Map Based Localization to Assist Commercial Fleet Operations

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MAP-BASED LANE DETECTION AND DRIVER ASSIST - A FINAL PROJECT REPORT TO VOLVO COMMERCIAL TRUCKING

Project Sponsored by
Volvo Group
7825 National Service Road
Greenzboro, NC 27409

FINAL REPORT

August 31, 2014

Report Number LTI 2015-14

PENNSTATE

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Mechanical Testing Certificate 3172.01
Quality Approval:

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Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
PSU-2013-08		

4. Title and Subtitle	5. Report Date
Map-based Lane Detection and Driver Assist - A Final Project Report to Volvo Commercial Trucking	August 15, 2014
	6. Performing Organization Code
7. Author(s)	**8. Performing Organization Report**
Alexander Brown, Bobby Leary, David Corbin, and Sean Brennan	LTI 2015-14
9. Performing Organization Name and Address	**10. Work Unit No. (TRAIS)**
The Thomas D. Larson Pennsylvania Transportation Institute The Pennsylvania State University 201 Transportation Research Building University Park, PA, 16802-4710	**11. Contract or Grant No.** SRA 151518
12. Sponsoring Agency Name and Address	**13. Type of Report and Period Covered**
Volvo Group 7825 National Service Road Greensboro, NC 27409 US Department of Transportation Research & Innovative Technology Administration UTC Program, RDT-30 1200 New Jersey Ave., SE Washington, DC 20590	Final Report 5/15/2013 - 8/15/2014 **14. Sponsoring Agency Code**

15. Supplementary Notes

16. Abstract

This report outlines key recent contributions to the state of the art in lane detection, lane departure warning, and map-based sensor fusion algorithms. These key studies are used as a basis for a discussion about the limitations of systems that do not take advantage of map information, and outlines ways in which current map-based technologies can be improved. Finally, the methodology proposed for the development of a lane departure warning system that tightly integrates map, inertial, and vision sensors is described, followed by a rough outline of project timeline and scope.

17. Key Words	18. Distribution Statement
Lane detection, lane departure warning, sensors, map-based technologies, map-aided perception, roadside obstacle, data fusion	No restrictions. This document is available from the National Technical Information Service, Springfield, VA 22161

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	23	

Form DOT F 1700.7 **(8-72)** **Reproduction of completed page authorized**

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Alexander Brown, Bobby Leary, David Corbin, Sean Brennan

May 2014

Abstract

This report outlines key recent contributions to the state of the art in lane detection, lane departure warning, and map-based sensor fusion algorithms. These key studies are used as a basis for a discussion about the limitations of systems that do not take advantage of map information, and outlines ways in which current map-based technologies can be improved. Finally, the methodology proposed for the development of a lane departure warning system that tightly integrates map, inertial, and vision sensors is described, followed by a rough outline of project timeline and scope.

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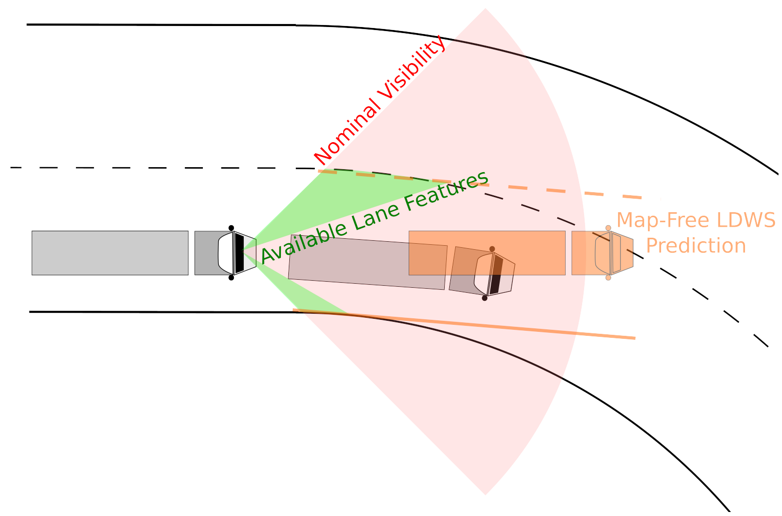

Figure 1: Potential response of a map-less lane departure warning algorithm to an occluded scene

1 Introduction

Living organisms do not rely solely on feedback control architectures when ambulating, grasping, driving, or performing other control and perception tasks. In general, this is a consequence of the fact that biological systems are capable of learning, or storing information about their environment for recall at a later time. The cognitive psychology community maintains that biological systems use heirarchical maps for navigation [7]. Even in relatively simple limb movement tasks, data suggest that humans generally rely on both feedforward and feedback for controlling their own motion [8], which implies that maps, or reservoirs of stored information collected via past experience, are useful in motion planning and control.

Unfortunately, although feedforward and preview-based control methods, bearing very close mathematical resemblance to explicit map-based control methods, have been in widespread use in the autonomous vehicles community for decades [9, 10, 11, 12, 13, 14] and have been studied as approximations of human driver behavior [15, 16], analogs in perception warning systems have only surfaced en masse in the last 10 years. Even today, a typical lane departure warning system available on a passenger car may deal with an occluded scene, as shown in Figure 1. Because the system has no stored information about the upcoming road geometry, or the vehicle's position within the environment outside of its immediate perceptible area, the algorithm would not alert the driver of the vehicle, even if the current state and input sequence could result in an imminent lane departure. But the algorithm's job is to "beat" an impaired human pilot, whether said impairment is a result of drowsiness, or environmental factors like reduced visibility. However, it is likely that an attentive human could use contextual and experiential clues not accessible to the lane departure warning system to avoid a lane departure (or the threat of one). This is the key advantage of the tight integration of maps, or learned information, into perception and warning systems for vehicles. By requiring more of past experience, algorithms can rely less and less on perfect operating conditions, expensive sensor suites, and computationally intensive filtering and data preprocessing steps. To realistically attack the task of designing a lane-keeping system that outperforms its human copilot in even the most dubious driving environments, the algorithms have to lean on mapped information to "fill in holes" caused by perception faults and unpredictable environments.

Based on scoping discussions with Volvo personnel, the current project scope encompasses the following for a map-based lane keeping assistance system:

1. Demonstrate camera and lane marking and map combination

2. Demonstrate IMU/longitudinal position improvements for localization

3. Demonstrate augmented display in vehicle

4. Demonstrate auditory or Haptic Warning

5. Demonstrate autonomous "takeover" for correcting imminent lane departure

To address each of these desired deliverables without repeating prior or parallel work, and to ensure the project's commercial and academic relevance, the following pages outline the current state of the art in perceiving a vehicle's driving environment by measuring road shape (lane detection), warning a driver of impending lane departure (lane departure warning systems), and integrating mapped information into vehicle state and environment estimation. This discussion is followed by an outline of the map integration tools intended to push lane departure warning systems for Volvo tractor trailers to the cutting edge of robustness and reliability.

2 Prior Work in Lane Detection and Lane Departure Warning Systems

While it is true that maps have gained popularity for localization and state estimation tasks, commercial lane departure warning systems and current lane detection strategies rarely make use of mapped information to increase robustness to occlusions, changing light and weather conditions, sensor dropouts, or other adverse circumstances. The following sections identify some key trends in the areas of lane detection and lane departure warning and make the case for improving the state of the art using maps.

2.1 Lane Detection

The following section outlines common approaches for lane detection used in current research, including the coordinate domains used for point correspondence between the world and the image, standard image processing techniques for lane detection, and commonly used camera specifications. Figure 2 shows a potential scenario where standard lane detectors may perceive a road on the back of the truck, but the use of a map would provide context to the detected lanes.

Figure 2: Example of how vision without context can be misconstrued
Source: http : //www.blogcdn.com/www.switched.com/media/2009/12/switched_truck.jpg

2.1.1 Coordinate Domains

There are three standard coordinate domains often used in image-based lane detection: 3D, 2D with respect to the global frame, and 2D with respect to the imaging plane. Three-dimensional coordinates rely on either stereoscopic vision [17, 18] or monocular-based Simultaneous Localization and Mapping (SLAM) [19, 20, 21]. These methods require the detection and temporal tracking of defined features such as edges and corners throughout multiple image frames to recover 3D features. The second approach, 2D with respect to the global frame, uses an algorithm named Inverse Perspective Mapping, which transforms the camera perspective to a bird's eye view of the road [22, 23, 1, 24, 17, 25]. Figure 3 depicts the inverse perspective mapping of a road scene. The benefit to using this method is that lane features become a constant width, but this is dependent on a planar road. The inverse perspective method is computationally expensive, as the entire image must undergo the perspective transformation, and therefore does not provide any true gain for lane detection. Within an image, there is a small subset of pixels that provide useful information for lane detection. Therefore, the third approach, 2D with respect to the imaging plane, leaves the camera perspective intact where features approach a common vanishing point. This is how standard cameras perceive the world and do not require any extra processing.

