Cooperative Clothoidal-Estimation Based Lane Detection For Vehicle Platooning

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(ABSTRACT)

Vehicle platooning is an advanced vehicle maneuver that allows for the simultaneous control of several vehicles traveling on the roadway [2]. Automated platoons, when activated in tractor trailer convoys, have a high potential of increasing the fuel efficiency and improving the utilization of roadways by allowing more vehicles to share the road at the same time. The increased fuel efficiency translates to lower cost on goods and motivates a more environmentally friendly and sustainable economy. In order to achieve the promised fuel savings from vehicle platooning, the vehicles need to follow each other at shorter headways than in typical driving scenarios. The reduced separation distance between the lead and follow vehicle reduces visibility and the reaction time available for the follow vehicle; this renders most modern Active Driver Assist Systems (ADAS) ineffective since they are not designed for operation in such short headway conditions. The focus of this work is related to understanding and improving the failures of Lane Keep Assist (LKA) systems in the follow vehicles of a platoon.

In this work, the source of lane detection degradation when using a monocular forward facing camera in short headway platooning is identified. Furthermore, a novel lane augmentation algorithm is proposed to improve the lane detection capability of follow vehicles in a platoon. The lane augmentation process utilizes a longitudinal transformation of lane parameters from the lead to the follow vehicles. The transformation utilizes an accurate understanding of the relative spatial position and orientation of the two vehicles. The transformation also requires a reliable communication system between the two vehicles such as a Vehicle-to-Vehicle (V2V) module.

The work presented in this thesis develops theory, simulation and verification using real world data of the proposed cooperative lane augmentation. The results of this work indicate that it is possible to improve vehicle platooning performance by distributing the required sensing across multiple agents of the platoon.

Cooperative Clothoidal-Estimation Based Lane Detection

For Vehicle Platooning

Sena A. Hunde

(GENERAL AUDIENCE ABSTRACT)

Vehicle platooning is an advanced vehicle maneuver that allows for the simultaneous control of several vehicles traveling on the roadway [2]. Automated platoons, when activated in tractor trailer convoys, have a high potential of increasing the fuel efficiency and improving the utilization of our roadways by allowing more vehicles to share the road at the same time. The increased fuel efficiency translates to lower cost on goods and motivates a more environmentally friendly and sustainable economy. In order to achieve the promised fuel savings from vehicle platooning, the vehicles need to follow each other at closer distances (headway) than in typical driving scenarios. The reduced separation distance between the lead and follow vehicle reduces visibility and the reaction time available for the follow vehicle; this renders most modern Active Driver Assist Systems (ADAS) ineffective since they are not designed for operation in such short headway conditions. The focus of this work is related to understanding and improving the failures of Lane Keep Assist (LKA) systems - the automated system used to keep the vehicle in the center of the lane - in the follow vehicles of a platoon.

In the proposed scenario, the LKA uses a single forward facing camera to detect the lane lines ahead of the vehicle. The detected lanes serve as inputs to the lateral position (steering) controller in order to keep the vehicle in the center of the lane. In this work, the source of lane detection degradation in a follow vehicle of a short headway platoon is identified. Furthermore, a novel cooperative lane detection algorithm is proposed to improve the lane detection capability of the follow vehicles. The proposed algorithm utilizes lane information transformed from the lead to follow vehicle frame. The transformation utilizes the relative spatial position and orientation of the two vehicles. Additionally, a reliable communication protocol between the vehicles is required to transport the lane information.

The work presented in this thesis develops theory, simulation and verification using real world data of the proposed algorithm. The results of this work indicate that lane keeping performance in a platoon can be improved using cooperative lane detection.

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Chapter 1

Introduction

1.1 Background on Vehicle Platooning

The latest developments in vehicle communication systems such as Vehicle-to-Vehicle (V2V) and Vehicle-to-Everything (V2X) have created several opportunities for more safe and efficient transportation systems. V2V enables vehicles to share safety messages [13], traffic patterns, road quality, weather and much more. Advanced applications of V2V and V2X encompass coordinated vehicle maneuvering such as Cooperative Adaptive Cruise Control (CACC) and Vehicle Platooning. Vehicle platooning is an advanced vehicle maneuver that allows for the simultaneous control of several vehicles traveling on the roadway. [2]

Vehicle platooning has several benefits such as optimized traffic control, fuel consumption reduction and increased roadway capacity utilization. V2V communication allows platooning vehicles to share diagnostics, position, orientation, routing and driving patterns seamlessly. An effective platoon requires such information sharing in order to meet the performance requirements that help achieve the promised capabilities. An example of an application that utilizes information shared over V2V can be seen in applications such as real time paired simultaneous braking as presented in Masahiko et al. [1]. Such functions not only make normal operations safer but also enable closer-than-normal following distances between vehicles. The reduced following distances are what allow for maneuvers that significantly improve fuel efficiency and increase utilization of the roadway. [14]

A vehicle following another vehicle closely faces less air resistance ahead; it also simultaneously reduces the drag force induced on the lead vehicle. The decrease in air resistance and drag force are inversely proportional to the following distance (headway) between the lead and the follow vehicle. Class 8 truck engines provide a significant amount of energy to push the air ahead in addition to moving the payload behind. The closely following vehicle reduces the drag force induced by vortexes behind the lead vehicle [15]. The improved aerodynamic characteristics result in a significant amount of fuel savings for the combined platoon. The following figure shows the potential decrease in the drag coefficient converted to fuel savings in a study performed in Lammert et al. [7]. It can be seen that shorter headways result in higher fuel savings.

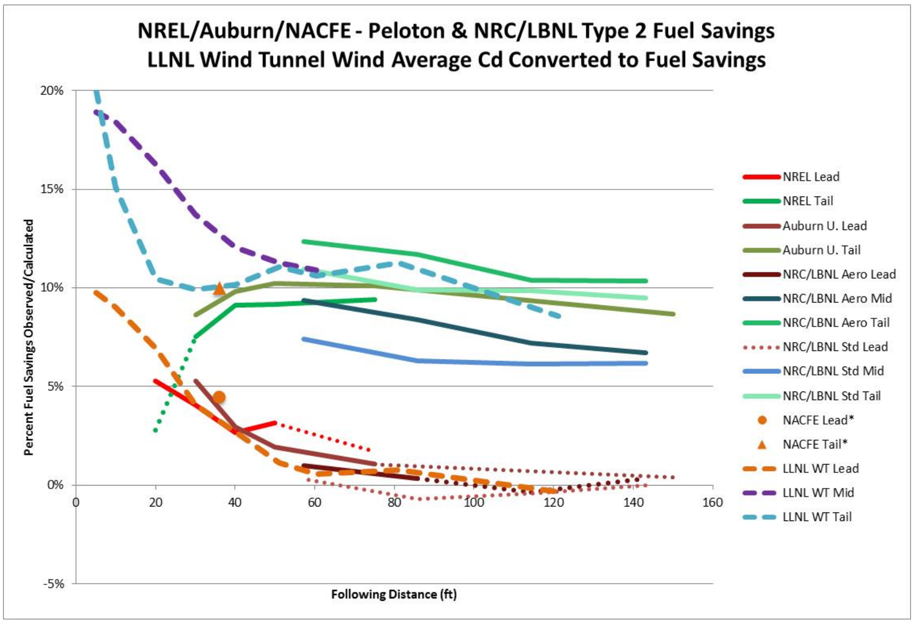

Figure 1.1: Analytical and experimental results of Vehicle Platooning fuel savings in percentage for different following distances for lead and follow(tail) vehicles [7].

Shorter platooning headways introduce system complexities such as decreased airflow in follow vehicles and the increased risk due to the reduced distance between vehicles driving at highway speeds. The system complexities introduced by short headways have led to identifying an optimal headway for vehicle platoons. The added risk of short headways has also motivated the development of cooperative driving systems by utilizing real-time communications enabled by V2V among vehicles in the platoon.

The real-time communication between vehicles in a platoon enables safety-critical systems, especially braking and lane keeping, in the following vehicle. The shorter the platooning headway, the less time the follow vehicle has to respond to changes in the lead vehicle's velocity. The follow vehicle also has a limited field of view of the road ahead making traditional mono-camera lane detection more challenging. This work aims at improving the performance of the lane detection while still using monocular lane detection. The improved detection will enable lane keeping in follow vehicles engaged in short headway platooning.

This work presents an expansion to the cooperative driving systems currently implemented in vehicle platooning to improve the lane detection of the follow vehicle. In this thesis, a novel approach is proposed to augment the lane detection of the follow vehicle by using lane detection results of the lead vehicle in the platoon. Simulated and preliminary experimental results of the proposed approach are presented in this work.

1.2 Problem Formulation

This work is focused on a platoon of two vehicles (pair), one lead and one follow vehicle. Both vehicles are equipped with ADAS comprising of a cab-center mounted forward facing mono-camera paired with an automated steering system for lane keeping, global positioning system (GPS), computing platforms, automated braking systems and forward facing range sensors. Both lead and follow vehicles are capable of operating manually as well as in a semi-automated fashion as part of the ADAS suite. The ADAS functionalities include automated longitudinal and lateral control as well as platooning when paired with another equipped vehicle. When pairing is active, the vehicles can perform cooperative braking using V2V communication.

Longitudinal control is defined as the ability to automatically maintain a prescribed velocity and headway while driving down the road. Lateral control is defined as the ability to automatically maintain a certain lane of the road. The vehicle is capable of actuating the steering, throttle and braking systems to enable the lateral and longitudinal control. The ADAS system considered in this work is only meant as an assistance to the human driver, who is ultimately responsible for controlling the vehicle.

Using the SAE J3016 levels of driving automation [4], the pairing systems considered in this work are at all times under human supervision. This means that even when pairing is active, the systems fall under the SAE level 2 of autonomy. The human driver is still responsible for setting, resetting and canceling the pairing mode; the driver is also expected to take control of the vehicle anytime there is an apparent hazard, regardless of pairing state. Figure 1.2 below presents a detailed definition of the SAE levels of automated driving.

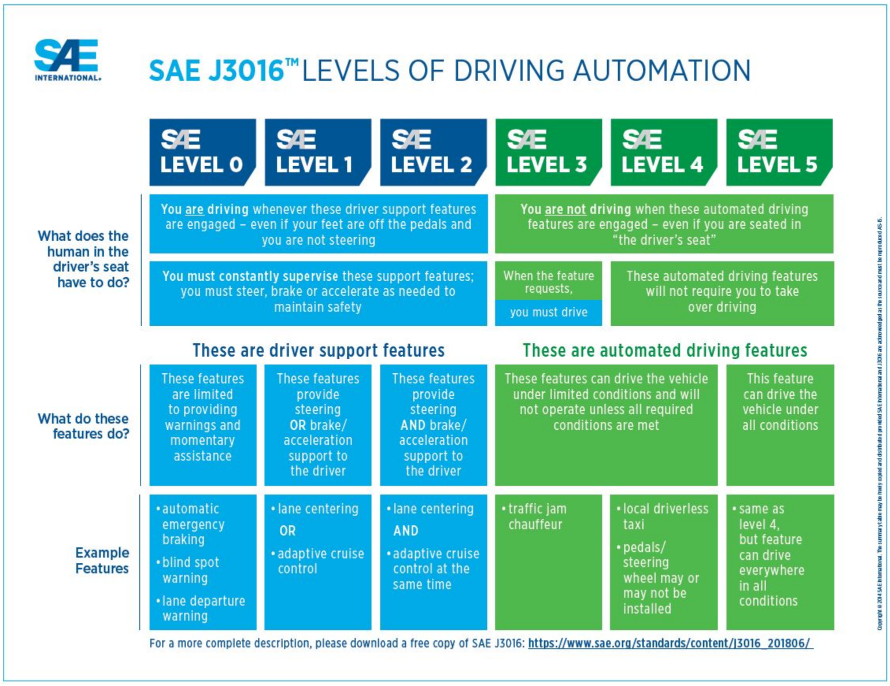

Figure 1.2: SAE ©International Autonomous Vehicle classification levels [4]

During pairing operations the longitudinal control strategy utilizes range measurements from radar in conjunction with GPS to maintain a constant headway between the lead and follow vehicles. In addition to providing position feedback, the GPS system onboard serves as a source of global time with respect to which computed processes are synchronized across vehicles.

The lateral control strategy uses the forward facing monocular cameras onboard the vehicles. Most highways in the United States are designed using clothoid based curves, curves that have a linearly varying curvature. Since the lateral control strategy is optimized for highway driving, modeling the lanes using a similar strategy on which they were designed leads to a better estimation. Therefore, the image frames from the onboard camera are processed with computer vision techniques that yield a clothoid-based lane line detection. The detailed lane model and the detection strategy will be discussed in further detail in this work.

The current platooning setup utilizes the standard lateral control strategy in both the lead and follow vehicles. While the standard lateral control strategy works well in the lead vehicle, it falls short in the follow vehicle because it is occluded by the lead vehicle, especially when the headway is small. The occlusion of the follow vehicle reduces the field of view of the mono-camera used for lane detection resulting in degraded lane detection and poor lateral control. This work aims to improve the performance of the lane detection even in the presence of occlusion in short headway pairing. The proposed approach to improve the lane detection in the follow vehicle utilizes the good lane estimates in the un-occluded lead vehicle. The lane estimates in the lead vehicle frame are transformed into the follow vehicle frame. The raw lane detection in the follow vehicle is augmented with the newly transformed detection from the lead vehicle. The augmented follow vehicle lane detection has better accuracy thus enabling improved lateral control.

1.3 Clothoid Lanes

Clothoids also known as a Euler spirals are curves that have a curvature changing linearly along the arc length. The central concept of a clothoid is the curvature defined by the ratio

$$C = \frac{1}{R},$$

where C is the Curvature and R is the radius of curvature of the arc.

Vehicles driving on the road follow transition paths induced by the delay between driver steering input and lateral acceleration, especially when entering or leaving a curve. Modern road designs account for the natural transition paths a normal driver experiences. Clothoid based curves are built into our modern roadways making easy-to-follow driving paths that require minimal lateral accelerations. In addition to providing a smooth transition from straight to curved sections of road, clothoid based transition curves also visibly enhance the roadway's appearance because continuity is maintained throughout the transitions [11].

The design of modern highway transition curves uses clothoidal approximations. Therefore, in this work, a clothoid approximation model based lane estimation is used to detect the lanes. The clothoid estimation based lane model is represented as follows

$$C(x) = y_0 + \phi x + \frac{1}{2}\rho x^2 + \frac{1}{6}\dot{\rho} x^3, \tag{1.1}$$

where the parameters $y_0,\ \phi,\ \rho,\ and\ \dot{\rho}$ are defined in Table 1.1 and are measured at the point of tangency between the heading of the vehicle and the lane line. This point of tangency is also the intersection point between the lane and the line perpendicular to the global heading of the vehicle.

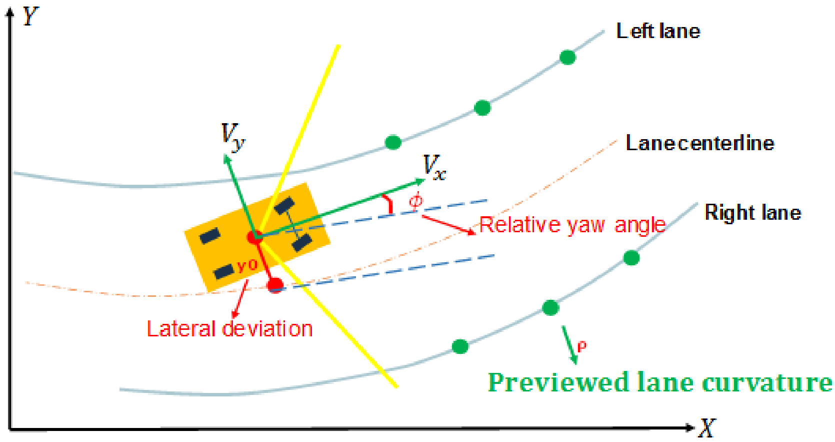

Figure 1.3: Graphical representation of the clothoid based lane detection model [10]

The clothoid lane model parameters are measured individually for the left and right lanes lines. The parameters are then defined as shown in Table 1.1.

Parameter	Definition
x	range for which the clothoid computed, measured with respect to the ego/subject vehicle frame origin
y_0	lateral position of the lane with respect to the ego/subject vehicle frame origin
ϕ	angle between the heading of the vehicle and the lane line tangent
ρ	estimated curvature of the lane
$\dot{\rho}$	estimated rate of change of the curvature of the lane

Table 1.1: Parameter definition of clothoid lane line estimates

1.4 Problem Definition

A major challenge introduced in short headway vehicle platooning is the occlusion of the follow vehicle's view of the road. The occlusion results in a reduced detection range that leads to a significant decrease in the accuracy of the relative yaw angle, curvature and rate of curvature change estimates.

Most interstate highways have two travel lanes which are bound by solid yellow lane lines and separated by striped white lines. The striped white lines are 3 meters long and separated by 9 meter gaps [5]. In this discussion, a 20 meter (65.6 ft) headway between lead and follow vehicle is assumed. The assumed platooning headway achieves fuel savings of about 2.5% and 9% for the two respectively (refer to Figure 1.1) using the Auburn University (Auburn U.) results.

