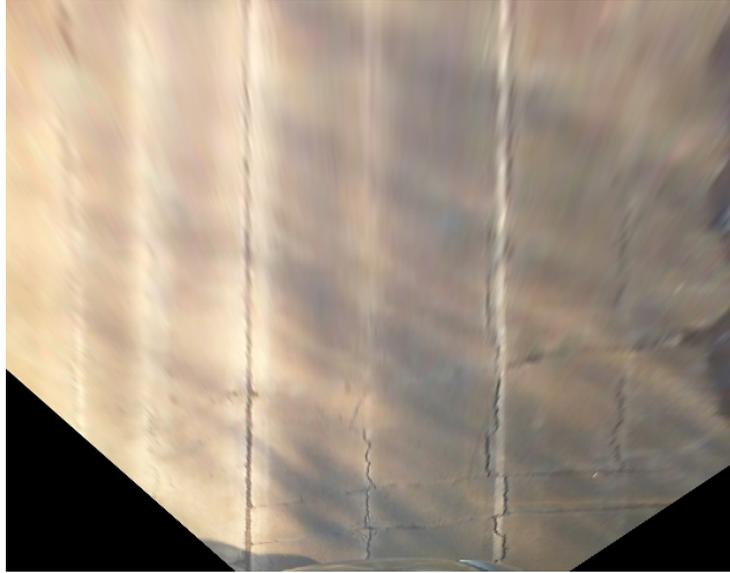


Figure 2.3: The front-view image of Figure 2.2. after the homography.



Figure 2.4: The ROI image.

The Hough transform [17-21] is then applied to the ROI image to find all vertical lines on the image and draws them as red lines as shown in Figure 2.5. Note that the Hough transform is a feature extraction technique used in image analysis and computer vision. Its original version is to detect straight lines and later the transform has been extended to identify arbitrary shapes, most commonly circles. We use the Hough transform to detect straight lines described by $y = mx + b$ where m is the slope parameter and b is the intercept parameter and these lines represent possible edges of a lane. But for computational reasons, actually a different pair of parameters (r, θ) is used for line detection in images, where r represents the distance between the line and the origin, while θ is the angle of the vector from the origin to the closest point on that line (in the polar coordinates). Therefore, a straight line can be written as $r = x \cos \theta + y \sin \theta$ [21]. And the

vertical lines have to have a specific score in order to be counted. This is known as the line score. To find the line score the image is split into columns and the pixel values are averaged in this column. This average is the line's line score. We then use the Hough transform to detect the most likely lane edge given in Figure 2.1. The Hough transform basically uses a voting scheme to detect the most likely edge of the lane. If the line with the most votes is higher than the threshold level (i.e., meets a certain score requirement) then that line is said to be the lane marker. This is done on the left half of the image to get the left lane marker and then performed again on the right half of the image to get the right lane marker as shown in Figure 2.7.

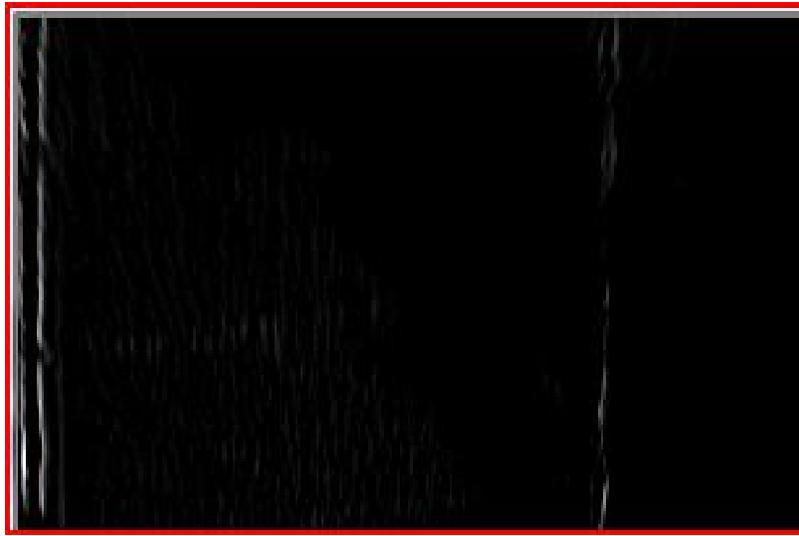


Figure 2.5: The filtered ROI after Gaussian filtering and smoothing.

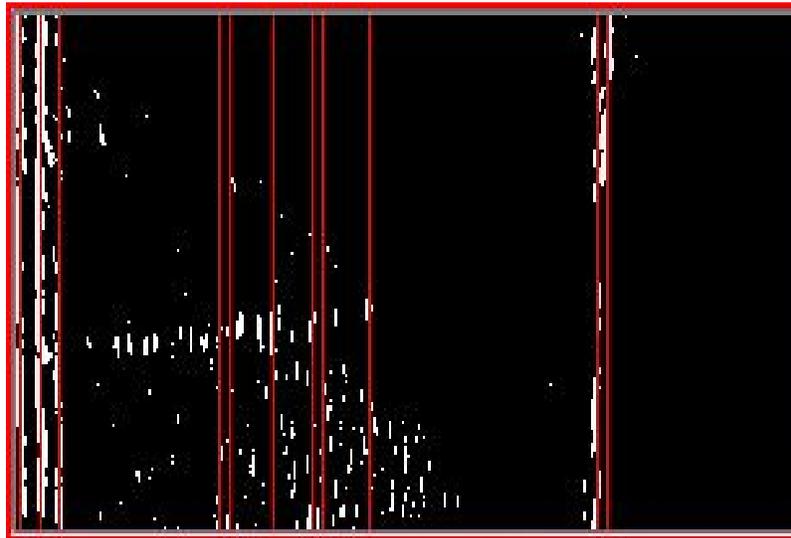
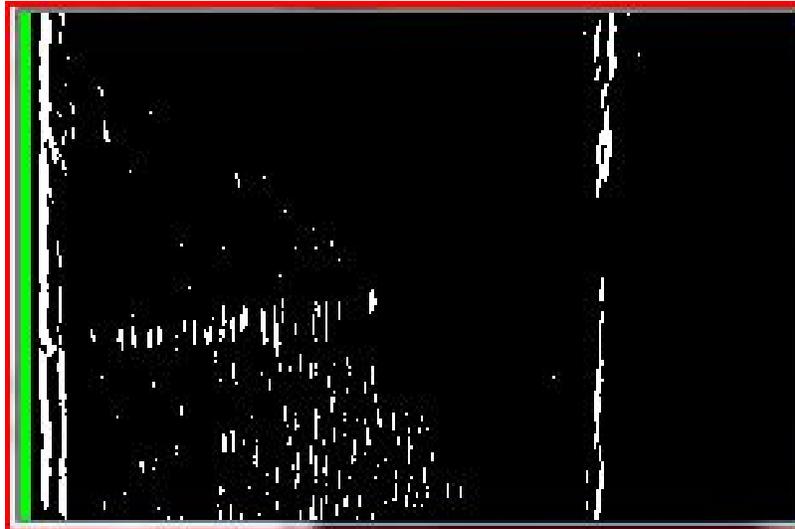
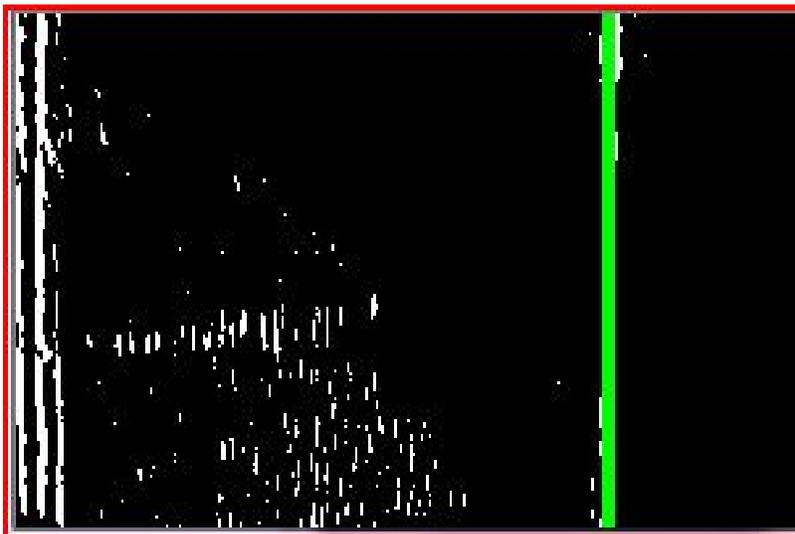


Figure 2.6: Vertical lines (shown in red) indicate possible lane edges.



(a) Left lane marker shown in green



(b) Right lane marker shown in green

Figure 2.7: Lane markers (shown in green) after performing the Hough transform.

Chapter 3. System Integration and Implementation

This chapter describes the prototype LDW system in some detail. Our system operation takes a mixed approach by using the Lucas-Kanade (L-K) optical flow method and the Hough transform-based lane detection technique in its implementation to enhance the overall system performance. The optical flow point tracking is used when the lane markers (boundaries) cannot be found in images, while the lane detection technique is used when the lane markers become available. The in-vehicle camera constantly captures images in real time for processing. In the meantime, the LDW system checks whether the lane markers are available, if they are, then that information is used to determine the vehicle's lateral position; and if not, then the L-K optical flow technique is applied to find the vehicle's heading angle and based on that information to determine the vehicle's lateral position. In the following section, we first briefly review the L-K optical technique we integrated into our system.

3.1 The Optical Flow Method

Optical flow can give important information about the spatial arrangement of the objects viewed and the rate of change of this arrangement. There are several methods available for determining optical flow including the phase correlation method [23], the block-based method [24], the differential methods [14, 25] and discrete optimization method [26], etc. The differential methods are based on partial derivatives of the image signal (e.g., the L-K method [14], the Horn-Schunck method [25]). The L-K algorithm is based on the following three assumptions: (a) brightness constancy, (b) temporal persistence (implies "small movements"), and (c) spatial coherence [14]. The first assumption means that a pixel from the image of an object in the scene does not change in appearance as it moves from frame to frame. That is, the brightness of a pixel does not change as it is tracked from frame to frame. The second assumption simply means that the image motion changes slowly in time, i.e., the motion is slow relative to the frame rate. The third assumption implies that neighboring points in a scene stay neighbors. In other words, the neighboring points belong to the same surface, have similar motion, and project to nearby points in the image plane. The method tries to calculate the motion between two image frames which are taken at subsequent time instants at every pixel position. This method is also called differential since it is based on the local Taylor series approximations of the image signal; that is, it uses partial derivatives with respect to the spatial and temporal coordinates.