Figure 3: An example of an inverse perspective transform of a road scene. [1]

2.1.2 Detection Algorithms

Lanes within an image are represented by straight and/or curved lines. There are various detection methods, including the Hough Transform, Thresholding, Adaptive Thresholding, and convolution methods using image kernels. As seen in Figure 4, the Hough Transform is primarily useful for detecting straight lines within an image, as lane curvature consists of many stitched lines [26, 27, 28, 2, 4].

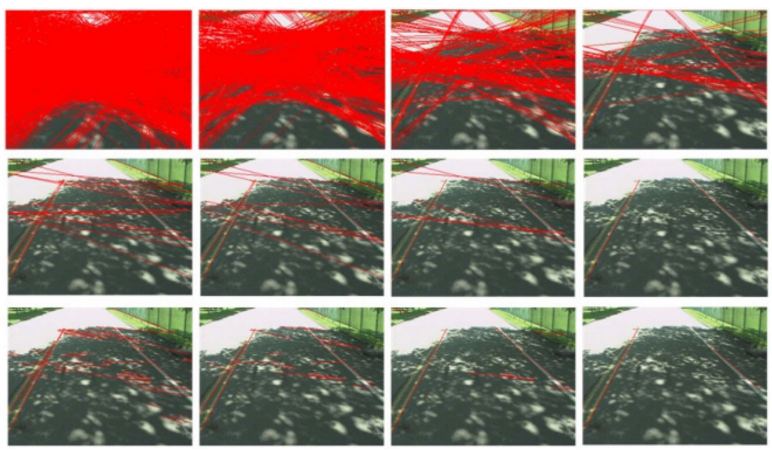

Figure 4: The results and down selection of a Hough Transform used for finding straight lines within the image. [2]

Another common lane detection algorithm is image thresholding [3, 24, 29, 27]. Thresholds remove all pixel intensities that are greater or less than a specific threshold value. Figure 5 shows the results of a basic binary threshold. The parameters for an image threshold must be fine tuned and change with different lighting conditions.

Lane markers, when compared to the surrounding road, create sharp edges within the image. It is a common task in image processing to determine edges using algorithms such as a Canny/Sobel filter [26, 30, 3], median filter [31], or kernel-based methods [23, 4, 32, 33]. Figure 6 shows an example of a kernel-based lane detector using a second derivative Gaussian filter scaled to the size of a standard lane marker width.

2.1.3 Robustness and Tuning

One of the key issues with the lane detection methods outlined above is robustness. Many papers list positive results with very low failure rates, but most fail to provide examples of when their algorithm fails, and nearly all tests were completed in perfect lighting and weather conditions. What is considered successful? What is an acceptable error between the detected and true position of the lane? One way to improve the robustness of the detection process is to determine the signal-to-noise ratio between the detected lane center and the surrounding intensity noise. A second method is the ratio of the detected lane center and the secondary peak. Combined, these methods help to quantify the confidence in the lane detection.

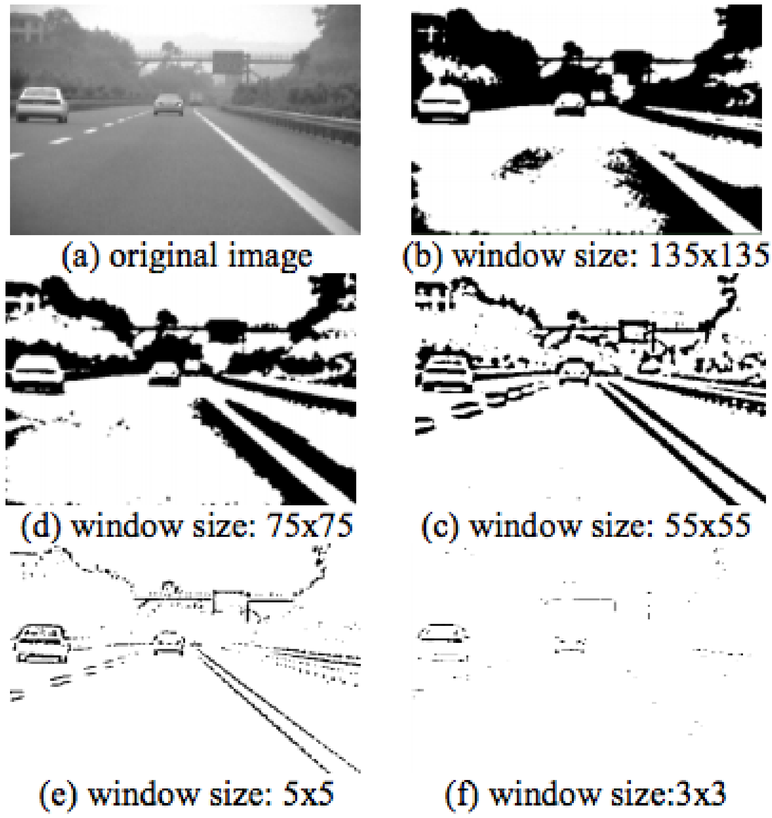

Figure 5: An example of adaptive thresholding using various window sizes. [3]

2.1.4 Camera Specifications

The most common camera specifications used in lane detection research are a resolution of 640x480 pixels, color images (converted to grayscale), and 8-bit images.

2.1.5 Commercial Implementations

Current commercial systems use monocular vision systems for algorithmic lane line detection. Some currently employed manufacturers are GM, BMW, Volvo, Infinity, Nissan, Kia, and Mazda. Mobileye ®, launched its LDWS within GM, BMW, and Volvo. The firm's success with driver assistance systems, however, is confined to optical sensors with motion detection algorithms. Commercial systems have yet to see map-based localization used as a supplement to lane detection and driver assist.

2.2 Lane Departure Warning Systems

Although it is generally considered mundane, maintaining a lane is a deceptively difficult task – particularly for sleepy or panicked drivers. Despite its apparent monotony, its importance for safe driving cannot be overstated. Lane-keeping is a delicate balance between perception and action, and under many common driving scenarios, perceiving a vehicle's state vector, along with that of the lane that bounds its acceptable trajectory, is extraordinarily difficult for a human, not to mention for an active safety system. In snow, fog, heavy rain, and very sunny conditions, a human pilot or its robotic assistant can lose the ability to track the vehicle's trajectory within the lane.

Despite the fact that humans are generally able to perceive their environment and ego-states handily, drowsiness or other adverse circumstances can cause problems for even the most experienced drivers. This has motivated the development of the Lane Departure Warning System (LDWS). An LDWS alerts the driver to take preventative measures when lane departure is imminent. Under normal driving conditions, lane geometries relative to the vehicle are determined geometrically, as seen in [34] and [35]. These, however, observe an established set of assumptions: "(1) Lane marks are painted in a brighter color than other parts, (2) the orientation of lane marks changes are small and smooth along the lane, and (3) lane marks are parallel to left and right from the center of the lane" [35]. These

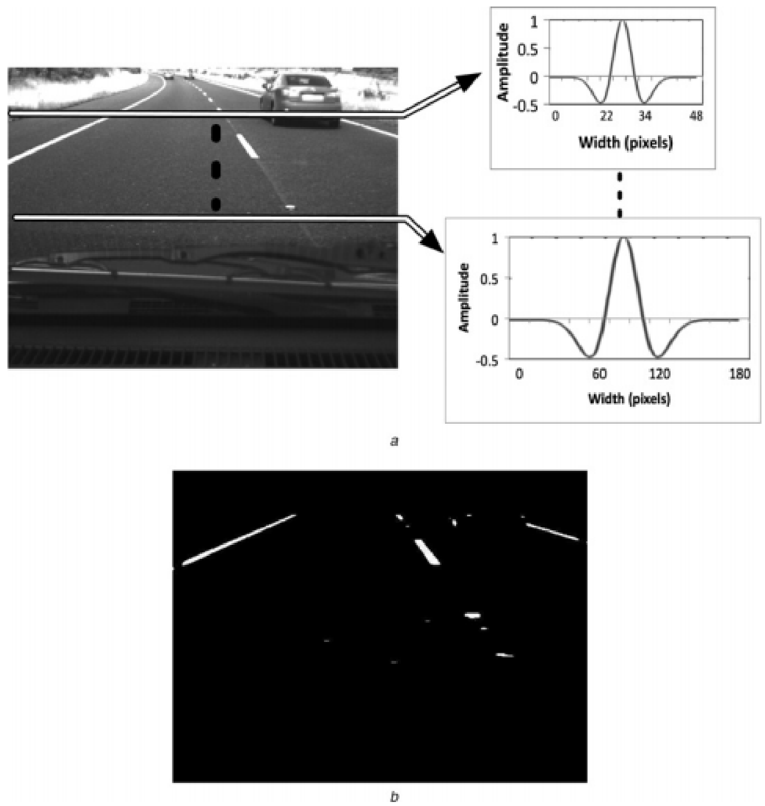

Figure 6: An example of using a kernel-based lane detector. This example uses a second-derivative Gaussian filter scaled to match the width of a standard lane marker. [4]

assumptions limit the efficacy of LDWS in typical driving situations (i.e., curved roads, occluded lane lines, faded lane lines, etc.).