Based on the selected 20 meter headway platoon and the previously outlined highway lane marking standards, the follow vehicle - traveling in the right lane - has at most two stripes of the left lane visible to the lane detection camera. The limited lane visibility leads to a degraded lane detection performance, thus resulting in poor and unreliable lane keeping of the follow vehicle in the platoon. At the same time, the lead vehicle has no occlusion ahead so the forward facing camera has a full view of the lanes allowing for a more accurate and reliable lane detection performance.

The work done in this project focuses on re-constructing the degraded lane in the follower vehicle's frame by using lane information (the clothoid parameters defined above) measured accurately by the lead vehicle. These parameters can be communicated over V2V with the appropriate spatial transformation.

So in summary, the motivating factor of this work is the weak performance of the follow vehicle of a short headway platoon to maintain the center of the lane. This loss in performance is a direct result of the occlusion of the monocular camera, which is used to detect the lane. The solution proposed in this work utilizes existing sensors in vehicles equipped with a single monocular camera capable of lane detection, a V2V communication module and an accurate Global Positioning System.

1.5 Contribution and Outline

This work makes two major contributions. The first contribution is a quantitative analysis of lane detection performance in an occluded follow vehicle as compared to the performance of the lead vehicle in a platoon. The analysis is performed based on real world data as well as using simulated data. The second contribution is the development of a novel cooperative lane detection augmentation technique for vehicles in a constant headway platoon. The proposed cooperative lane detection augmentation assumes that several base features are available and function independently in all vehicles of the platoon. The work presented in this thesis builds on already developed lane detection methods that utilize clothoidal approximations, accurate relative position measurement techniques and effective short range communication between vehicles. Using these existing techniques, a transformation between lead and follow vehicle can be computed that allows for estimating lane parameters in the occluded follow vehicle's frame. The new lane parameters allow for a more effective automated lane keeping performance.

In Chapter 2 of this thesis, real data collected from platooning experiments is analyzed and the challenges and shortcomings of the current lane detection system are identified. The outcome of this analysis leads into Chapter 3, where simulated data is used to prototype a solution that would enable the occluded follow vehicle to effectively detect lanes using transformed lane information from the un-occluded lead vehicle. Chapter 4 presents the experimental work done to verify the proposed lane augmentation algorithm. Lastly, in chapter 5, future work and additional contributions that can be made to this work are identified.

Chapter 2

Truck Pairing Lane Detection Baseline

2.1 Project Background

The work presented in this thesis was initially driven by results obtained from testing performed in the Daimler Trucks North America (DTNA) Truck Pairing project. The Truck Pairing project was an initial investigation of truck platooning using two trucks following each other at short headway distances. The project aimed to verify the performance of the platooning system including that of the ADAS functionality when the vehicles are in a paired state. The poor performance of the LKA system in the follow vehicle is what ultimately drove the work done in this thesis.

Figure 2.1: Daimler Truck Pairing short headway experiments

The truck pairing project utilized Freightliner Cascadia trucks equipped with ADAS. The ADAS package includes LKA, Active Brake Assist (ABA) and ACC. The safety case of platooning with short headways is mainly based on the ability that the pair can communicate in real-time using Dedicated Short Range Communication modules (DSRC). DSRC is a short range line of site based communication dedicated to V2V and V2X applications. The DSRC module enables the lead and follow vehicles to share safety critical information at 10Hz. Some safety critical information communicated over DSRC includes acceleration, velocity, braking state, GPS position, heading and ACC targets. Based on the communicated information, short headway platooning that utilizes cooperative adaptive cruise control

(CACC) has been implemented similar to work done in Xiao-Yun Lu et al. [8].

The truck pairing program used the built in LKA of the trucks; the lateral control system design of the vehicles was not included into the cooperative aspect of the platooning - each vehicle performed independent lateral control. Initial tests discovered that the LKA functionality of the follow vehicle was significantly degraded in short headway platooning. The truck pairing project exposed the deficiency of monocular camera based lane detection in occluded situations. This ultimately motivated the work done in this thesis.

In this section of the work, lane data collected during the truck platooning tests is quantitatively analyzed. The results of the analysis are used to uncover the cause behind the degraded LKA performance in short headway platooning. In addition to the quantitative analysis, a cooperative lane detection technique is proposed.

Figure 2.2: ADAS set implemented on DTNA Truck Pairing Program prototype vehicles https://freightliner.com/

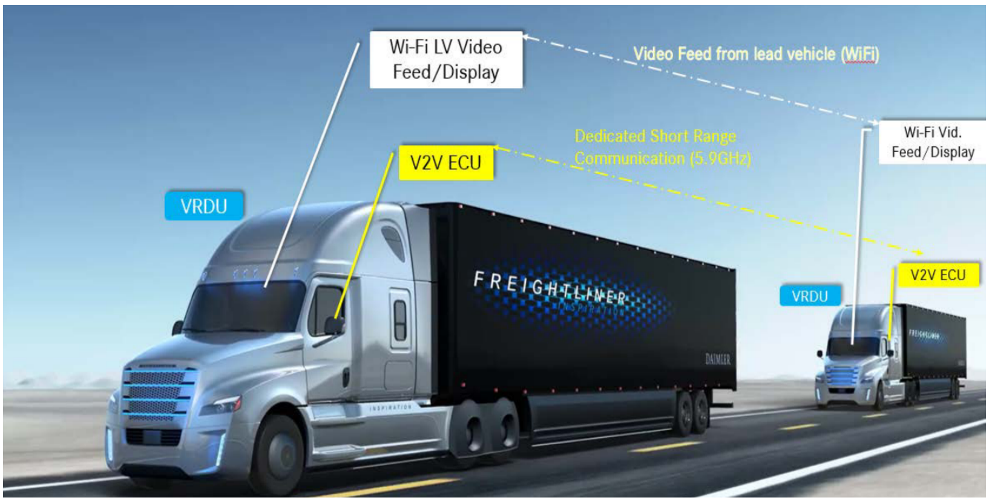

Figure 2.3: Truck pairing setup in simulation to demonstrate inter-vehicle communication used in the DTNA Truck Pairing project https://freightliner.com/

2.1.1 Baseline Evaluation Scope Definition

During the experimental testing of the DTNA truck platoons, the performance of the LKA in the follow vehicle was observed to be significantly degraded. Since the LKA performance of the lead vehicle was not affected, this indicated that the issue was related to the occlusion of the follow vehicle's lane detection camera. The initial scope of work naturally became understanding and quantifying the degradation of the monocular lane detection in the follow vehicle.

The major challenge associated with characterizing the sensor degradation was the fact that no diagnostic information or extended visualization was published by the LKA system. Therefore, this led to analyzing the performance of the follow vehicle in detecting lanes with respect to the lead vehicle's detection. The analysis compared lane parameters measured by the follow vehicle to those measured by the lead vehicle.

Comparing the lane parameters in post-processing requires that we know the relative position and orientation (relative configuration) of the two vehicles. The relative position of the two vehicles can be determined using either the reported GPS locations, the reported platooning headway or the radar based headway measurement. The relative orientation can be computed using the reported yaw angle for each vehicle from the onboard Inertial Measurement Unit (IMU).

The estimated parameters for each vehicle are associated with the vehicle configuration at the time of the measurement. Therefore, knowing the relative configuration between the two vehicles will allow for quantitatively comparing the lane parameters measured. The Lead-Follow transformation is presented in the following section.

2.2 Lead-Follow Vehicle Transformation

2.2.1 Vehicle Configuration Background

The physical state of a vehicle can be fully described by its position and orientation (yaw angle), $P(x, y, \theta)$ where:

- P is the state/configuration of the vehicle
- x and y are the euclidean coordinates of the vehicle's position
- θ is the global heading angle of the vehicle

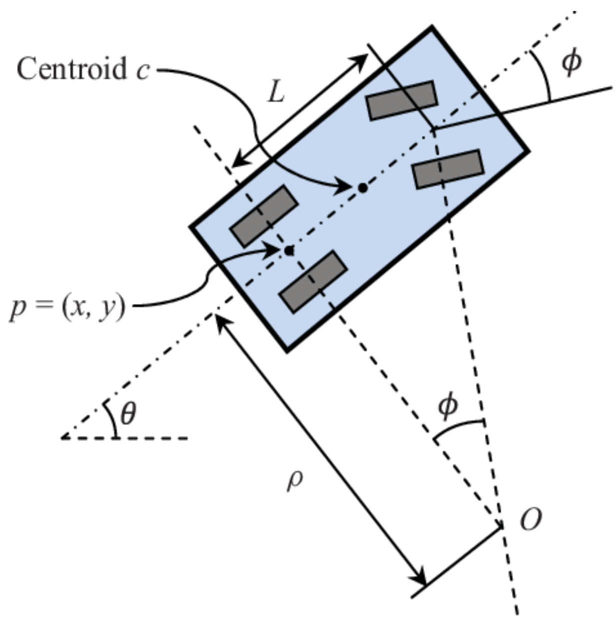

Figure 2.4: A representation of a vehicle's complete configuration in space. [9]

2.3 Paired Vehicle Relative Configuration

In our vehicle platooning scenario, the lead and follow vehicles have their individual configurations. Having a full understanding of both, we can perform a change of frame and thus transform lane parameters measured in the lead vehicle to the follow vehicle frame.

In Figure 2.5 below, Y is the longitudinal separation also known as the distance headway and X is the relative lateral separation. $\Delta\theta$, not shown is the relative heading (yaw angle) between the lead and follow vehicles.

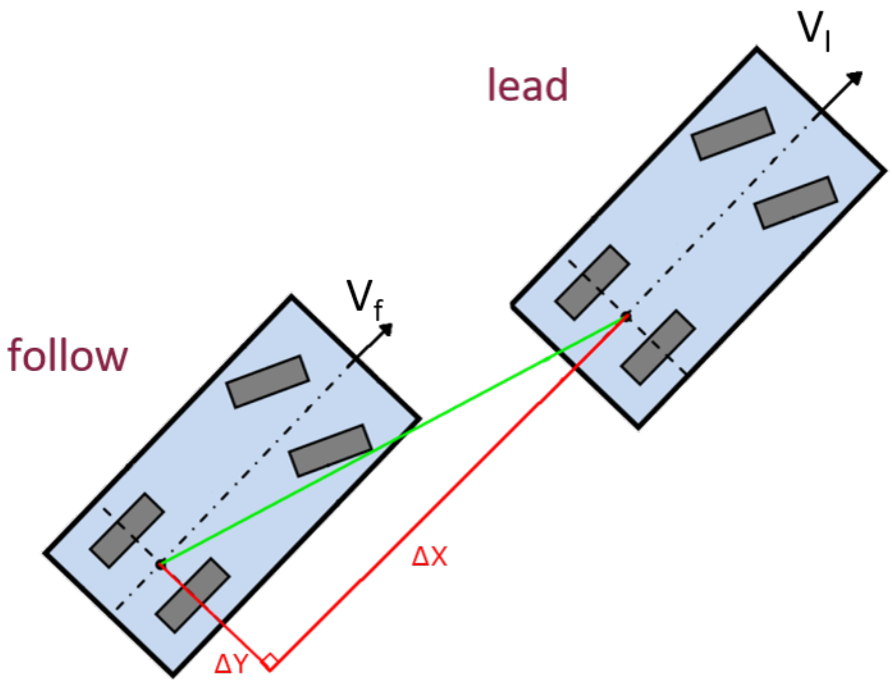

Figure 2.5: Spatial transformation between lead and follow vehicles of a platoon.

The complete relative configuration of the two vehicles in the platoon can be summed up into lateral, longitudinal and rotational components. Therefore, these components of the relative configuration are discussed in the following sections.

2.3.1 Relative Longitudinal Configuration

The relative longitudinal position between the lead and follow vehicles is critical to platooning. This is because it ensures the safety of the operation and is also the key variable in the fuel savings performance of the platoon. For this reason, the relative longitudinal positioning can be considered as a control input for the complete system; a platooning headway can be selected given a fuel saving and roadway utilization goal. Therefore, an effective platoon requires an accurate and stable longitudinal control implementation. For our use case, the relative longitudinal position of the platooning vehicles is assumed to be constant. As such, the distance headway can be represented in terms of a time difference

$$\Delta t = \frac{\Delta Y}{V_{follower}}. \tag{2.1}$$

In our use case, the velocity of the platooning vehicles and the headway is assumed to be constant; additionally, the reference time on which the two vehicles are operating is synchronized. Given these assumptions, the future time at which the follow vehicle will occupy the space currently occupied by the lead vehicle can be calculated using the headway time computed in (2.1). This is defined as the crossing time

$$HT = T + \Delta t. \tag{2.2}$$

In (2.2), HT is a time in the future and T is the global synchronized time. In implementation, synchronized timing between the lead and follow vehicles was not available so (2.2) was not implementable. Instead, the following computation was performed to find the crossing time

$$HT_{leader} = T_{leader} - \Delta t, \tag{2.3}$$

$$HT_{follower} = T_{follower} + \Delta t. \tag{2.4}$$

In (2.3), HT_{leader} is the headway adjusted time for the lead vehicle; it is used to calculate the time transformation between the lead and follow vehicles. Similarly $HT_{follower}$ is the follower time adjusted with the headway time to find the lead vehicle time with respect to that of the follower. This transformation has enabled the comparison of the lane data collected in the lead and follow vehicles of the platoon. The transformed times are used in a simple search algorithm that allows to compare lane estimates that have been transformed longitudinally. This enables the comparison of lead and follow vehicle lane detection performance in short headway platooning.

By computing the headway adjusted time, it is possible to find the time transformation between the lead and the follow vehicles. This is the key to comparing the values measured across the two vehicles; the values are acquired using the adjusted headway time as an index. Having the adjusted headway time index, the minimum transformed Euclidean Distance ED is identified in order to complete the longitudinal transformation between the vehicles.

The search algorithm is summarized below:

Algorithm 1 Search closest time

procedure AT EVERY TIME STEP
  compute new time headway $\rightarrow$ HT_{leader}
  minIdx = min ([startTime : currentTime] - HT_{leader})
  $ED_{plus} = ED(minIdx + 1)$
  $ED_{minus} = ED(minIdx - 1)$
  if $ED_{minus} > ED_{plus}$ **then**
    Idx = $minIdx + 1$
  else
    Idx = $minIdx - 1$
  Headway adjusted states = value(Idx)

Figure 2.6: Headway adjusted curvature rate of change parameter raw values. The lead and follow vehicle lane parameters are aligned for comparison.

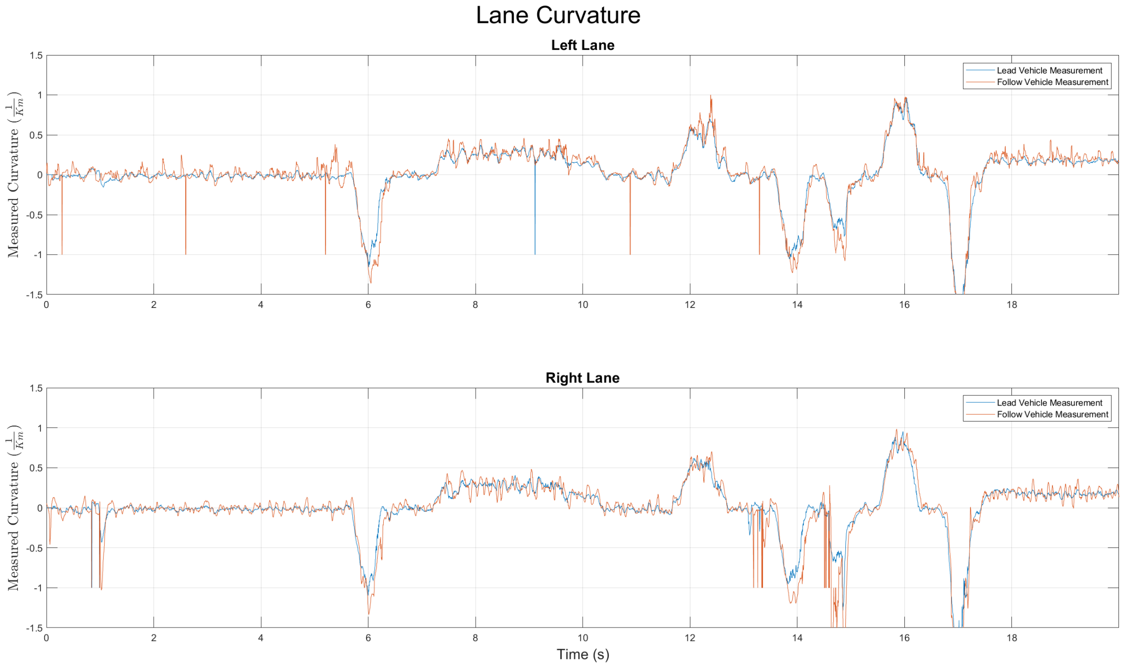

Figure 2.7: Headway adjusted curvature parameter raw values. The lead and follow vehicle lane parameters are aligned for comparison.

