Development of Predictive Vehicle Control System using Driving Environment Data for Autonomous Vehicles and Advanced Driver Assistance Systems

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In

Mechanical Engineering

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Abstract

In the field of modern automotive engineering, many researchers are focusing on the development of advanced vehicle control systems such as autonomous vehicle systems and Advanced Driver Assistance Systems (ADAS) [1, 2]. Furthermore, Driver Assistance Systems (DAS) such as cruise control, Anti-Lock Braking Systems (ABS), and Electronic Stability Controls (ESC) have become widely popular in the automotive industry. Therefore, vehicle control research attracts attention from both academia and industry, and has been an active area of vehicle research for over 30 years, resulting in impressive DAS contributions [3-12]. Although current vehicle control systems have improved vehicle safety and performance, there is still room for improvement for dealing with various situations.

The objective of the research is to develop a predictive vehicle control system for improving vehicle safety and performance for autonomous vehicles and ADAS. In order to improve the vehicle control system, the proposed system utilizes information about the upcoming local driving environment such as terrain roughness, elevation grade, bank angle, curvature, and friction. The local driving environment is measured in advance with a terrain measurement system to provide terrain data. Furthermore, in order to obtain the information about road conditions that cannot be measured in advance, this work begins by analyzing the response measurements of a preceding vehicle. The response measurements of a preceding vehicle are acquired through Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) communication. The identification method analyzes the response measurements of a preceding vehicle to estimate road data. The estimated road data or the pre-measured road data is used as the upcoming driving environment information for the developed vehicle control system. The metric that objectively
quantifies vehicle performance, the Performance Margin, is developed to accomplish the control objectives in an efficient manner. The metric is used as a control reference input and continuously estimated to predict current and future vehicle performance. Next, the predictive control algorithm is developed based on the upcoming driving environment and the performance metric. The developed system predicts future vehicle dynamic states using the upcoming driving environment and the Performance Margin. If the algorithm detects the risks of future vehicle dynamics, the control system will intervene between the driver’s input commands based on estimated future vehicle states. The developed control system maintains vehicle handling capabilities based on the results of the prediction by regulating the metric into an acceptable range. By these processes, the developed control system ensures that the vehicle maintains stability consistently, and improves vehicle performance for the near future even if there are undesirable and unexpected driving circumstances. To implement and evaluate the integrated systems of this work, the real-time driving simulator, which uses precise real-world driving environment data, has been developed for advanced high computational vehicle control systems. The developed vehicle control system is implemented in the driving simulator, and the results show that the proposed system is a clear improvement on autonomous vehicle systems and ADAS.
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Yong Suk Kang

**General Audience Abstract**

In the field of modern automotive engineering, many researchers are focusing on the development of advanced vehicle control systems such as autonomous vehicle systems and Advanced Driver Assistance Systems (ADAS). Furthermore, cruise control, Anti-Lock Braking Systems, and Electronic Stability Controls have become widely popular in the automotive industry. Although vehicle control systems have improved vehicle safety and performance, there is still room for improvement for dealing with various situations.

The objective of the research is to develop a predictive vehicle control system for improving vehicle safety and performance for autonomous vehicles and ADAS. In order to improve the vehicle control system, the proposed system utilizes information about the upcoming driving conditions such as road roughness, elevation grade, bank angle, and curvature. The driving environment is measured in advance with a terrain measurement system. Furthermore, in order to obtain the information about road conditions that cannot be measured in advance, this work begins by analyzing a preceding vehicle’s response to the road. The combined road data is used as the upcoming driving environment information. The measurement that indicates vehicle performance, the Performance Margin, is developed to accomplish the research objectives. It is used in the developed control system, which predicts future vehicle performance. If the system detects future risks, the control system will intervene to correct the driver’s input commands. By these processes, the developed system ensures that the vehicle maintains stability, and improves vehicle performance regardless of the upcoming and unexpected driving conditions. To implement and evaluate the proposed systems, a driving simulator has been developed. The results show that the proposed system is a clear improvement on autonomous vehicle systems and ADAS.
Dedication

I would like to dedicate this dissertation to God. My work was only possible because of him. I also dedicate my work to my father who has been a motivator and an unwavering support for me. And, I, with a full heart, dedicate my work to my mother. I will always remember her encouragement and consistent love.
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First and foremost, I would like to thank God. This dissertation would not have been possible without him. I would like to express my deepest appreciation to my advisor, Professor John Ferris, for his guidance, unwavering support, and having faith in me throughout my graduate career. I am deeply grateful for the opportunity to work with him. I would like to give special thanks to my committee members, Professor Andrew Kurdila, Professor Saied Taheri, Professor Alfred Wicks, and Professor Craig Woolsey, for their valuable comments and suggestions on this dissertation. I would also like to express my gratitude to my Master’s advisor, Professor Doyounɡ Jeon, who has made this possible.

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Every effort is made to use terminology and nomenclature that are consistent with SAE J670 [13]. Without loss of generalization, the cornering concepts in this work are developed for a left turn.

**Ground Plane**
A horizontal plane normal to the gravitational vector (no slope or cross-slope).

**Road Plane**
A plane representing the road surface passing through the tire contact patches, supporting the tires and providing the friction necessary to generate tire shear forces.

**Vehicle Axis System**
An axis system centered at the vehicle center of mass, with $X_V$ directed forward in the Road Plane, $Y_V$ directed laterally in the Road Plane, and $Z_V$ normal to the Road Plane.

**Ground Axis System**
An axis system centered at the vehicle center of mass, with $X$ directed forward in the Ground Plane, $Y$ directed laterally in the Ground Plane, and $Z$ normal to the Ground Plane parallel to the gravitational vector.

**Tire Traction**
The vector sum of the tire shear forces acting in the Road Plane at the tire contact patch.

**Theoretical Tire Limit**
The vector sum of the maximum Tire Traction force for each tire that could be generated for the specific operating condition.
<table>
<thead>
<tr>
<th><strong>Vehicle Traction</strong></th>
<th>The vector sum of the actual Tire Traction forces, which act in the Road Plane, generated for the specific operating condition.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Available Vehicle Traction</strong></td>
<td>The maximum Vehicle Traction force, which acts in the Road Plane that could be generated for the specific operating condition.</td>
</tr>
<tr>
<td><strong>Required Vehicle Traction</strong></td>
<td>The minimum Vehicle Traction force, which acts in the Road Plane that must be generated for the specific operating condition.</td>
</tr>
</tbody>
</table>

\[
F_c \quad \text{Centripetal Force originating at the vehicle center of mass, acting in the Ground Plane, where the positive sense acts toward the center of the turn.}
\]

\[
F_{X_v} \quad \text{Vehicle Longitudinal Force—The Vehicle Traction acting in the Road Plane along } X_v.
\]

\[
F_X \quad \text{Longitudinal Force—The Vehicle Traction acting in (projected onto) the Ground Plane along } X.
\]

\[
F_{Y_v} \quad \text{Vehicle Lateral Force—The Vehicle Traction acting in the Road Plane along } Y_v.
\]

\[
F_Y \quad \text{Lateral Force—The Vehicle Traction acting in (projected onto) the Ground Plane along } Y.
\]

\[
F_{Z_v} \quad \text{Vehicle Normal Force—The total normal force resolved in the Vehicle Axis System, originating at the tire contact patches and acting along } Z_v.
\]
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_{brk}$</td>
<td>Tire Braking Force—The magnitude of a negative tire longitudinal force acting in the Road Plane along $X_V$.</td>
</tr>
<tr>
<td>$mg$</td>
<td>Vehicle Operating Weight.</td>
</tr>
<tr>
<td>$g$</td>
<td>Gravitational Constant (9.81 $m/s^2$).</td>
</tr>
<tr>
<td>$A_c$</td>
<td>Centripetal Acceleration—Defined herein as the centripetal force, $F_c$, which acts in the Ground Plane, divided by the Vehicle Operating Weight, $mg$.</td>
</tr>
<tr>
<td>$A_{Xv}$</td>
<td>Normalized Vehicle Longitudinal Force—Defined herein as the Vehicle Longitudinal Force, $F_{Xv}$, which acts in the Road Plane, divided by the Vehicle Operating Weight, $mg$.</td>
</tr>
<tr>
<td>$A_X$</td>
<td>Normalized Longitudinal Force—Defined herein as the Longitudinal Force, $F_X$, which acts in the Ground Plane, divided by the Vehicle Operating Weight, $mg$.</td>
</tr>
<tr>
<td>$a_{Xv}$</td>
<td>Longitudinal Acceleration—The scalar value of the component of vehicle acceleration in the direction of the $X_V$ axis.</td>
</tr>
<tr>
<td>$A_{Yv}$</td>
<td>Normalized Vehicle Lateral Force—Defined herein as the Vehicle Lateral Force, $F_{Yv}$, which acts in the Road Plane, divided by the Vehicle Operating Weight, $mg$.</td>
</tr>
</tbody>
</table>
Normalized Lateral Force—Defined herein as the Lateral Force, $F_Y$, which acts in the Ground Plane, divided by the Vehicle Operating Weight, $mg$.

