Lane Tracking using Multilayer Laser Scanner to Enhance Vehicle Navigation and Safety Systems

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BIOGRAPHY

Jordan is currently a master’s student and research assistant at Auburn University’s GPS and Vehicle Dynamics Laboratory (GAVLAB). He received his B.S. degree in electrical engineering in 2008. His current research interests include sensor fusion and autonomous vehicle navigation and control.

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

ABSTRACT

It is of great interest in advanced driver assistance systems to prevent lane departure warning. Over half of all traffic fatalities in 2007 were caused by unintended lane departure [1]. Lane departure warning (LDW) systems often include passive sensors such as cameras to detect the lane and warn the driver of a lane departure. The most critical element of any lane keeping assistance system is the availability of reliable lane position information. Currently available LDW systems have shown that cameras can provide lane position information; however these systems suffer from technical limitations in areas where lane markings may be missing or difficult to detect due to lighting, rain, or snow [3][4]. However, LiDAR (Light Detection and Ranging) can be used to supplement other LDW sensors by providing lane position data accurately and consistently even in cases of varying outdoor conditions. It can provide additional robustness to a navigation solution by providing a lane position in the case of GPS outages.

The objective of this research is to show that a multilayer LiDAR is capable of detecting and tracking lane markings that could supplement a LDW or on road navigation system. This will be realized using an Ibeo multilayer laser scanner that is capable measuring both distance and reflectivity data. The algorithm implemented is operating using the principle that the lane’s surface is less reflective than the lane markings [6]. Therefore points of high reflectivity of the scan act as potential lane markings.

Based on the distance to the lane markings, the user’s position in the lane can be determined which will act as supplemental information to a navigation or safety system.

Currently lane markings are capable of being found during post processing on both static and dynamic tests. Dynamic real-time data was taken at a NCAT test track aboard a Hyundai Sonata. LiDAR results of these tests were overlaid onto vision data, which were acquired simultaneously with the LiDAR data for a rough visual metric. Additionally the test track previously mentioned has been surveyed and will serve as a truth measurement in order to validate the methods used to acquire and track lane markings.

This paper will cover in-depth the algorithm and processes used to acquire lane markings as well as techniques used to mitigate false readings.

INTRODUCTION & MOTIVATION

The goal of this research is to utilize a LiDAR (Light Detection and Ranging) to detect lane markings for the purpose of enhancing vehicle navigation and safety systems such as a lane departure warning system. Lane departure warning (LDW) systems often include passive
sensors such as cameras to detect the lane and warn the driver of a lane departure. The most critical element of any lane keeping assistance system is the availability of reliable lane position information. Currently available LDW systems have shown that cameras can provide lane position information; however these systems suffer from technical limitations in areas where lane markings may be missing or difficult to detect due to lighting, rain, or snow [3][4]. However, LiDAR can be used to supplement other LDW sensors by providing lane position data accurately and consistently even in cases of varying outdoor conditions [5]. It can provide additional robustness to a navigation solution by providing a lane position in the case of GPS outages. In addition, many vehicles are now being equipped with LiDAR for active cruise control; therefore, it could be extremely useful to use this same equipment for additional safety.

This accurate lane position is provided through the use of bounding, discrimination, and by finding a best match solution to an expected value. The mechanics of an algorithm used to detect lane markings is presented. This algorithm will use the principle that the lane markings are more reflective than the road’s surface at the same distance to detect lane markings [6]. The lane position will be given as a function of distance from the center of the lane.

HARDWARE OVERVIEW

The LiDAR used was an Ibeo ALASCA XT which is a multilayer laser rangefinder. Multilayer in this particular case means that the LiDAR actually performs four horizontal scans with each rotation of the mirror. The beams have a maximum divergence from zero of +1.2°, +0.4°, -0.4° and -1.2°. This particular LiDAR is also capable of measuring both reflectivity intensity, a measurement known as echo width, as well as distance. Now the optimal location of the LiDAR would be to place it incident to the road’s surface to maximize the laser’s reflectivity. However, for this application the LiDAR is mounted to a conventional roof rack, which allows it to be forward looking as well as obtain adequate reflectivity data. Additionally, this allows the sensor to easily be transferred to multiple test vehicles, if desired. Reflectivity and distance data was captured with the LiDAR was at 10Hz and quantized into half degree angle measurements. If multiple echo widths existed, due to the presence of precipitation or dead insects on the LiDAR’s screen, those echo widths were averaged together.

A camera is also used as a rough visual metric to determine where the LiDAR perceives the road edge. This allows for better quantification of causes of error or success. The camera used is a simple webcam, a Logitech QuickCam® Pro 9000. It is capable of achieving up to 30 FPS, which allowed us to take a picture corresponding to each LiDAR scan. It was simply mounted to the front of the LiDAR for similar pitch and yaw.