2.2.1 Warning Basis

A simple method for warning drivers of impending lane departure relies on a set lateral position deviation threshold [34]. However, many drivers often drive with a fixed offset from the center of the lane. A more robust method of triggering Lane Departure Warning is use of an algorithm based off the vehicle's lateral position and lateral velocity [36]. Such algorithms utilize a Time-to-Line-Crossing (TLC) metric [37]. Unfortunately, lateral velocity is not easily observed and is invalid when lateral velocity varies [38]. A more robust method for computing TLC utilizes Distance-to-Line-Crossing (DLC) [39], so that

$$TLC = \frac{DLC}{u} \text{ for } u > 0, \text{ else } TLC = \infty \tag{1}$$

where u is the vehicle forward speed [5].

DLC is calculated differently depending on whether the lane is straight or curved (Figures 7 and 8). As observed in the figures, if DLC runs parallel to the lane lines, DLC goes to infinity. Thus, so does TLC. In either calculation, DLC is a function of geometric quantities (i.e., radius of curve, perpendicular distance to lane marker, etc.) and current vehicle states (e.g., steering angle, forward velocity, lateral velocity). Obviously, including a map could make the calculation of TLC much simpler because all road geometries are known, and the system cannot fall victim to the scenario shown in 1, as long as the algorithm is able to localize the vehicle on the map.

Use of TLC metrics, as opposed to strict lateral velocity thresholding, limits the frequency of false alarms that may trigger during a recovery to the lane center following a slow lateral drift to the lane edge.

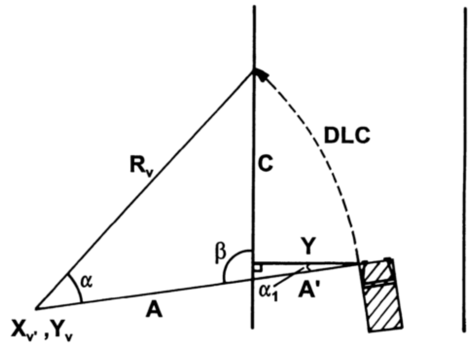

Figure 7: DLC on a straight road [5]

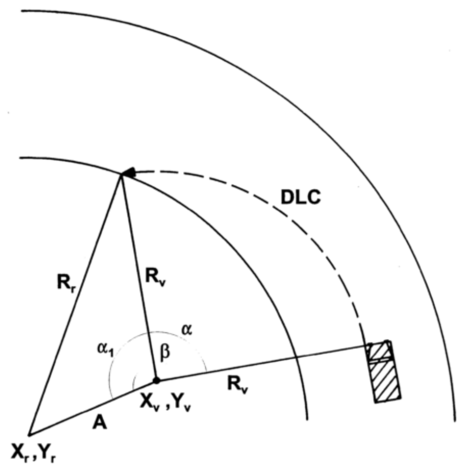

Figure 8: DLC within a curve [5]

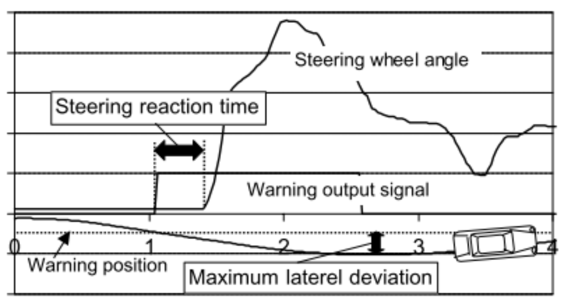

Figure 9: Example of lateral deviation resulting in steering angle [6]

3 Key Strengths in Map-Aided Perception

While the preceding sections outlined the state of the art in lane departure warning and lane detection strategies, and summarized key recent contributions in the field, the use of maps has gotten more and more popular in recent years. Many of the studies in map-aided vehicle technology use lasers [40] or vision systems [41, 42, 43] in combination with precision maps to achieve highly accurate 2D or 3D vehicle pose estimates. These methods are almost universally very computationally intensive, and many rely on features that may or may not be available in all driving scenarios. If the algorithm cannot find visual features, it cannot match them with a mapped database.

Recent work by the authors at Penn State has shown that a low-dimensional map of road pitch can be used to obtain longitudinal (1D) position estimates with a high degree of accuracy without GPS or any other sensors [44, 45, 46]. In a parallel vein of research, Gupta and Brennan explored the use of a camera in conjunction with a GPS, IMU, and map to obtain 3D pose estimates of an arbitrary vehicle [47]. More recently, Brown and Brennan showed that a 3D map of road lane features could be used in combination with a longitudinal position estimate, a vision system, and a yaw rate gyro to obtain highly accurate vehicle state and road geometry estimates without the computational complexity of competitive map-based vision systems [48].

However, the use of maps specifically for an LDWS application is decidedly scarcer. Bevly et al. [49] developed a map-based positioning system for an LDWS. They employed a high-accuracy map for locally positioning the vehicle in a lane, using a map to turn a global GPS position measurement into a local position measurement, and then estimating GPS bias with an Extended Kalman Filter (EKF). This work allowed for a high level of robustness against GPS dropouts, and the fusion of GPS and inertial measurements with relative position estimates from a camera-based lane measurement system proved effective in estimating vehicle states. However, the algorithm's use of a map of lane features could have been more complete. The lane measurement system provided a measurement of vehicle lateral position to the Kalman Filter, but the lane geometry itself was not considered as a candidate for estimation.

It is important to point out that lane geometry itself is just as important to estimate accurately as a vehicle's position within the lane when the goal is to predict when a vehicle will cross a lane boundary in the future. This is a concept that has not been adequately explored in the literature. For instance, in [49], the lane measurement step did not benefit implicitly or otherwise from the inclusion of mapped data, so while the method proved robust in lateral position estimation to dropouts from either GPS or camera measurements, it did not make complete use of mapped information to improve both the vehicle's position estimate and its estimate of the environment around it. Finally, the methodology in [49] relied exclusively on GPS measurements to achieve map registration, and GPS was the only connection the algorithm had to the map. In other words, if GPS were absent for a significant period of time, the algorithm could no longer benefit from mapped information.

Therefore, in deference to the limitations of current lane detection and lane departure warning systems when faced with limited visibility due to occlusion, road geometry considerations (such as blind hills or turns), or weather, this project aims to use mapped road geometry and meta-data to improve the robustness of an integrated vehicle state estimator, lane detector, and lane-departure warning system. The proposed methodology will show significant benefits over the current state-of-the-art in these specialized circumstances and allow for the use of the system in a wide range of operating conditions.

While passenger car LDWS systems may not benefit in a large majority of circumstances from the inclusion of map information, tractor trailers can. Tractor trailers require a greater amount of look-ahead or preview than passenger cars, because they typically operate closer to the edge of the performance envelope, especially on steep grades and through geometrically complex road features like switchbacks and sweeping turns. To set the stage for the project work to follow, the following sections will outline some key strategies that will be employed in the final map-aided lane departure warning system to ensure that the system reaps the largest possible benefit from the inclusion of map data.

3.1 Mapping Process and Map Content

In the preceding sections, references to "the map" have been purposefully vague. The exact definition of what does and does not constitute mapped information is fluid and inexact. Map data can be structured in a typical geometric fashion, where a "map" provides information about the three-dimensional location of discrete features of interest. However, map information can also include statistical information about past traversals of a piece of road by other drivers, or lighting quality, or other special considerations or context an algorithm may need for success. In general, however, the map is comprised of a set of three-dimensional features generated using a combination of a defense-grade real-time kinematic (RTK) differential GPS paired with a Honeywell HG1700 ring laser gyroscope and a downward-facing Light Distance and Ranging (LIDAR) sensor. A typical mapping vehicle as instrumented and calibrated by the research team is shown in Figure 10. This setup, with the inertial navigation system positioned directly above the LIDAR scanner, allows for quick, accurate coordinate transformations from LIDAR coordinates to global measurements. These can be compiled in their most dense form as point clouds with intensity data as shown in Figure 11. In addition, the data can be downsampled if all points are not needed by an algorithm, leaving only features of interest, like road geometry (grade and bank angles) or lane stripe locations (extracted from LIDAR intensity data). The algorithms developed by the research team for past projects generally use very compact representations of the raw map data shown in Figure 11 to reduce data throughput and computational horsepower requirements, although some prior work in map-based vehicle tracking uses maps with data densities approaching those of the raw LIDAR point clouds [40].

Figure 10: Vehicle equipped with downward facing LIDAR.