Lateral Acceleration—The scalar value of the component of vehicle acceleration in the direction of the $Y_V$ axis.

Available Acceleration Defined herein as the maximum vector sum of the Longitudinal and Lateral Acceleration acting in the Ground Plane that could be generated for the specific operating condition.

Required Acceleration Defined herein as the minimum vector sum of the Longitudinal and Lateral Acceleration acting in the Ground Plane that must be generated for the specific operating condition.

Cross-Slope (crossfall, camber, bank angle)—The slope between the Road Plane and the Ground Plane projected onto the $(Y, Z)$ plane, where the positive sense is such that the lower side of the Road Plane is closer to the center of the turn (a properly banked road).

Slope (grade)—The slope between the Road Plane and the Ground Plane projected onto the $(X, Z)$ plane, where the positive sense is such that the vehicle is heading uphill.

Vehicle Longitudinal Velocity of the vehicle along $X_V$.

Longitudinal Velocity of the vehicle acting in (projected onto) the Ground Plane.
\( v_{Y_V} \)  
Vehicle Lateral Velocity of the vehicle along \( Y_V \).

\( R \)  
Path Radius of the turn in the Ground Plane.

\( \mu \)  
Coefficient of Friction—Defined herein as the Available Traction divided by the Vehicle Normal Force for a specific operating condition. Note: the traction forces defining the coefficient of friction are defined in the Road Plane, not the Ground Plane.

\( S_X \)  
Tire Longitudinal Slip Ratio—The ratio of tire longitudinal slip velocity to the reference wheel-spin velocity.

\( \alpha \)  
Slip Angle—The angle from the \( X_T \) axis to the normal projection of the tire trajectory velocity onto the Road Plane. The orientation of the \( X_T \) axis is defined by the intersection of the wheel plane and the road plane.

\( \delta \)  
Steer Angle—For each road wheel, the angle from the \( X_V \) axis to the wheel plane, about the \( Z_V \) axis.

\( \omega_{Z_V} \)  
Yaw Velocity (Yaw Rate)—The scalar value of the \( Z_V \) component of vehicle angular velocity.

\( I_{Z_V} \)  
Vehicle Yaw Moment of Inertia—The moment of inertia of the total vehicle at a given load condition, taken about an axis parallel to the \( Z_V \) axis, that passes through the vehicle center of gravity.
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_{aero}$</td>
<td>Aerodynamic Disturbance Input—A change in wind direction or speed relative to the vehicle, resulting in a change in aerodynamic forces acting on the vehicle.</td>
</tr>
<tr>
<td>$F_{rolling}$</td>
<td>Rolling Resistance Force—The force due to rolling resistance at the tire.</td>
</tr>
<tr>
<td>$L$</td>
<td>Wheelbase—The distance between the contact centers of the tires on the same side of the vehicle, measured parallel to the $X$ axis, with the vehicle at rest on a horizontal surface, at a prescribed load condition, set of vehicle trim heights, or set of suspension trim heights, with zero steer angle.</td>
</tr>
<tr>
<td>$L_1$</td>
<td>The longitudinal distances from the front axle centerlines to the vehicle center of gravity.</td>
</tr>
<tr>
<td>$L_2$</td>
<td>The longitudinal distances from the rear axle centerlines to the vehicle center of gravity.</td>
</tr>
<tr>
<td>$T$</td>
<td>Track (Track Width, Wheel Track)—The distance between the contact centers of a pair of tires on an axle, measured parallel to the $Y$ axis, with the vehicle at rest on a horizontal surface, at a prescribed load condition, set of vehicle trim heights, or set of suspension trim heights.</td>
</tr>
<tr>
<td>$h$</td>
<td>The height of the vehicle center of mass above the Road Plane.</td>
</tr>
</tbody>
</table>
$\phi$ Roll Angle—The angle from the Road Plane to the $Y_V$ axis, about the $X_V$ axis.
1. Introduction

This dissertation is focused on developing a predictive vehicle control system to improve the vehicle performance and safety for autonomous vehicles and Advanced Driver Assistance Systems (ADAS). The developed system uses information about the upcoming local driving environment such as terrain roughness, elevation grade, bank angle, curvature, and friction as an input. The local driving environment is measured in advance with a terrain measurement system to provide terrain data. Furthermore, in order to obtain the information of road conditions that is not able to be measured in advance, this work begins by analyzing the response measurements of a preceding vehicle. It is assumed that the following and preceding vehicle are capable of Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) communication. By analyzing the response measurements of the preceding vehicle, the upcoming road information is estimated for a following vehicle.

The metric that objectively quantifies vehicle performance, the Performance Margin, is developed to accomplish the control objectives in an efficient manner. The Performance Margin is defined as the additional performance capability available before the vehicle reaches the performance limit. The metric is used as a control reference input and continuously estimated to predict current and future vehicle performance. Next, a predictive control algorithm using the upcoming driving environment data and the performance metric is developed. The final updated upcoming driving information, consisting of the pre-measured road data and the estimated road data, is used for the prediction of future vehicle dynamics. By using the metric, the algorithm is used to predict situations in which the vehicle exceeds its handling capabilities. If the situation is detected, the developed predictive controller intervenes in driver commands. The intervention strategy maintains vehicle handling capabilities based on the results of the prediction by making corrections to the driver’s throttle and brake commands to regulate the metric into an acceptable range. Through this process, the predictive control system ensures that the vehicle maintains stability consistently and improves vehicle performance for the near future even if there are undesirable and unexpected driving circumstances. For the
development and evaluation of the integrated systems of this work, an integrated driving simulator, which is able to use precise real-world driving environment data, has been developed for novel vehicle control systems [1].

The remainder of this chapter provides the motivation for this research on developing a predictive vehicle control system as presented in Section 1.1. The problems that this research seeks to address are identified in Section 1.2. The thesis statement and scope of work are introduced in Section 1.3, followed by main contributions in Section 1.4. Lastly, a brief outline of the dissertation is presented in Section 1.5.

1.1 Motivation

In the field of modern automotive engineering, many researchers are focusing on the development of advanced vehicle control systems such as autonomous vehicle systems and Advanced Driver Assistance Systems (ADAS) [1, 2]. Furthermore, Driver Assistance Systems (DAS) such as cruise control, Anti-Lock Braking Systems (ABS), and Electronic Stability Control (ESC) have become widely popular in the automotive industry. Therefore, automotive technologies are increasingly relying on electromechanical control systems [2]. Vehicle control research attracts attention from both academia and industry and has been an active area of the vehicle research for over 30 years, resulting in impressive vehicle control system contributions [3-12]. These vehicle control systems help to reduce driver burden and also make drivers less likely to be involved in accidents [2]. For example, ABS typically stops the vehicle in a shorter distance than a human driver and ESC helps to maintain stability during agile movement by applying different braking forces to each of the four wheels [14].