CALIBRATION

The LiDAR will report the vehicle’s horizontal position in the lane; however, before this position can be reported, a transformation of the distances from the LiDAR’s pitched perspective has to be converted into the vehicle frame. For this to be accomplished, the LiDAR’s height and/or pitch must be known. This height is calibrated each time the algorithm is initialized and must be performed on a flat level surface. The equations necessary are shown in (1),(2) where \( \Delta \theta \) is the previously given as a divergence from zero of +1.2°, +0.4°, -0.4° and -1.2°. The LiDAR measurement is considered the hypotenuse of the triangle, \( h_n \). The variable representing height as measured from the LiDAR’s mirror perpendicular to the road’s surface is \( y \), and the true pitch of the LiDAR is simply \( \theta \), as measured from \( y \) to the center of the zero divergence position (i.e. at 0° between +0.4°, -0.4°).

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Figure 1 Noisy scan of road reflectivity
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Camera data was calibrated to the LiDAR’s data by determining where the LiDAR scans would hit the road’s surface based on the LiDAR’s pitch and height information. Placing orange cones at those locations provided a visual correlation on the image of where the LiDAR scans were hitting. One hundred LiDAR scans and pictures were then taken while the vehicle was stationary. This was performed while in a lane so that lane information would also be available. Once this was done, the lane’s actual width was then measured, and suitable conversion factor from meters to pixels was determined based on the location of where the scans were measuring. If the LiDAR scan was hitting closer to the hood of the vehicle, a smaller conversion factor could be used as opposed to the LiDAR scanning closer to the image’s vanishing point. Thus data was overlaid onto the image in the location of where the LiDAR was scanning.

**BOUNDING**

As seen in figure (1) the reflectivity of the road’s surface is not always as consistent as shown in figure (2) which is the ideal scan of a road’s reflectivity. Noise especially increases as the scan measures reflectivity off the road’s surface. If the echo width scan is noisy, it can be difficult to make a clear distinction of where the road begins and ends. Because of this, boundaries are established as a means to minimize false positive as well as a means to reduce unneeded processing of the data.

The boundaries establish within what region of the data the algorithm should search for a potential lane marker. The boundaries are established using a nominal lane width of 12ft or 3.6576m as established by the department of transportation [2]. That width is used to establish a maximum window in which to search for the lane within. In order to assure that a lane marker is detected if one exists, regardless of the vehicles position in the lane, the algorithm processes data in a region of twice that of the nominal lane width, centered about the vehicle, such that if the vehicle is straddling two lanes, for an instant, the LiDAR would acquire the center, left most, and right most lane markings.

This was implemented by finding the lateral distance between the zero degree distance measurement and those distance measurements associated with positive angles until the lateral distance between the two measurements is greater than the nominal lane width. The angle at which that event occurs is stored. The same procedure is followed for distance readings corresponding to negative angles. Thus when the algorithm attempts to find a lane
using the echo width data, it need only concern within the angles it should process data.

**DETECTION**

A nominal scan of a road’s echo width is shown in figure (2). Ideally, there would be four distinct spikes indicating an increase in reflectivity, implying a lane marker’s location as shown in figure (3). Additionally, there is also a distinct region of uniform levels of echo width that separate the spikes, implies a consistent road surface. With this knowledge in hand an expected lane’s echo width scan is generated. The minimum RMS error of this expected lane’s echo width compared to the actual scan yields the location of the lane markings.

The ideal scan is created by first establishing a “baseline”. This region will represent what ideally would be the consistent area of the scan between the peaks indicating lane markings. It is constructed by scanning approximately .6m of the road’s surface in front of the car and averaging all the echo widths within that region. To mimic the actual lane markings the baseline is simply increased by a factor of 1.75; this part of the ideal scan is referred to as side lobes as seen in figure (4). Thus the ideal scan has been created based off of the actual scan’s data, which allows lanes to be detected in noisy scans.

![Figure 4 Algorithm generated ideal scan](image)

Once this algorithm-generated ideal scan has been created, the RMS comparison can be performed. This is done by placing the left most side lobe at the leftmost scan boundary that was previously established and shifting it by half-angle increments until that side lobe has reached the center of the scan at zero degrees. With each shift of the left side lobe, the right most side lobe is placed at the center of the scan and stretched until the right most side lobe is equal to the rightmost scan boundary. The algorithm generated ideal scan is stretched by simply adding in another baseline measurement between the side lobes. To mitigate erroneous results with each shift, the distance between the leftmost side lobe and rightmost side lobe is checked to assure that the width is greater than the minimum expected lane width, and less than some maximum expected lane width, as set forth in [2]. The minimum RMS error generated from comparing the actual LiDAR scan to the algorithm generated ideal scan is saved. The location of the innermost side lobes denote the lane angle corresponding to the lane marking. Using that information the distance from the center of the vehicle to the lane marking can be computed.