In [16], we used the L-K optical flow method to determine the vehicle's heading angle via the top-view image processing. The movement obtained from each frame is accumulated to obtain the lateral position of the camera and thus, the vehicle's lateral position relative to its previous position. The feature selection and tracking of the consecutive top-view images, via the optical flow method [14, 15], were used. A point of our interest in an image is a point which has a well-defined position and can be robustly detected and tracked. The feature selection/detection and tracking are based on the top-view images. At each time frame, a set of "good" features (or "corners") are determined. Trackable (and reliable) features are points that contain enough information to be picked from the current frame to the next frame. They should have brightness constancy, sufficient texture variations, and do not deform much over time [15]. Trackable points are called "corners", and the words "corner" and "feature" are sometimes used interchangeably in literature. If we choose a point that is unique (i.e., a "good" feature) in an image frame then we

have a pretty good chance of finding that point again in the next image frame. In practice, the point or feature we select should be unique, or nearly unique, and should be parameterizable in such a way that it can be compared to other points in another image. The most commonly used definition of a corner was provided by Harris [22] based on the second-order derivatives of the image intensities. However, in [16] instead of using the Harris's method, we used the Shi and Tomasi's method [27] to determine good corners (features).

3.2 System Integration

In this section, we describe the system we developed and also implemented. To improve the overall system performance and reduce the possibility of false alarms, our system operation takes a mixed approach by using the Lucas-Kanade (L-K) optical flow technique described in [16] and the Hough transform-based lane detection method in the previous chapter. Even though both the L-K optical flow and lane detection techniques are used in our system, only one method is activated at any given time because each technique has its own advantages and disadvantages. (please refer to Section 4.3).

The L-K method is used by tracking points from frame to frame to determine where the vehicle is located in respect to the center of the lane and in which direction the vehicle is headed. The schematic diagram of the data flow and signal processing to determine the vehicle's heading angle and thus, its lateral position is shown in Figure 3.1. Figure 3.2 gives the flow chart implementation of Figure 3.1, where θ_i represents the vehicle's heading angle at time instant i , that is, the angle between the vehicle moving direction and its longitudinal at time i [16]. Note that in Figure 3.1, the OpenCV software package [15] is used to process the image conversion and transformation. OpenCV, originally developed by Intel, is an open source library of programming functions with a strong focus on real-time applications.

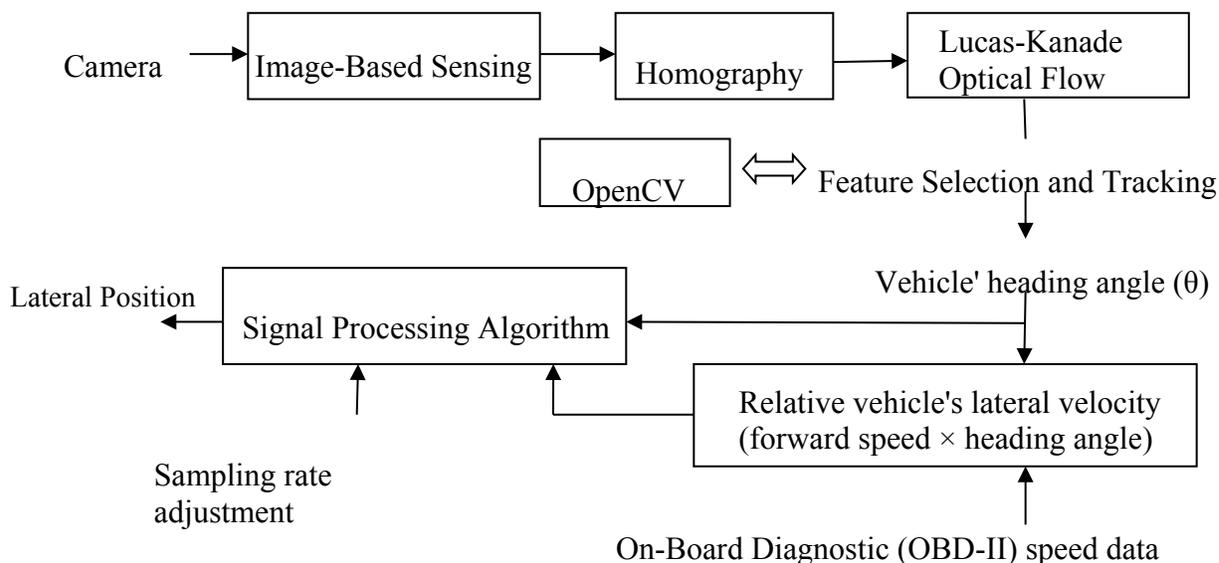


Figure 3.1: Vehicle's lateral position determination via the L-K optical flow method.

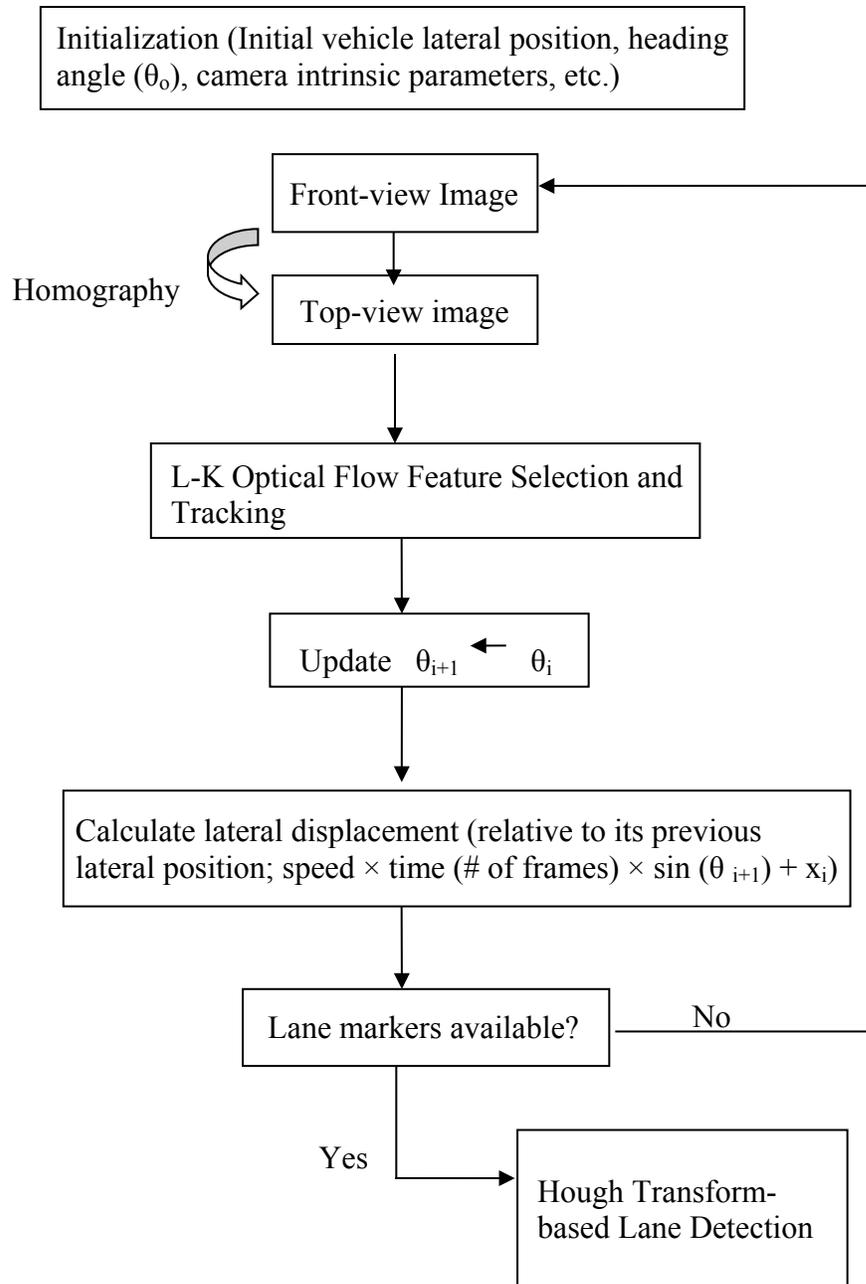


Figure 3.2: The L-K optical flow implementation flow chart.

As described in Chapter 2, the Hough transform-based lane detection method looks for the lane boundaries painted on each side of the road and if available, then the system calculates the distance to it, and compares that to a past value to determine where the vehicle is in the lane and in which direction it's headed. Combining both methods, the overall system has been implemented based on the signal flow chart given in Figure 3.3.

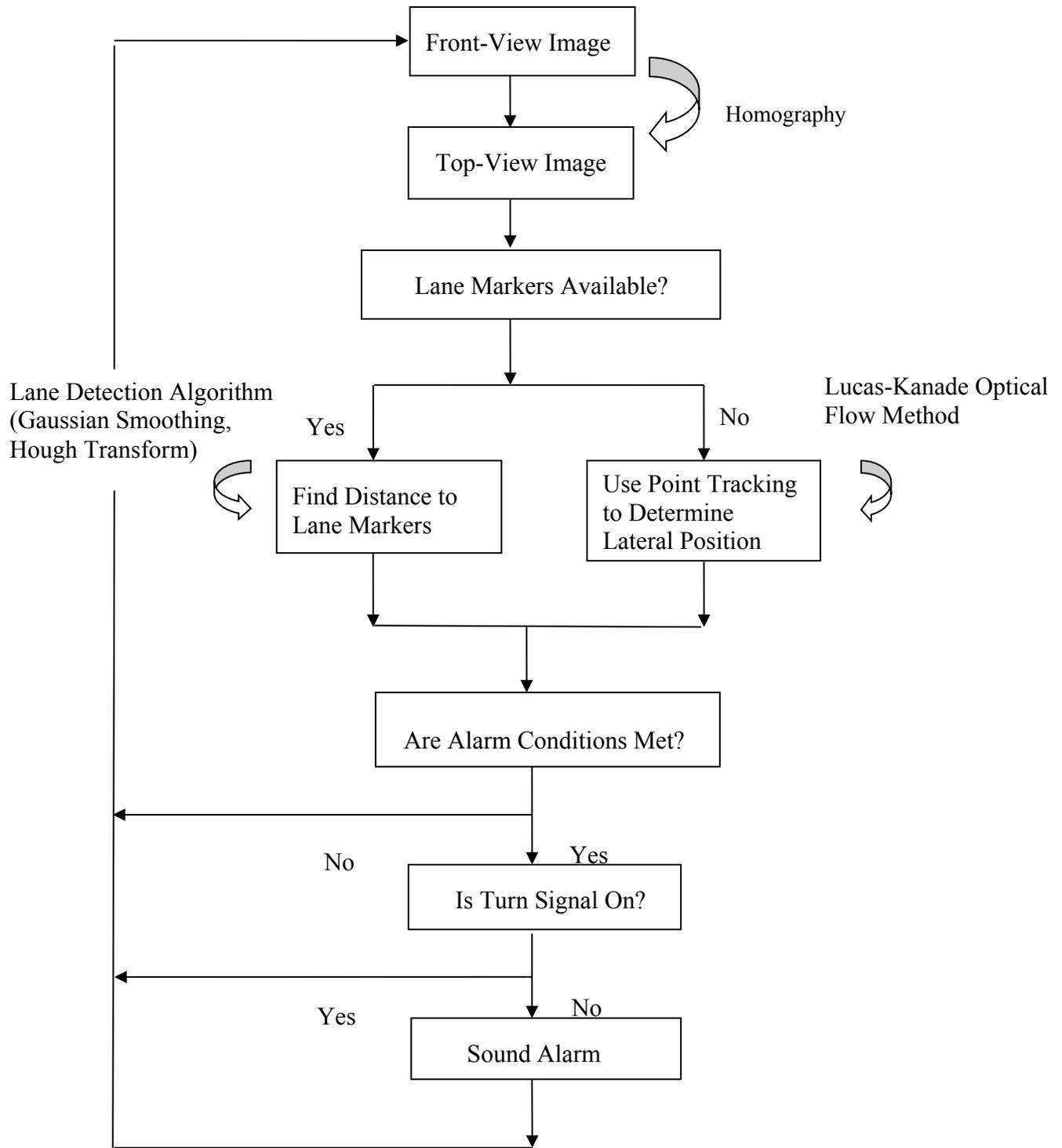


Figure 3.3: Flow chart of the developed LDW operation.