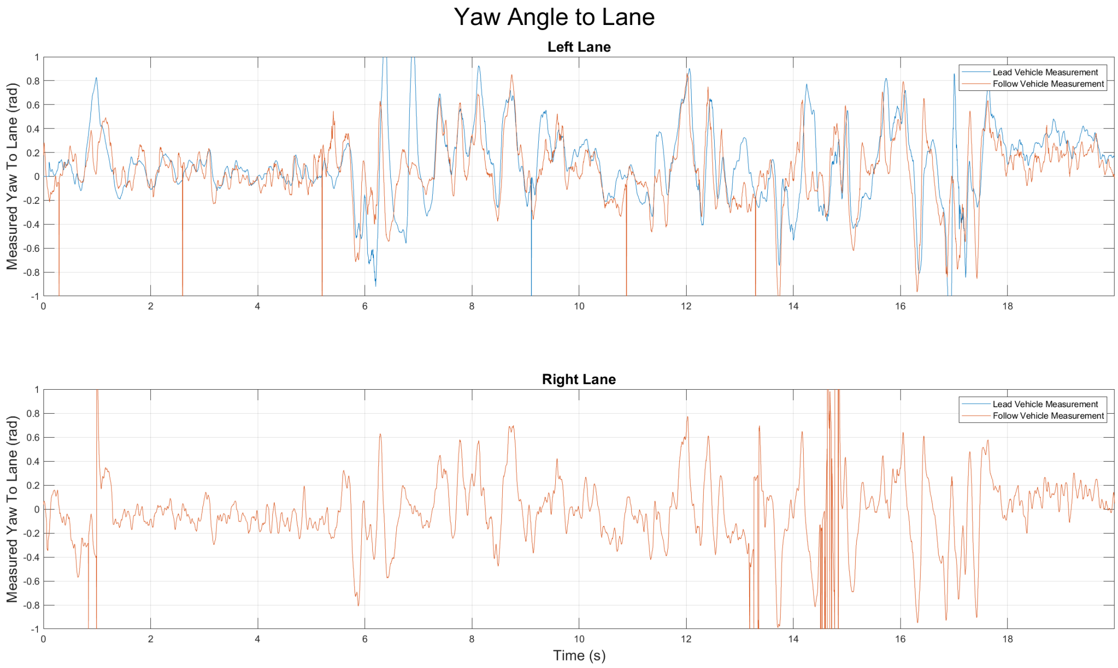

Figure 2.8: Headway adjusted yaw angle to lane parameter raw values. The lead and follow vehicle lane parameters are aligned for comparison.

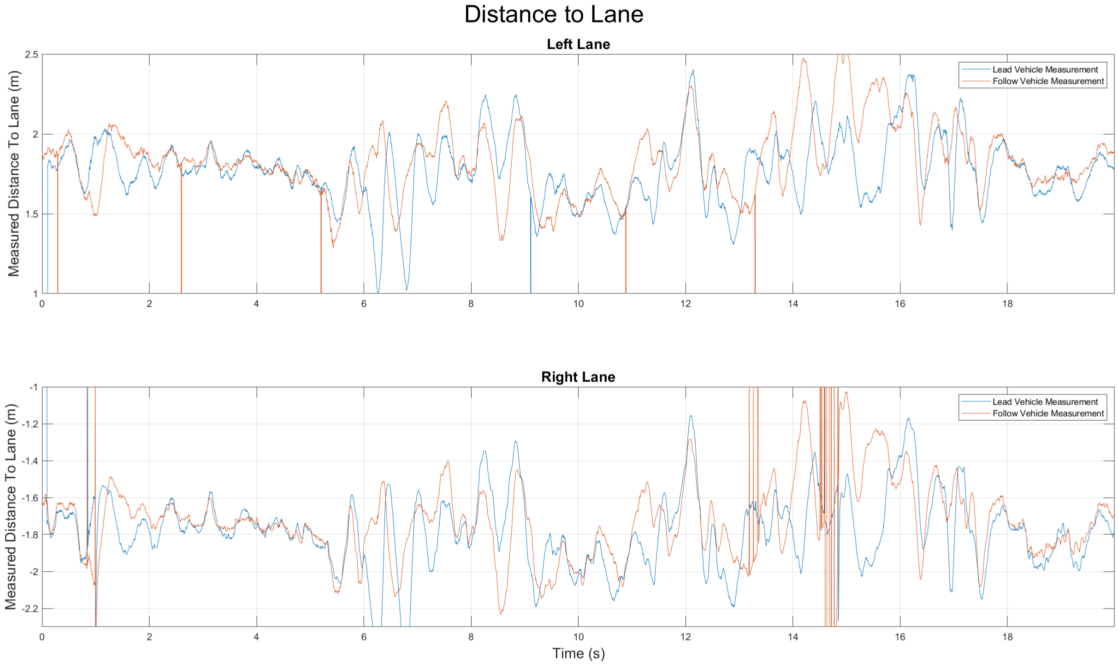

Figure 2.9: Headway adjusted distance to lane parameter raw values. The lead and follow vehicle lane parameters are aligned for comparison.

With an effective longitudinal transformation, the headway adjusted values between lead and follow vehicles can be compared. An example application can be seen in Figure 2.10, where the lead and follow vehicle lane estimates are displayed adjacently on the same time axis.

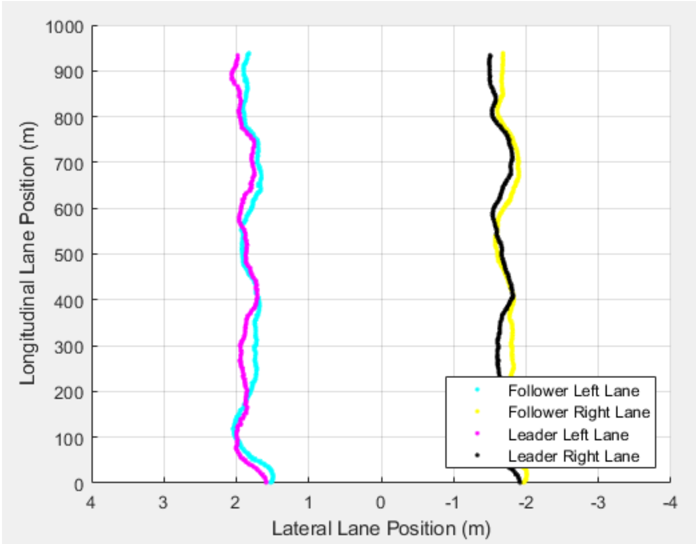

Figure 2.10: The lead and follow vehicle lane lines plotted adjacently after longitudinal transformation in a 40m platoon.

2.3.2 Relative Lateral Configuration and Yaw Angle

The longitudinal transformation provides an adjusted headway time, which can be used to synchronize the lead and follow vehicle times. The synchronized timing provides a common index, which is used to query values for the comparison of the two vehicle states. From the longitudinal transformation, we know the relative longitudinal states. Additionally, from the query mechanism described above, it is possible to compute the relative heading angle (yaw angle) of the two vehicles. Having the relative vehicle states, it is possible to effectively compare the lane estimates.

As such, the relative heading angle can be defined as

$$\Delta\theta = \theta_{lead} - \theta_{follow}, \tag{2.5}$$

where θ_{lead} and θ_{follow} are the individual heading angles measured by each vehicle.

The relative lateral positioning between lead and follow vehicle is the most challenging to measure. Ideally, the relative lateral position can be computed using a highly accurate GPS, comparing the detected lane positioning between the lead and follow vehicles or using object detection to measure the lateral offset between the lead and follow vehicles by looking at the rear of the lead vehicle. In the DTNA truck platooning project only a standard GPS unit with an accuracy of just up-to $\pm 1.5m$ was used; this made GPS based relative positioning calculations not an option. Using object detection to compute the relative lateral position would not be ideal either because the trucks have trailers with kingpins whose position relative to the truck cab is not known. Therefore, the only option left was determining the relative lateral position using the lateral component of the detected lanes from the clothoid lane model presented in (1.1).

$$C(x) = \boldsymbol{y_0} + \phi x + \frac{1}{2}\rho x^2 + \frac{1}{6}\dot{\rho} x^3.$$

In this model, y_0 represents the ego/subject vehicle's linear distance from the detected lane line. The distance to the left and right lane lines can be represented with y_{0L} and y_{0R} respectively. Such that, the width of the lane can be estimated as

$$width = y_{0L} + y_{0R}. \tag{2.6}$$

Computing the lane width from the lead vehicle perspective will be useful in estimating the distance to the left and right lanes in the occluded follow vehicle. This will be presented in detail in later sections.

2.4 Lane Detection Performance Analysis

The DTNA truck pairing program was an experimental approach to understand the benefits, feasibility and system level performance of truck platooning on long-haul rural highways. The experiments performed utilized two prototype Freightliner Cascadias equipped with all the necessary instrumentation and computing systems as presented in Figures 2.2 and 2.3. After build-up and integration, the prototype vehicles were tested on public roads with pairing mode engaged whenever safe and possible.

The experimental pairing operation was performed on the Interstate 84 (I-84) corridor north of Portland, Oregon as well as on the Interstate 10 (I-10) corridor between Phoenix and Tucson, Arizona. The relatively minimal elevation changes and preferable weather conditions motivated the selection the I-10 corridor for the test runs. The I-84 corridor was utilized mainly due to its close proximity to the DTNA headquarters where design efforts were mainly based. The analysis performed in this work and, more specifically, in this chapter of the thesis is focused on rural sections of road that were built in accordance to the [11] design regulations. Therefore, the data recorded during the truck pairing experiments were pre-filtered by location to ensure that the data represented rural roads.

The main goal of the public road testing was to collect data from active pairing sessions. The data logged during the tests was to be analyzed in order to identify system issues and find solutions. In addition to logging the data, the performance of both lead and follow vehicles were annotated by engineers onboard. The notes played a significant role in understanding the performance of the pairing system and guide the post-processing efforts.

The initial tests performed on the I-10 corridor were focused on 15m and 35m headway pairing - pairing was activated with the lead vehicle 15m and 35m ahead of the follow vehicle. A major deficiency exposed by the short headway pairing was the degraded performance of the Lane Keeping Assist system in the follow vehicle. The base vehicle reported that the LKA was not available due to lack of lane visibility. This poor performance of the LKA due to poor lane detection in the follow vehicle motivated the analysis of the follow vehicle lane data with respect to the lead vehicle lane data. In essence, the analysis considers the lead vehicle as the ground-truth with the assumption that its view of the lane lines is not occluded.

As discussed in prior sections, lane detection for the LKA is performed by fitting clothoidal curves through the detected lane lines. The curves are then represented by using parameters for the curvature rate of change, curvature, relative yaw angle and lateral distance to the lane for each respective lane line. These parameters are represented in individual time series which are then used to compute the aggregate curve representing the lane.

The challenge of analyzing the lane detection performance of one vehicle with respect to another is that the two vehicle logs are based on asynchronous clocks; the two vehicle clocks are however synchronized to GPS time. Therefore, the relative vehicle transformations described in Section 2.3 along with GPS time-sync allowed for the pairwise comparison of lane parameters measured by the two vehicles. The detailed comparison approach and results are presented in the following section.

2.4.1 Quantitative Lane Detection Performance Analysis

The follow vehicle's lane detection analysis was intended to get a quantitative understanding of its lane detection performance. This quantitative analysis was done on prior logged data in post processing. The analysis needed to yield a statistically accurate result that accounted for the nature of the logged data. A euclidean-distance-based analysis was initially explored for this purpose.

In using the euclidean-distance-based analysis, the lane parameter logs were first transformed longitudinally as presented in the previous section. After the transformation, an iterative calculation was performed to determine the distance between the lead and follow vehicle's measured parameters. It was quickly obvious that the data was too noisy, making the euclidean distance analysis ineffective.

It was further made apparent that it is necessary to calculate the similarity between the lead and follow vehicle measurements. The similarity between two sets of data can be measured using statistical methods. In this work, we used the Mahalanobis Distance [6] as a comparison tool.

The Mahalanobis Distance (MD) is a statistical validation technique used to determine the validity of measurement updates when solving estimation problems [3]. When estimating a state, it is ideal to know how close the measurement is to the ground truth value. This however is not possible since the ground truth value is typically not known, which is why the estimation is needed in the first place. The MD compares the new measurement to the prior belief state; where the belief state is the value representing the state estimate before the measurement update is applied. The MD gives a value that can then be compared to a threshold and determine if the measurement is accurate enough to be used as an update. The MD is represented by the following equation

$$MD(\boldsymbol{x}, \boldsymbol{y}) = \sqrt{(\boldsymbol{x} - \boldsymbol{y})C^{-1}(\boldsymbol{x} - \boldsymbol{y})'}. \tag{2.7}$$

In (2.7), $\boldsymbol{x}$ and $\boldsymbol{y}$ are two vectors, representing measured parameters, that are compared to find the MD. In our application, the MD represents the similarity between the lead and follow vehicle lane parameter measurements after accounting for the longitudinal translation. A smaller the MD value represents higher similarity.

Based on the clothoidal lane model, we know that the lane parameters are dependent on the vehicle's position and orientation in the lane. Furthermore, the relative position and orientation between the lead and follow vehicle could result in variation of the lane parameter measurements between the two vehicles. The MD accounts for co-variance in the comparison making it an ideal tool for our application. Using the MD, we were able to get good insight into how well the follow vehicle can estimate lane characteristics (curvature rate of change, curvature and yaw angle) as compared to the lead vehicle.

From the clothoidal lane model and our analysis, we learned that the curvature rate of change and curvature parameters are static characteristics of the lane; they should not change regardless of the ego/subject vehicle's state. The yaw angle to the lane parameter is dependent on the vehicle global orientation as well as the lane's global orientation. The distance to the lane parameter on the other hand is dependent on the vehicle's distance to the lane line.

Therefore, the most useful value of the analysis lies in the comparison of the curvature rate of change and curvature parameters using the MD. The comparison of the Yaw angle to the lane line parameter requires that the measurement is rotated with respect to the relative yaw angle between the two vehicles.

During the MD calculation, each lane and its parameters are considered individually. Therefore, the MD yields several comparisons for each lane line. A set of results of the MD analysis for a 15m pairing episode is presented below.

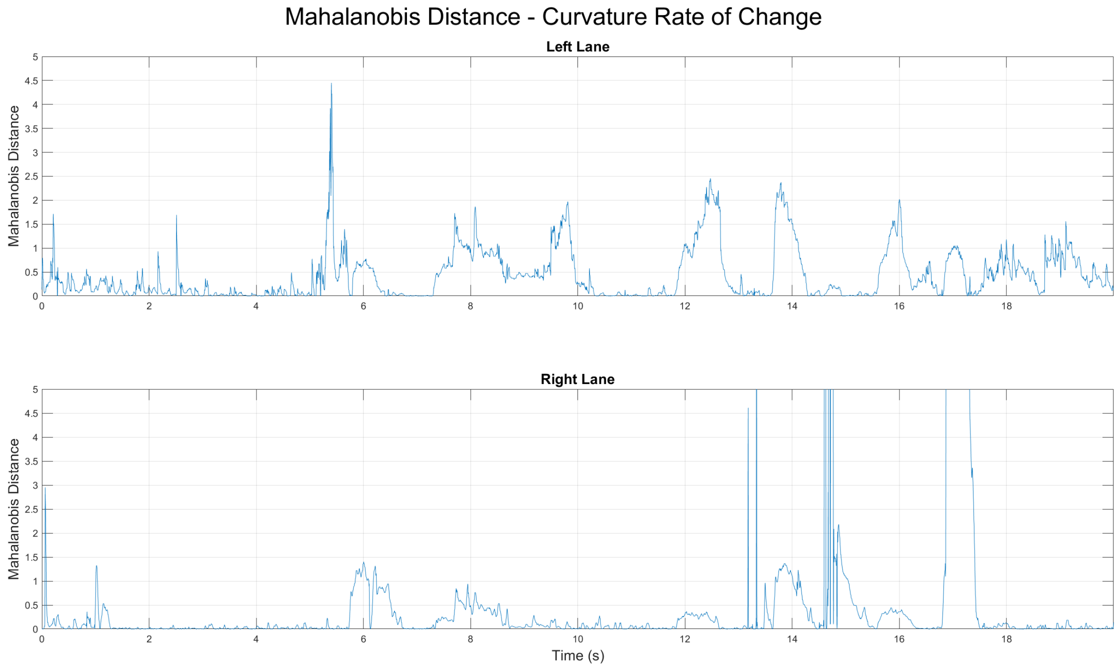

Figure 2.11: MD comparison of lane curvature rate of change of the left and right lanes measured in the lead vehicle versus the follow vehicle during a 15-meter headway truck pair.

It can be seen in Figure 2.11 that there are several points where the MD increases. These regions are where the follow vehicle's measurement of curvature rate of change differs from that of the lead's. It can also be seen that the left lane MD is generally higher than the the right lane MD. This indicates that the follow vehicle's measurement of the left lane's curvature rate of change is more degraded for this specific case.