The National Highway Transportation Safety Administration (NHTSA) estimated the number of lives saved by ESC systems. According to the NHTSA’s research note, ESC systems saved an estimated 446 lives among passenger car occupants, and 698 lives among light truck and van occupants, for a total of 1144 lives in 2012. In 2012, there were 21667 occupant fatalities. Only 2732 of these fatalities were in a passenger vehicle with ESC standard system. Furthermore, ESC system saved 3888 lives during the 5 year period from 2008 to 2012 [15]. Consequently, NHTSA now requires ESC system on all passenger vehicles under 4536 kg.
Although current vehicle control systems have improved vehicle safety and performance, there is still room for improvement. For example, the commercialized vehicle control systems such as ESC, ABS and active rollover prevention system are activated mostly based on the current vehicle state. Thus, the performances of the control systems are closely affected by the characteristics of the electromechanical devices such as sensor capability, computational power of Electronic Control Unit (ECU), and actuating power. Although a fine electromechanical device provides high sensing capability and computational power, sometimes the vehicle controller encounters difficulties in controlling the high-energy vehicle system having high speed, acceleration, and inertia because of the limitation of actuating power. This example is addressed in more detail with the simulations in Section 4.2.1.

To avoid some of the problems found with reactive methods, predictive methods are attracting increasing interest in the field of robotics and vehicle research [14, 16-19]. Also, there are some commercialized vehicle control systems that are predictive in nature such as Collision Avoidance Systems and Lane-Keeping Systems [14]. However, these vehicle control systems usually utilize limited information on the driving environment factor (e.g., curvature, elevation changes, bank angle, and road roughness). In order to design or evaluate a ground vehicle system, three fundamental factors need to be understood: the vehicle, the driver, and the environment. Herein the environment includes the geometric properties of the terrain [20]. Despite the fact that the driving environment is a significant factor affecting vehicle behavior, these vehicle control systems usually utilize limited information on the driving environment or simply assume the road as an ideally flat. However, in the real world, vehicle dynamics rely heavily on elements in the driving environment. Consequently, the precise road information provides the better prediction of future vehicle dynamics and gives the better performance of a predictive type control. Also, as more advanced automation is implemented, measures of vehicle performance become more urgent. It is increasingly important to objectively quantify vehicle performance to accomplish the advancing control objectives in an efficient manner [21].

This work proposes a predictive-type control system using the high-fidelity upcoming driving environment and a vehicle performance metric. By using the future
vehicle dynamics information, the predictive controller enables a vehicle system to avoid situations in which it loses stability and improve the performance of the vehicle system. As a result, proposed method provides improved assistance to the human driver as another step in the progress with ADAS and autonomous vehicle systems.

1.2 Problem Statement

Autonomous vehicles and ADAS cannot be commercialized without sufficient reliability in safety and performance. In order to demonstrate reliability, agile object recognition with precision and appropriate reaction to the environment around it are essential capabilities in the advanced vehicle systems. Moreover, robustness in the ability to cope with unexpected environments and various circumstances is significant for applications in the real world. The capability of the object recognition and reaction are dependent on the characteristics of the electromechanical devices. As sensor technology advances, the capability of the object recognition and reaction improves. In contrast, the robustness of a vehicle control system is reliant on process logic. Thus, this study is focused on developing algorithms rather than electromechanical sensory devices.

As mentioned in Section 1.1, although current vehicle control systems provide a helpful assistance for driving, there are still uncertainties with regard to the reliability. A large number of the commercialized vehicle control systems are the reactive type. These vehicle control systems are activated mostly based on a current vehicle state [14]. Thus, even though a high performance electromechanical device provides a high sensing capability and computational power, the reactive type controllers encounter the difficulties in controlling a high-energy vehicle system because of the limitation of actuating power. For example, one of the highly valued vehicle controllers is Electronic Stability Control (ESC) system which is a typical reactive control system. However, the ESC system may be insufficient and ineffective in some circumstances. For example, if ESC systems are activated after or near a loss of handling, then in some circumstances it may be too late to recover stability of the vehicle after speed and acceleration have exceeded a certain threshold. In this case, a large actuating effort will be required to bring a vehicle back to a stable state. Likewise, other reactive systems such as ABS and active rollover prevention system have similar uncertainties due to their reactive nature. Therefore, from this point of
view, a predictive type approach is advantageous to resolve the limitations of a reactive system. This problem is addressed in more detail with simulation results in Section 4.2. Presently, some commercialized vehicle control systems, such as Collision Avoidance Systems and Lane-Keeping Systems, are being developed that are predictive in nature, rather than reactive [14]. However, these systems usually utilize limited information on the driving environment. Even though an autonomous vehicle has perfect cruise control and Lane-Keeping Systems, it can encounter unexpected situations because of road conditions. In this case, if a human driver perceives these unexpected circumstances, a human driver may perform a better handling maneuvers than an advanced control systems which assumes the road as ideally flat. Therefore, an improvement to advanced vehicle control system is the ability to consider the driving environment as part of vehicle control performance and safety. Simulations of these detail examples are addressed in Section 4.2.1 to show how the perception of a local driving environment is critical to an advanced vehicle control.

High-fidelity road surface data (a component of the driving environment data) can be obtained using a terrain measurement system capable of scanning the complete topology of a three-dimensional terrain surface while simultaneously tracking the position, orientation, and speed of the vehicle [1]. For example, the Vehicle Terrain Measurement System (VTMS) acquires 941 terrain data samples transversely across a 4.2 m wide path each millisecond with the scanning laser [22-24]. However, there is a possibility that the road surface may have undergone changes after the measurement because of road construction, for example. Since it is impossible to measure every place all the time, there is still the limitation on using the terrain data for an advanced vehicle control system. Therefore, an advanced vehicle control system should be able to deal with the limitation of driving environment to achieve a high performance and reliability. However, so far, despite the uncertainties mentioned above, there have been relatively few studies about vehicle control systems that are predictive in nature and utilize local driving environment information.

Also, as mentioned in Section 1.1, measures of vehicle performance are a critical element of advancing automation technology. Therefore, it is increasingly important to quantify vehicle performance or handling capability for vehicle control systems. Furthermore, this measure needs to be both accurate and computationally efficient for
practical use. Several methods have been developed for measuring the capability of a vehicle [25-28]. Typically, these methods represent a vehicle’s handling capability and are helpful for the design of a vehicle. However, these methods are not suitable for advanced vehicle control systems and estimation of an operating vehicle capability such as current or future handling characteristics [21].

1.3 Thesis Statement and Scope of Work

**Thesis Statement:** A predictive vehicle control system can be developed that improves vehicle safety and performance by utilizing upcoming local driving environment information and a metric that quantifies vehicle performance.

The primary goal of this research is to develop a predictive vehicle control system to improve vehicle performance and safety for autonomous vehicle and ADAS. This task is divided into three processes: developing the real-time driving simulator for an advanced vehicle control system, developing the metric that efficiently quantify vehicle performance for vehicle control systems, and developing the predictive vehicle control system with identification of the preceding vehicle to estimate upcoming local driving environment information. The focus of this work is developing algorithms rather than electromechanical sensory devices. This work assumes that the proposed system utilizes Basic Safety Message (BSM) of V2V defined by the SAE J2735. Also, it is assumed that BSM is transmitted with a 0.1 second sampling time over Dedicated Short-Range Communications (DSRC). This work assumes that the proposed system has access to a high-fidelity baseline measurement of the road surface, but adapts to changes in this baseline measurement.