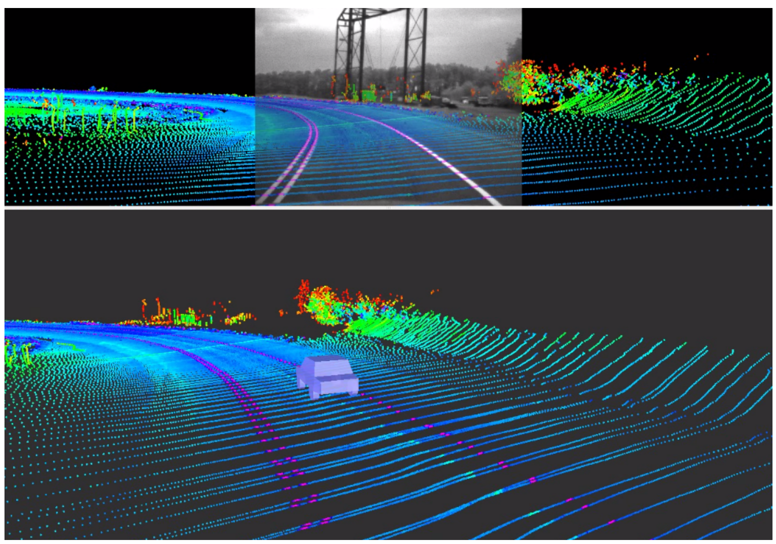

Figure 11: Maps generated can be as dense as necessary.

3.2 Map-Aided Lane Detection

Current methods for lane detection assume that the camera provides a full and accurate representation of the local environment. This assumption deteriorates as the information within the image is occluded by weather, such as rain, fog, and direct sunlight, vehicles, or changes in terrain. The use of a map is particularly useful in not only the prediction step of where the lane features exist, but also provides robustness by recovering occluded features otherwise unknown to the raw camera image.

The proposed method for lane extraction fuses the camera and map data, as outlined in Figure 13. The camera provides a two-dimensional representation of the world, and the map provides the vertical elevation in terrain relative to the car, allowing for full three-dimensional point projections. This removes the common assumption that the road ahead of the vehicle is flat. From the point projections, image kernels are created on the a priori knowledge of the size of lane features relative to the vehicle. The use of terrain data allows for the width of the image kernels to be adjusted for inclined roads. In parallel, multiple kernels of the lane features are used to detect the lane center, searching for features such as a double yellow lane stripe, a single white lane stripe, and a combined full lane feature profile of the double yellow and white lane stripe, and the space between them. When convolved with a row of the image, each kernel produces a correlation profile with a maximum peak at the expected center of the lane. Each kernel provides an input into a voting algorithm to verify the lane center. The location of highest correlation is the center of the lane. Figure 12 depicts the correlation profiles for a particular row in the image.

The benefit to using an image kernel approach is that it removes the variability that occurs in basic image thresholding and edge detection. Where methods such as edge detectors or basic thresholding require specific

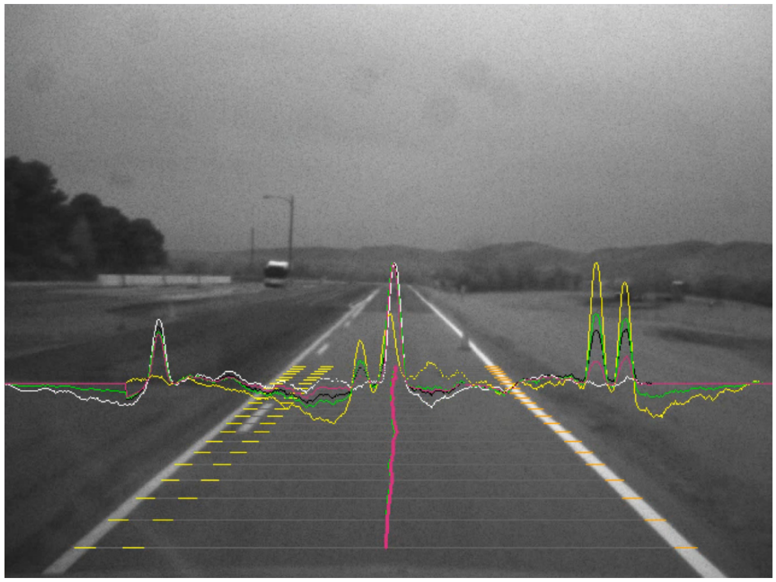

Figure 12: Correlation profiles using image kernels for double yellow lane stripes, single white lane stripe, and full lane. The lane center is determined through a voting algorithm of the correlation profiles.

parameters for various lighting and environmental situations, the image kernels work on the basis of real-world measurements: the size of the lane markers.

3.3 Data Fusion Methodology

Previous work by the authors [48] aimed to fuse a lane detector with odometric and inertial sensors in combination of a 3D map of lane features using a simple, linear Kalman Filter. This work used the concept of temporal preview to assemble an augmented state vector for estimation that includes not only the vehicle's states, but also the locations of the lane markers relative to the vehicle. In a sense, this methodology uses concepts similar to SLAM algorithms, but with far less computational complexity. This framework allows for lateral velocity and yaw rate estimates to help improve lane geometry estimates even when lanes are not visible, and allows each available measured lane feature to improve vehicle state estimate quality. However, this methodology requires a good vehicle model. Because tractor-trailers' parameters change widely, a model-free approach that maintains the above framework's simplicity was developed. The approach is based on the use of a breadcrumb map of lane center geometry referenced to a particular *longitudinal* road position. This is shown in Figure 15.

The Volvo truck is equipped with a camera system that's measuring the coordinates of the road center relative to the vehicle at discrete points ahead using the lane detection algorithm in 3.2, as shown in Figure 15. Each of these points has a coordinate y_j relative to the vehicle-fixed x, y coordinate system. The x_r, y_r coordinate system is attached to the road tangent at the closest point to the vehicle's CG, and the X, Y coordinate system is fixed (East,North). y_v is the lateral offset of the vehicle, which is unknown along with relative yaw angle between the vehicle and the road tangent, ψ_v.

It is important to note that the camera measures geometry for which a map already exists. This map is easy to pull down from data servers if we know where the vehicle is *along* the path. This call to the map database tells the algorithm where the points representing the road center are expected to be relative to the coordinate system x_r, y_r. Any local camera measurement $[x_j, y_j]$ can be expressed in terms of the expected location of the point $x_{r,j}, y_{r,j}$ as:

$$\begin{bmatrix} x_j \\ y_j \end{bmatrix} = \begin{bmatrix} \cos\psi_{rel} & \sin\psi_{rel} \\ -\sin\psi_{rel} & \cos\psi_{rel} \end{bmatrix} \begin{bmatrix} x_{r,j} \\ y_{r,j} - y_v \end{bmatrix} \tag{2}$$

Assuming small angles, Equation 2 can be linearized, yielding Equation 3.

$$y_j = -x_{r,j}\psi_{rel} + y_{r,j} - y_v \tag{3}$$

Then, individual measurements x_j, y_j can be stacked into matrix form.

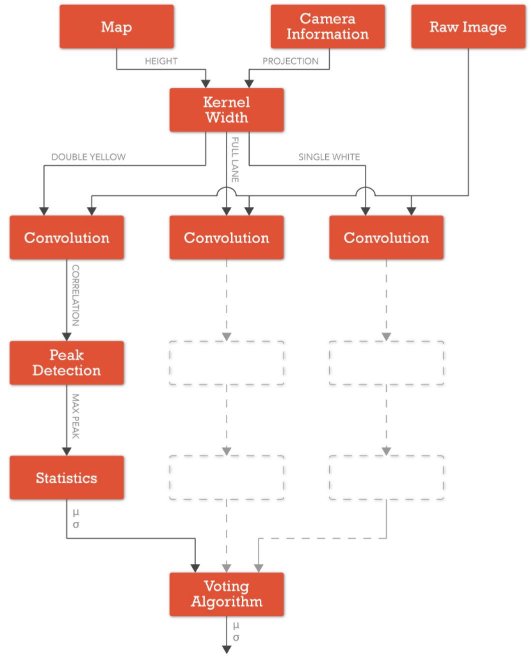

Figure 13: Map-aided lane measurement algorithm

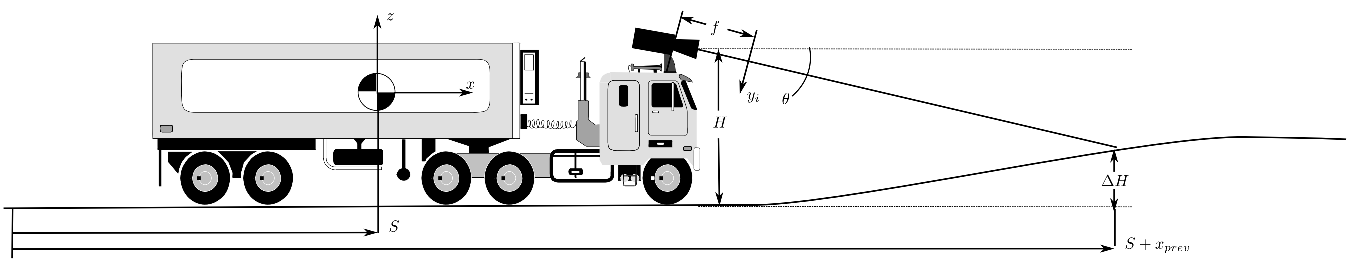

Figure 14: Map-aided transformation from physical to image coordinates for improved lane measurement

$$\underbrace{\begin{bmatrix} y_{r,1} - y_1 \\ y_{r,2} - y_2 \\ \vdots \\ y_{r,N} - y_N \end{bmatrix}}_{\vec{y}} = \underbrace{\begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_N \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} y_v \\ \psi_{rel} \end{bmatrix}}_{\vec{x}} \tag{4}$$

Then, it is simple to recognize that Equation 4 can be solved as a simple linear least-squares estimation problem and find that:

$$\vec{x} = (A^T A)^{-1} A^T \vec{y} \tag{5}$$

Once measurements of y_v, ψ_v are obtained using the least-squares estimator, these estimates could be sent through a kinematic Kalman Filter for temporal smoothing, but in the initial implementation outlined here, were used by themselves to obtain a very fast estimate of the vehicle's lateral alignment with the road map.