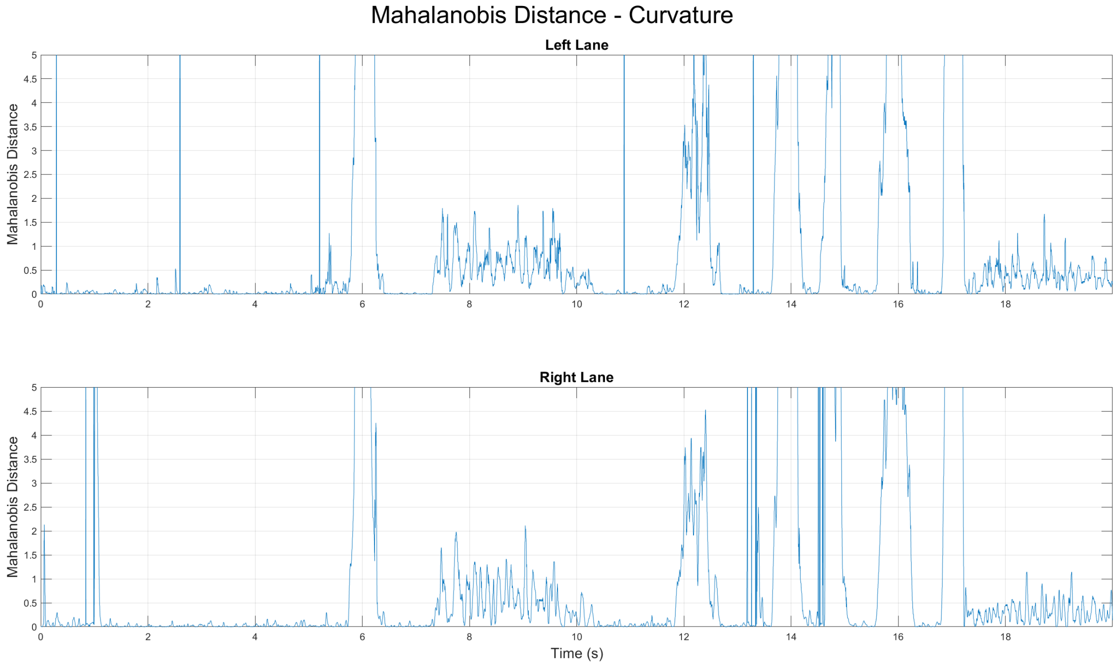

Figure 2.12: MD comparison of lane curvature of the left and right lanes measured in the lead vehicle versus the follow vehicle for 15-meter headway truck pair.

In Figure 2.12, the MD for both the left and right is very similar. The increased MD, where the curvature estimate is degraded, occurs at about the same time in the left and right lanes. This indicates that for this data set, the estimate of the curvature is degraded equally in both left and right lanes. Additionally, it is good to note that the degraded curvature occurs at the same time the curvature rate of change degrades in Figure 2.11; the two plots cover the same time period.

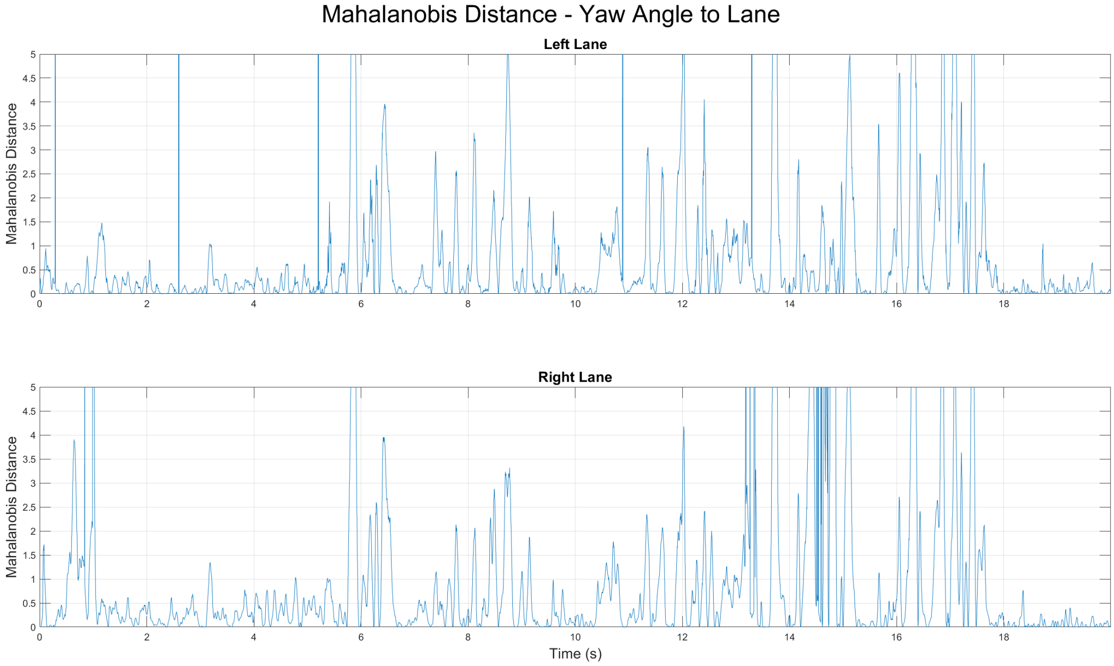

Figure 2.13: MD comparison between lane yaw angle to the left and right lane measured in the lead vehicle versus the follow vehicle for 15-meter headway truck pair.

It can be seen in Figure 2.13 that the MD for the yaw angle to the lane parameter is generally higher compared to the MD for the curvature and curvature rate of change. This is because the measured yaw angle to the lane parameter depends on the vehicle's orientation (yaw) and we did not take the relative yaw angle between the lead and follow vehicle into account when computing the MD. In the areas the MD is relatively lower, the vehicles are driving through a straight section of road, which means they likely had a small relative yaw angle.

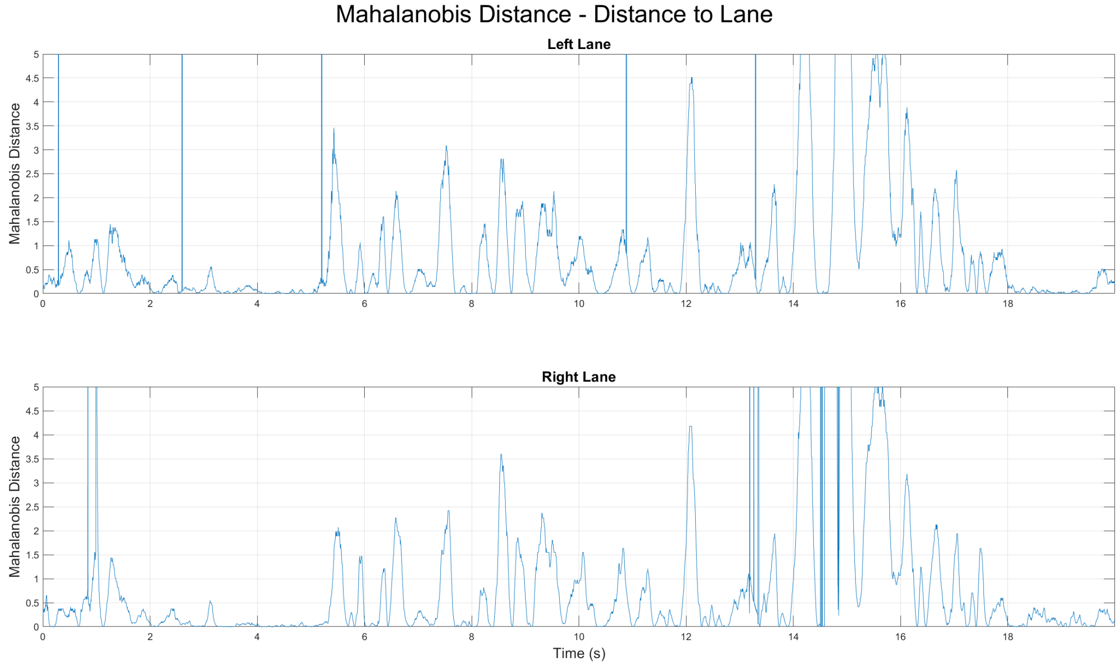

Figure 2.14: MD comparison between distance from left and right lane measured in the lead vehicle versus the follow vehicle for 15-meter headway truck pair.

It can be seen in Figure 2.14 that the MD for the distance to lane parameter is overall higher than all the other parameters; this is because of the relative lateral position between the two vehicles. As with the yaw angle to the lane parameter, the regions where the distance to lane MD is lower correspond with straight sections of road, in which both vehicles likely maintained the center of the lane.

In addition to using the MD to evaluate the individual lane parameter estimates between the lead and follow vehicle, it is also useful to compare the whole clothoidal lane generated by the parameters. This can be done by first performing the longitudinal transformation of the lead vehicle's lane parameters to the follow vehicle frame. Next, the follow vehicle and transformed lead vehicle lane parameters are used to compute the clothoidal curve using the clothoidal lane model defined in (1.1); the same maximum range is used for both vehicles and the curve is computed by discretizing the selected maximum range. With the curves computed, the range normalized area between them is defined as

$$A_n = \frac{\int C_L dx - \int C_F dx}{D}, \tag{2.8}$$

where A_n is the area between the lane curves normalized by the maximum longitudinal range, C_L is the lane curve generated by the lead vehicle, C_F is the lane curve generated by the lead vehicle and D is the maximum longitudinal range used used to compute the clothoidal curves. Figure 2.15 shows the area between the lead and follow vehicle estimations of the left and right lanes; the same data set from Figures 2.11, 2.12, 2.13 and 2.14 is used.

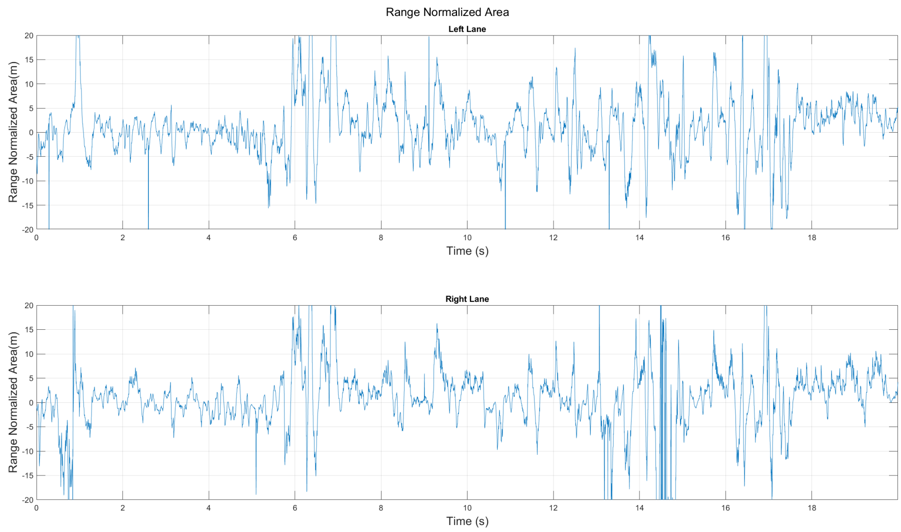

Figure 2.15: Range normalized area between the lead and follow vehicle lane detection for 15-meter headway truck pair.

The normalized area represents the distance between the lanes estimated by the lead and follow vehicles. In Figure 2.15, it can be noted that the higher normalized area values align with the increased MD values for the different lane parameters presented above. Additionally, the normalized area is able to effectively represent the similarity between lead and follow vehicle measurements, even when the MD fails due to noise. Therefore using the two measures of similarity allowed us to effectively evaluate the performance degradation of the follow vehicle's lane detection.

Refer to Appendix A for the combined figures containing the raw parameter values, mahalanobis distance and normalized area between clothoidal curves.

The results of this analysis were useful in understand the source and type of degradation in the lane detection. The post processing of noisy data that is prone to environmental factors as well as driving conditions had limitations, preventing the analysis from being conclusive and reliable. Furthermore, the results of the data analysis were insufficient to design the necessary lane augmentation to improve the detection accuracy in the follow vehicle. Therefore, this warranted further investigation using simulated lane data. This is the main motivation for the simulation based analysis presented in Chapter 3.

2.5 Summary

The DTNA truck pairing tests helped expose a significant issue with the existing single-forward-facing-mono-camera Lane Keep Assist (LKA). It was discovered that the follow vehicle LKA was unable to perform effectively when in short headway platoons. The failure of the LKA is due to the occlusion of the follow vehicle's cameras by the lead vehicle, degrading the lane detection performance.

The consequence of the occlusion was identified by comparing the detected lane parameters between the follow and lead vehicles. During the experiments, the ground truth location and profile of the lanes were not recorded. Therefore the lane detection of the lead vehicle were considered the ground truth source and the post-processing analysis was performed based on that assumption.

The lead and follow vehicle lane detection performance was compared using euclidean distance, mahalanobis distance and by computing the range normalized area between the lane estimates of the two vehicles. During the analysis, the results of the mahalanobis distance and range normalized area were found to be more representative and useful. The vehicle lane estimates are in the form of coefficients of the clothoidal lane expression defined in (1.1); these coefficients are stored as independent time series. After performing the appropriate longitudinal time transformation, the lane parameter time series were compared using the preferred analysis techniques. The result of the analysis provided an understanding of the impact of occlusion on the measurement of different lane parameters. Additionally, the analysis provided insight into the nature of the lane characteristics which was useful in the design of the cooperative lane detection.

Overall, the post-processing of the DTNA truck pairing lane data, collected in an actual platooning scenario, was helpful in making qualitative inferences. However, the results of this analysis were insufficient to form conclusive thoughts and understand the quantitative performance of the lane detection in the follow vehicle. Even though the analysis was useful in understanding the degradation, the result was highly affected by noise, the environment, and the general driving patterns during the data collection. This motivated the use of a simulation to fully characterize the failure. Furthermore, a simulation was needed for the design of the cooperative lane detection; designing an algorithm using the post-processed data alone is impractical due to noise, the lack of ground truth and the limited time in which pairing was activated.

Chapter 3

Cooperative Lane Detection Design and Simulated Results

The results of the post-processing work done on the DTNA truck pairing experiments indicated that all parameters used to estimate the lane (curvature rate of change, curvature, yaw angle to the lane line and distance to the lane) were degraded in the follow vehicle when compared to the lead vehicle detection. The post-processing results were based on the assumption that the lanes are detected perfectly in the lead vehicle and that the global position and orientation of the lead and follow vehicle can be calculated effectively.

Even though the results of the analysis indicated a consistent degradation of lane detection quality in the follow vehicle, those results were at best qualitative and there was no ground truth source of lane data. Additionally the transformation was based on GPS and Range (radar based) sensing which could be noisy. This motivated the need for a simulated pairing scenario with a controllable scene capable of generating simulated lanes and sensor models.

The Mathworks Automated Driving Systems (ADS) Toolbox provided all of the requirements needed to perform an effective analysis. In addition to providing ground truth data and a sensor model for the monocular camera, the Automated Driving Systems Toolbox simulates the effect of occlusion on lane detection. This made it even more useful in understanding the consequence of short-headway platooning on the follow vehicle's lane detection performance. Furthermore, the actor global positions and orientations are also available in the simulation making it possible to determine all of the appropriate transformations.

The results of the simulated degradation analysis as well as the lane augmentation design approach are presented in this chapter of the thesis.

3.1 Simulation Environment

The driving scenario designer was used to create several driving situations involving straightaways, left-turns, right-turns and S-shaped maneuvers. The simulations were performed using preset waypoints. The driving scenario designer generates a Matlab script that can be modified to accommodate specific needs. In the scene building for the analysis and design of the augmented lane detection, the scene files were modified to provide the appropriate pairing setup to generate sensor data with both lead and follow vehicles as the ego/subject vehicles. This enabled the collection of accurate lane data and degraded data due to the simulated occlusion. Below are some images showing snapshots of the driving scenario designer and the simulated lane detection simulation.

The vehicle waypoints are randomized by adding randomly generated offsets simulating a realistic driving behavior. The random offsets change the next waypoint location; the waypoints are constrained to be within the lane of travel.

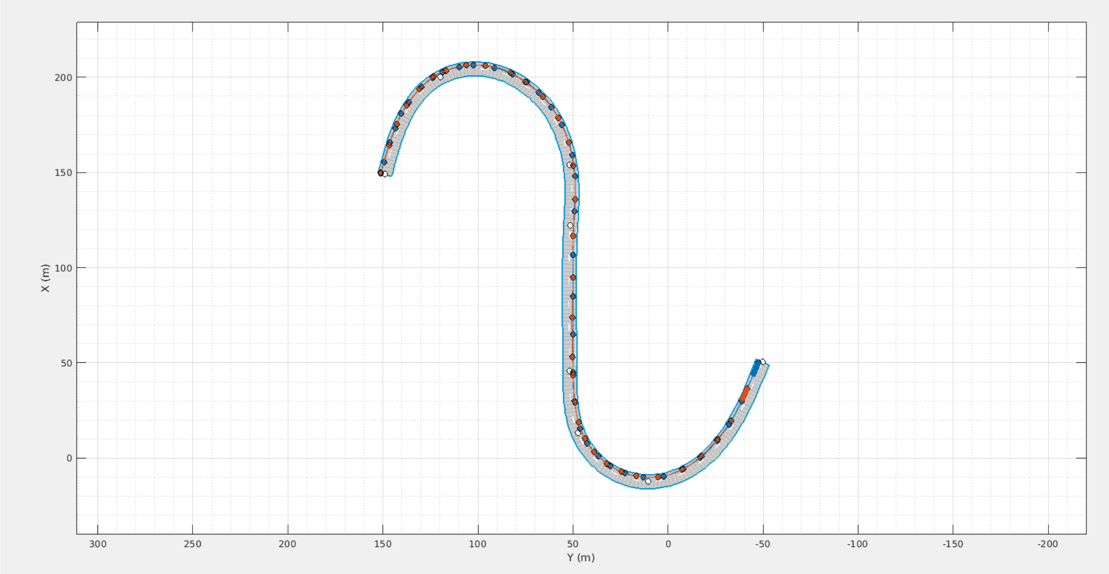

Figure 3.1: Long S driving scenario road and waypoints with lead and follow actors. Orange and Blue boxes represent actors and corresponding points represent waypoints.