3.3 Conditions for Issuing an Alarm

Since the U.S. Interstate Highway System uses a 12-foot standard for lane width, we followed this standard width to implement our LDW operation algorithm. If the vehicle is moving along the center of the lane, then there is roughly about 6 feet distance to both the right and left edges of the road. The conditional statement for the alarm is established as follows: if the vehicle is within 3 feet of the lane boundary (edge) and its current distance to this lane boundary is smaller than it was in the previous frame (i.e., the vehicle is moving toward the lane boundary), then the alarm will sound, otherwise no alarm. Figure 3.4 shown below briefly illustrates how we determine the alarm condition based on possible scenarios.

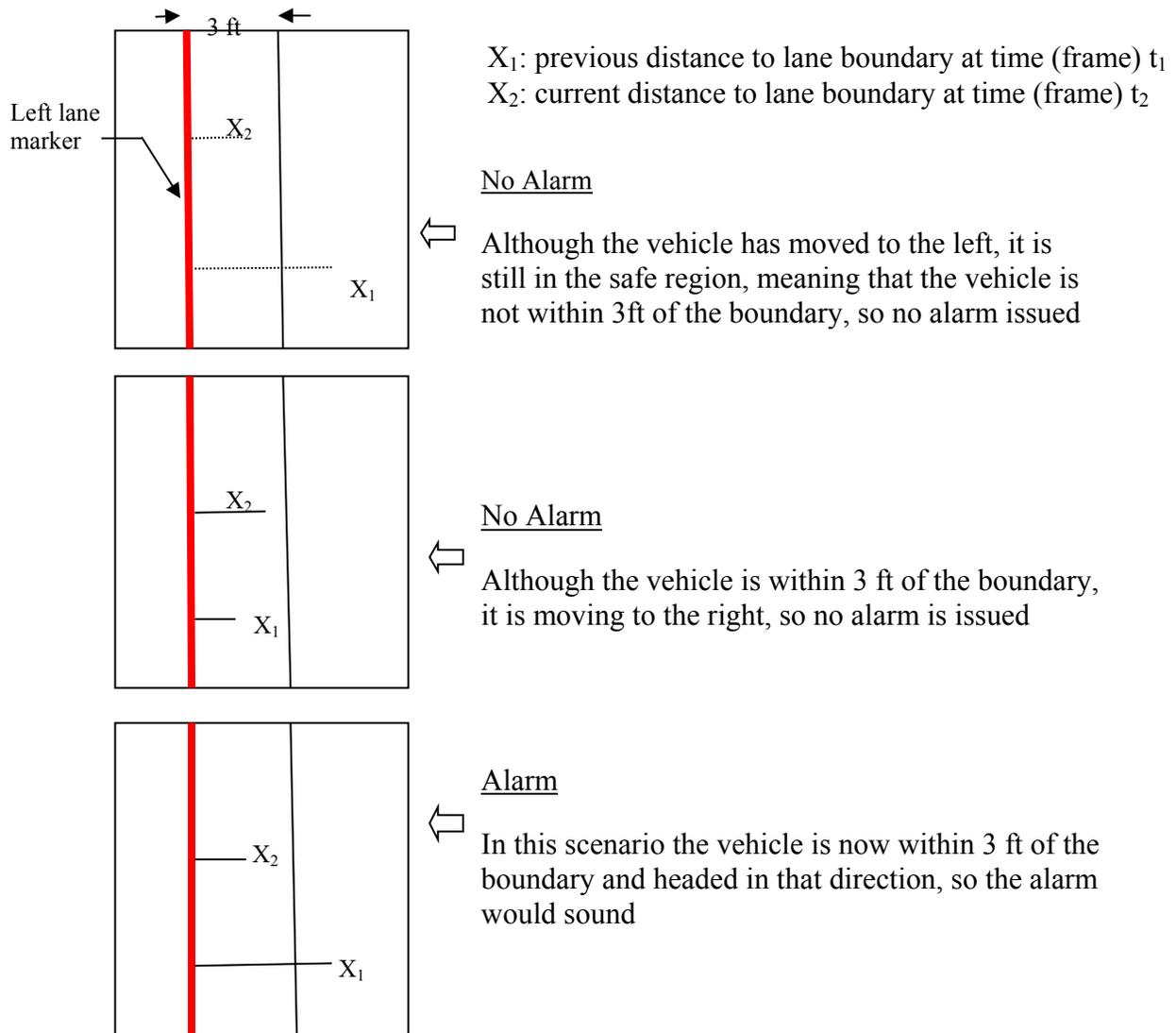


Figure 3.4: Conditions of issuing an alarm.

The sequence of this operation includes: 1) load frame from camera, 2) find any lane boundaries, 3) find the distance to the detected boundaries, 4) compare lane distance to previous frame, 5)

sound alarm if conditions are met, and 6) load next frame. The steps 1) to 6) keep repeating as the vehicle is moving. Note that if the lane boundaries cannot be detected then the optical flow point tracking operation is activated to determine the vehicle's lateral position.

Note that it is possible to find the heading angle using Figure 3.4, but it isn't necessary. For example, let $dx = X_1 - X_2$ (i.e., the change in distance from t_1 to t_2), $dt = t_2 - t_1$, lv (lateral velocity) $= dx/dt$, then (heading angle) $= \sin^{-1}(lv/v)$, where v is the vehicle's forward speed via the OBD-II access.

3.4 A Switch Mechanism for Lane Changing

It is possible that the vehicle deviates from its current lane due to the driver changes the lane. If this is the situation, then the alarm should not be issued. To deal with the situation of the driver intentionally changing the lane without issuing an alarm, two conditions need to be satisfied at the same time. That is, the vehicle's later position is within the 3-ft zone of the lane edge and the driver also turns on the turn signal light. To implement this, a two-switch mechanism attached to the signal control lever is shown in Figure 3.5. The circuit consists of a Altec portable speaker powered by a AAA battery plus two limit switches. The output from the speaker is fed into the computer code run by a laptop computer. The speaker is modified in such a way that we are able to control its operation through two limit switches connected in parallel. These switches are further connected to the vehicle's turn signal light indicator lever such that it works in synchronous with the turn signal control. When the vehicle's deviates from its lane center more than three feet and the turn signal control is triggered, then the alarm system will be switched off, indicating the situation that the driver is changing the lane.



Figure 3.5: Part of the LDW system showing the two switches connected with the turn signal control.

The system showing the alarm (speaker) and camera is given in Figures 3.6 and 3.7. Extensive road tests were conducted on I-35, US-53, Rice Lake Road, Martin Road, and Jean Duluth Road outside of the city of Duluth to test the performance of the developed system. In the next chapter, we will describe our test results and findings together with some discussions.



Figure 3.6: The LDW system showing the in-vehicle camera and alarm speaker.



Figure 3.7: The LDW system with the camera and alarm speaker shown.

Chapter 4. Results and Findings

The vehicle's lateral position is determined by implementing the schematic diagram shown in Figure 2.12. We use the Open Source Computer Vision Library functions, known as OpenCV, to implement the operation algorithm. OpenCV is an open source computer vision library originally developed Intel [15]. The library is written in C and C++ and runs under Linux, Windows and Mac OS X. There is active development on interfaces for Matlab, and other languages. OpenCV was designed for computational efficiency and with a strong focus on real time applications. Its library contains over 2,500 optimized algorithms that span many areas in vision, including medical imaging, user interface, camera calibration, stereo vision, and robotics. Therefore, we use the open source library functions OpenCV 2.3.1 to implement our operation algorithms. In this chapter, we discuss about the results and finding during our road tests.

4.1 Road Tests

We conducted road tests to check the accuracy of our LDW operation algorithm in issuing a warning sound when the deviation of the vehicle from the center of its moving lane exceeds a preset threshold. The developed system was set up in a 2001 Buick Century vehicle. Sets of images were taken on highways surrounding the Duluth area; these highways included Interstate I-35, US-53, Rice Lake Road, Martin Road, and Jean Duluth Road. These roads varied in speed limit, curvature, amount of traffic, number of lanes, and road construction, which gives a richer diversity in the data. Each test contains 200 consecutive images looking out the front of the test vehicle. This corresponds to about 45 seconds of driving. Over 20 tests have been done which gives a total data set of over 4,000 images. In each test the test vehicle maintained a constant speed using the cruise control, speeds ranged from 45 miles per hour (mph) to 70 mph depending on the speed limit of the highway. The tests were taken at different times of day and in different conditions. By purposely departing from the lane we can tell if the system is working or not. If the system is working then a warning is issued to the driver only when the vehicle is about to leave the lane.

4.2 Test Results

In this section, we explain part of the findings we found while conducting various road tests on I-35, US-53, Rice Lake Road, Martin Road, and Jean Duluth Road. One of the road tests we conducted and will be used to explain the test results later was on US-53 with the vehicle heading south at 45 mph speed at 1:15 pm on June 29, 2012. Figure 5.1 shows the vehicle's heading angle and its lateral position versus time together with other information. In the following, we will explain the results shown in this figure. We found very similar results in many other road tests.

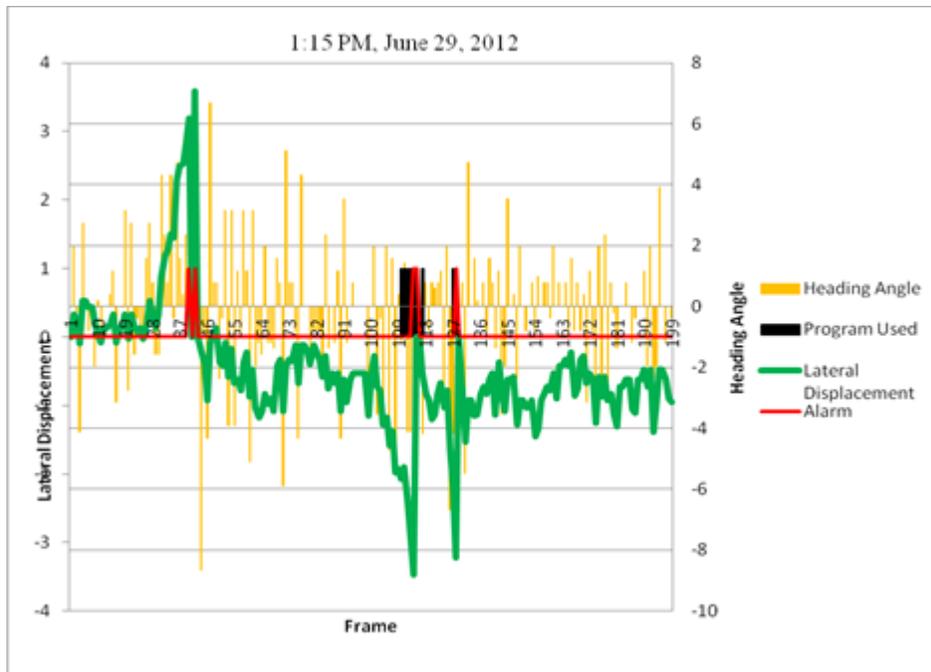


Figure 4.1: South bound on US-53 with speed 45 mph.