1.4 Main Contributions

The main contributions of this research are:

1) The vehicle performance measure for vehicle control system
   a. The metric, which is defined as the additional performance available before the vehicle reaches the limit, is used to quantify vehicle handling capability for vehicle control system
b. The metric is estimated using the basic vehicle sensor data in real time for practical use
c. The metric can be used as a feasible reference value for advanced vehicle control system

2) The predictive vehicle control system using upcoming local driving environment information and the vehicle performance metric
   a. The method identifies the road profile of a vehicle using response measurements in real-time
   b. Disturbance Observer (DOB) and the pre-measured road surface data are used to detect a deformation of a road after terrain measurement
   c. The predictive vehicle control system is developed to maintain vehicle stability
   d. The vehicle performance metric is used as a controlled value in the control system

3) The real-time driving simulator for an advanced vehicle control system
   a. High computational advanced vehicle controllers such as a predictive type controller can be implemented in real-time
   b. Real-world driving environment data can be imported and simulated with a full vehicle dynamics model
   c. Improved quality of virtual reality is provided with a game engine
   d. Integrated systems run in low-cost operation with UDP network

1.5 Dissertation Outline

This work is organized as follows. Chapter 1 motivates the research and presents the scope of work, research objectives, and main contributions. Autonomous vehicle and ADAS technologies, terrain measurement technologies, handling capability metrics, and Vehicle-to-Vehicle communication are reviewed in Chapter 2. The proposed metric, Performance Margin, and its estimator for real-time applications is developed using typical vehicle sensor data in Chapter 3. A real-time future terrain identification system using preceding vehicle dynamics and a predictive vehicle control algorithm based on the
upcoming driving environment and the proposed metric are developed in Chapter 4. In Chapter 5, development of the driving simulator for an advanced vehicle controller with real-world data is presented, which is used to validate the algorithms developed in Chapter 3 and 4. Lastly, Chapter 6 concludes the dissertation by summarizing the main contributions.
2. Background

Chapter 2 comprises germane concepts and recent advances in automated vehicle research, terrain measurement, and vehicle performance metrics. First, vehicle control systems are introduced to provide a background of autonomous vehicle and ADAS. Next, the terrain measurement methods are described to provide a background of terrain measurement techniques used in this work. Next, vehicle performance metrics, including the Performance Margin (PM), are presented. Finally, a background of the Vehicle-to-Vehicle (V2V) communication system utilized for this work is introduced.

2.1 Autonomous Vehicle and Advanced Driver Assistance Systems

2.1.1 Autonomous Vehicle Technologies

An autonomous vehicle is a vehicle equipped with technology capable of perceiving environments, selecting a path to a destination, and executing commands to complete the planned paths with minimal driver input [29, 30]. Such vehicles use sensors, such as RADAR and LIDAR, cameras, Global Positioning System (GPS), and telecommunications to obtain its current spatial coordinates, which in turn are used to make independent decisions via vehicle controllers [31].

The National Highway Transportation Safety Administration (NHTSA) released a Preliminary Statement of Policy Concerning Automated Vehicles in May 2013. According to NHTSA, the levels of vehicle automation are defined from a vehicle that does not have any of control authority of the systems (level 0) through a fully autonomous vehicle (level 4) as shown in Table 1 [31]. Currently, many vehicles are manufactured with level 1 technologies such as cruise control, ESC, and ABS. Moreover, modern vehicles include advanced automation features such as Forward Collision Warning, Adaptive Cruise Control, Lane Departure Warning, and Lane Keeping System [29, 32-36]. Recently, some manufactures began offering level 2 automation features that combine adaptive cruise control with lane keeping systems. For example, Tesla Motors’ Autopilot feature, which has been applied on the Model S since September 2014 and the Model X, allows a vehicle to steer within a lane, change lanes with a turn signal, and adjust longitudinal speed via
adaptive cruise control [37]. In addition, Volvo Car Corporation’s 2016 Volvo XC90 offers Pilot Assist, which helps drivers automatically transition between lanes while simultaneously maintaining a target speed or a distance from a preceding vehicle [38].

There are also Google’s Self-Driving Cars, which are level 3 and 4 prototypical vehicles. The level 3 prototype vehicle is a modified Lexus SUV and the level 4 prototype vehicle is designed to be fully autonomous [39]. As of August 2016, The prototypical vehicles have driven 1,969,078 miles autonomously since the start of the project in 2009 [40].

Table 1. Levels of vehicle automation, NHTSA, adapted from [31]

<table>
<thead>
<tr>
<th>Level</th>
<th>Definition</th>
<th>Existing Technologies</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>No-Automation</td>
<td>Collision warning, Lane departure warning, Blind spot monitoring</td>
</tr>
<tr>
<td></td>
<td>• Vehicle has no control authority</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Driver has full control authority</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Function-specific Automation</td>
<td>ESC, Cruise control, Adaptive cruise control, Automatic braking, Lane keeping</td>
</tr>
<tr>
<td></td>
<td>• Vehicle has one or more specific control functions operated independently from each other</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Driver has overall control but can choose to cede limited authority</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Combined Function Automation</td>
<td>Adaptive cruise control in combination with lane keeping</td>
</tr>
<tr>
<td></td>
<td>• The level involves automation of at least two primary control functions designed to work in unison</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Driver is still responsible for monitoring and must be ready to control the vehicle safety</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Limited Self-Driving Automation</td>
<td>Prototype vehicles</td>
</tr>
<tr>
<td></td>
<td>• Vehicle enable the driver to cede full control</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Driver is available for occasional control, but with sufficiently comfortable transition time</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Full Self-Driving Automation</td>
<td>Prototype vehicles</td>
</tr>
<tr>
<td></td>
<td>• Vehicle performs all safety-critical driving functions and monitor roadway conditions for an entire trip</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Driver provides destination or navigation input but is not expected to be available for control at any time during the trip</td>
<td></td>
</tr>
</tbody>
</table>
In spite of the progress of autonomous vehicle technologies, significant technical improvement is required to readily accomplish level 4 of vehicle automation. According to Google’s 2015 Self-Driving Car Testing Report, the Self-Driving Cars experienced 272 disengagements, or deactivations of the autonomous driving mode due to technology failures, from September 2014 to November 2015 [41]. Table 2 shows fewer disengagements of the Self-Driving Cars despite a growing number of miles driven each month. The autonomous miles driven per disengagement has risen from 785 in the fourth quarter of 2014 to 5318 in the fourth quarter of 2015. Despite this significant improvement, 5318 miles per disengagement is still insufficient to commercially deploy level 3 and 4 autonomous vehicles since a failure of autonomous technology can be deadly to occupants. Thus, autonomous vehicle technologies have high-performance requirements with robust software algorithms and electromechanical devices such as sensors, ECU, GPS, and telecommunications [42].

Table 2. Disengagements of autonomous mode of Google Self-Driving Car related to detection of a failure of the autonomous technology, adapted from [41]

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of Disengages</th>
<th>Autonomous miles on public roads</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014/09</td>
<td>0</td>
<td>4207.2</td>
</tr>
<tr>
<td>2014/10</td>
<td>14</td>
<td>23971.1</td>
</tr>
<tr>
<td>2014/11</td>
<td>14</td>
<td>15836.6</td>
</tr>
<tr>
<td>2014/12</td>
<td>40</td>
<td>9413.1</td>
</tr>
<tr>
<td>2015/01</td>
<td>48</td>
<td>18192.1</td>
</tr>
<tr>
<td>2015/02</td>
<td>12</td>
<td>18745.1</td>
</tr>
<tr>
<td>2015/03</td>
<td>26</td>
<td>22204.2</td>
</tr>
<tr>
<td>2015/04</td>
<td>47</td>
<td>31927.3</td>
</tr>
<tr>
<td>2015/05</td>
<td>9</td>
<td>38016.8</td>
</tr>
<tr>
<td>2015/06</td>
<td>7</td>
<td>42046.6</td>
</tr>
<tr>
<td>2015/07</td>
<td>19</td>
<td>34805.1</td>
</tr>
<tr>
<td>2015/08</td>
<td>4</td>
<td>38219.8</td>
</tr>
<tr>
<td>2015/09</td>
<td>15</td>
<td>36326.6</td>
</tr>
<tr>
<td>2015/10</td>
<td>11</td>
<td>47143.5</td>
</tr>
<tr>
<td>2015/11</td>
<td>6</td>
<td>43275.9</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>272</strong></td>
<td><strong>424331</strong></td>
</tr>
</tbody>
</table>
As shown in Figure 1, an autonomous vehicle technologies can be generally divided into four fundamental areas: multi-sensor fusion based environment perception and modeling, vehicle localization and map building, path planning and decision-making, and low-level motion control [29, 43]. The environment perception and modeling area acquires data of environment structures with multiple sensors and builds a model of the surrounding environment including moving objects, static obstacles, vehicle position relative to the current road, road profiles, and more [29]. Multi-sensor fusion is the fundamental component of sensing and detecting technologies. Combining various sensors, such as RADAR, LIDAR, and visual cameras, results in a wider field of view and therefore can be used to provide more accurate environmental models. Collected sensor data can be processed in low-level fusion integrating with raw sensor data at an early stage of signal processing, high-level fusion integrating with filtered sensor data, and hybrid fusion [29, 44, 45].