3.3.1 Lane Departure Warning Strategy

The preceding review of lane departure warning systems indicated that on an algorithmic level, there is only very sparse literature suggesting the use of mapped geometry and other meta-information to trigger lane departure warnings. Adding the use of mapped geometry to a map-based perception system, and augmenting this perception

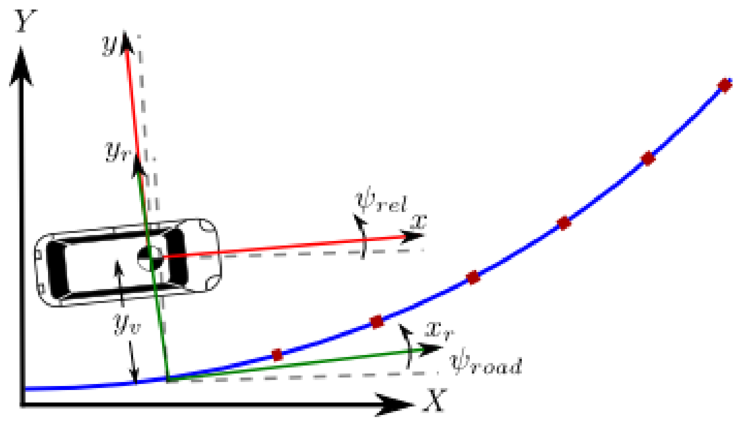

Figure 15: Setup of the prototype map-based least-squares planar pose estimator

system with a TLC-type warning metric should produce a very robust extension of the current state-of-the-art in departure warning. The false negative warning shown in Figure 1 is much less likely to occur, and using the methods outlined above, minimum visibility requirements to maintain sufficient map registration accuracy can be obtained.

While the inclusion of the mapped planar lane geometry in a TLC-type metric could help alleviate robustness problems associated with poor visibility, the researchers will also consider the effects of road bank angle and other disturbances on the final TLC reading used by the warning or intervention system. These effects may be negligible in some cases for passenger vehicles, but with their large side area and lower cornering performance, tractor trailers are susceptible to significant lateral deviations resulting from road bank angles and crosswinds. Mapped information about these disturbances will allow the proposed LDWS to account for these in computing TLC values, and ultimately in deciding whether to warn a driver.

In a broader sense, research team plans to investigate the use of other, more abstract map information, such as statistical steering characteristics of past driver behavior at a particular location on the road, as well as crosswind and weather data to improve the robustness of the system. Map features inclusive of past disturbance and control inputs, rather than road geometry alone, could help mitigate false warnings based on steering behavior that cannot be captured in a simple forward vehicle model that might be used for a TLC prediction.

4 Hardware

4.1 Mapping Vehicle Setup

The process of map-based lane detection and driver assist begins with data collection within a static environment using a sensor-equipped mapping vehicle. A Volkswagen Passat was used as the mapping vehicle (Figure 16). Instrumented with a 2-D SICK LIDAR, a forward facing monocular camera, two downward facing monocular cameras, and an integrated GPS-IMU system, this vehicle collected and stored all relevant data necessary for real-time lane detection and lane following to an onboard data-acquisition computer.

The stand-alone mapping vehicle is composed of the overlying power system and the equipped sensors. The following sections overview the systems assembled on the vehicle.

4.1.1 Power System

As a vehicle could be expected to collect and store hundreds of miles of data in a mapping trip that may last an entire day, it is necessary to create a reliable power system to ensure that the sensors stay powered and perform correctly without faults.

Powering a network of sensors requires a reliable power source. The vehicle's alternator cannot suffice as a reliable power source due to the voltage fluctuation as a result of engine speed. An auxiliary 12V battery can supply a steady voltage and thus is used as the primary power source. Keeping this battery charged for the duration of a mapping trip requires constant backup charging, which can be attained from the vehicle's alternator or a 110VAC power supply when available. The configuration of the power supply with backup charging can be seen in Figure 17.

Further, a power monitoring system implemented within the system allows for direct observation of the status of the power supply. The above power supply configuration allows for several hours of operation until the supply voltage drops below 11.8V (a voltage threshold that could allow for "brown outs"). During testing of the implemented power

Figure 16: Mapping vehicle

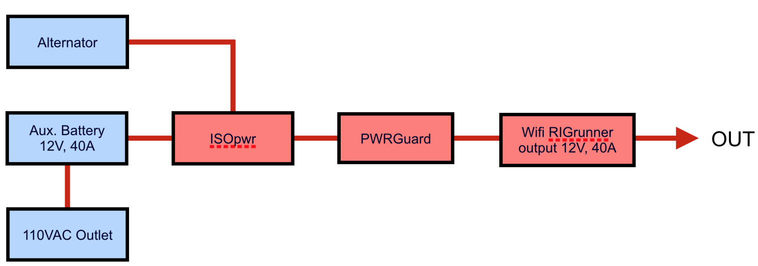

Figure 17: Power supply of mapping vehicle with back-up charging capabilities

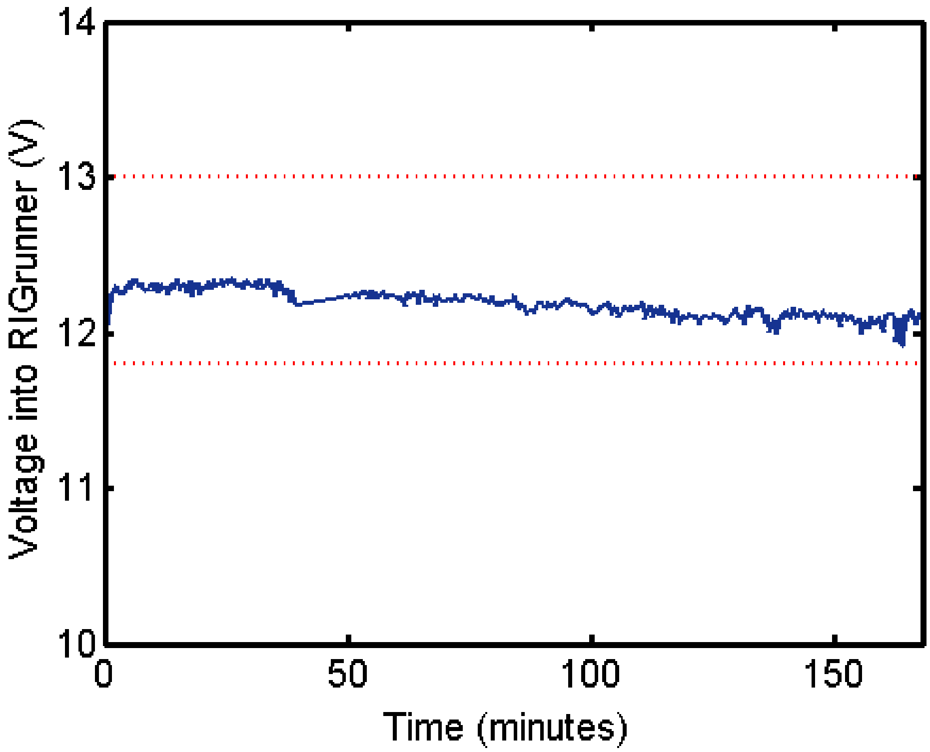

Figure 18: Power supply discharge over time

system, the battery remained above the threshold, dropping to its lowest point of 11.98V over nearly 3 hours (Figure 18).

4.1.2 Sensor Configuration

The supply voltage is distributed to each sensor through a 12VDC power controller and distribution system. This creates a network of powered sensors, all from the same supply and with each connected to the data-acquisition computer through a high-speed gigabit network switch (see Figure 19).

The following sensors comprise the mapping vehicle.