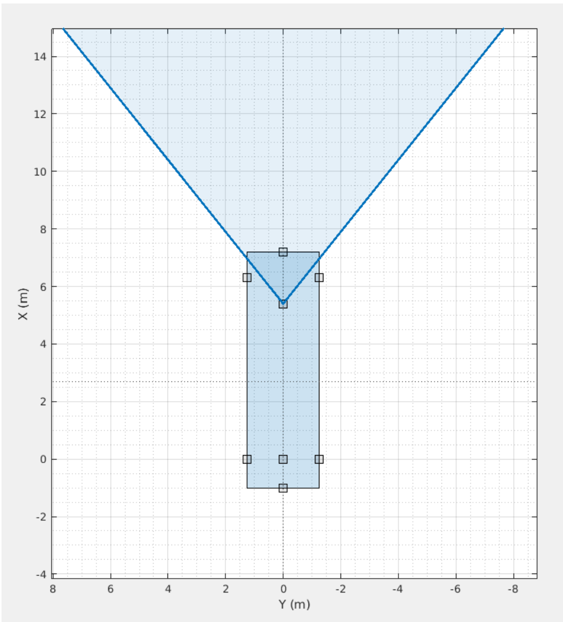

Figure 3.2: Vehicle camera configuration in the driving scenario designer.

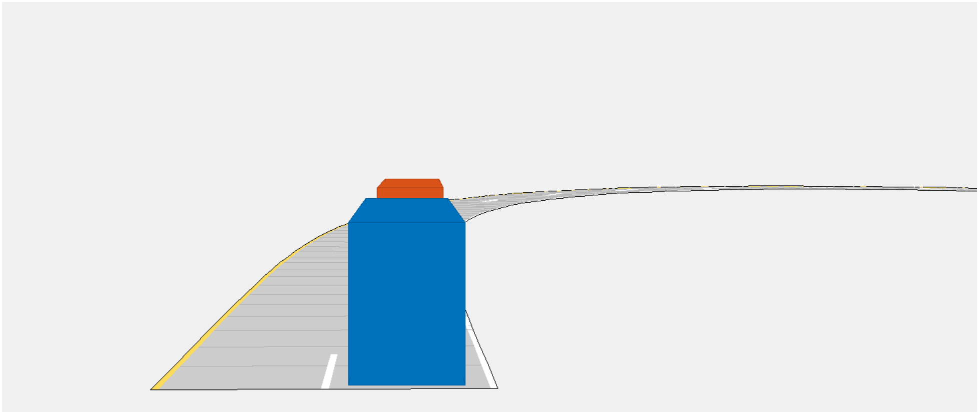

Figure 3.3: Simulation scenario from the Follow Vehicle perspective.

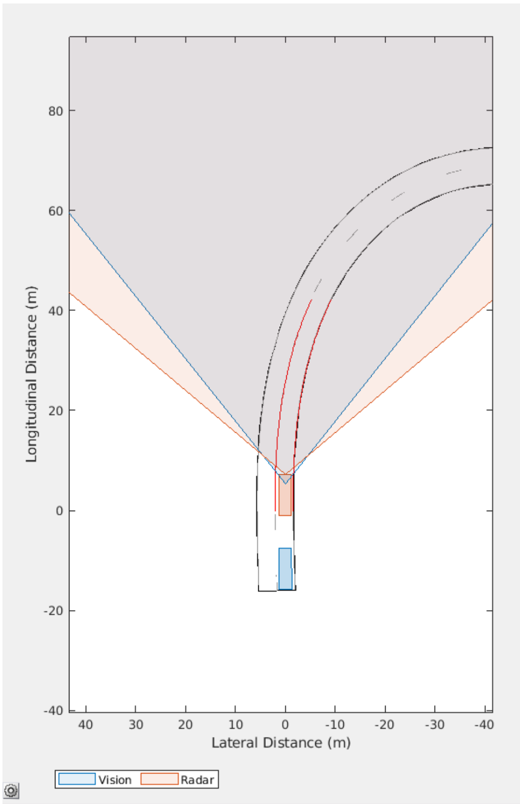

Figure 3.4: Lead vehicle lane detection in a right turn free of occlusion.

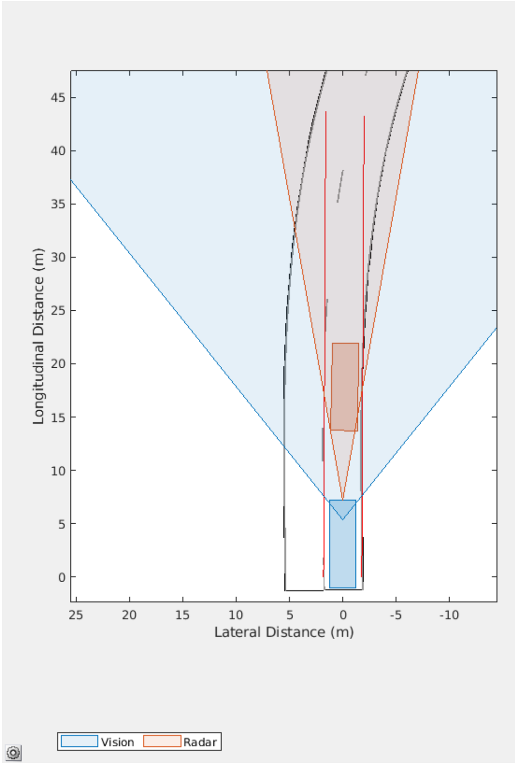

Figure 3.5: Follow vehicle lane detection in a right turn degraded by occlusion from the lead vehicle.

The simulation environment provides a global position and orientation for each actor in the scene. The global position was utilized to perform the longitudinal transformation necessary to compute the time headway between the lead and follow vehicle. The longitudinal transformations of values from lead to follow vehicle are performed by finding the time delta as shown in (2.1). The rotational transformation is achieved because the global heading (Yaw) angle of both lead and follow vehicles are also provided by the simulation. After performing the appropriate transformation, lane information from the lead vehicle can be compared to that of the follow vehicle. Furthermore, the information from the lead vehicle can be used to augment lane parameters in follow vehicle and enable the cooperative lane detection.

In performing the cooperative lane detection by parameter augmentation, we can directly use road characteristics as measured by the lead vehicle to reconstruct the lane in the follow vehicle's frame. The road characteristic parameters are the curvature (ρ) and curvature rate of change ($\dot{\rho}$). We know that the road characteristics do not change between the time the lead and follow vehicles pass through the same point. Therefore, in an ideal situation, the measurement of these parameters by the lead and follow vehicle should be the same. This is shown in the following figures where the estimation of the curvature and curvature rate of change are compared between an occluded and un-occluded vehicle.

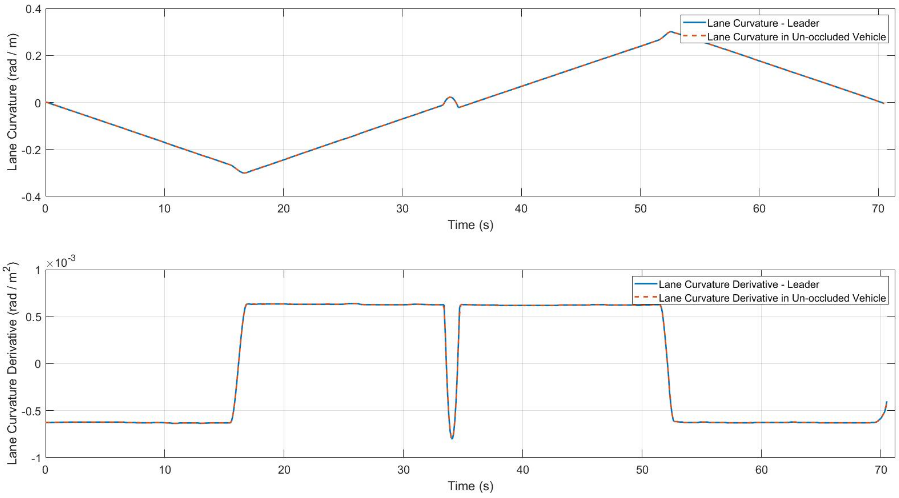

Figure 3.6: Comparison of lead and un-occluded follow vehicle performance in estimating curvature and curvature rate of change of the left lane when tracking the same way-points.

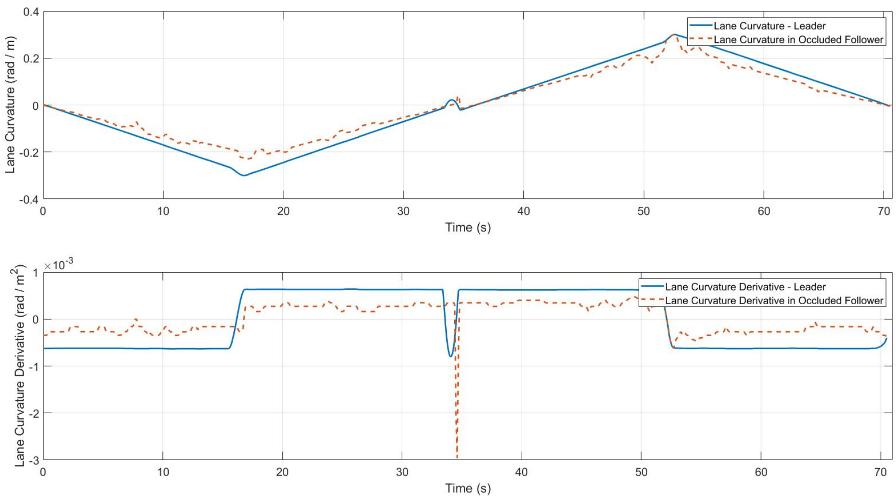

Figure 3.7: Comparison of lead and occluded follow vehicle performance in estimating curvature and curvature rate of change of the left lane when tracking the same way-points.

It can see from Figures 3.6 and 3.7 that the lead vehicle, when un-occluded, has the ideal measurement of road characteristics therefore those measurements are used directly in the reconstruction. However, we need to pay more attention in transforming the distance-to-lane and yaw-angle-to-lane measurements.

After obtaining the relative yaw angle between the two vehicles as defined in (2.5), the rotation matrix is applied to a the lead vehicle's lane curve. The distance to the lane parameter is set to *zero* for the purposes of generating the lane curve here since it has no effect on the yaw angle parameter, and it simplifies the calculation. The lead vehicle lane curve is computed to a sufficiently large range x; in this work $x = 100\ m$ is used. This provides a value pair of curve points and longitudinal range values

$$P(\mathbf{x}, \mathbf{C}(\mathbf{x})) = \begin{bmatrix} x_1 & C(x_1) \\ x_2 & C(x_2) \\ \vdots & \vdots \\ x_n & C(x_n) \end{bmatrix}. \tag{3.1}$$

The value pair vector of points $P(\mathbf{x}, \mathbf{C}(\mathbf{x}))$ is rotated by the relative yaw angle between the lead and follow vehicles

$$P' = P(\mathbf{x}, \mathbf{C(x)}) * \begin{bmatrix} cos(\Delta\theta), & -sin(\Delta\theta) \\ sin(\Delta\theta), & cos(\Delta\theta) \end{bmatrix} \tag{3.2}$$

After the rotation in (3.2) is applied, a third order curve is fitted to the range and curve value pair. The coefficient of the first order term of the fitted curve becomes the transformed yaw angle to the lane parameter of the augmented lane; this aligns with the clothoidal lane model defined in (1.1). The results of the augmented yaw angle calculation compared to that of the un-occluded vehicle is presented in the figure below. It can be seen that the augmentation matches closely with the measurements of the un-occluded vehicle.

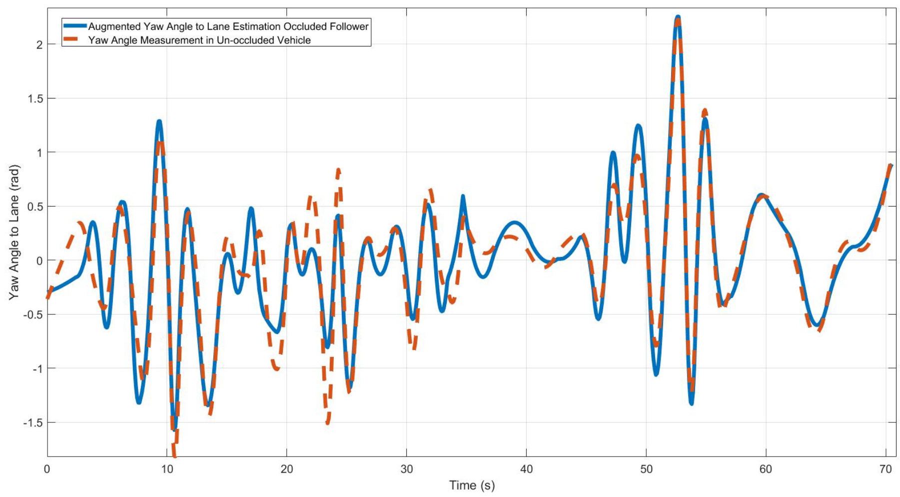

Figure 3.8: Cooperatively augmented yaw angle to the left lane of an occluded follow vehicle versus the actual measurements the same vehicle when un-occluded.

As described briefly in Section 2.2, distance-to-lane estimation is performed using the lane that is least occluded as identified by the variance. The least occluded lane is defined as the lane side with the lowest variance. The variance is computed for an arbitrary number of samples in the past; 10 samples is used in this case; the number of samples used is a tuneable parameter.

The lane width, computed by using (2.6), is sent from the lead to follow vehicle after accounting for the appropriate longitudinal transformation. After identifying the least occluded lane, the most occluded lane can easily be calculated by taking the difference between the lane width and the distance to the least occluded lane. It is important to keep the conventional sign in mind. The left lane distance from the center line is assumed to be positive, while the right lane distance from the center line is considered negative. The lane line augmentation can be shown as

$$y_{aR} = width - y_{FL}, \tag{3.3}$$

$$y_{aL} = width + y_{FR}, \tag{3.4}$$

where y_{aR} and y_{aL} are the augmented distance from lane parameters when the left distance to lane y_{FL} and right distance to lane y_{FR} are degraded respectively and the lane $width$ is obtained from (2.6). The distance to lane parameters with the least variance represent the more accurately measured lane. In the figure below, the augmented distance to lane estimate in an occluded vehicle is compared to distance to lane measurements of the same vehicle when un-occluded; the vehicle is tracking the same waypoints in both cases.

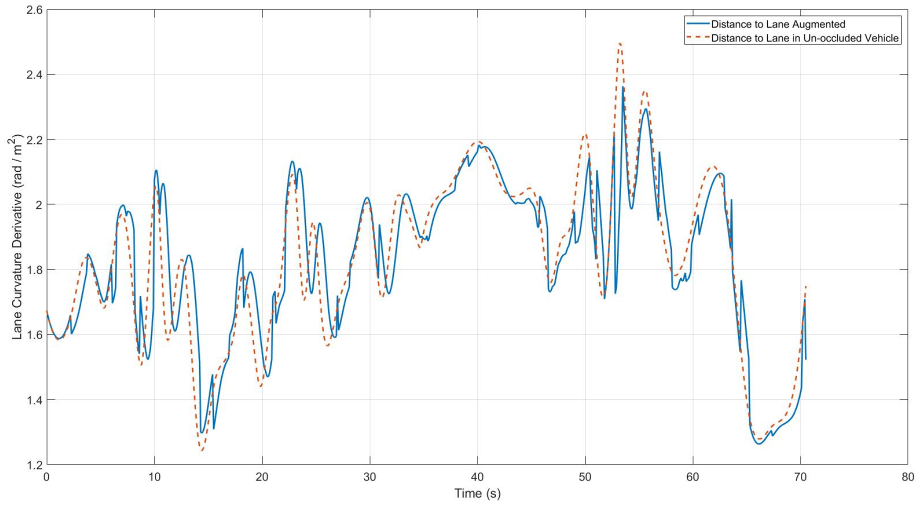

Figure 3.9: Estimated distance to the left lane of an occluded follow vehicle versus the actual measurements of an un-occluded vehicle.

It can be seen that the estimated values and the actual values are close, but not perfect. The un-occluded vehicle's measurements of distance to the lane is a lot smoother as compared to the augmented results. The augmented results have high variation and noise levels. The distance to lane parameter needs to be filtered before it can be used to compute the clothoid lane curve. The minor difference can be corrected by using an averaging filter that would utilize the actual measurements from the follow vehicle to correct the augmented estimates. This will be discussed in further detail in the following section.

Additionally, a sensor, such as a camera, can be added specifically to measure the linear distance from the lane lines. This sensor can be optimized to measure the linear distance instead of trying to fit a clothoidal curve. This could yield better distance measurement results. This possibility was not explored in this work but could be investigated in further research on this topic.

With the augmented distance to lane line, the cooperative lane detection in the follow vehicle frame is complete. Both lane lines have been augmented using accurate measurements from the lead vehicle. The results of the simulation and cooperative detection are discussed in the following section.

3.2 Simulated Results

3.2.1 Assumptions

The following assumptions summarize the process through which the lead vehicle lane detection is transformed to the follow vehicle frame, as detailed in prior sections.

- Full vehicle state (position and heading) of both lead and follow vehicles are available and known.

- A common base clock between the lead and follow vehicles is available. This can be achieved by using GPS time synchronization.
- The times at which platooning/pairing starts and ends can be clearly distinguished.
- A constant time headway platooning/pair is used. This means that the time separation between lead and follow vehicle is constant or close to constant.
- Both lead and follow vehicles are assumed to be traveling forward at a constant speed.
- A forward facing monocular camera mounted to the center of the vehicle frame is used for lane parameter measurements (lane detection).
- The lead vehicle is un-occluded and can see down the road sufficiently; the lead vehicle is capable of detecting the lane lines with good confidence.
- There are sufficient lane markings based on which the lead vehicle can estimate the lane.
- There is reliable communication, V2V or otherwise, between lead and follow vehicle that enables information sharing.
- The lead and follow vehicles will NOT be following the same exact waypoints.