In Figure 4.1, the x -axis represents the time (frame), 1 would be the very first frame of the test and 200 would be the very last frame. This corresponds to about 45 seconds of driving. The heading angle (shown in yellow bars) represents the direction the vehicle is going. Traveling straight ahead would give a heading angle of 0 degrees. If the vehicle turned to the left then the heading angle would be negative, and to the right would be positive. Heading angle is given in degrees and will be shown in this way in the rest of other figures in this section. It is calculated using the previous frame and the current frame. The lateral displacement (in green line) represents how far away the vehicle is from the center of the lane. It is given in feet in all the figures. When the center of the vehicle is in the center of the lane, this would correspond to a lateral displacement of 0 ft. If the vehicle moved to the left, the displacement would be negative, and if the vehicle moved to the right it would be a positive displacement. Since the width of a standard (and also typical) U.S. highway is 12 ft, this means that if the lateral displacement was 6 ft, then the center of the vehicle would be on the right lane boundary, and if the lateral displacement was -6 ft then the center of the vehicle would be on the left lane boundary. The words "Program Used" (in black bars) in Figure 4.1 indicate whether the operation algorithm in Figure 3.3 used the lane detection method or the L-K optical flow method to determine the vehicle's position. For example, the black bars shown in Figure 4.1 from frame 110 to 115 indicated that the optical flow method was used because no lane markers were detected during that period of time. Clearly, it is used much less than the lane detection method. The alarm status (in red line) shows if and when an alarm was sounded. If the alarm spikes up to 1 this means that a warning was issued. We issue an alarm if the lateral displacement is more than ± 3 ft, and the vehicle is moving closer to the edge. We choose 3 ft for our test vehicle because that is when the vehicle's tires would be right on the lane boundary.

In the following, we explain this test on US-53 in some detail. In the beginning of this road test we started with our vehicle in the middle of the road which corresponds to a lateral displacement

of 0 ft. From Figure 4.1, it can be seen that for about the first 30 frames we do not stray very far from the center of the road. To test if an actual warning would sound we intentionally drove the vehicle towards the edge of the right lane and indeed an alarm sounded and indicated at frames 40 and 42.



Figure 4.2: The front-view image captured at frame 30.



Figure 4.3: The front-view image captured at frame 40 with the vehicle intentionally driven toward the edge of the right lane.

Note that in each of these frames the lane detection method was used, which means that the lane boundaries were found and the distance to them was saved. The lateral displacements at frames 40 and 42 were 3.1888 ft and 3.5904 ft, respectively. This means that the vehicle is about to drive out of the lane and so a warning is issued to the driver. After these warnings were issued we corrected our position in the lane and back towards the center. The program was running well until frame 109. For the next 6 frames (i.e., frame 110-115) since no lane markers were found (see Figure 4.4, for example), the optical flow point tracking method was used.



Figure 4.4: The front-view image captured at frame 114 where the left lane marker not available.

In this test the road curved to the left slightly (as can be seen from Figure 4.5 in the far end) so the driver had to follow the road. The optical flow method in this case was working, and it returned a heading angle that was negative which means the vehicle was moving to the left. However, the optical flow method assumes that the driver are driving on a straight road, and since the road curved to the left there is currently no way to tell the program that the driver should be driving in that direction, and the program thought the vehicle was leaving the lane and in reality it wasn't, so false warnings were issued in frames 114 and 115. We are currently trying to fix this problem of road curvature for the optical flow point tracking method. The exact same problem occurred in frame 128 (the heading angle is -8.29387°), the road was still curving to the left, and since the point tracking method currently cannot handle a curvature in the road it eventually ended up in a false warning being issued.

For the rest of the frames, 129 to 200, lane markers were found and so the optical flow method was no longer used. The lane detection method, which does not assume a straight road, produced good results for this portion of the test returning lane displacements just slightly negative, which means that the vehicle is driving just a bit to the left of the center of the lane.



Figure 4.5: The front-view image captured at frame 38 with the road curving showing in the far distance.

We conducted extensive road tests at different times on different days on I-35, US-53, Rice Lake Road, Martin Road, and Jean Duluth Road. During these tests, the vehicle was traveling at different speeds. Some of the results are summarized in the following Figures 4.6-4.13 with the explanation similar to that of Figure. 4.1. Note that in these figures, the alarm status indicated in red line shows if and when an alarm was sounded.

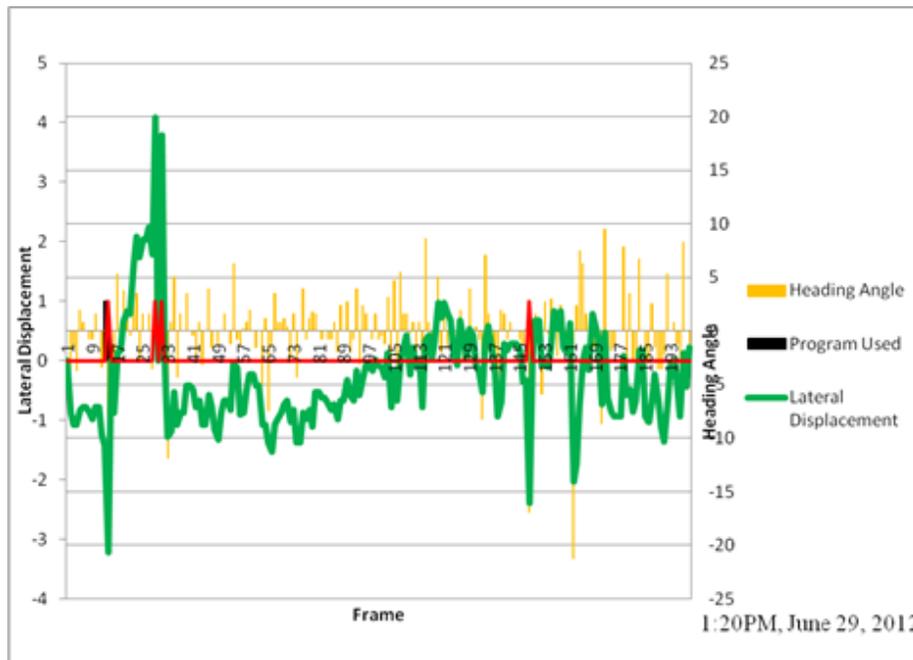


Figure 4.6: South bound on US-53 with speed 40 mph.

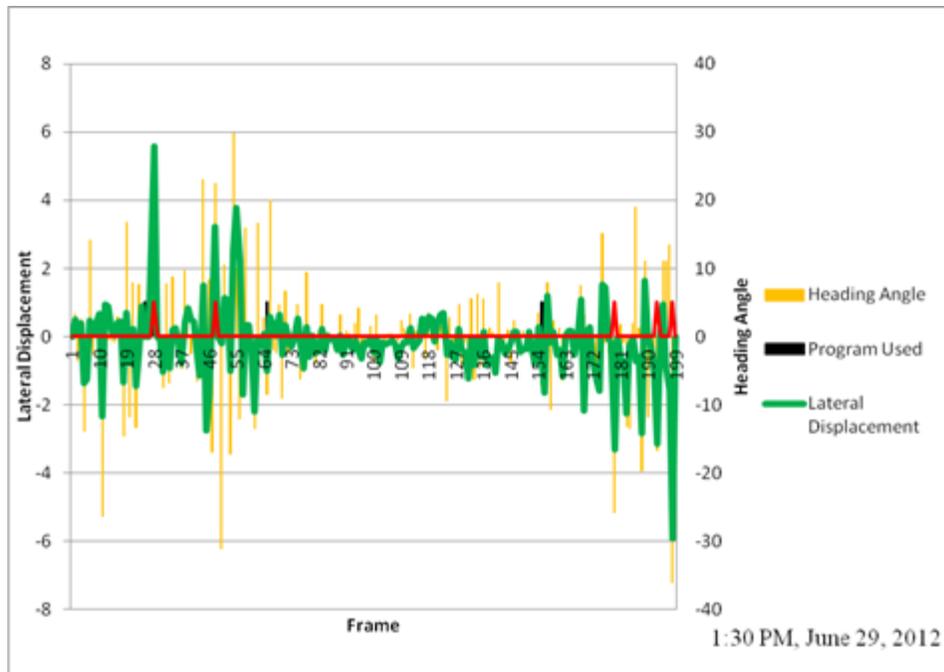


Figure 4.7: South bound on I-35 with speed 50 mph.

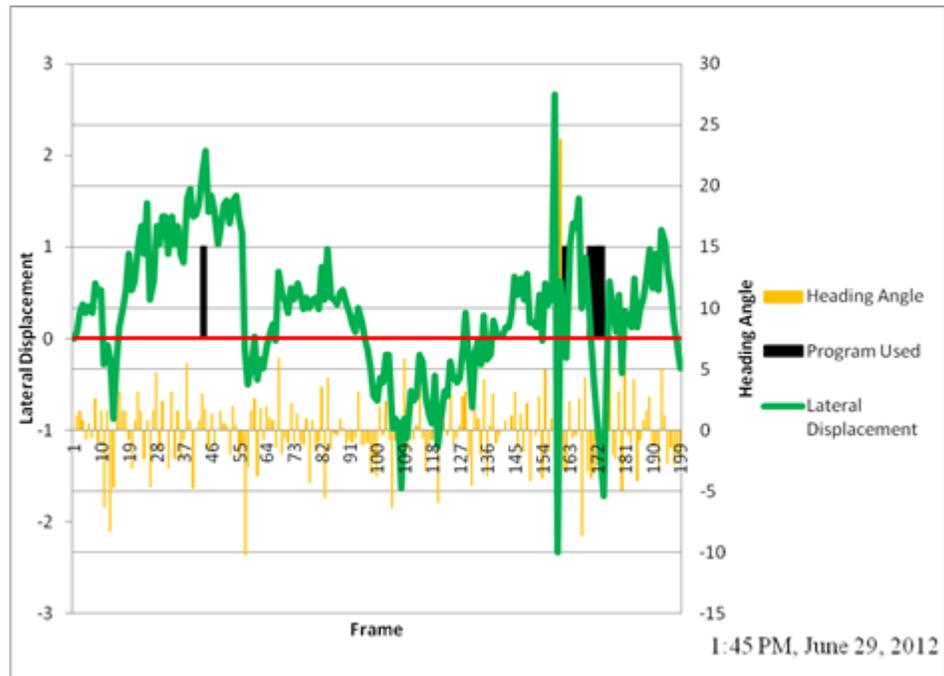


Figure 4.8: North bound on I-35 with speed 50 mph.