LIDAR sensor: The LIDAR system is a SICK LMS 511-10100 PRO mounted on the rear of the vehicle. The LIDAR system has a user-configurable sampling speed, accuracy, and angular resolution; for these experiments, the sensor was set to an angular resolution of 0.1667°, a measurement variance of ±6mm, and a scan speed of 25 Hz revolution rate.

GPS-IMU sensor: The vehicle is also equipped with an integrated GPS-IMU Novatel SPAN system to collect the position and the orientation information of the vehicle. This is a defense-grade system whose position errors in the latitude and longitude data, with full satellite visibility, are about 2 meters (one sigma) and the errors in the orientation angles are 0.017°, 0.02°, and 0.042°(one sigma) for the roll, pitch, and yaw angles, respectively.

Cameras: The environment of the vehicle is mainly recorded by the use of 3 color CCD Point Grey gigabit ethernet cameras, one forward-facing camera set to a 640x480 resolution collecting at 15Hz and two downward-facing cameras set to a 1000x300 resolution collecting at 20Hz. The downward-facing cameras are symmetrically angled outward to collect a wider field of view.

4.2 Truck Setup

The truck used as the demonstration vehicle is a Volvo 770 tractor cab. This vehicle was instrumented with a Hemisphere GPS system, an ADIS IMU, and one forward-facing monocular camera. The map database is stored in an onboard computer. Further, the vehicle houses an HD screen for augmented reality displays.

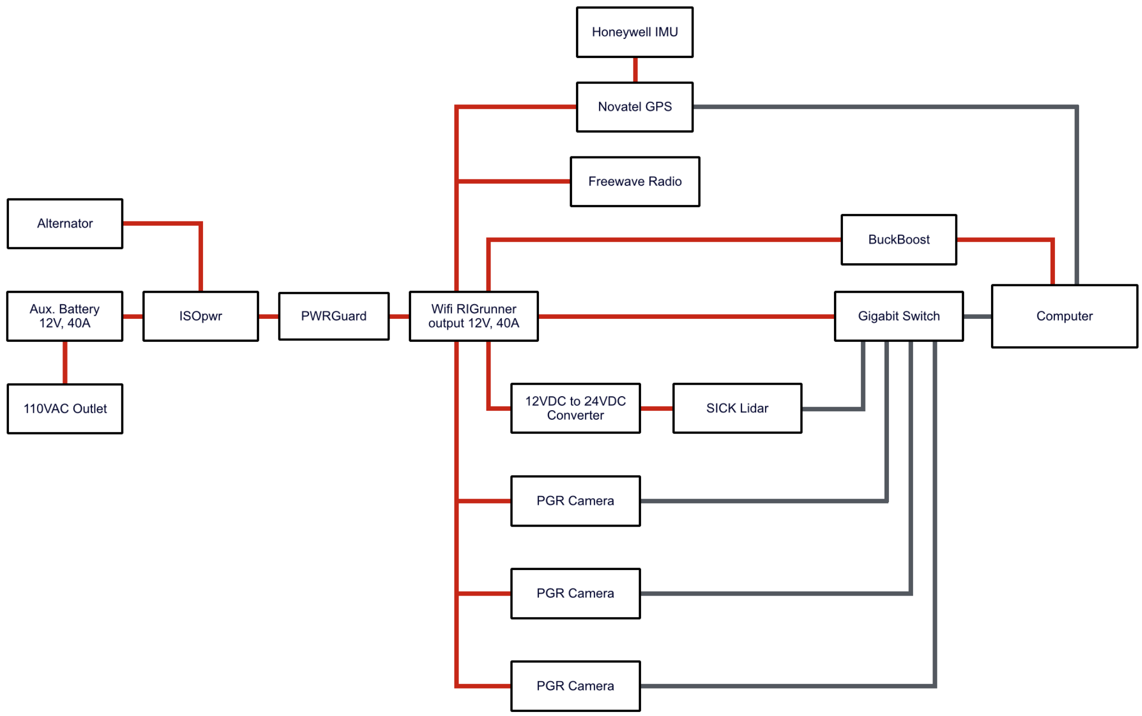

Figure 19: Power distribution to the network of sensors

4.2.1 Power System

As with the mapping vehicle, it is important to have a reliable power source for all sensors and components. Due to the power requirements of the HD screen, power is utilized from both an auxiliary battery and the truck's alternator. Introducing a second power source as a supply requires careful attention to possible ground fault loops and unbalanced voltages.

4.2.2 Sensor Configuration

Similar to the setup of the mapping vehicle, the network of sensors is powered by the 12 VDC power controller and distribution system. Different from the mapping vehicle, the truck has no on-board LIDAR sensor, and only one ethernet camera (see Figure 20) emphasizing the map-based approach for lane detection rather than a real-time, sensor-heavy method.

The demonstration vehicle is equipped with the following sensors.

GPS-IMU system: The vehicle is equipped with a Hemisphere GNSS smart antenna to detect the position of the vehicle and an ADIS ten-degrees-of-freedom inertial sensor to detect the orientation information of the vehicle.

Camera: A Point Grey gigabit ethernet camera is used, the same as is used in the mapping vehicle.

5 Experimental Protocol

As the entire system of sensors and power distribution equipment is contained in two completely assembled units (a roof rack housing the LIDAR, Novatel GPS/IMU system, power distribution and monitoring components; and a bin housing the auxiliary battery, battery charger, and embedded computer), the experimental procedure setup is relatively simple.

5.1 Mapping Procedure

The procedure for mapping an environment for perception involves the following steps:

- Connect to data-acquisition computer

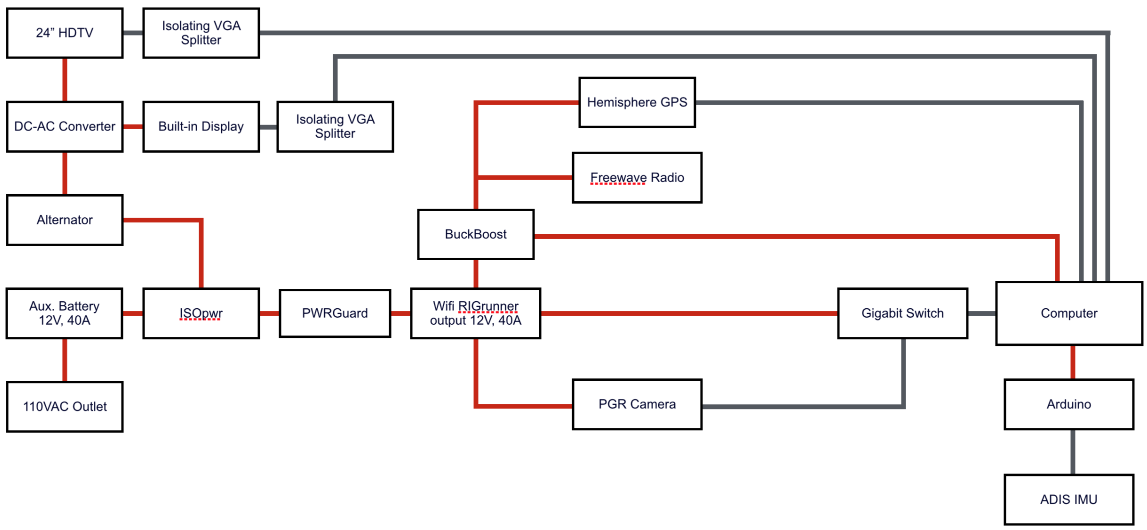

Figure 20: Power distribution to the network of sensors on the truck

- Perform sensor calibration
  - Calibrate monocular cameras
  - Calibrate GPS alignment
- Verify data stream for each component
- Record data streams

First, all commands for data collection are run from the embedded computer. However, due to its location within the vehicle, it is not easily accessible. As a solution, the embedded computer is controlled from a secure shell from a connected laptop. Next, the sensors are calibrated. The cameras undergo a series of calibration methods performed from a built-in Robot Operating System (ROS) function. Using a checkerboard calibration target, the cameras go through a simple monocular rectification to transform each image pixel to its corresponding output pixel location.

Utilizing ROS, we then launch the data streams of each sensor and begin to collect data, all recorded on the same master clock to ensure a synchronized time stamp. To verify healthy data streams of each sensor, we echo each sensor's stream and run a built-in GUI visualizing tool to verify the streams are operating appropriately.

Understandably, this operation requires frequent updating to refine the measurements of lane markers and subsequently to create a more accurate map. Furthermore, frequent updating allows adjustment due to any changes of the environment, namely caused by construction.

6 Extensions to Current Work

By taking advantage of mapped LIDAR data and elementary obstacle detection techniques, we can generate feature maps of roadside obstacles by processing the mapped LIDAR data offline. Obstacle classes considered in this report are: rollover, positive obstacles, and pavement edge drop-offs, and the techniques used to detect these obstacles are outlined in the following section. Each obstacle detection technique finds an obstacle based on a predefined metric, then finds that obstacle's location relative to the lane center.