Full Lane Augmentation Based Results

In this section, the lane reconstruction results using only augmented data are presented. The augmentation uses all parameters, including the distance to the lane estimated by the lead vehicle to correct the lane detection of the follow vehicle. The results shown here utilize the parameter transformation from the lead vehicle frame to the follow vehicle frame. The driving scenario shown in Figure 3.1 is used to demonstrate the results in this section.

Since the goal of this project is to improve lane estimation of a vehicle with an occluded view of the road, the best validation is to compare the newly constructed lane with the lane estimation performed by the same vehicle following the same way-points but without any occlusion. This comparison can be performed by finding the area between the clothoid curves generated by the vehicle when occluded and un-occluded.

In order to compute the area between the two approximations in a meaningful manner, both clothoids are estimated to the same maximum range. The area between the curves is then computed by integrating each clothoid's lateral position $C(x)$ over the total longitudinal range $x \in [0,\ x_{max}]$. The area between the curves then becomes the difference between the two integrals, computed for each sample time. The area is then normalized by the maximum range x_{max} to estimate the distance between the curves in meters. The nominal area between the augmented lane and the lane detected by the un-occluded vehicle is *zero*. The results of this analysis are presented below.

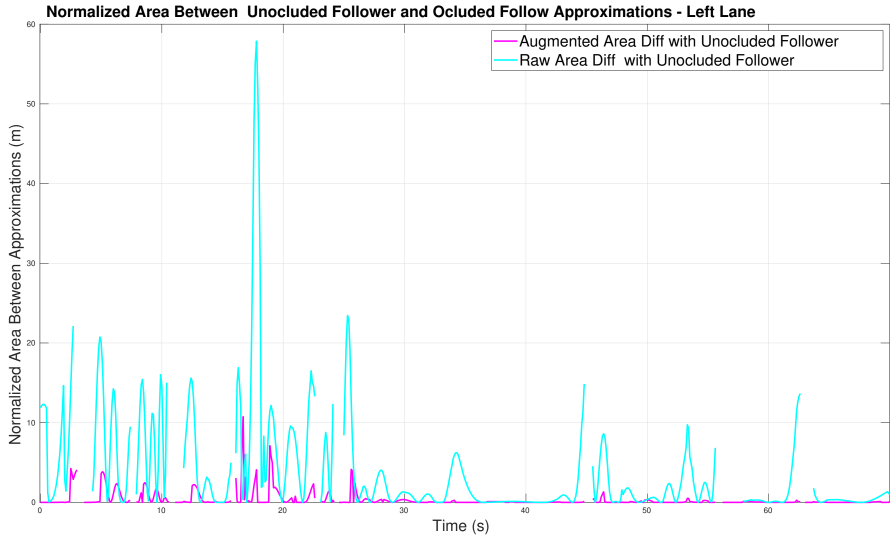

Figure 3.10: Estimated distance between the left lane approximations of an occluded vehicle versus that of an un-occluded vehicle in simulation.

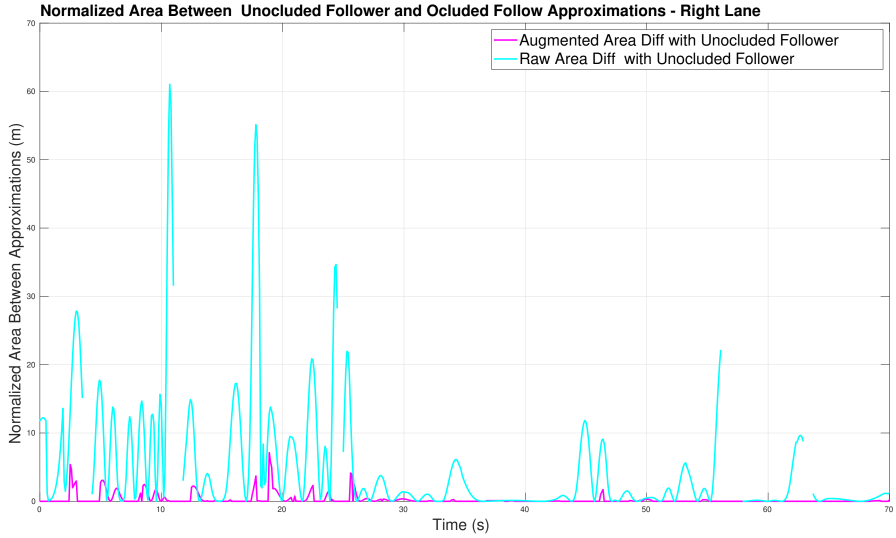

Figure 3.11: Estimated distance between the right lane approximations of an occluded vehicle versus that of an un-occluded vehicle in simulation.

It can be seen in Figures 3.10 and 3.11 that the full lane augmentation significantly improves the detection accuracy; the normalized area between the lanes detected by the occluded and un-occluded vehicle have significantly been reduced by using the transformed and augmented lane estimates. It can be seen that the normalized area after augmentation still has regions where it is above nominal. The source of this inconsistency is the distance to the lane augmentation. In the following section, the same data set is augmented only using the curvature rate of change, curvature and yaw angle to the lane measurements from the lead vehicle; the distance to the lane line is used as measured by the follow vehicle.

3.2.2 Partial Lane Augmentation Results

The lane augmentation using the distance to lane measurements from the lead vehicle has a low accuracy; this was also observed in Figure 3.9. The source of the reduced accuracy is the presence of variation in the relative lateral position of the two vehicles. This affects the distance to lane measurement and is not compensated in the transformation. Therefore, the distance to lane parameter is used directly as measured by the follow vehicle. The result of the partial lane augmentation (excluding the distance to lane parameter) is presented below. As defined in the prior section, the plots below compare the areas between the lane curves of an occluded and un-occluded follow vehicle when augmented versus raw.

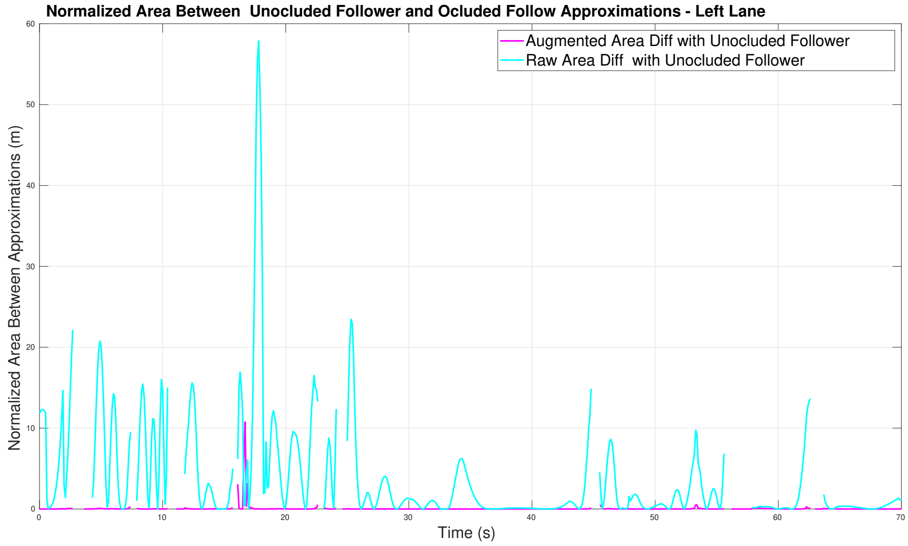

Figure 3.12: Estimated distance between the left lane approximations of an occluded vehicle versus that of an un-occluded vehicle in simulation. In this case, the lane augmentation uses the measured distance to lane parameter.

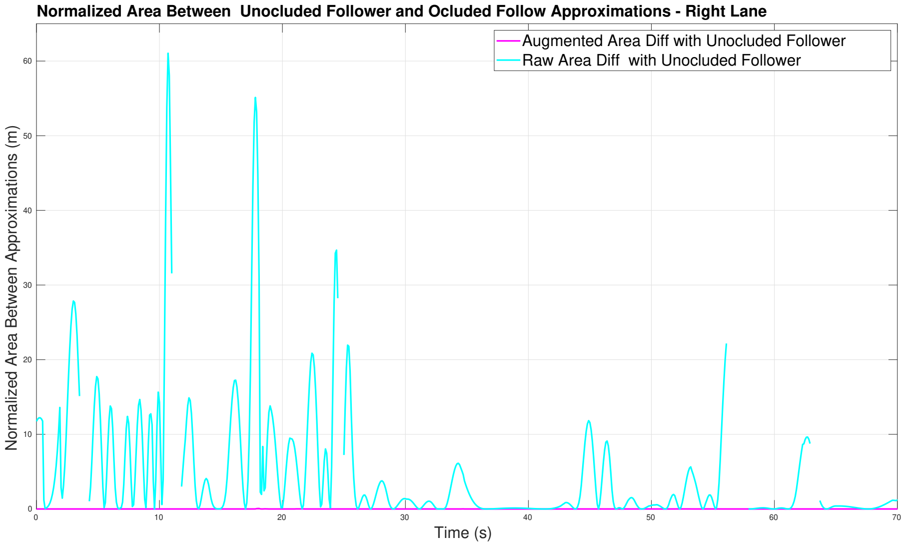

Figure 3.13: Estimated distance between the right lane approximations of an occluded vehicle versus that of an un-occluded vehicle in simulation. In this case, the lane augmentation uses the measured distance to lane parameter.

The data is initially filtered by the euclidean distance between the two vehicles. The filter works by comparing the current distance between the two vehicles to a threshold. If the distance is above the threshold, even slightly, that data frame is dropped and is not used for the analysis. This is the source of the discontinuities seen in the plots.

It can be seen in Figures 3.12 and 3.13 that the normalized area between lane estimates in the lead and follow vehicle drop significantly, attaining the nominal. It can be seen in Figure 3.12 that there is a momentary drop in accuracy; this is caused by a bad distance to lane measurement in the follow vehicle at the first right turn of the scenario.

The improved overall accuracy indicates that transforming the distance to the lane estimation reduces the performance of the augmentation. The single point in which the accuracy dropped momentarily shows that it is necessary to use a reliable distance to lane measurement technique in the follow vehicle. One example of this is a separate lane detection mechanism optimized to measure linear distances instead of clothoid curves.

3.3 Summary

The simulation based degradation evaluation has reinforced the results presented in Chapter 2. From the simulations, we have learned that the clothoidal lane parameter estimation is significantly degraded for the curvature rate of change, curvature and yaw angle to the lane line parameters.

Based on the results of the degradation analysis, the lane augmentation has been designed to use the transformed lead vehicle measurements of the parameters representing the lane characteristics; the distance to the lane lines is used directly as measured by the follow vehicle. The full lane curve is generated using the augmented lane model.

The lane augmentation is analyzed by calculating the area between the lane curves of an occluded vehicle to that of an un-occluded vehicle. The same area calculation is performed using the raw lanes detected by the occluded vehicle. The comparison between the areas of the augmented and raw lanes indicates that there is a significant improvement in lane accuracy when augmentation is utilized. Furthermore, it has been shown that measuring the distance to the lane line directly by the follow vehicle leads to better performance than the proposed transformation.

Chapter 4

Experimental Cooperative Lane Detection

In this chapter, the proposed cooperative lane detection between lead and follow vehicles of a platoon is verified experimentally. The verification is performed using a pair Unmanned Ground Vehicles (UGVs) Terrestrial Unmanned Robots for Teamed Learning and Exploration (Turtles). The Turtles are designed for use as a research platform in the development of automated driving systems including cooperative autonomy. The Turtles provide a platform to rapidly prototype and test algorithms making them an ideal candidate for use in this work. The hardware and software integration performed in the verification of the proposed lane detection strategy is discussed in this section of the thesis. Additionally, the results of the analysis performed to evaluate the lane augmentation is also presented.

The Turtles have a differential drive mechanism powered by a pair 24VDC brushless motors driven by a two-channel Roboteq HBL2360 motor controller. The motor controller is powered by the onboard battery which provides a peak of 240W of power to the drive motors. The Turtles utilize a 27V/100Ah Lithium Iron Phosphate (LiFePo) battery pack, a Battery Management System (BMS) and a power distribution board providing 12VDC/5VDC/3.3VDC to provide electrical power to the drive system and other peripherals. The Turtle frame is mounted on top of two front caster wheels and the two rear drive wheels using an air-suspended sub-frame for stability and vibration isolation of the components mounted on the frame (see Figure 4.1) [12].

The Turtles are also outfitted with an onboard computer, a local networking switch, a Novatel Span-CPT Inertial Navigation System (INS), a Ubiquity radio module and a Logitech USB camera (used for lane detection). In addition to the onboard components, the Turtle platform has a dedicated base station serving as a communications hub as well as a source of Real-time kinematic (RTK) correction in the form of Radio Technical Commission for Maritime Services (RTCM) from a Trimble BD960 unit; the RTK corrections allow for centimeter level ($\pm$ 2cm) GPS positioning. Both onboard and base station computers run on an Ubuntu 16.04 operating system. The Ubiquity radio system is used to create a LAN bridge between the lead and follow turtles as well as the base station. The main task of the on-board computer is to run low level software such as serial communication with the motor controller, acquiring camera images and communication with the onboard INS. The base station computer in turn handles the network communication, lane detection, test operator user interface and cooperative lane augmentation.

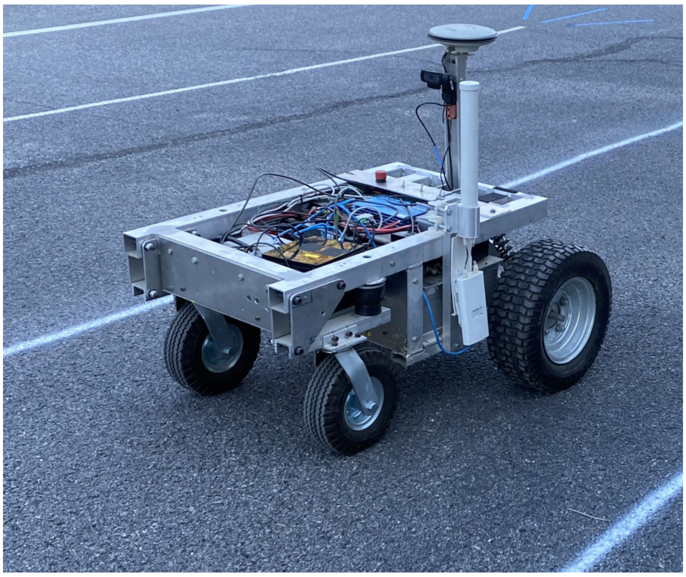

Figure 4.1: Turtle platform

Figure 4.2: Turtles in a paired configuration

The cooperative lane augmentation algorithm proposed in this work was developed in Matlab; the Turtle control, sensor data acquisition and other lower level operations were developed in C++ and python. The different components were integrated using the Robot Operating System (ROS) as a middleware; ROS allowed for the synchronized operation of the full system. The Turtles are operated by a human driver via teleoperation to collect data logs which are used for development, testing and verification of the lane augmentation algorithm that has been developed. The verification performed as part of this work demonstrates that cooperative lane augmentation works in constant headway vehicle pairs including short headway cases. Since the turtles are a reduced size platform than the platforms of intended application - which would be full size truck platoons, the algorithm will need to be tested on the appropriate platform and optimized further.

The high level system architecture of the test setup can be seen in the figure below.

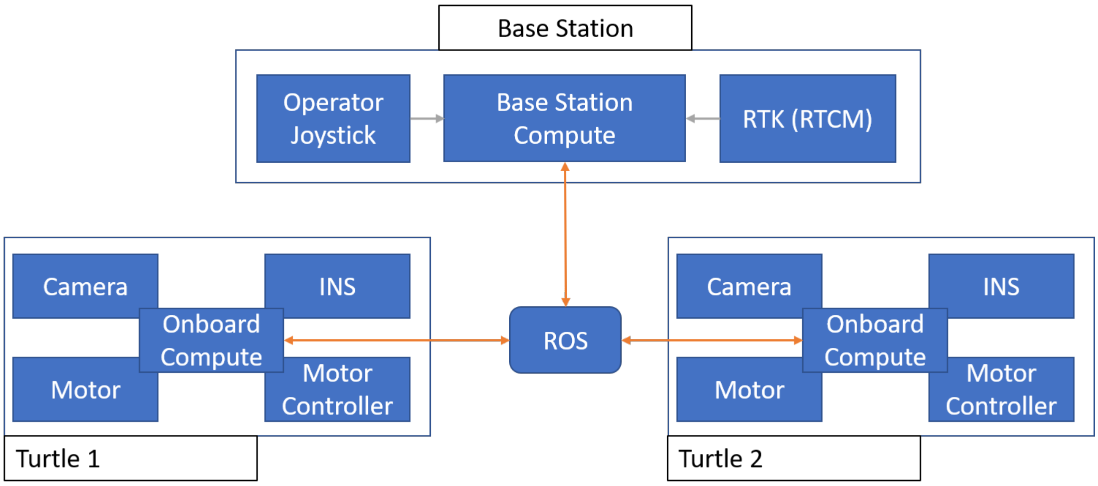

Figure 4.3: High level system architecture of the cooperative lane augmentation

Figure 4.4: Post-processing ROS graph shows inputs and outputs of the lane detector, lane center estimator, follow lane augmenter and visualization

The ROS graph shown in Figure 4.4 presents the communication of the different ROS nodes in the augmentation of the follow vehicle lanes. The two separate namespaces namely trex and trex2 represent the local ROS nodes running on Turtle 1 and Turtle 2 respectively.