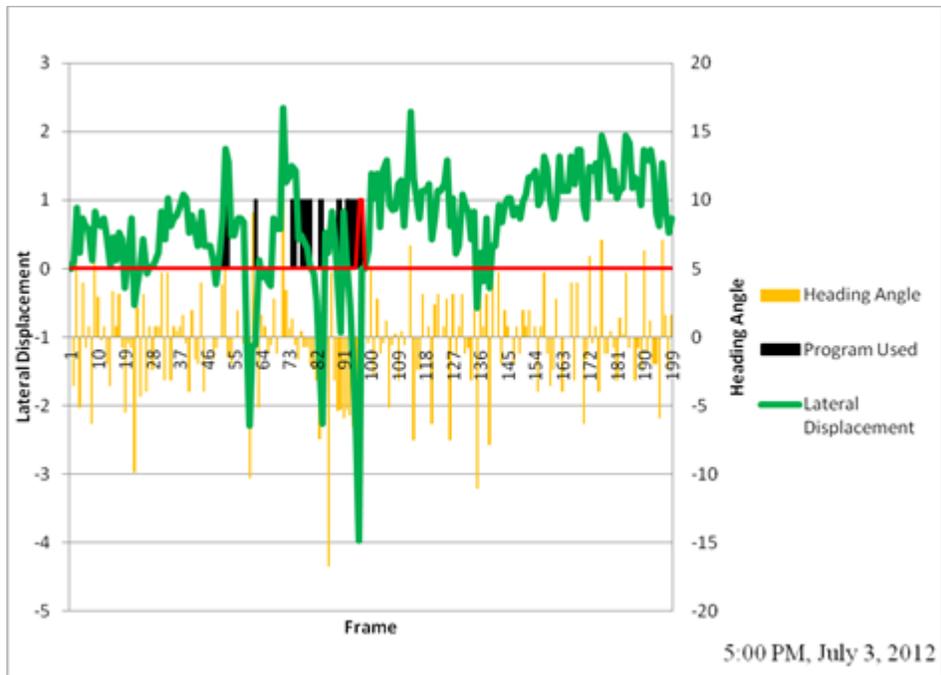


Figure 4.9: South bound on I-35 with speed 70 mph – Case I.

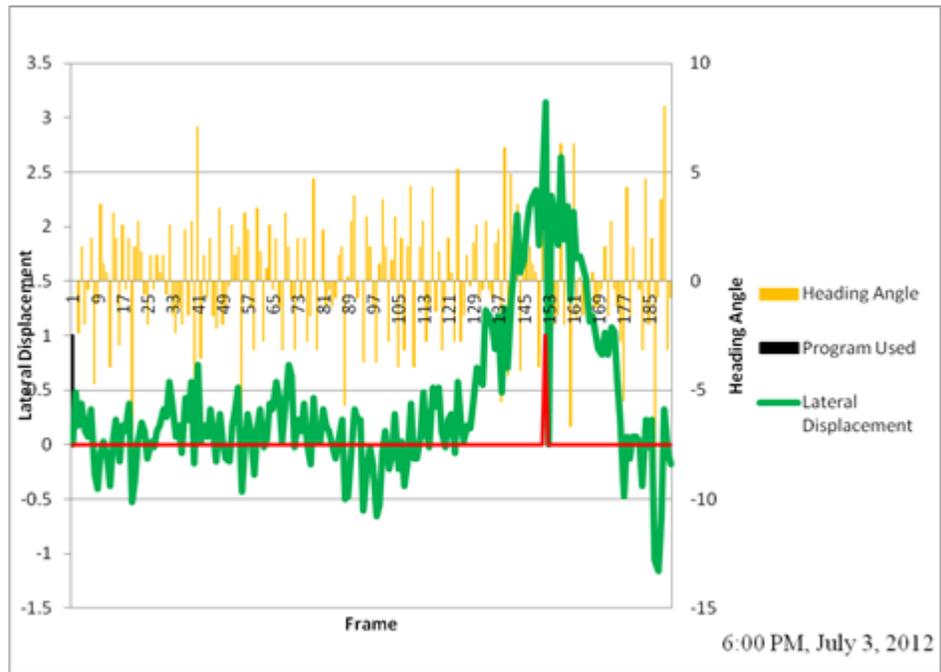


Figure 4.10: South bound on I-35 with speed 70 mph – Case II.

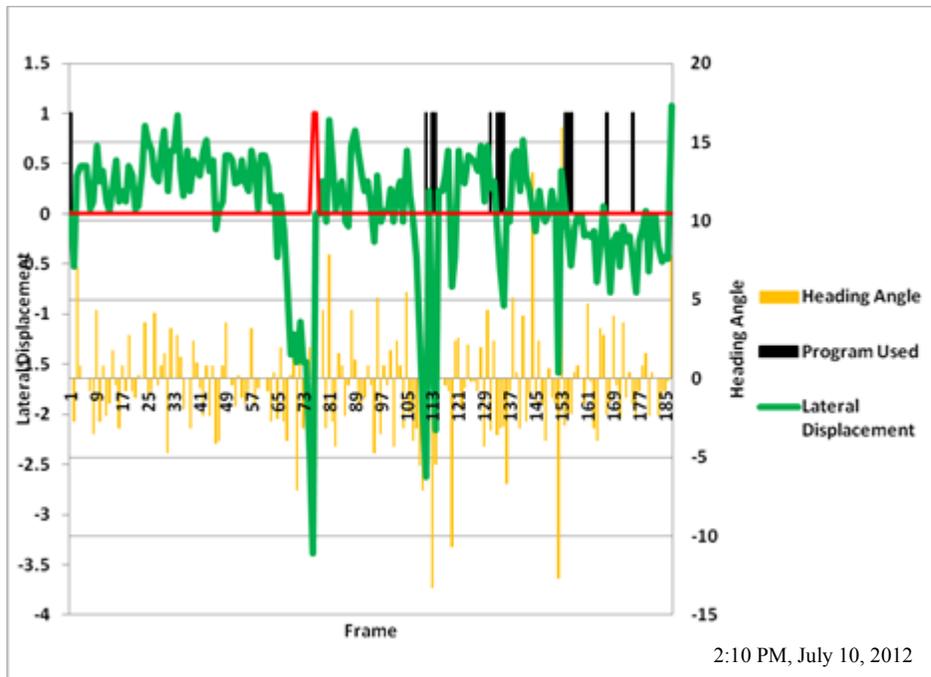


Figure 4.11: East bound on Martin Road with speed 50 mph.

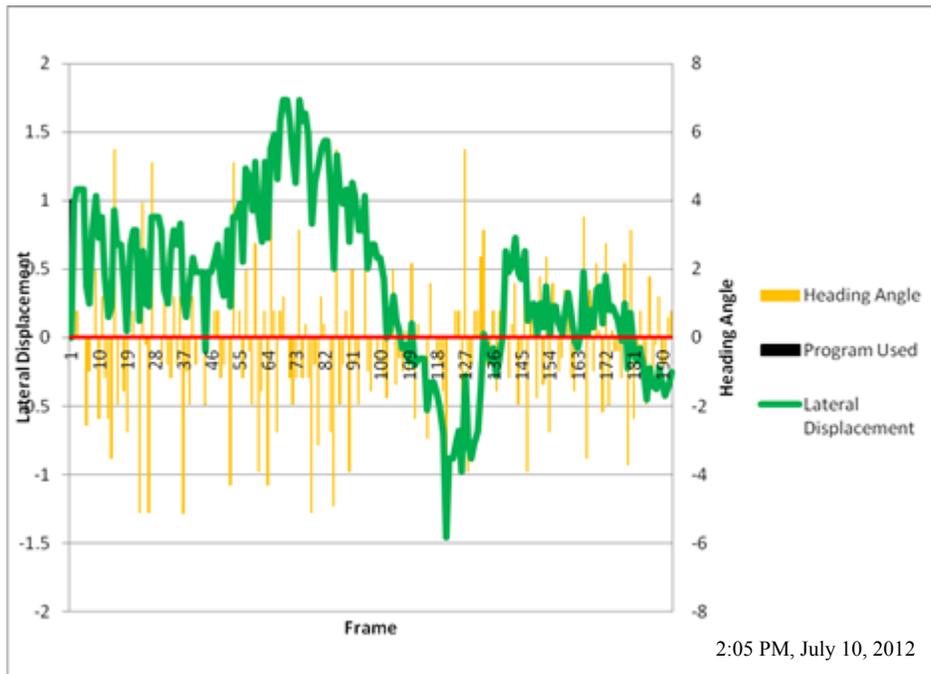


Figure 4.12: South bound on Rice Lake Road with speed 50 mph.

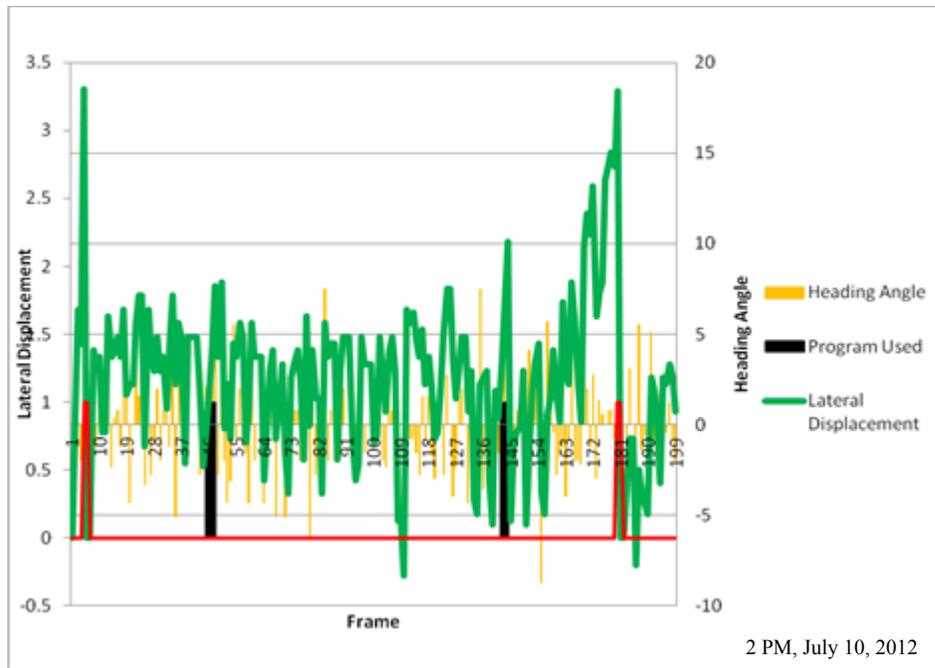
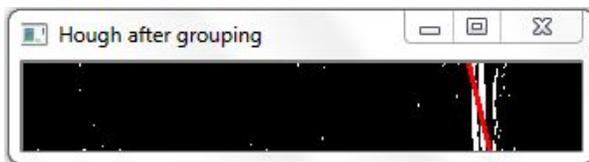


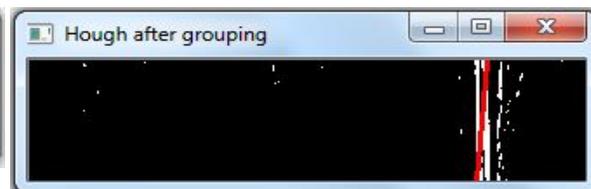
Figure 4.13: West bound on Martin Road with speed 50 mph.