6.1 Roadside Obstacle Detection Techniques

6.1.1 Rollover Detection

In this report, rollover is determined when a roll angle threshold is exceeded, which triggers a warning to the vehicle operator. To determine all possible rollover slopes that the vehicle may experience in the areas surrounding the roadway, the vehicle stability is evaluated at each lateral position within a particular profile. To do this, each LIDAR scan is evaluated at each lateral point by sliding the vehicle's width across the Earth-fixed representation of the geometric profile and determining the contact points of the right and left tires within that profile. The approximate

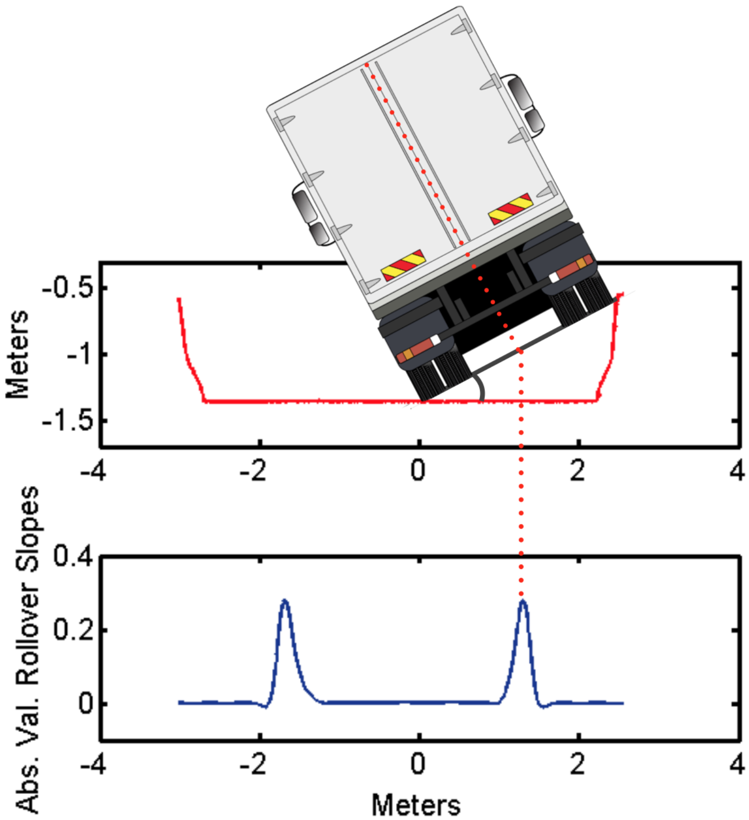

Figure 21: Slope data presenting impending backhoe rollover

static roll angle of the vehicle is then obtained from the slope of the line connecting the two contact points, assuming the vehicle's heading is normal to the plane of the LIDAR scan and that the suspension deflection is negligible. Figure 21 shows how the rollover slopes correspond to the vehicle's configuration in the LIDAR scan. The plot in red represents the cross-section of the environment, whereas the blue plot represents the slope of the specific vehicle when its center lies at that particular lateral position.

6.1.2 Positive-Obstacle Detection

Obstacles that protrude from the ground plane, known as positive obstacles, are detected through a slope analysis of LIDAR data. Reducing the dimensionality of raw range data through a combined feature extraction process generates line segments representative of the environment. A rules-based classification technique based on the height and slope of extracted segments then classifies said segments as obstacles or non-obstacles. The severity of the classified obstacle is analyzed along with its location relative to the lane center.

6.1.3 Pavement Edge Drop-off Detection

In this report, a pavement edge drop-off is defined as a vertical elevation difference between two adjacent surfaces, paved or unpaved. Pavement edge drop-offs are detected in the same fashion as positive obstacles. After completing feature extraction of range data, a series of best-fit lines and slope approximations are performed, to which edge drop-offs are classified through a thresholding technique. Again, the severity of the classified obstacle is then analyzed along with its location relative to the lane center.

7 Path Planning/Warning System

The above methods produce a classification of potential threats to vehicle motion nearby the current lane. These are readily stored in a database and even presented to a driver as a warning. One possible warning system is a "heat map" of threats shown through a heads-up display. This warning concept entails displaying every feature in

Figure 22: Example of a heads-up display presenting a “heat map” of surrounding hazards

one map with each feature labeled as individual obstacles. When the driver approaches the location of an obstacle, an auditory warning system can direct the driver’s attention to the obstacle that he/she is approaching. Figure 22 illustrates the heads-up display “heat map” concept by projecting obstacles’ locations onto the windshield for the driver to see. This example figure only displays one hazard marked in red.

Accordingly, each obstacle detected is weighted by severity. Rollover takes a high severity weight due to the extreme severity of such accidents; similarly, non-rollover angles are weighted slightly less proportional to an obstacle’s proximity to the rollover threshold. Positive obstacles are weighted based on the height of the obstacle. Pavement edge drop-offs are weighted based on their slope and length. These severities become useful in certain operating situations where split-second decision-making is critical. For instance, in a scenario where the driver needs to depart the drivable area for some reason and his/her options are between driving over a 20° embankment or into a 1-m-tall barrier, the operator could be advised to travel over the embankment instead of through a possibly immobilizing positive obstacle.

7.1 Warning System

These detection techniques can form the foundation upon which multiple safety systems can be implemented and tested. The knowledge of obstacle locations within an integrated feature map is very useful; this allows the vehicle to alert drivers of their location relative to surrounding obstacles through a heads-up display. Additionally, by comparing mapping results to each other over time, very robust estimates of hazard areas can be obtained. Through integration with GPS, these same algorithms can significantly decrease the false positive detection rate and more robustly classify obstacles. And with GPS, one can present obstacle warnings to conventional vehicle operators without the need to equip their vehicles with high-cost LIDAR mapping sensors.

8 Conclusions and Future Work

This report outlined the high-level functionality of a mapping system and an online map-based lane departure warning system (LDWS) for a Volvo tractor trailer. The authors demonstrated a functioning map-aided lane detection system and lane departure warning system to Volvo personnel, including the production of a road marking and geometry map spanning the distance between Penn State University and Volvo headquarters in Hagerstown, MD.

Developing the tools necessary to deliver a fully integrated map-aided lane departure warning system was broken down into several incremental steps. To recount, the expected project deliverables for the project term included:

1. Demonstrate camera and lane marking and map combination.
2. Demonstrate IMU/longitudinal position improvements for localization.
3. Demonstrate augmented display in vehicle.
4. Demonstrate auditory or haptic lane departure warning.

While the systems developed during this project were functional, more refinement of the algorithms, hardware calibration methodology, and road map format is necessary before the system is ready for production. This refinement is planned for future collaboration with Volvo.

References

[1] G. Liu, F. Wörgötter, and I. Markelić, "Stochastic lane shape estimation using local image descriptors," 2013.

[2] T. Sun, S. Tang, J. Wang, and W. Zhang, "A robust lane detection method for autonomous car-like robot," in *Intelligent Control and Information Processing (ICICIP), 2013 Fourth International Conference on*. IEEE, 2013, pp. 373–378.

[3] H. Ding, B. Zou, K. Guo, and C. Chen, "Comparison of several lane marking line recognition methods," in *Intelligent Control and Information Processing (ICICIP), 2013 Fourth International Conference on*. IEEE, 2013, pp. 53–58.

[4] D. Cualain, C. Hughes, M. Glavin, and E. Jones, "Automotive standards-grade lane departure warning system," *IET Intelligent Transport Systems*, vol. 6, no. 1, pp. 44–57, 2012.

[5] W. van Winsum, K. a. Brookhuis, and D. de Waard, "A comparison of different ways to approximate time-to-line crossing (TLC) during car driving." *Accident; analysis and prevention*, vol. 32, no. 1, pp. 47–56, Jan. 2000. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/10576675

[6] K. Suzuki, "An analysis of driver's steering behaviour during auditory or haptic warnings for the designing of lane departure warning system," *JSAE Review*, vol. 24, no. 1, pp. 65–70, Jan. 2003. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/S0389430402002473

[7] M. F. Brown and R. G. Cook, *Animal Spatial Cognition: Comparative, Neural and Computational Approaches*. Comparative Cognition Press, November 2006.

[8] W. D. Gray, D. A. Rosenbaum, B. J. Martin, M. D. Byrne, B. E. John, and U. Raschke, "Models of motor control and performance," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 52, no. 13. Sage Publications, 2008, pp. 903–906.

[9] P. Falcone, F. Borrelli, J. Asgari, H. Tseng, and D. Hrovat, "Predictive active steering control for autonomous vehicle systems," *Control Systems Technology, IEEE Transactions on*, vol. 15, no. 3, pp. 566–580, 2007.

[10] T. Keviczky, P. Falcone, F. Borrelli, J. Asgari, and D. Hrovat, "Predictive control approach to autonomous vehicle steering," in *American Control Conference, 2006*. IEEE, 2006, pp. 6–pp.