4.1 Cooperative Lane Detection Augmentation

The lane detection algorithm implementation utilizes the Mathworks ADAS Toolbox. The Toolbox provides several libraries that allow for lane detection using both traditional computer vision techniques and other methods. For this work, lane detection was performed by using images from the monocular camera onboard each turtle. The cameras were calibrated using the Matlab camera calibration toolbox; this allowed for the determination of the camera intrinsic parameters such as the Principal Point and Focal Length, which are essential in the image space transformations.

Figure 4.5: Frame from the lead vehicle front camera - prior to processing

Using measurements of the camera's mounting configuration (position and orientation) with respect to the Turtle frame and its intrinsic parameters from calibration, a bird's-eye view transform is performed. The bird's-eye view transformed image is then converted to gray scale to create a contrast between the white lane lines and the black pavement.

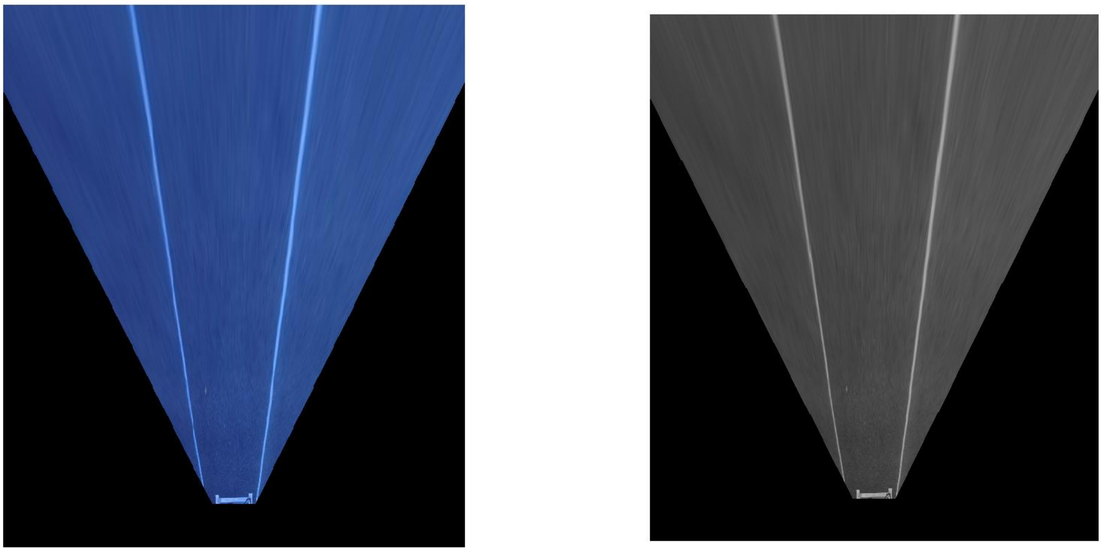

Figure 4.6: Frame from the lead vehicle front camera: (LEFT) bird's-eye view transformation, (RIGHT) gray scale bird's-eye transformation

After the image frame is transformed and converted to gray scale, the image is segmented to isolate the lane line. The lane line segmentation is performed based on the contrast from the gray scale image, camera configuration measurements and some assumptions about the lane characteristics such as the lane line marker widths and lane line separation distance (lane width).

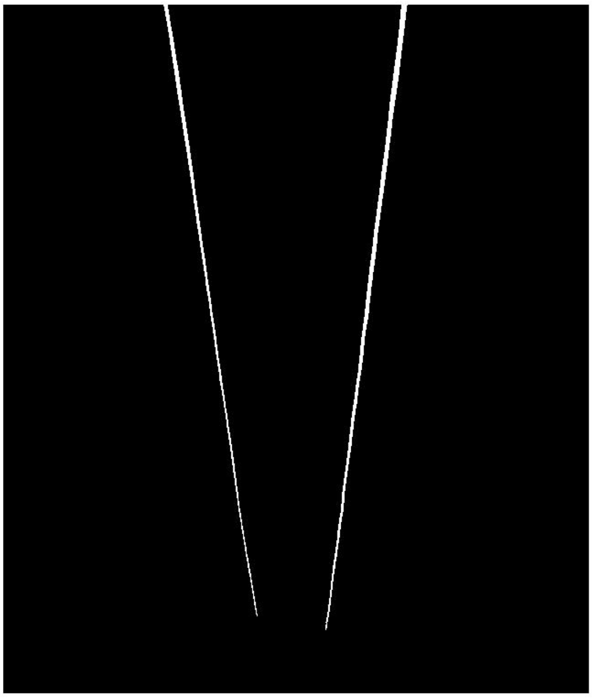

Figure 4.7: Frame from the lead vehicle front camera - segmented lanes in bird's-eye view perspective.

After the segmentation of the bird's-eye view gray scale image, third order curves are fitted to the segmented lines. These third order curves are the clothoidal representation of the lane; the coefficients of each term in the third order polynomial is a clothoidal parameter. The clothoidal representation of the lane utilizes the curvature rate of change, curvature, yaw angle to the lane line and distance from the lane parameters as shown in (1.1). Clothoid lane parameters are generated for the left and right lane lines and the center lane is estimated using the detected left and right lanes.

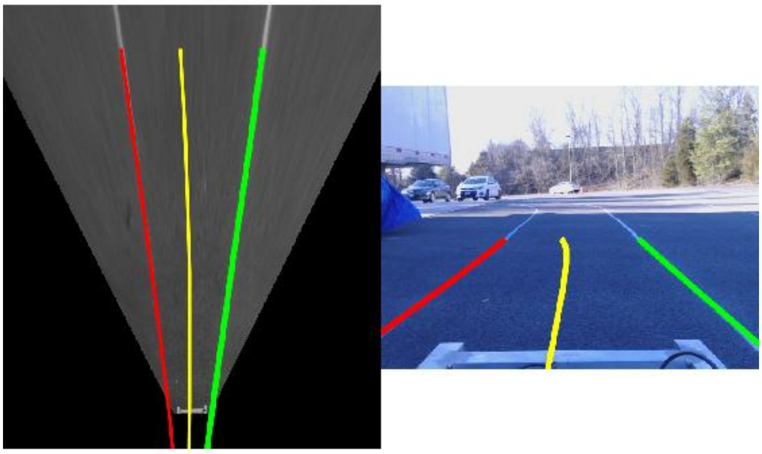

Figure 4.8: Frame from the lead vehicle front camera with detected clothoidal lanes overlaid on top of the bird's-eye view on the left and the original image on the right respectively.

Algorithm 2 Detect lane lines from monocular camera frame

1: Acquire image frame
2: Bird's-eye transform
3: Gray scale transform
4: Segment gray scale bird's-eye view image by intensity
5: Fit third order curves to segmented image
6: Extract lane parameters from third order curves for the left and right lane lines
7: Estimate the center lane based on the left and right lanes

The result shown below in Figure 4.9 are of a scene in which the follow vehicle is trailing at a 2 meters headway behind the lead vehicle. The image serves to demonstrate the consequence of being occluded on the lane detection algorithm, especially on the bird's-eye view image which suffers a distortion due to the occlusion by the lead vehicle ahead. The lane detection results are not usable in this state; it can be seen visually that the detection of the left lane curvature, orientation and distance are incorrect thus adversely affecting the quality of the center lane estimate. The proposed cooperative lane augmentation algorithm is used to improve the lane detection by transforming the lane characteristics and orientation from the lead vehicle to the occluded follow vehicle.

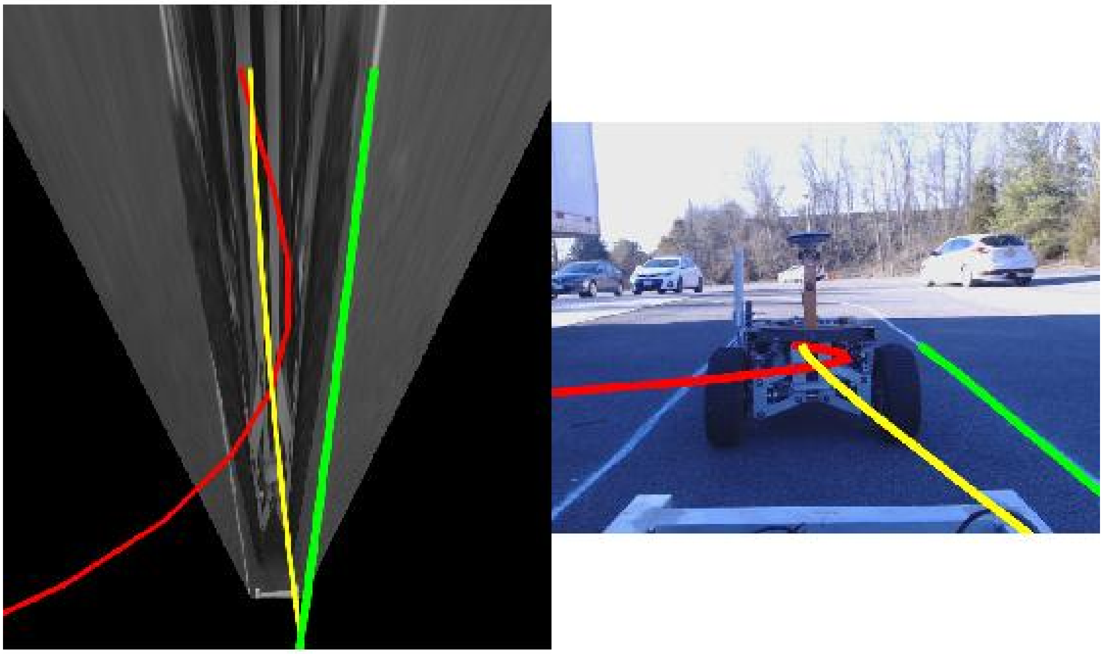

Figure 4.9: Frame from the follow vehicle front camera with poorly detected clothoidal lanes overlaid on top of the bird's-eye view on the left and the original image on the right respectively. Red - Left Lane; Green - Right Lane; Yellow - Center Estimate

4.2 Cooperative Lane Detection and Results

The cooperative lane detection is implemented by utilizing the lanes detected by the lead and follow vehicles individually and the localization results that produced the position and the orientation of the two vehicles in the world frame of reference. The left and right lanes from both vehicles represented as clothoids are used to compute the center lane also represented as a clothoid. The center lanes detected in the lead and follow vehicle are in the frame of each vehicle respectively. The lane augmentation algorithm utilizes the localization solution to transform the lead center lane to the follow vehicle frame to improve the lane detection result.

The lane transformation uses the position and orientation of the lead and follow vehicles. After the lead vehicle center lane is transformed to the follow vehicle frame, the parameters that represent the lane characteristics (i.e the curvature and curvature rate of change) measured in the follow vehicle are replaced by the transformed values measured by the un-occluded lead vehicle. The yaw angle to the lane is rotated with respect to the relative yaw angle between the lead and follow vehicle. The distance from the center lane measured by the follow vehicle is used directly in the augmented solution. The lane augmentation process is summarized in the following flowchart.

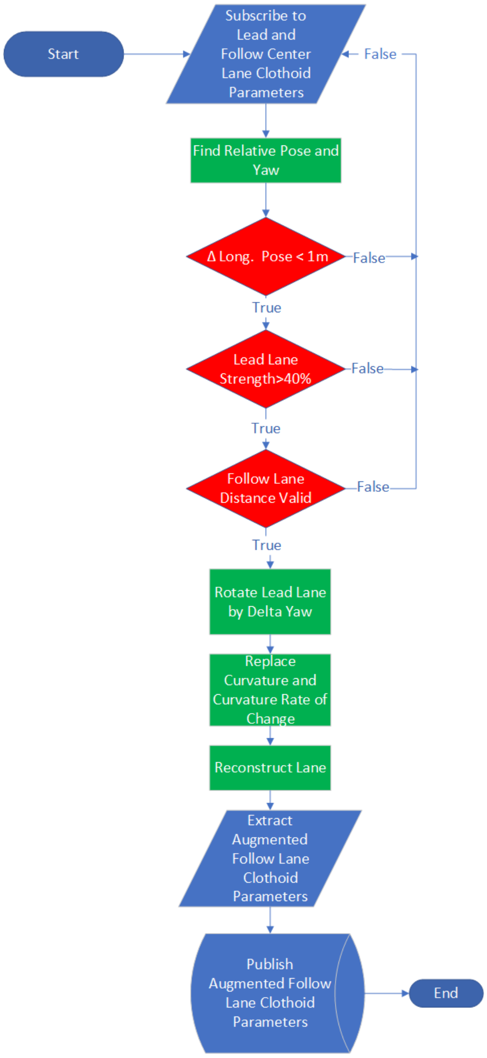

Figure 4.10: *High level cooperative lane augmentation process*

The result of the lane augmentation relies on the ability of the follow vehicle to detect the distance from the left and right lanes. A good estimate of the distance from left and right lane is critical in the calculation of the accurate lateral position of center lane with respect to the vehicle frame. As can be seen in Figure 4.9, it is sometimes not possible to detect any lanes thus making it impossible to measure the lateral distance of the vehicle from either left or right lane. In such cases, where the quality of the lane estimate in the follow vehicle is too low, the lane augmentation cannot be performed due to lack of sufficient lane information in the follow vehicle frame. Additionally, if the lead vehicle lane detection strength is too low (defined as 40 % for the purposes of the verification experiments) then lane augmentation is not performed.

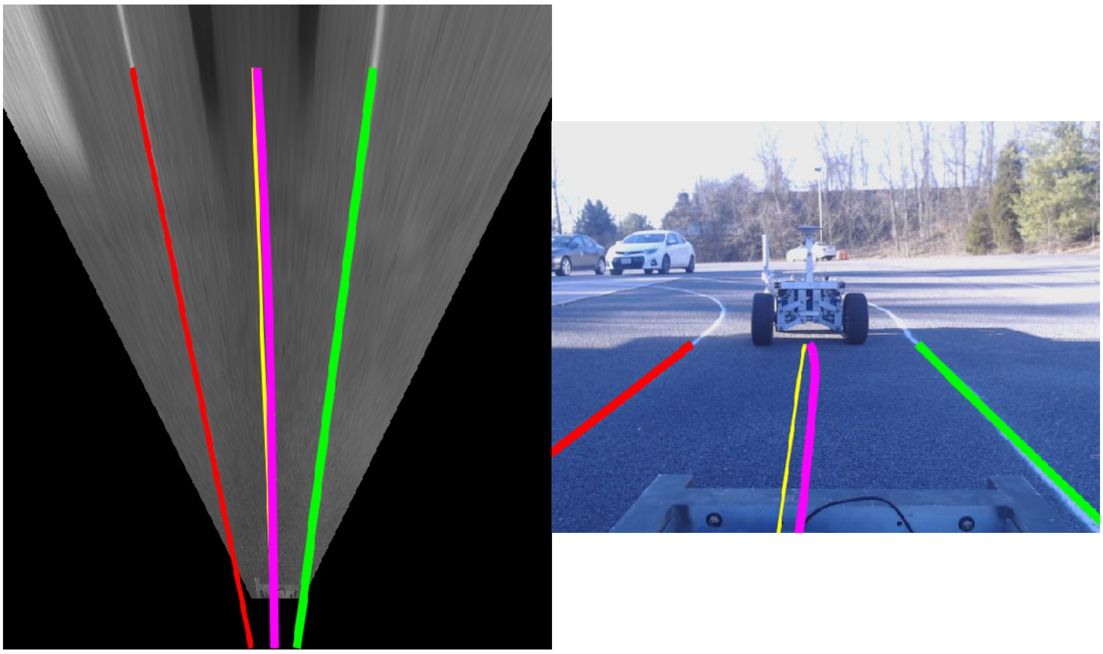

Figure 4.11: The augmented lane overlayed onto the detected raw lane in the follower frame in an un-occluded scene.

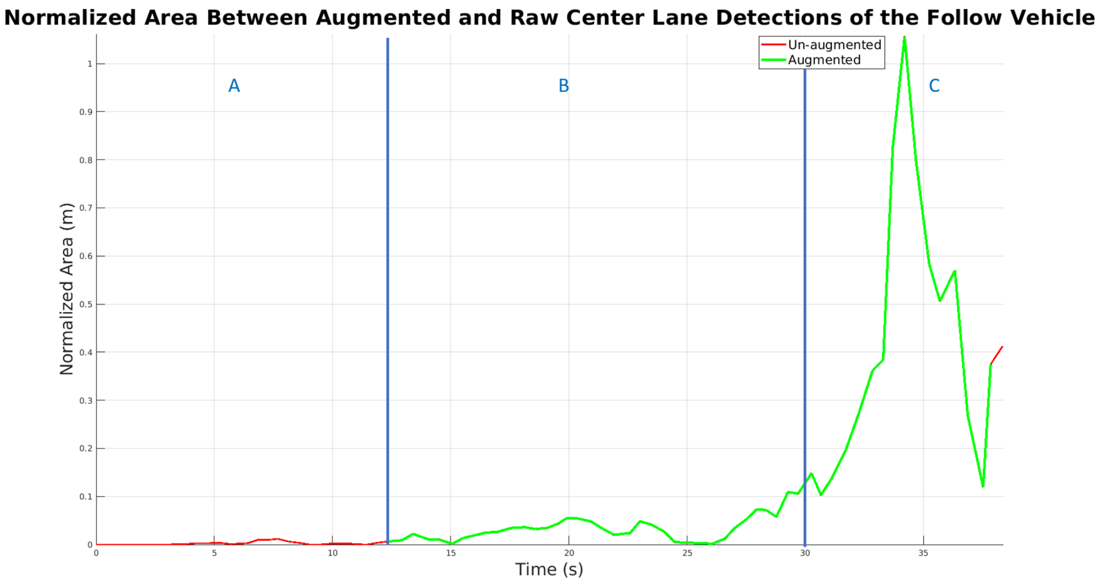

Figure 4.12: Normalized area between augmented and raw center lane detection of the follow vehicle in an un-occluded scene. Cooperative lane detection is active in regions marked B and C. The performance of the cooperative lane detection is degraded in region C due to experimental setup limitations.