It is typical however for there to be only one lane marking due to striped lane markings. To determine whether one or not lane marking actually exists, the locations of where the RMS side lobes match up to the actual scan are compared. If the average echo widths of the side lobes’ position in the actual scan are not at least 1.4 times greater than the previously established baseline, then a lane marking is considered not to exist for that particular side lobe location. It can then be reported if a lane marking was found to the vehicle’s left or right, or whether no lane marking was found at all. This process is performed for each of the four horizontal LiDAR scans, which ideally would yield four measurements of a lane’s location.

For each of the four solutions, a distance from the center of the vehicle to the left lane marker and right lane marker is computed if one existed. Those results are low-pass filtered in a single state Kalman filter as a means of reducing any spikes in the data resulting from an erroneous result. Once the left and right distances have been filtered, they are then put through a weighted average. The weights are a function of how much a scan has varied in the past 17 scans; thus, more weight is given to scans that have varied less, as shown in equations (3)(4)(5). Seventeen was chosen because it was simply the value that gave us the best results.

\[
W = \begin{bmatrix}
\frac{1}{\sigma_{L/R}^2} & \frac{1}{\sigma_{L/R}^2} \\
\frac{1}{\sigma_{2L/R}^2} & \frac{1}{\sigma_{2L/R}^2} \\
\frac{1}{\sigma_{3L/R}^2} & \frac{1}{\sigma_{3L/R}^2} \\
\frac{1}{\sigma_{4L/R}^2} & \frac{1}{\sigma_{4L/R}^2}
\end{bmatrix}
\]  

\[
H = \begin{bmatrix}
1 \\
1 \\
1 \\
1
\end{bmatrix}
\]  

\[
y_{posL/R} = (H^T WH)^{-1} H^T W y_{LPF 1-4L/R}
\]  

Once these filtered and averaged left and right distances have been computed, the vehicles position in the lane can...
be calculated. Thus if reported as an offset from the center of the lane, the offset can be computed as shown in equation (6) assuming that either distance left or right is negative, to denote which side of the vehicle the result favors.

$$\frac{y_{pos, L} + y_{pos, R}}{2} \quad (6)$$

TEST PROCEDURE

To confirm the functionality of the algorithm, truth data was gathered by surveying the National Center for Asphalt Technology’s (NCAT) 1.7 mile closed track located in Opelika, Alabama [7]. With the aid of differential GPS, each lane marking was surveyed on the outside lane if a marker existed, for the entirety of the track. Those two measurements where averaged to acquire the location of the center of the lane, where the vehicle’s position would be based. The lane markings to the right of the car were solid white, and lane markings to the left of the car were striped white. Despite being a closed track, it is a very realistic representation of actual driving condition due to having multiple types of asphalt, sections where no lane markings exist, as well as sections of bordering lanes having different types of asphalt which provide different reflectivity readings. The test vehicle was driven around the track at realistic highway speeds ranging from 32.2KPH (20MPH) to 144.8KPH (90MPH) with the bulk of the testing in the 96.5KPH (60MPH) to 128.7(80MPH) range. The test vehicle was also equipped with differentially corrected GPS measurements updated at 2Hz, to provide reliable and accurate truth measurements. The hardware and test setup can be seen in figure (5).

Figure 5 Hardware test setup

In addition to the truth data gathered at the NCAT test track, hundreds of miles of test data have been logged driving throughout the southeastern United States. Despite not having a truth solution based on GPS in these instances, overlaying the LiDAR data onto the visual data taken from the camera has allowed for a rough truth metric. Processing can be done on this data to show when the algorithm is functional and when, if ever, errors occur.

TEST RESULTS

All test results are post processed solutions. Because our truth data had a small bias, data was processed in small sections in an attempt to minimize the affect of that bias. However, as seen in figure (6) the algorithm presented here is capable of high accuracy with a standard deviation of .0435m and an average error of .0355m. This data was taken at approx 65KPH (40MPH).

![Figure 6 Test results, 65KPH](image)

Errors do occasionally occur when two bordering lanes have different types of asphalt. The algorithm will occasionally track the changes in asphalt change as opposed to the lane marking. When no lane marking is present, the LiDAR will occasionally track the rumble strip bordering the roadside, which causes a bias in the results. Additionally, if grass is directly bordering lane markings, the algorithm will occasionally track the grass or simply jump back and forth between the lane markings and the grass.

CONCLUSION & FUTURE WORK

As seen in the previously presented results, this algorithm is capable of detecting and tracking lanes for extended periods of time with centimeter accuracy despite occasional errors. In the future, this algorithm should be made more robust by adding the ability to distinguish these types of error prone situations from lane markings. Additionally, added bounding may be necessary to aid in preventing the data from spiking. Future work will also include implementing this detection method in real-time as well as blending it with other sensors.
ACKNOWLEDGMENTS

The Federal Highway Administration is funding this project and others across the range of issues that are critical to the transportation industry through the Exploratory Advanced Research (EAR) Program. For more information, see the EAR Web site at http://www.fhwa.dot.gov/advancedresearch/about.cfm#focus

John Allen is responsible for the survey of the track and truth data collected for testing.

REFERENCES