Next, during the vehicle localization and map building stage, the sensor data is interpreted to determine the vehicle’s position and creates a global and local map based on the environment [29]. Vehicle localization is related to position filtering, coordinate frame transformation of the vehicle pose, and road profile estimation using the sensors such as GPS and Inertia Navigation System (INS) [43]. Map building is usually conducted simultaneously with the vehicle localization; this process is known as Simultaneous Localization and Mapping (SLAM) [46].
During the third stage, path planning, the optimal desired path to the target position is generated without obstacle collisions. Also, decision-making conducts mission planning and behavioral reasoning [29, 47]. The mission planner updates the local map with the new observations and generates a new rule for the behavioral reasoning algorithm. Based on the results of the mission planning, the behavioral system plans decisions such as road following, lane changes, obstacle avoidance, and recovering from abnormal conditions [29, 48].

The low-level motion control executes commands such as throttle, brake, and steering to accomplish the decisions from the path planning and decision-making stages. There are two fundamental parts in the low-level control: longitudinal and lateral control. The longitudinal control alters the vehicle’s longitudinal speed and distance from a preceding vehicle. The throttle and brakes are actuators used in the longitudinal control. The lateral control changes the lateral position and yaw of the vehicle. Thus, it is usually used for lane keeping, lane change, and yaw stability control by using steering and brake force distribution [2, 29]. For example, in the low-level motion control of standard longitudinal speed control, the upper-level controller determines the desired acceleration and then the lower level controller determines the throttle input to track the desired acceleration. Engine map data and nonlinear control methods are used with vehicle dynamic models to calculate the throttle input in real-time [2, 9-12].

2.1.2 Advanced Driver Assistance Systems (ADAS) Technologies

Advanced Driver Assistance Systems (ADAS) have been developed to help reduce driver burden and accidents. The commercialized ADAS started with Adaptive Cruise Control (ACC) in the late 1990s. Other ADAS such as Collision Avoidance System (CA), Lane Departure Warning (LDW), Lane Keeping System (LKS), Electronic Stability Control (ESC), Rollover Prevention, and Driver Monitoring Systems are commercially available nowadays [2, 49]. Furthermore, there are various ADAS which have been thoroughly researched and are expected to be commercialized in the near future. In this section, the prevalent commercialized ADAS technologies are discussed, namely Adaptive
Cruise Control, Collision Avoidance Systems, Lane Departure Warning, Lane Keeping Systems, and Yaw Stability Control Systems.

**Adaptive Cruise Control (ACC)**
Adaptive Cruise Control, introduced in the late 1990s, is an enhancement of the standard cruise control. Most ACC systems are equipped with RADAR to measure the distance and longitudinal speed difference from preceding vehicles. Unlike standard cruise control systems, if a preceding vehicle is detected, the ACC system determines whether or not to activate the spacing control. This feature maintains a specified distance to the preceding vehicle by command inputs such as throttle and brake [2, 34, 49-53]. Early stage ACC systems could be activated at speeds above 50 km/h without braking. However, modern ACC systems have Stop & Go functionality, which automatically controls the brakes until the vehicle comes to a standstill and then automatically moves on as soon as the sensor detects the absence of preceding vehicles [49, 54].

**Collision Avoidance Systems (CA)**
A Collision Avoidance (CA) system is designed to detect and assess threats and to intervene without the driver’s commands. A CA system algorithm identifies targets, calculates paths, assesses threats, and executes operations using the sensor data like an ACC system [2, 32-34, 55]. There are four general maneuvers that CA systems take in the event of an imminent collision: warning the driver, applying the brakes, reducing the throttle, and manipulate steering. The warning system alerts the driver so that they can resume longitudinal control [2, 55]. The braking mechanisms such as the Advanced Emergency Braking System allows the vehicle to detect an obstacle and apply the brake if necessary [38, 56]. Collision avoidance by steering is more appropriate than the braking maneuver at high vehicle speeds [57].

**Lane Departure Warning (LDW)**
A Lane Departure Warning (LDW) system monitors the lateral position of the vehicle with respect to the lane. If the system detects an unintended lane departure, it warns the driver to make a correction. The most important technology in an LDW system is recognizing the lane marking on the road. The system typically employs video sensors with image recognition software to identify the lane markings. The software algorithm of an
LDW calculates and predicts an unintended lane departure based on the sensor data. Because LDW systems rely heavily on visual sensors, its functionality is limited by the weather and road conditions such as snow and faded lane markings [2, 35].

*Lane Keeping Systems (LKS)*

As expected, a Lane Keeping System (LKS) is designed to automatically keep the vehicle in its lane. The system uses devices such as a vision camera to recognize the lane, a steering actuator to control the front wheels, and an Electronic Control Unit (ECU) for the algorithms and data processing [2, 58, 59]. Additionally, there are other methods to measure the lateral vehicle position with respect to the lane, including differential GPS and embedded magnets [60-63]. An example of a LKS-equipped vehicle is Nissan’s 2001 Cima [64]. The CCD camera mounted on the rearview mirror is used to identify the lane and the steering actuator force is calculated by the algorithm based on the current speed and the steering angle. However, there are drawbacks: the system can only be activated between 65 km/h to 100 km/h and it operates only on straight roads or roads with a large radius. Recently, several automotive manufactures have released vehicles with LKS. For example, Hyundai’s Genesis, Mercedes-Benz (C, E, S class, and GLC, GLE, GLS, CLS class), Toyota’s Lexus (RX and GS), and Audi (A4, Q7) have LKS called by various names such as Lane Keeping Assist System (Honda), Lane Keep Assist (Hyundai), Active Lane Keeping Assist (Mercedes-Benz), Lane Keeping Assist (Toyota), and Active Lane Assist (Audi).

*Yaw Stability Control/Electronic Stability Control Systems*

A yaw stability control system, often referred to as an Electronic Stability Control system (ESC), is designed to prevent a vehicle from uncontrolled spinning during a limit handling maneuver. The system acts to restore the yaw velocity to the desired trajectory set by the driver [2, 65]. Like other vehicle control systems, the yaw stability control system consists of the upper-level controller and lower level controller. The upper-level controller computes the desired yaw torque based on the difference between the desired yaw rate and current yaw rate of the vehicle. The low-level controller determines the actuating input required to track the desired yaw torque. There are three fundamental types to achieve the objective of the system: Differential braking, steer-by-wire, and active
torque distribution [2, 66-72]. A differential braking system typically uses solenoid-based hydraulic modulators to obtain the different brake pressures from each four wheels. For example, the system generates a counter-clockwise yaw moment by creating high brake pressure at the left wheel compared to the right wheel [2, 66, 69]. A steer-by-wire system modifies the steering command of the driver to prevent spinning. The controller uses wheel speeds, lateral accelerations, yaw rates, and steering angles as inputs [2, 67, 68], whereas the system itself has steering actuators and sensors to accomplish a low-level feedback control [73]. An active torque distribution system resolves the longitudinal response limitation caused by the differential braking reducing the vehicle’s acceleration. The system utilizes independent drive torque control with All-Wheel Drive technology. All-Wheel Drive (AWD) system is the drive system operating in 2-Wheel Drive (2WD) until the system judges that 4WD is needed. Thus, using an AWD system, the active torque distribution system provides active control of both traction and yaw moment [2, 69-72]. Recently, many automotive manufactures have commercialized the system on newly released car models [2].

The purpose of this work is to enhance existing autonomous vehicle technologies and ADAS rather than replace them. That is, the proposed system is activated in harmony with existing autonomous vehicle technologies and ADAS through modest intervention in the driver’s commands or autonomous vehicle control. The intervention makes modest corrections to brake and throttle commands given by human drivers or vehicle controllers to avoid the situations in which the vehicle exceeds its handling capabilities. This work focuses on the longitudinal control of the vehicle rather than lateral control.