4.3 Effect of ROI Size on Performance

In the image processing, we choose the size of the ROI to be a 100 pixel by 320 pixel rectangular box image and it is part of the image taken from the corresponding top view image (480 pixel \times 640 pixel). To reduce real-time computation, this ROI has been made small. However, too small size of ROI can affect the image-based system performance. In order to get an idea for the “optimal” ROI for the lane marker detection, in this subsection we studied the effect of the size of ROI on the performance. We run the lane detection algorithm while varying the size of ROI to find how many false alarms were generated with each particular ROI. The five different ROI sizes chosen are 50, 75, 100, 125, and 150 pixels (in the vertical direction) and are shown in Figure 4.14. Note that the horizontal width (320 pixels centered) is kept fixed.



ROI = 50



ROI = 75

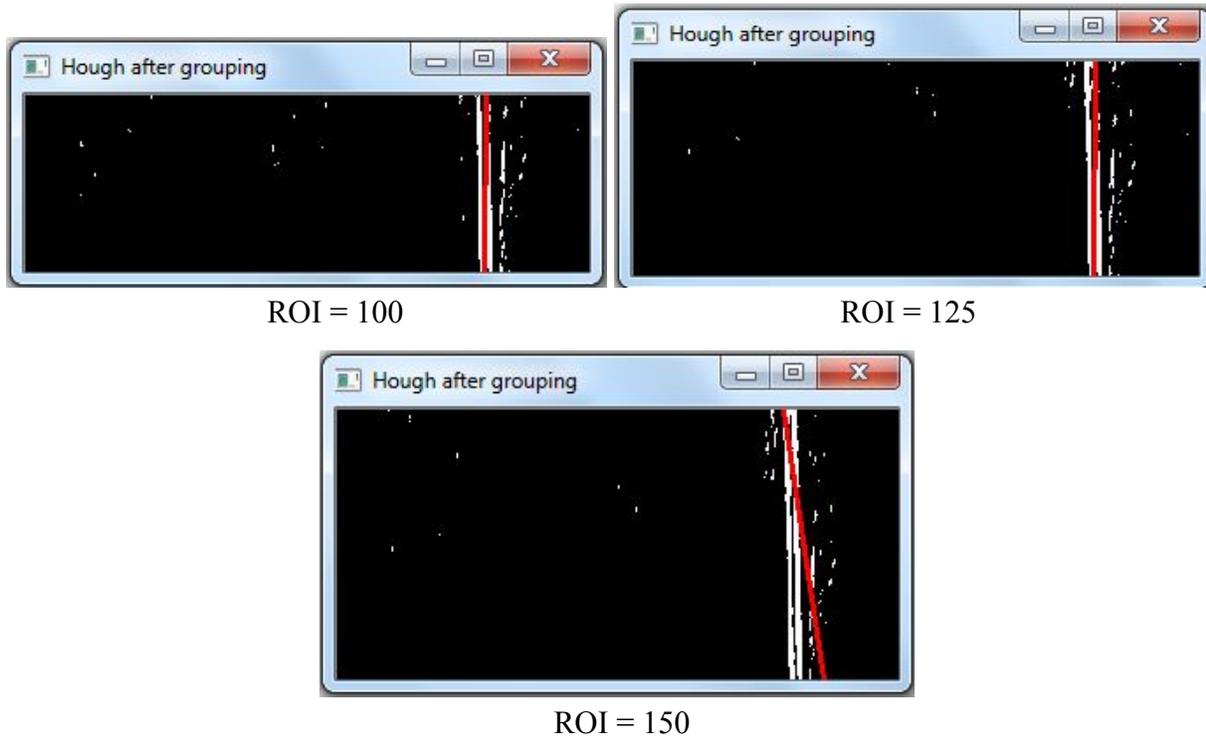


Figure 4.14: Different sizes of ROI.

Nine different road tests were conducted. Figures 4.15-4.19 show one of these nine test results on Martin Road in the westbound direction at 40 mph.

Note that each test consists of 300 pictures taken at 5 frames per second, which gives a test that lasts exactly 1 minute. The pictures from each test are then processed 5 times, with the only difference being a change in the vertical size of the ROI for the lane marker detection algorithm.

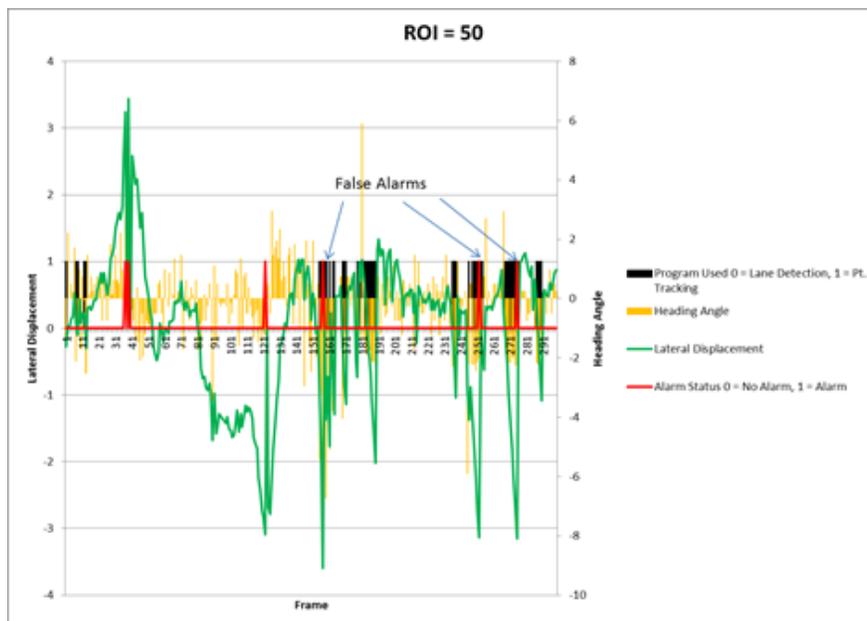


Figure 4.15: West bound on Martin Road with speed 40 mph and ROI size 50 pixels.

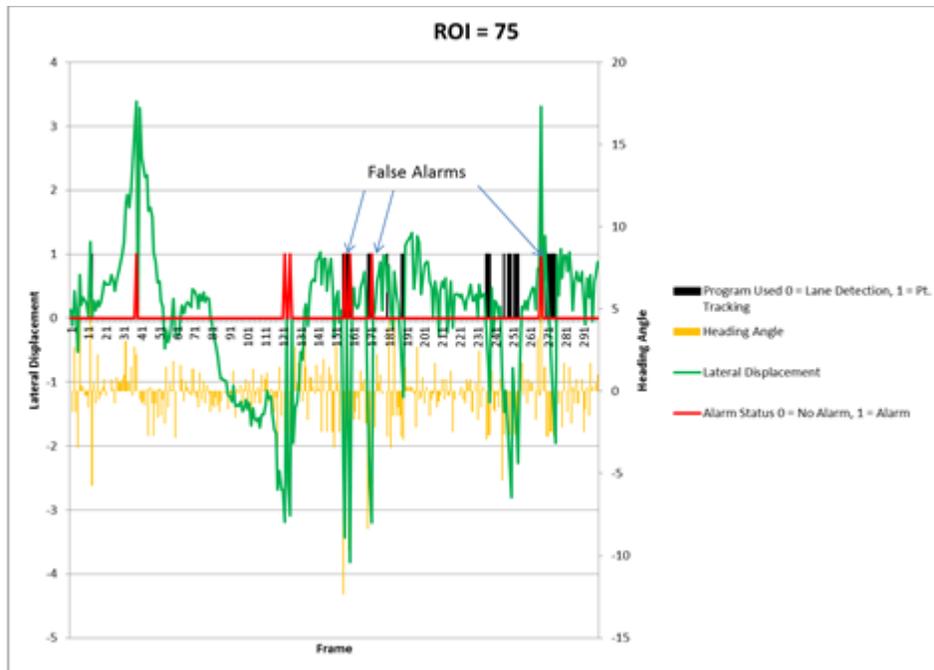


Figure 4.16: West bound on Martin Road with speed 40 mph and ROI size 75 pixels.

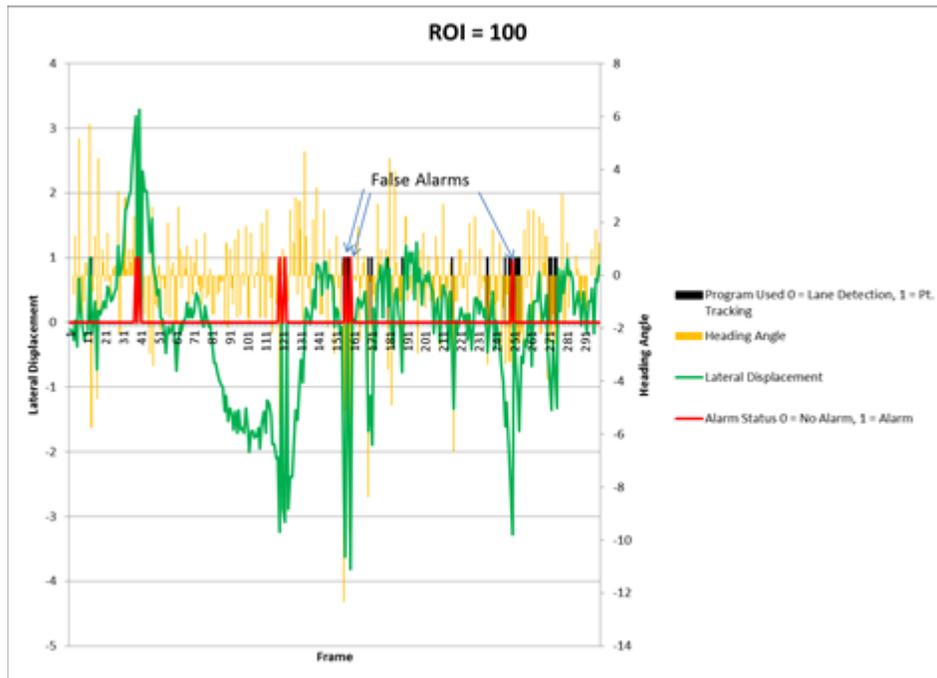


Figure 4.17: West bound on Martin Road with speed 40 mph and ROI size 100 pixels.



Figure 4.18: West bound on Martin Road with speed 40 mph and ROI size 125 pixels.