[11] R. Sharp and V. Valtetsiotis, "Optimal preview car steering control," *Vehicle System Dynamics*, vol. 35, pp. 101–117, 2001.

[12] J. Guldner, H. Tan, and S. Patwardhan, "Study of design directions for lateral vehicle control," in *Decision and Control, 1997., Proceedings of the 36th IEEE Conference on*, vol. 5. IEEE, 1997, pp. 4732–4737.

[13] H. Peng and M. Tomizuka, "Preview control for vehicle lateral guidance in highway automation," in *American Control Conference, 1991*. IEEE, 1991, pp. 3090–3095.

[14] S. Shladover, C. Desoer, J. Hedrick, M. Tomizuka, J. Walrand, W. Zhang, D. McMahon, H. Peng, S. Sheikholeslam, and N. McKeown, "Automated vehicle control developments in the path program," *Vehicular Technology, IEEE Transactions on*, vol. 40, no. 1, pp. 114–130, 1991.

[15] C. Macadam, "Understanding and modeling the human driver," *Vehicle System Dynamics*, vol. 40, no. 1-3, pp. 101–134, 2003.

[16] D. Cole, A. Pick, and A. Odhams, "Predictive and linear quadratic methods for potential application to modelling driver steering control," *Vehicle System Dynamics*, vol. 44, no. 3, pp. 259–284, 2006.

[17] M. Bertozzi and A. Broggi, "Gold: A parallel real-time stereo vision system for generic obstacle and lane detection," *Image Processing, IEEE Transactions on*, vol. 7, no. 1, pp. 62–81, 1998.

[18] R. Danescu and S. Nedevschi, "Probabilistic lane tracking in difficult road scenarios using stereovision," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 10, no. 2, pp. 272–282, 2009.

[19] M. Montemerlo, S. Thrun, D. Koller, and B. Wegbreit, "Fastslam 2.0: An improved particle filtering algorithm for simultaneous localization and mapping that provably converges," in *International Joint Conference on Artificial Intelligence*, vol. 18. LAWRENCE ERLBAUM ASSOCIATES LTD, 2003, pp. 1151–1156.

[20] L. A. Clemente, A. J. Davison, I. Reid, J. Neira, and J. D. Tardós, "Mapping large loops with a single hand-held camera," in *Robotics: Science and Systems*, 2007.

[21] M. J. Milford and G. F. Wyeth, "Single camera vision-only slam on a suburban road network," in *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on.* IEEE, 2008, pp. 3684–3689.

[22] I. M. Chira, A. Chibulcutean, and R. G. Danescu, "Real-time detection of road markings for driving assistance applications," in *Computer Engineering and Systems (ICCES), 2010 International Conference on*, vol. 30. IEEE, 2010, pp. 158–163.

[23] M. Felisa and P. Zani, "Robust monocular lane detection in urban environments," in *Intelligent Vehicles Symposium (IV), 2010 IEEE.* IEEE, 2010, pp. 591–596.

[24] A. Borkar, M. Hayes, and M. T. Smith, "A novel lane detection system with efficient ground truth generation," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 13, no. 1, pp. 365–374, 2012.

[25] A. Broggi, A. Cappalunga, C. Caraffi, S. Cattani, S. Ghidoni, P. Grisleri, P. P. Porta, M. Posterli, and P. Zani, "Terramax vision at the urban challenge 2007," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 11, no. 1, pp. 194–205, 2010.

[26] S. Zhou, Y. Jiang, J. Xi, J. Gong, G. Xiong, and H. Chen, "A novel lane detection based on geometrical model and gabor filter," in *Intelligent Vehicles Symposium (IV), 2010 IEEE.* IEEE, 2010, pp. 59–64.

[27] R. K. Satzoda, S. Sathyanarayana, and T. Srikanthan, "Hierarchical additive hough transform for lane detection," *Embedded Systems Letters, IEEE*, vol. 2, no. 2, pp. 23–26, 2010.

[28] J. Wang, Y. Wu, Z. Liang, and Y. Xi, "Lane detection based on random hough transform on region of interesting," in *Information and Automation (ICIA), 2010 IEEE International Conference on.* IEEE, 2010, pp. 1735–1740.

[29] A. Amditis, M. Bimpas, G. Thomaidis, M. Tsogas, M. Netto, S. Mammar, A. Beutner, N. Mohler, T. Wirthgen, S. Zipser *et al.*, "A situation-adaptive lane-keeping support system: overview of the safelane approach," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 11, no. 3, pp. 617–629, 2010.

[30] W. Jian, S. Sisi, G. Jingchao, and C. Yu, "Research of lane detection and recognition technology based on morphology feature," in *Control and Decision Conference (CCDC), 2013 25th Chinese.* IEEE, 2013, pp. 3827–3831.

[31] P. Foucher, Y. Sebsadji, J.-P. Tarel, P. Charbonnier, and P. Nicolle, "Detection and recognition of urban road markings using images," in *Intelligent Transportation Systems (ITSC), 2011 14th International IEEE Conference on.* IEEE, 2011, pp. 1747–1752.

[32] D. Gao, W. Li, J. Duan, and B. Zheng, "A practical method of road detection for intelligent vehicle," in *Automation and Logistics, 2009. ICAL'09. IEEE International Conference on.* IEEE, 2009, pp. 980–985.

[33] A. Haselhoff and A. Kummert, "On visual crosswalk detection for driver assistance systems," in *Intelligent Vehicles Symposium (IV), 2010 IEEE.* IEEE, 2010, pp. 883–888.

[34] D. Hanwell and M. Mirmehdi, "DETECTION OF LANE DEPARTURE ON HIGH-SPEED ROADS," 2009.

[35] J. W. Lee, "A Machine Vision System for Lane-Departure Detection," *Computer Vision and Image Understanding*, vol. 86, no. 1, pp. 52–78, Apr. 2002. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/S1077314202909586

[36] T. Jochem and D. Pomerleau, "AURORA: a vision-based roadway departure warning system," *Proceedings 1995 IEEE/RSJ International Conference on Intelligent Robots and Systems. Human Robot Interaction and Cooperative Robots*, vol. 1, pp. 243–248, 1995. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=525803

[37] H. Godthelp, P. Milgram, and G. J. Blaauw, "Human Factors : The Journal of the Human Factors and Ergonomics Society," 1984.

[38] W. Kwon and S. Lee, "Performance Evaluation of Decision Making Strategies for an Embedded Lane Departure Warning System," vol. 19, no. 10, pp. 499–509, 2002.

[39] S. Mammar, S. Glaser, and M. Netto, "Time to Line Crossing for Lane Departure Avoidance: A Theoretical Study and an Experimental Setting," *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 2, pp. 226–241, Jun. 2006. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1637677

[40] J. Levinson, M. Montemerlo, and S. Thrun, "Map-based precision vehicle localization in urban environments," in *Proceedings of the Robotics: Science and Systems Conference.* Citeseer, 2007.

[41] O. Pink, "Visual map matching and localization using a global feature map," in *Computer Vision and Pattern Recognition Workshops, 2008. CVPRW'08. IEEE Computer Society Conference on.* IEEE, 2008, pp. 1–7.

[42] Y. Lee, W. Yu, J. Cho *et al.*, "Adaptive localization for mobile robots in urban environments using low-cost sensors and enhanced topological map," in *Advanced Robotics (ICAR), 2011 15th International Conference on.* IEEE, 2011, pp. 569–575.

[43] M. Noda, T. Takahashi, D. Deguchi, I. Ide, H. Murase, Y. Kojima, and T. Naito, "Vehicle ego-localization by matching in-vehicle camera images to an aerial image," in *Computer Vision–ACCV 2010 Workshops.* Springer, 2011, pp. 163–173.

[44] A. Dean, R. Martini, and S. Brennan, "Terrain-based road vehicle localisation using particle filters," *Vehicle System Dynamics*, vol. 49, no. 8, pp. 1209–1223, 2011.

[45] A. Dean and S. Brennan, "Terrain-based road vehicle localization on multi-lane highways," in *American Control Conference, 2009. ACC'09.* IEEE, 2009, pp. 707–712.

[46] A. Dean, P. Vemulapalli, and S. Brennan, "Highway evaluation of terrain-aided localization using particle filters," in *Proceedings. 2008 Dynamic Systems Control Conference*, 2008, pp. 20–22.

[47] V. Gupta and S. Brennan, "Terrain-based vehicle orientation estimation combining vision and inertial measurements," *Journal of Field Robotics*, vol. 25, no. 3, pp. 181–202, 2008.

[48] A. Brown and S. Brennan, "Global and local frameworks for vehicle state estimation using temporally previewed mapped lane features," in *IV2013 Workshop on Environment Perception, 2013 IEEE.*

[49] J. M. Clanton, D. M. Bevly, A. S. Hodel, and S. Member, "A Low-Cost Solution for an Integrated Multisensor Lane Departure Warning System," vol. 10, no. 1, pp. 47–59, 2009.