2.2 Terrain Measurement

2.2.1 Vehicle Terrain Measurement System

Terrain measurement systems are capable of scanning the terrain surface in 3 dimensions, while simultaneously tracking the vehicle’s position, orientation, and speed. The system uses sensors which fall into two broad categories: mapping sensors and navigation sensors. Mapping sensors determine the position of remote terrain points relative to the platform on which theses sensors are mounted. LIDAR, RADAR, and SONAR are usually used as mapping sensors. Navigation sensors, typically Global
Positioning System (GPS) and Inertial Measurement Unit (IMU), provide the data used to estimate the position and orientation of the mapping sensors with respect to a fixed mapping coordinate system [74, 75].

One example of such a system is the Vehicle Terrain Measurement System (VTMS) developed by Virginia Tech’s Vehicle Terrain Performance Laboratory (VTPL) [22-24, 76, 77]. The Vehicle Terrain Measurement System (VTMS) used in this work is capable of scanning the terrain surface in three dimensions, while simultaneously tracking the vehicle’s position, orientation, and speed. The latest version of the VTMS (Figure 2) is equipped with five high-resolution scanning lasers (LMI Gocator 2375) for the mapping sensors that can cumulatively scan an entire lane width (4.2 m) of the road for with millimeter accuracy. The specified horizontal resolution of each laser is 0.27 to 0.8 mm while the vertical resolution is 0.154 to 0.56 mm. Each laser sends out a single line scan at a rate of 1000 scans/second. Each scan in turn consists of about 640 data points. Cumulatively the entire system generates approximately 3.2 million data points per second. A Global Positioning System (GPS) and an Inertial Measurement Unit (IMU) are used for the navigation sensors. The data from the VTMS is processed to produce a three-dimensional, high-fidelity terrain surface as shown in Figure 3 [76, 77].

Figure 2. 2014 Vehicle Terrain Measurement System (VTMS).
2.2.2 Measured Terrain Data Processing

The raw terrain data collected from the different mapping sensors of the terrain measurement system is measured in the respective sensor coordinate systems. Also, the data are acquired with non-uniform spacing because of variations in the speed and movement of the terrain measurement system. However, data with a unified coordinate system and uniform spacing are necessary for efficient data storage and simulation. In order to convert the raw measurement data to usable terrain data, the raw measurement data are processed through coordinate transformations and a gridding technique. The gridding technique used in this work converts dense irregularly spaced terrain point clouds into a curved regular grid (CRG) format. Additionally, the gridding techniques used in this work can be used to generate random vehicle paths, and corresponding curved regular grids, for a single road [23, 24, 78-84]. As shown in Figure 4, the CRG has a path coordinate, \( u \), and a perpendicular coordinate, \( v \), in the horizontal plane. Discrete longitudinal locations along coordinate \( u \) are defined as a vector \( u \). Likewise, discrete transverse locations are defined in terms of a vector \( v \). Vectors \( u \) and \( v \) are indexed by \( i \) and \( j \) respectively and the vector points of CRG are regularly spaced within this grid [24]. In addition, there are the techniques characterizing the terrain as a realization of an underlying stochastic process. The stochastic models developed by VTPL characterize terrain surfaces and describe their physical characteristics. These stochastic models can be used to create synthetic terrain surfaces. Autoregressive Modeling, Continuous-State Markov Chains, Hidden Markov Models, Wavelets, Kriging, and Morphological filtering are used for the terrain modeling [78, 85-90].
CloudMaker is used to accumulate the raw point clouds of data from VTMS and to create a registered point cloud of terrain data in a unified three-dimensional coordinate system. The input data of CloudMaker include the data from the Inertial Navigation System (INS) and the Scanning Lasers. The data from these sensors are filtered to remove unwanted noise and then synchronized in time before the point cloud can be generated. Next, CloudMaker performs the coordinate transformations to unify the coordinate system of the terrain data. Finally, it provides a registered point cloud of terrain data via $x$, $y$, and $z$ coordinates with respect to the fixed origin such as the location of the GPS base station [24, 80-82].

CloudSurfer is used to convert non-uniformly spaced raw terrain data to uniformly spaced terrain data with a CRG. Also, the center path of terrain data is automatically generated. As shown in Figure 4, the CRG has a path coordinate, $u$, and a perpendicular coordinate, $v$, in the horizontal plane. Discrete longitudinal locations along coordinate $u$ are defined as vector $u$. Likewise, discrete transverse locations are defined as vector $v$. Each of vector $u$ and $v$ are indexed by $i$ and $j$ respectively, where $i \in [1, 2, ..., m]$ and $j \in [1, 2, ..., n]$. These vector points of CRG are regularly spaced. The terrain height corresponding to each grid point $(u, v)$ is determined as $z_{ij}$ [24, 78, 79, 83, 84].
2.3 Handling Capability Metrics

There are several methods that have been developed for analyzing vehicle handling capabilities. This section reviews a selection of the methods including the Performance Margin.

2.3.1 Dugoff Tire Model

The resultant tire-road stress, \( \sigma_{res} \), at the tire contract patch on the X-Y (horizontal) plane is generated by an alteration of speed or steering angle [25, 91]. Alterations of speed and steering angle cause longitudinal stress, \( \sigma_x \), and lateral stress, \( \sigma_y \). And the resultant tire-road stress is represented by Equation 1.

\[
\sigma_{res} = \sqrt{\sigma_x^2 + \sigma_y^2} \quad \text{Equation 1}
\]

The maximum allowable resultant stress at any point in the contact patch is determined by \( \sigma_{max} \) which varies over the contact patch. The main influence determining \( \sigma_{max} \) is the normal pressure distribution on the contact patch. Dugoff et al. assume that the pressure is uniform over the contact patch for simplicity in the model [25]. The resultant stress limit, \( \sigma_{max} \), is expressed as Equation 2.

\[
\sigma_{max}A_{contact} = \mu F_{ZTire} \quad \text{Equation 2}
\]

where \( \mu \) is the average coefficient of friction over the contact patch area, \( A_{contact} \) is the contact patch area, \( F_{ZTire} \) is the average normal force acting at the tire contact patch. In using the Dugoff Tire Model, care should be taken to enforce the constraint that the interface at the tire contract patch is a unidirectional geometric constraint, so that there can be no negative vertical force exerted by the ground. It should also be clear that this relationship is true only in the limiting case, at the limit of handling capability. That is, the definition of the coefficient of friction is a function of the maximum product of stress and contact area (i.e., the maximum horizontal force) with respect to the normal force.
2.3.2 Milliken Moment Method

The Milliken Moment Method (MMM) is a method for analyzing the stability and control of a vehicle [26, 91]. Combining the MMM with dynamic simulations provides useful and measurable handling capability information derived based on current vehicle states. The MMM provides quantitative values with graphical portrayal by analyzing the forces and moments acting on a vehicle. As shown in Equation 3 and Equation 4, the MMM is represented by a normalized longitudinal and lateral force.

\[ \bar{F}_{X_v} = \frac{F_{X_v}}{\mu F_{Z_v}} \]  

Equation 3

\[ \bar{F}_{Y_v} = \frac{F_{Y_v}}{\mu F_{Z_v}} \]  

Equation 4

A normalized resultant force in the Road Plane is equivalent to the vector addition of these normalized forces. The method is able to be used for analyzing peak performance through a corner as well as identification of vehicle characteristic sensitivity [26].