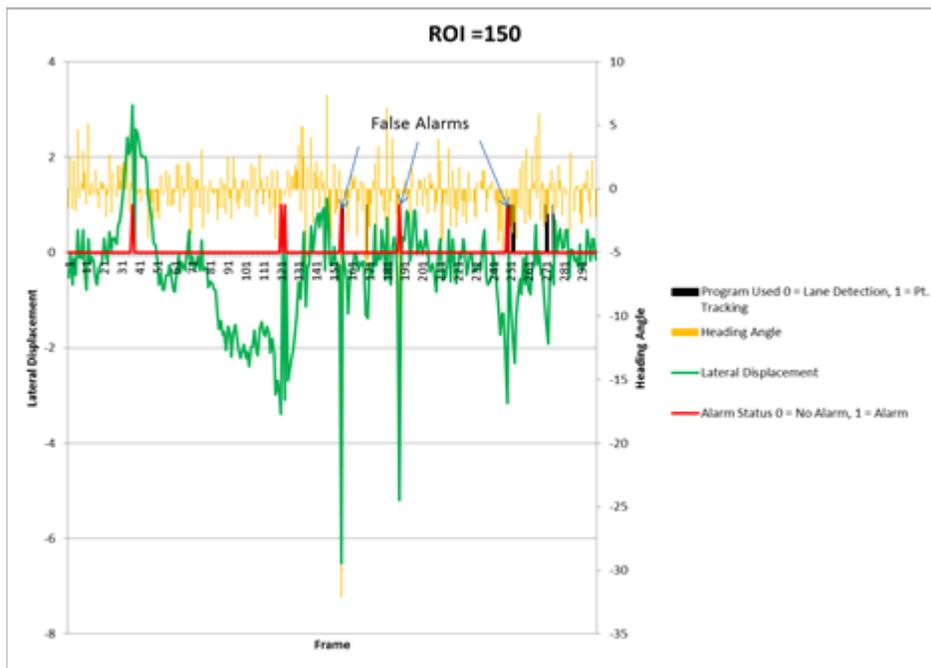


Figure 4.19: West bound on Martin Road with speed 40 mph and ROI size 125 pixels.

The nine road tests were conducted on the following roads: Arrowhead Road (west bound), Kenwood Road (north bound), Martin Road (west bound), Rice Lake Road (north bound), County Road 258W/Beyer Road (east bound), County Road 258W/Beyer Road (west bound), Rice Lake Road (south bound – case I), Rice Lake Road (south bound – case II), and Highway

53 (south bound). They are labeled as Set 30- Set 38 and the results are summarized in Tables 4.1 and 4.2.

Table 4.1: Effect of ROI size on number of false alarms - test set I

ROI Size (in pixel)	Set 30 False Alarms	Set 31 False Alarms	Set 32 False Alarms	Set 33 False Alarms	Set 34 False Alarms
50	2	1	3	1	7
75	2	1	3	0	4
100	0	1	3	0	6
125	1	1	0	0	5
150	1	1	3	0	4

Table 4.2: Effect of ROI size on number of false alarms - test set II

ROI Size (in pixel)	Set 35 False Alarms	Set 36 False Alarms	Set 37 False Alarms	Set 38 False Alarms	Total False Alarms
50	0	0	8	1	23
75	0	0	5	1	16
100	1	0	4	0	15
125	0	0	4	0	11
150	2	0	3	0	14

From these two tables, we can see that with an ROI of 50 pixels, 23 false alarms occurred. This happens probably because having such a small ROI there may not be a lane marker visible as often as when the ROI is bigger. Not having a lane marker visible causes the optical flow method with point tracking to run, which is prone to generating more false alarms.

Imagine the scenario where the only lane marker visible would be the dashed center line. The center line is less likely to show up in an ROI that is smaller than in an ROI that is bigger. However, having an ROI that is too large can also increase the amount of false alarms, note that the total number of false alarms increased when we increased the ROI from 125 pixels to 150 pixels. Having the ROI too large allows more noise to pass through the filtering, which can throw off the Hough Transform which tells the computer where the lane marker should be drawn. Increasing the ROI also increases the computation time which is undesirable.

Based on these results, we can see that having the ROI either too big or small can generate extra false alarms, and so a balance between the two extremes has to be found. With only 9 tests conducted we cannot be absolutely sure what size of the ROI would give the optimal results. However, with the tests we conducted an ROI of 125 pixels seems to give the best results.

4.4 Performance Study of Night Time Driving

In this section, we study the performance of our developed LDW system during the night time driving. An IR distance mini USB infrared web camera ELP-UC308 is used to replace the original Microsoft H5D LifeCam camera and this camera allows us to see during both night and day, The CMOS USB infrared camera has minimum illumination of 0.5 Lux with effective 0.3-3

million pixels and its IR range is 30 meters. Figure 4.20 shows a typical image taken at night with the infrared camera and its corresponding top-view image is given in Figure 4.21.



Figure 4.20: A snapshot of a front-view image using the ELP-UC 308 infrared camera.

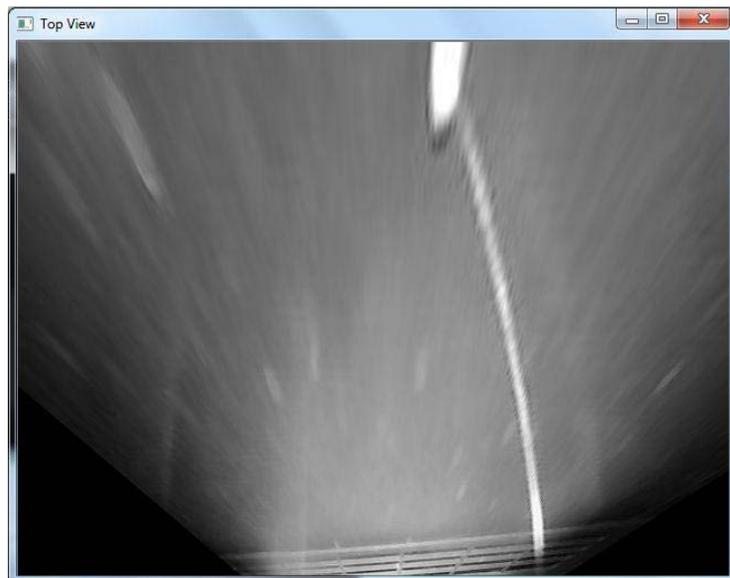


Figure 4.21: The corresponding top view image of a front view image taken at night.

Our main purpose is to examine how the system performed with these night time images, and see what, if any adjustments, must be made for night time driving. We found that the Hough-transform based lane marker detection method, which is used to find the center and outside lane markers painted on the road, seems to be running just as well during the night as it did during the day.

Figure 4.22 shows one of the test results in which the system was able to find lane markers on every frame, and so the optical flow point tracking method was not used at all. This test was done on interstate I-35 driving north at 70 mph. Notice that in Figure 4.22, no alarms were sounded. This was what we would expect because we were driving within the lane boundaries during this test and so no alarms should have been sounded. Figure 4.23 show the lane markers of the processed images from the lane marker detection method during night time driving. It is clear that the lane markers show up very nicely. Our operation algorithm doesn't have any trouble finding the lane markers and the cars distance to them. However, we found that the optical flow point tracking method does not work as well at night. For example, Figure 4.24 shows the test results on I-35 north by the exits for Cloquet, Minnesota, in which the optical flow method was used a lot.

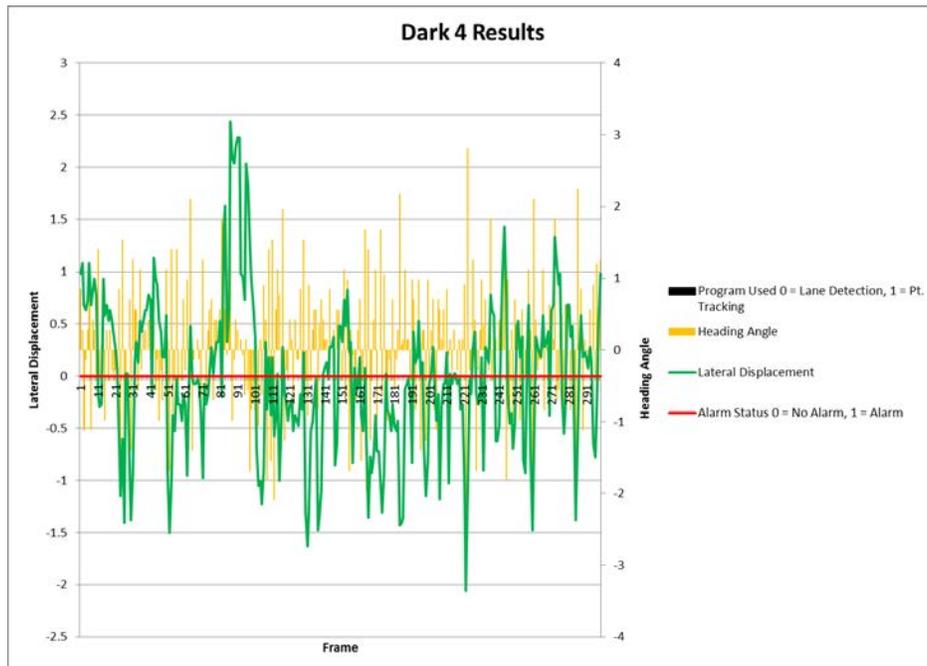


Figure 4.22: Night time driving on I-35 N with speed 70 mph.



Figure 4.23: Lane markers shown after performing the Hough transform.

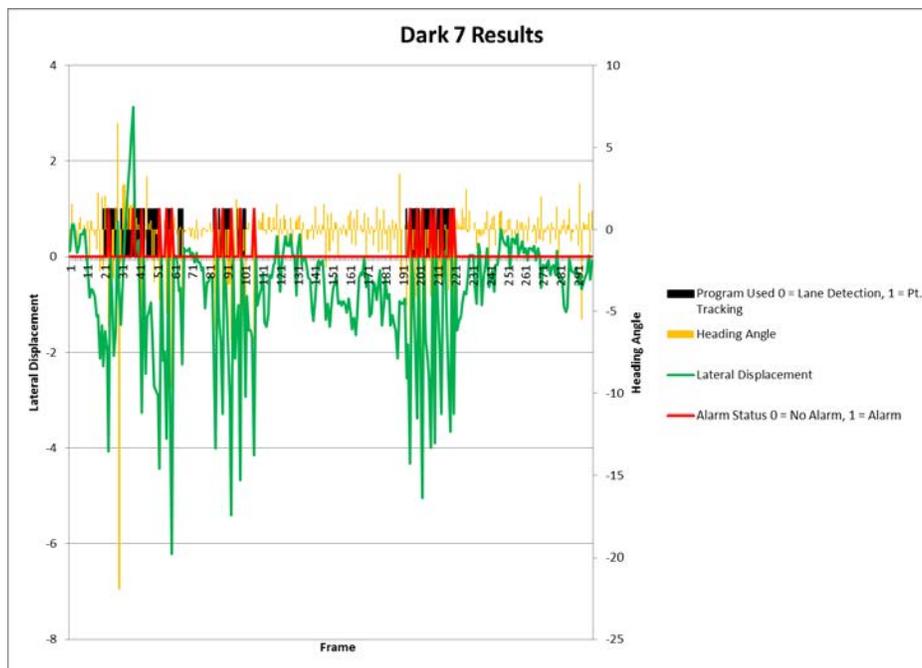


Figure 4.24: Night time driving on I-35 N close to the Cloquet exit with speed 70 mph.