Figure 4.12 shows the range normalized area between the raw and augmented center lane detection of the follow vehicle. This result is from a scene in which the platooning headway was sufficient enough that the follow vehicle was not occluded allowing for an accurate detection of the lane line. This scene is used to demonstrate the performance of the lane detection algorithm with respect to the raw detection of the follow vehicle as a ground truth. Region **A** shown in red is where lane augmentation is not active; this region represents the space covered by the follow vehicle at the beginning of the platooning period. Region **B** marks a period where augmentation is active and working effectively. The results in region

B are comparable to the simulation results shown in Figures 3.12 and 3.13.

Region **C** represents a portion of the platooning period where augmentation is active but the results are degraded; the range normalized area increases rapidly during this time frame. This is caused by an increased curvature which made the lane lines fall outside of the field of view (FOV) of the onboard cameras used for lane detection.

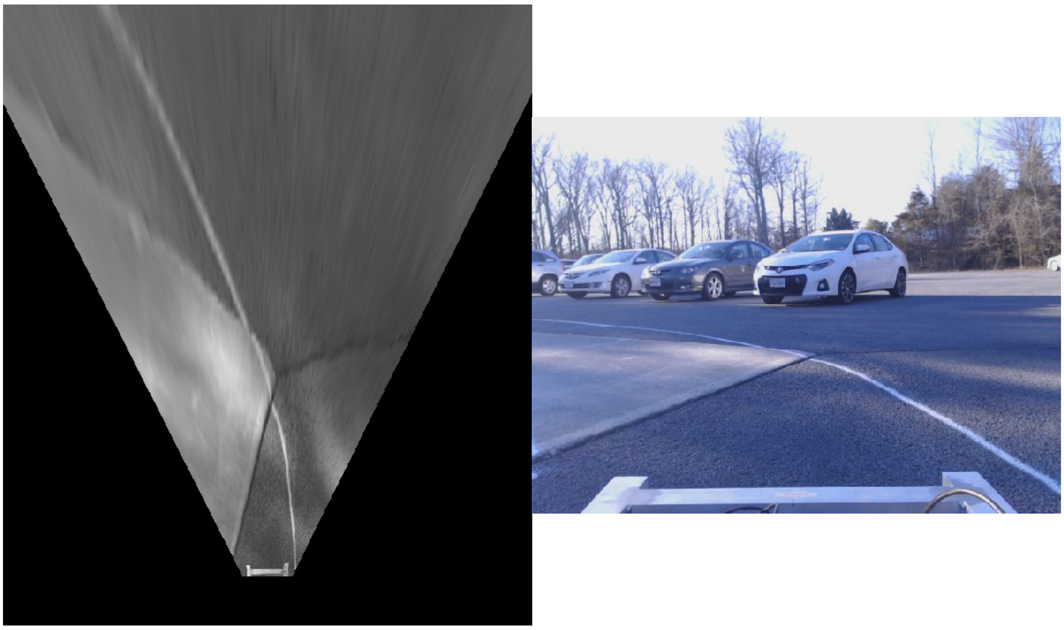

Figure 4.13: No lanes detected because image field of view too narrow to capture all lanes.

The lane lines in the high curvature section of the course were out of the FOV of both vehicle cameras; this degradation was caused by the limitation of the experimental setup and can be improved by using appropriate cameras with a sufficient horizontal FOV.

4.3 Summary

The lane detection augmentation of the follow vehicle works well in short headway vehicle pairs. The performance of the augmentation algorithm requires a stable connection between the lead vehicle, follow vehicle and the base station. Additionally, an accurate localization solution is critical in enabling the transformation of the lane from the lead frame to the follow frame. As discussed above, the distance from center lane parameter of the follow vehicle has to be used as measured therefore it is critical to ensure this measurement is accurate; a potential option to guarantee this is to use a dedicated downward facing camera optimized to measure distance from the lane. An appropriate camera with sufficient FOV is also critical in getting accurate detection of the lane in the lead vehicle prior to augmentation.

The design of the system to use a separate base station and distributed computing allowed for rapid prototyping. ROS was useful in achieving this by providing a framework used to synchronize the distributed systems. ROS comes with its disadvantage of increased latency, especially with the wireless LAN network; the delays in ROS affect the accuracy and performance of the lane detection and augmentation. The delays can be improved by doing more computations onboard the vehicles and relying less on communication to the base station. Additionally a more integrated design that minimizes the use of interpreted code will reduce the latency and improve the augmentation results.

Chapter 5

Conclusions and Future Work

The work done in this project was intended to improve the degraded Lane Keeping Assist (LKA) performance of occluded follow vehicles in short headway platoons. The occlusion results in the lane detection failure which impacts the LKA performance.A novel cooperative lane augmentation technique was developed to improve the lane detection of an occluded follow vehicle in a platoon. The cooperative lane augmentation utilizes lane parameters transformed from the lead to the follow vehicle frame. This algorithm was inspired by the results of the lane detection performance analysis done on data collected during the DTNA truck pairing tests as well as using simulated lane data.The cooperative lane detection framework developed in this thesis capitalizes on the clothoidal lane model, which serves as the basis of the framework.

The transformation of lane information relies heavily on a good relative localization between the two vehicles. The results of this work demonstrate that the cooperative lane detection framework is effective. The curvature rate of change, curvature and yaw angle to the lane parameters can effectively be transformed from the lead to the follow vehicle frame. However, the framework requires the follow vehicle to measure its own lateral distance from the lane lines. The overall results of this work are promising; the performance of the lane detection in the follow vehicles of short headway platoons could significantly be improved using the developed framework.

The overall vehicle localization can be further improved by integrating more sensors; the additional sensors should include a way to accurately measure the distance to the lane lines by the follow vehicle. The added sensors will also allow for a better perception of the environment which can also be shared among the vehicles of the platoon. In addition to more sensors, the lane detection performance can be improved by utilizing the past lane measurements instead of only relying on the updates from the camera; this should be investigated in future work done on this subject.

Lastly, the cooperative lane detection system was intended for use on platoons of class 8 trucks. For continued development of this work, it is important to optimize the software run-time speed and improve its reliability for use on full sized vehicles.

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Appendices

Appendix A

Lane Data Analysis Results

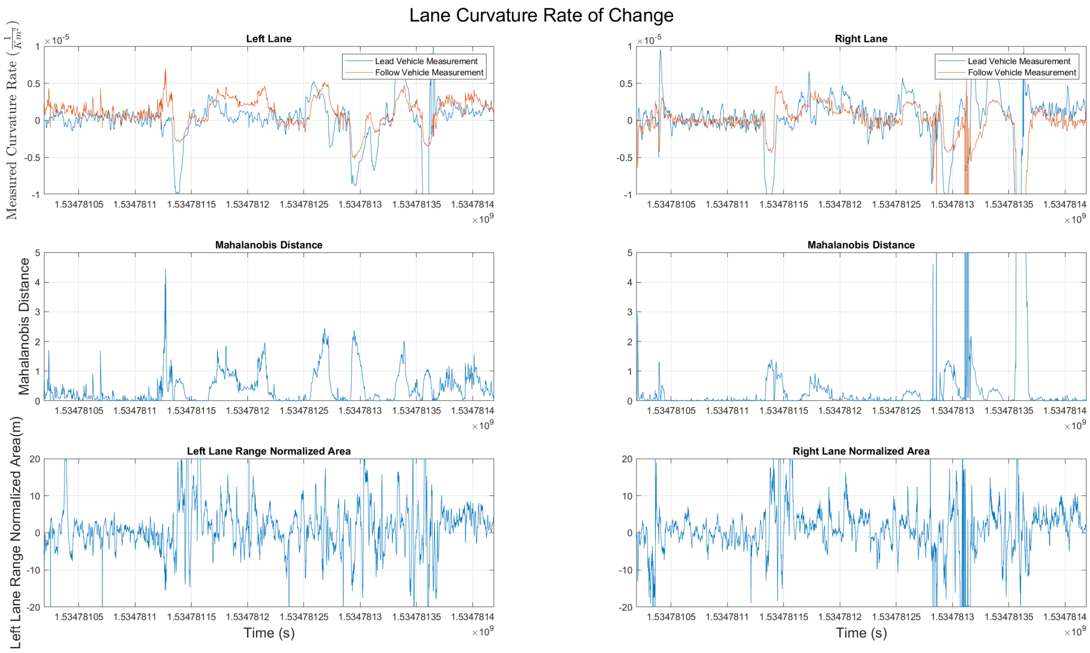

Figure A.1: A combined set of plots for evaluating lane degradation using the raw curvature rate of change values, the mahalanobis distance and the normalized area between clothoid lane curves generated using the clothoid model and the measured lane parameters in a 15 meter headway truck pair.

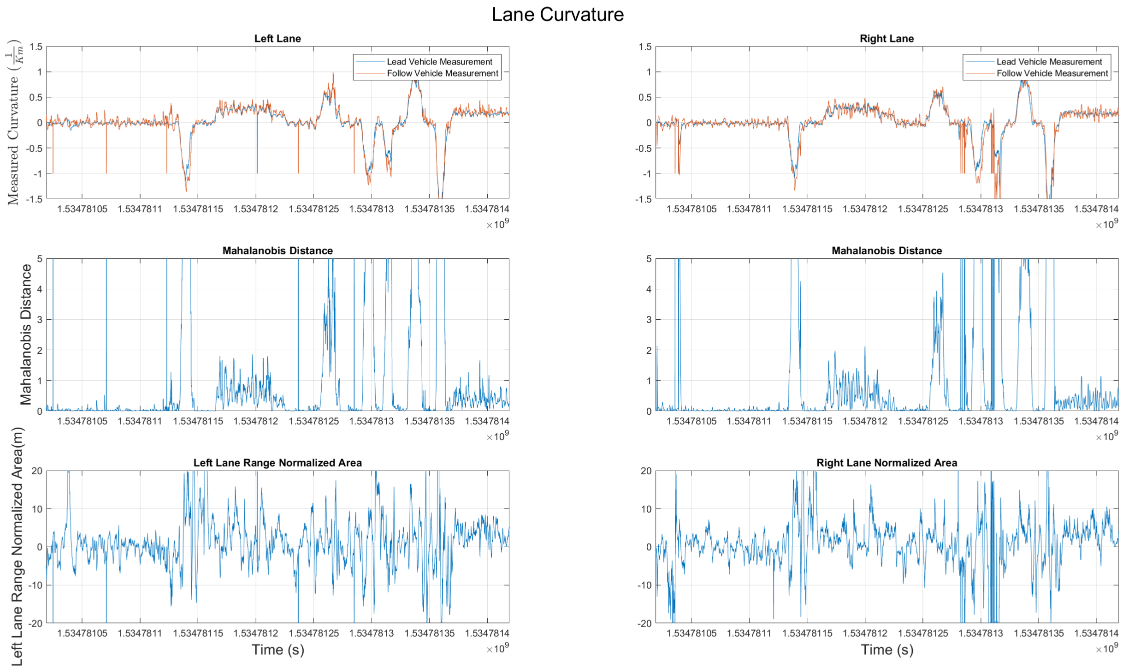

Figure A.2: A combined set of plots for evaluating lane degradation using the raw curvature values, the mahalanobis distance and the normalized area between clothoid lane curves generated using the clothoid model and the measured lane parameters in a 15 meter headway truck pair.

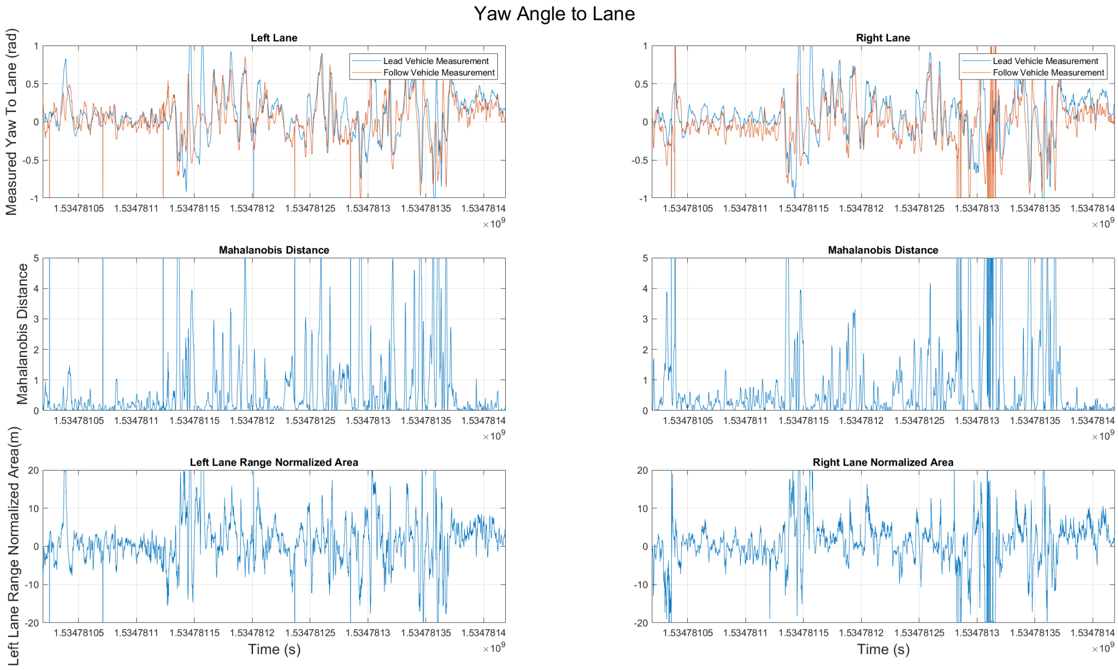

Figure A.3: A combined set of plots for evaluating lane degradation using the raw yaw angle to the lane values, the mahalanobis distance and the normalized area between clothoid lane curves generated using the clothoid model and the measured lane parameters in a 15 meter headway truck pair.

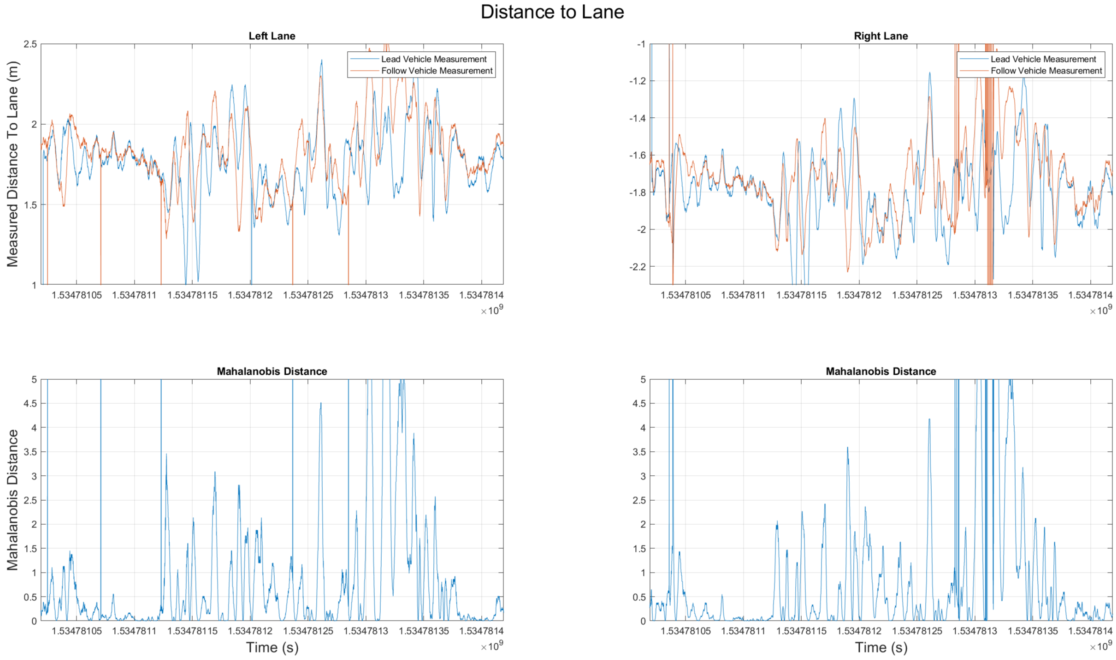

Figure A.4: A combined set of plots for evaluating lane degradation using the distance to the lane values and the mahalanobis distance. The normalized area between clothoid lane curves is not presented in this figure since it is computed independent of the distance to the lane parameter.