2.3.3 Original Performance Margin

The original Performance Margin, developed by Matthews et al. [91] is a metric that quantifies the Vehicle Traction required for a steady-state operating condition relative to the maximum Vehicle Traction that could be generated for that operating condition. This original definition stems from, and incorporates, various traditional handling metrics. The Dugoff stress relationship is reformulated as equivalent tractive forces and the Milliken Moment Method’s normalization is integrated into the original PM formulation [25, 28]. As shown in Equation 5 and Equation 6, the original PM value is defined as the ratio of required resultant tractive force to the maximum available tractive force at the front and rear axles respectively.

\[ PM_{orgf} = \frac{\Sigma_{i=1}^{2} \left( F_{X_{vl_i}}^2 + F_{Y_{vl_i}}^2 \right)}{\Sigma_{i=1}^{2} \mu F_{Z_{vl_i}}} \]  

Equation 5
The front left and right tire are indexed by $i = 1, 2$ and the rear left and right tire are indexed by $i = 3, 4$. A PM value of unity implies that the required tractive forces are equal to the maximum tractive forces. When this occurs, the tires will lose traction and spin (if the rear tires saturate before the front) or plow (if the front tires saturate before the rear). This original formulation is computationally efficient and robust in analyzing vehicle dynamics when individual tire forces are known and is useful to define the state of the front and rear tires for controllability and stability analyses. This original definition of the Performance Margin (PM) is somewhat counter-intuitive in that the PM increases as the vehicle approaches the limit handling condition. This is contrary to control concepts such as phase margin and gain margin which decrease as the system approaches instability.

2.3.4 Friction Ellipse

The notion of a Friction Ellipse (also called a “g-g” diagram) is a useful tool to visualize the load generating capabilities of an individual tire, or the global maneuvering capabilities of an entire vehicle. The Friction Ellipse provides an objective measure of the relationship between the driver’s actions and the vehicle’s performance capability [26, 27, 92]. The Friction Ellipse for an individual tire graphically represents the maximum traction (the vector addition of the longitudinal and lateral tire force) that can be generated by a single tire for a given operating condition. The Performance Envelope of the vehicle must include not only the individual tire characteristics, but the vehicle dynamics. The simplest example of this difficulty is that the normal force acting on a single tire contact patch is assumed to be given (or knowable) when developing a Friction Ellipse for a tire, but the vehicle dynamics and road surface determine the normal force act on all four tires. In this way, the complex vehicle dynamics are an integral part of the vehicle Performance Envelope. That is, the vehicle Performance Envelope is not simply the sum of the four tire Friction Ellipses.

In an effort to describe the vehicle Performance Envelope in a similar fashion as the tire Friction Ellipse, a particle model of the vehicle is assumed, but the properties
associated with that simple vehicle model are not assumed to be simply the net force exerted by the tires. The Theoretical Tire Limit is the sum of the maximum Tire Traction force for each tire that could be generated for the specific operating condition, shown as a dashed line in Figure 5 [26]. This theoretical limit is unachievable for the vehicle because of losses due to factors including limit understeer, brake proportioning, load transfer, and powertrain limitations. The solid line shows the Performance Envelope that is achievable when the vehicle dynamics and powertrain limitations are considered. Note that the road surface friction is not changing, but rather the losses associated with achieving stable dynamics manifest a Performance Envelope with slightly diminished performance than the Theoretical Tire Limit.

Figure 5. Performance Envelope for full vehicle (not individual tire), adapted from [26].

2.4 Vehicle to Vehicle Communication (V2V)

Vehicle-to-Vehicle (V2V) communication allows vehicles to communicate to each other by transmitting traffic information from which, for example, warnings may be sent to the driver to help avoid imminent danger. In order to receive and transmit data, and provide vehicle position, V2V communication requires at least two Dedicated Short-Range Communications (DSRC) radios and a GPS receiver. DSRC works similarly to a Wi-Fi network. DSRC has 5.9 GHz band with a bandwidth of 75 MHz and provides long detection distance with a range of approximately 0.3 km or about 10 seconds at highway speed. By using these devices, the V2V communication system provides comprehensive situational information not only in the direct line of sight but also in a 360-degree field of
view. Furthermore, V2V communication can be integrated into an existing Electronic Control Unit (ECU) and can use an inertial measurement unit to acquire vehicle information such as speed, acceleration, and driver commands [93, 94].

SAE J2735, the second version of the vehicular networks standard, defines Basic Safety Message (BSM) sets supporting all V2V enabled safety applications [95]. The BSM is split into two parts: BSM Part I and BSM Part II. As shown in Table 3, BSM Part I has core data elements for vehicle safety such as vehicle position, speed, acceleration, steering wheel angle, braking status, and vehicle size. It has higher priority than BSM Part II, therefore, the information of BSM Part I is transmitted more often with approximately a 0.1 second sampling time over DSRC. BSM Part II contains a variable set of information that can vary by vehicle models. It consists of an extensive list of optional elements such as path history, tire conditions, wiper status, lights status, vehicle type and so on. BSM Part II data are transmitted when an event happens such as ABS activation, air bag deployment, flat tire, traction control loss, and emergency response [93-95]. In this work, it is assumed that the following and preceding vehicle are capable of utilizing BSM of V2V defined by the SAE J2735. Also it is assumed that BSM is transmitted with a 0.1 second sampling time over DSRC.
Table 3. Contents of BSM Part I, adapted from [93, 94]

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<tr>
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<th>Data Element (DE)</th>
</tr>
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<td>Elevation</td>
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<td>Longitude</td>
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<td>Lateral acceleration</td>
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<td></td>
<td>Vehicle length</td>
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</table>
Abstract

Although several methods exist for measuring the performance capability of a vehicle, many require detailed knowledge of the forces acting at each tire contact patch or do not account for both the vehicle dynamics and the road geometry. Furthermore, as more advanced vehicle control systems are implemented, the ability to predict and control the vehicle becomes more urgent. Specifically, measures of vehicle performance, on which control strategies are developed, are a critical element of advancing automation technology. Therefore, it is increasingly important to objectively quantify vehicle performance to accomplish the advancing control objectives and the geometric road design. In this chapter, the Performance Margin is developed for both geometric road design and vehicle control; both of which are crucial as transportation agencies and vehicle manufacturers prepare for the introduction of autonomous vehicles. First, a simple vehicle model is proposed to estimate the upper limit of performance capability for a given operating condition (the Performance Envelope) based on the Effective Friction and the road geometry. The Effective Friction accounts for both the vehicle dynamics and road surface properties and is estimated, through simulation or experimentation, using two standard vehicle dynamics tests: constant radius cornering and straight-line braking. The Performance Margin is defined as the additional performance capability available before the vehicle reaches the Performance Envelope. Next, the PM for a control system has been developed using typical vehicle sensors and the concept of PM-based control is developed to demonstrate the PM’s application in a vehicle control system. The estimated PM has been defined to efficiently and suitably quantify vehicle handling capability for real-time applications. The compensation factor has been defined to distinguish and compensate between saturated and unsaturated tires. These improvements and their effects have been demonstrated with simulations of various scenarios. The estimator of the PM using the basic vehicle sensor data has been proposed for a practical application to vehicle systems. The estimator has been validated with simulations spanning three different roads, which pushes the vehicle to its limit for evaluating the estimator in high-demand situations. Also, the concept of

3. Performance Margin
prediction control based on the PM has been introduced briefly and implemented to demonstrate the PM’s potential efficacy for application in vehicle systems.

3.1 Performance Margin for Geometric Road Design

Modern automotive engineering has focused on the development of advanced vehicle control systems, such as Advanced Driver Assistance Systems (ADAS), in preparation for autonomous vehicles. Driver Assistance Systems (DAS) such as cruise control, Anti-Lock Braking Systems (ABS), and Electronic Stability Control (ESC) have been widely equipped for passenger, as well as commercial vehicles [2]. The development of vehicle control systems has been an active area of vehicle research for over 50 years both in academia and industry. As control systems become more crucial in a vehicle system, analyzing vehicle performance becomes more important. However, vehicle performance is not only a function of the vehicle design, but the environment in which the vehicle performs. The road condition plays a major role in the vehicle performance. For example, the road geometry (e.g. grade and cross-slope) and roughness directly affect how rainfall produces a film of water on the road surface causing a reduction in effective friction. A performance measure must be developed that accounts for both the environment and the dynamic response of the vehicle to this environment.

Several methods have been developed for measuring the performance capability of a vehicle, including the original formulation of the Performance Margin (PM) [91]. The original formulation is relatively simple and robust, but requires detailed knowledge of the forces acting at each tire contact patch. The vehicle dynamics are correctly accounted for, but there are limitations in its use for practical applications such as geometric road design. It is proposed that the PM be redefined for a more general application, while maintaining its inclusion of vehicle dynamics and simplicity of implementation.