In Figure 4.24, all 19 of the red spikes are false alarms and they were all generated by the optical flow method. It's hard to say exactly what is causing all of these false alarms, but one thing is for certain the points in the images are not being tracked accurately. The infrared light emitted by the camera reflects off of the windshield and for some reason shows up more when the image histogram equalization function is used and this may be the cause of all the false alarms since the bright spot covers up points that need to be tracked. However, we found that eliminating the signal processing of the image histogram equalization (to reduce the image contrast) will not

reduce false alarms. Apparently, the system works well during the night time if only the lane detection method is used.

4.5 Discussion

In this section, we will discuss the performance of our developed LDW system based on the road tests results collected. In addition, our findings and further improvement of the developed LDW system are also given.

1. Valid Warnings

We found that out of the entire data set there were 52 times when a warning should have been issued to the driver. A warning is issued if the vehicle is 3 feet from the center of the lane and moving closer to the lane boundary. The system correctly sounded a warning 48 out of the 52 times it should have been given. This means that the system correctly sounded a warning to the driver about 92% of the time.

2. False Warnings

False Warnings mean that the LDW system issued a warning when it shouldn't have. There were a total of 47 frames where false warnings were delivered to the driver out of the approximate total of 4,000 frames. The system sounded a false warning about 1.18% of the time. Out of the 47 false warnings, 35 of them were delivered when the optical flow point tracking method was used and 12 false warnings were given when the lane detection method was used. False warnings were issued by the optical flow method 74.5% of the time, and 25.5% of the false warnings were caused by the lane detection method.

3. Optical Flow Point Tracking

The L-K optical flow (or point tracking) is used when lane boundaries cannot be found on an image. It is used by tracking points from frame to frame to determine where the vehicle is located in respect to the center of the lane and in which direction the vehicle is headed. Note that as of now the point tracking method is unable to handle curvature in the road. In the system we developed, we tried to limit the amount that the point tracking method is used because it is slow computationally, and has proved to be less reliable (in the majority of cases) than the lane detection method. Out of the approximate 4,000 frames it was only used 196 times, about 4.9%. In those 196 frames in which the point tracking method was used a false warning was issued in 35 of them. This means that when the point tracking method was used it generated a false warning 17.86%.

4. Lane Detection

The lane detection method looks for the lane boundaries painted on each side of the road. If the program finds what it thinks is a lane boundary it calculates the distance to it, and compares that to a past value to determine where the vehicle is in the lane and in which direction it's headed. This method is used the majority of the time, out of the 4,000 frames it was used 3,804 times, or 95.1% of the time. Out of those 3,804 frames when the lane detection method was used a false warning was generated in 12 of them, or 0.32%. Note that both the L-K optical flow and lane

detection techniques are used in our system, but only one is active at any given time because each method has some advantages and disadvantages.

5. Discussion

The system is affected by several different factors, this includes but not limited to: quality of the road, the quality of the image read into the system, shade, reflections, and weather. In this subsection, we discuss each factor separately.

Road Quality

One of the biggest factors in the performance of the system is the quality of the road. If the road is new black top with bright consistent lane boundaries painted on the sides, the lane detection works great. There is very little noise in the image after filtering and the lane boundaries are easy to detect. If the road is very worn down with cracks, paint worn off, and light in color the lane detection program begins to struggle. The cracks can pass through the filtering and be detected as the lane boundaries (markers). If the lane boundary paint has worn off of the road it would of course be very difficult to detect. And if the road is light in color the lane detection method has trouble seeing the light colored lane boundaries. For comparison, Figure 4.25 shows how road quality can affect the lane detection method. On the left of Figure 4.25, we can see a light colored road with cracks and streaks, where the image is passed to the lane detection method it generates a lot of noise which can be seen in Figure 4.26 (left). In this case, the red line is what the program thinks is the right lane boundary and a false warning alarm is generated. For the image shown in the right side of Figure 4.25, the road looks like new. It has a nice consistent dark color and bright colored lane markers. When it is passed to the lane detection method, we can see that the boundaries show up great with hardly any noise. The red line indicates correctly the right lane boundary (marker).



Figure 4.25: Two front-view images captured by the in-vehicle camera.

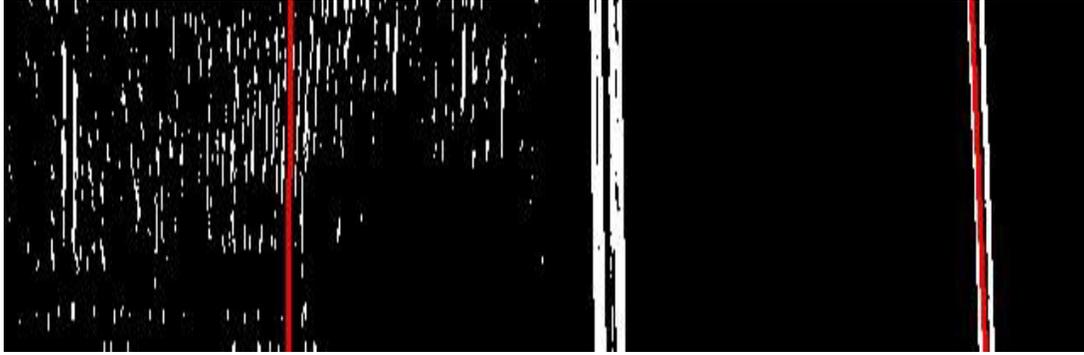


Figure 4.26: The two processed top-view images.

However, we found that the optical flow point tracking method acts in the opposite manner to the quality of the road. When the road is of poor quality with cracks and imperfections it actually has better results than if the road was smooth and consistent. This makes perfect sense because a poor road filled with imperfections offers great points to track from frame to frame, and the imperfections themselves are what can be tracked. However, on a smooth consistent road it becomes very hard to find unique features to track.

Image Quality

The quality of the image feed into the LDW system obviously affects the performance of the system. While testing we found that every now and then the camera becomes out of focus (see Figure 4.27 for example) and the image becomes blurred. This causes problems for both the lane detection method and optical flow point tracking method. In the previous section, we mentioned that the optical flow point tracking method was responsible for 35 false warnings. This isn't entirely true because some of the false warnings were actually due to the camera being out of focus. They are listed as being caused by the optical flow method because this is the last resort of the system. That is, the lane detection method is unable to find lane boundaries in this blurred image and so passes it to the optical flow method. However, since the image is blurred it causes the optical flow method to give poor results and can result in a false warning. Blurred images caused 9 false warnings.

Shade

This rarely causes problems but in some instances where the shade is very dark such as an overpass, it can cause the system to issue a false warning. If the shade is dark enough where the lane boundaries cannot be found, it passes the image to the optical flow point tracking method which struggles to correctly find and track points in the dark. Also the change in brightness when going from dark to light and vice versa can cause the camera to become out of focus. Figure 4.28 is an example of how the lane detection method struggles while the test vehicle going under an overpass. Figure 4.29 shows the output from the lane detection method and clearly the input image is too dark to find anything useful.



Figure 4.27: A front-view image captured by an out of focus camera.



Figure 4.28: A front-view image taken while the vehicle is moving under an overpass.

Reflections

Since the camera is located inside the vehicle, it has to look out through the windshield. If there are reflections in the windshield they will appear on the images the camera gives to the system. It is possible for the system to think that a reflection in the windshield is the lane boundary or for the system to track points of the reflection, both of which would be detrimental to the operation of the system. Actually even any debris on the windshield could cause the system to operate improperly. Reflections mainly depend on how bright it is, what time of day it is, and which direction the vehicle is traveling.

Here are a few other notes on the systems performance at night. Debris on the windshield really shows up on night time images. The infrared light brightens up the debris which shows up in the images. This definitely can affect the systems performance. Depending on the shape of the debris the system may think that it is a lane marker. As for the point tracking method, if the debris is there frame after frame the system thinks that those points aren't moving anywhere and it can throw off the heading angle Figure 4.20 calculation.

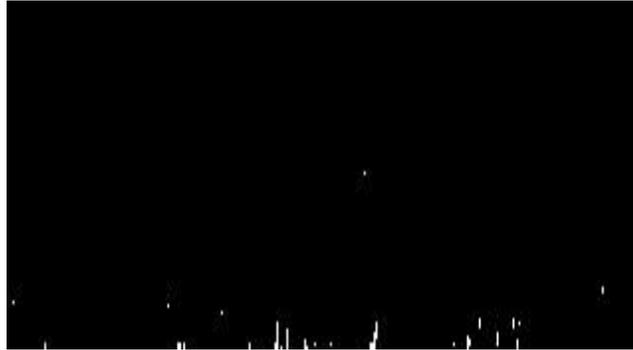


Figure 4.29: The processed image.

Weather

The performance of the LDW system can be affected by the weather outside. For example, the system cannot operate in the rain. With rain drops, and windshield wipers constantly moving across the windshield neither the lane detection nor the optical flow point tracking method will be able to work properly. The system seems to work best when the sky is slightly overcast, this situation reduces shadows, reflections, and brightness (which can cause problems with the camera).

Overall, for the most part the system operates correctly, we would just like to further improve the valid warnings percentage and further reduce the false warnings produced. Some ways the system could be improved include: tweak the filtering so that road quality is less of an issue, develop a way for the optical flow point tracking method to handle road curvature (possibly using a vanishing point technique), enhance the speed and precision of the point tracking method, try using a polarized lens in front of the camera to reduce reflections, glare, and brightness. Keep in mind that the data from all tests does not fully represent all possible conditions, much more testing has to be done to verify the operation of the system.

Chapter 5. Conclusion

The use of rumble strips on roads has proven to be an effective means of providing drivers lane departure warning (LDW). However, rumble strips require an infrastructure and do not exist on a majority of roadways. Development of various techniques such as LDW systems can improve traffic safety significantly. General working principle of camera-based systems is to track lane markers on the road to see if the vehicle is straying outside the lane. But there is no guarantee that the lane markers will always be present on the road. Various environmental factors such as rain and heat might wear out the lane markings. The presence of snow on the road might affect the visibility of road marking. Hence, a system is desired that makes use of lane markings when they are available, but can also work when lane markings become invisible for a short period of time.

This report presents an image-based LDW system with minimum knowledge of lane markers needed, and, in addition, it doesn't rely on the vehicle GPS position information. The system takes a mixed approach by using the L-K optical flow method and the Hough transform-based lane detection method in its implementation. L-K point tracking is used when the lane boundaries cannot be found, while the lane detection technique is used when they become available. Even though both the L-K optical flow and lane detection techniques are used in our system, only one method is activated at any given time because each technique has its own advantages and disadvantages. An operation algorithm via the mixed techniques is implemented with some detailed explanation. Based on the implemented hardware/software system, we conducted extensive road tests on I-35, US-53, Rice Lake Road, Martin Road, and Jean Duluth Road. These roads varied in speed limit, curvature, amount of traffic, number of lanes, and road construction, which gives a richer diversity in the data. The road test results are presented. Overall, for the most part, our system operates correctly as expected with a false alarm occurring only about 1.18% of the operation time. Various factors that could affect the system performance are also discussed. Since our approach only needs the minimal set of information to characterize the vehicle lateral characteristics, this makes it more feasible in a vehicle application.

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