It is proposed that the Performance Margin be redefined as a measure of any additional performance capability that is available beyond the performance required by the current operating condition. The upper limit of performance capability for a given operating condition defines the Performance Envelope. The bounds of this Performance Envelope are determined by the road geometry and Effective Friction. The Effective Friction is defined as the maximum fraction of the normal force that can be used to generate
tractive forces by the vehicle at the current operating condition. This differs from the traditional concepts of friction in that the Effective Friction accounts for both the vehicle dynamics (e.g., limit understeer and brake proportioning) and road surface properties (e.g., roughness). In this section, the redefined PM is developed in terms of the Performance Envelope and the Effective Friction which varies due to vehicle dynamics and road conditions. Two traditional vehicle dynamics maneuvers (constant radius handling and straight-line braking) are used to demonstrate the use of the proposed performance measure.

3.1.1 Redefining Performance Margin in terms of the Road Geometry

The Performance Margin is redefined as the additional performance capability that can be drawn upon beyond that which is demanded by the current operating condition. Clearly this definition requires knowledge of both the current performance requirements and the limits of performance capability. The Performance Envelope describes the limit of performance capability that can be drawn upon during any maneuver (at any operating condition) and is developed in terms of the effective friction, which varies due to vehicle dynamics and road conditions (including effects such as roughness and water film thickness). A rigorous definition of the Performance Envelope is the first step in redefining the Performance Margin.

The Performance Envelope is defined by the locus of points for which the Vehicle Traction equals the Available Vehicle Traction (both acting in the Road Plane), or equivalently the locus of points for which the Required Acceleration equals the Available Acceleration (both acting in the Ground Plane). The components of the Required Acceleration for a given operating condition are written as \((A_x, A_y)\), indicated by a cross in Figure 6, and the components of the Available Acceleration are written as \((A_x^*, A_y^*)\); shown as a solid curved line in Figure 6, where the asterisk notation denotes the boundary of the Performance Envelope. The Performance Margin, PM, for this operating condition is then the minimum difference between the Required Acceleration for a given operating condition and the locus of points that define the Available Acceleration.

\[
PM = \min \left[ \sqrt{(A_x - A_x^*)^2 + (A_y - A_y^*)^2} \right], \forall A_x, A_y
\]  

Equation 7
Some advantages of the redefined Performance Margin (PM) for geometric road design are that vehicles with different operating weights can be more easily compared, the units are the intuitive units of gravity, and the measure is convenient when including the unitless coefficient of friction. Specifically, the PM typically has a value between zero and one; the value of zero indicates that the limiting performance capabilities have been reached and there is no additional traction remaining. The choice of defining the Performance Margin in the Ground Plane rather than the Road Plane enables a more concise representation of the concept and a more intuitive tool for geometric road design. The Performance Envelope is a function of the road geometry and the Effective Friction. The Effective Friction is defined as the maximum fraction of the normal force that can be used to generate tractive force by the vehicle at the current operating condition. This definition of the Effective Friction is not the traditional relationship between a single tire and the road surface, but accounts for both the limitations imposed by the vehicle dynamics and road surface properties. For example, vehicles may be designed such that the front tires reach their performance limits before the rear tires in order to maintain directional stability (but not directional control). This implies that the front and rear tires will not reach their performance limits simultaneously and correspondingly the Available Vehicle Traction is less than the Theoretical Tire Force. The Effective Friction may also be influenced road roughness and by water or contaminates on the surface.
Consider two specific cases from which a generalization is made: the effective coefficient of friction in the longitudinal direction, $\mu_x$, and effective coefficient of friction in the lateral direction, $\mu_y$. Specifically, consider that the point on the Performance Envelope for pure braking is simply the sum of the effective coefficient of friction, $\mu_x$, and the grade; this point is indicated in Figure 6 by a small black dot on the braking axis. Similarly, the point on the Performance Envelope for pure cornering is the sum of the effective coefficient of friction, $\mu_y$, and the cross-slope; this point is indicated in Figure 6 by a small block dot on the cornering axis. The Effective Friction is developed for these limiting cases from which a generalization to the Performance Envelope is made. One issue to note is that the coefficient of friction acts in the Road Plane, which requires the Performance Envelope to be developed in both the Road Plane and Ground Plane. This Road Plane is identified with the addition of the subscript ‘$V$’ (for vehicle), which is consistent with SAE notation.

3.1.2 Effective Friction Estimation

To estimate the coefficient of friction, either through simulation or experimentation, two standard vehicle dynamics scenarios, performed on a flat road surface (i.e., the Road Plane is coincident with the Ground Plane), are used: a constant radius test and a straight-line braking test. During the constant radius test, the vehicle operates at increasing speeds around a constant radius circle to determine the maximum lateral force that can be generated. This condition is written in terms of maximum lateral acceleration, relative to gravity. The straight-line braking test involves a vehicle beginning at some prescribed initial speed, then the maximum braking effort is exerted and the maximum longitudinal deceleration is determined. Again, this deceleration is described in acceleration units relative to gravity.

Consider a particle model of a vehicle traveling in a circle prescribed in the Ground Plane. The effective coefficient of friction is estimated by increasing the vehicle speed until the vehicle can no longer maintain the circular path, at which point that maximum force in the horizontal plane is achieved $\mu_y = \max(m a_{y_v})/mg = \max(a_{y_v}/g)$. Accelerations defined in terms of units of gravity, or $g$’s, simplify this relationship, so that $\mu_y = \max(A_{y_v})$ where $A_{y_v}$ is in units of $g$’s and the description of the friction using
the vehicle’s acceleration information is straightforward. Similarly, \( \mu_x = \max(A_{Xv}) \) for straight-line braking in the Ground Plane in a steady-state (trim) operating condition. For the remainder of the work in this section, it is assumed that the vehicle is operating in steady-state (trim) operating condition, unless explicitly indicated otherwise. It should be clear that estimating the lateral and longitudinal coefficients of friction are critical in establishing the Performance Envelope.

**Lateral Friction, \( \mu_y \), Estimation**

Consider the simplest model of a vehicle traversing a properly banked curve (positive cross-slope) without any grade (slope), as shown in Figure 7. The Centripetal Force, \( F_C \), which acts in the Ground Plane, is generated by forces acting on the vehicle in the Road Plane, \( F_{Yv} \) and \( F_{Zv} \). Similarly, the Vehicle Operating Weight, \( mg \), is balanced by forces acting on the vehicle in the Road Plane, \( F_{Yv} \) and \( F_{Zv} \).

\[
F_C = \frac{mv_y^2}{R} \quad \text{Equation 8}
\]

\[
F_{Zv} = mg \cos \theta - F_C \sin \theta \quad \text{Equation 9}
\]

\[
F_{Yv} = F_C \cos \theta - mg \sin \theta \quad \text{Equation 10}
\]
The Centripetal Acceleration, \( A_C \), is defined in terms of longitudinal velocity and the radius of the turn in Equation 11

\[
A_C = \frac{v_x^2}{gR} \quad \text{and} \quad A_C^* = \frac{v_x^{*2}}{gR} \quad \text{Equation 11}
\]

The *Required* Vehicle Lateral Acceleration is therefore given in Equation 12.

\[
A_{Y_V} = \frac{F_{Y_V}}{mg} = A_C \cos \theta_b - \sin \theta_b \quad \text{Equation 12}
\]

Consider the limiting condition of a banked, steady-state cornering maneuver, without any longitudinal force, in which the Performance Envelope is reached (as denoted with an asterisk). The Available Vehicle Lateral Force, \( F_{Y_V}^* \) is equal to the Available Traction and, using the definition of the coefficient of friction, is written as Equation 13. Note that the critical velocity at which this Available Vehicle Lateral Force is reached, \( v_x^* \), must be determined.

\[
F_{Y_V}^* = \mu_y F_{Z_V}^* = \mu_y \left[ mg \cos \theta_b - \frac{m v_x^{*2}}{R} \sin \theta_b \right] \quad \text{Equation 13}
\]

This Available Vehicle Lateral Force is normalized by the Vehicle Operating Weight to form the *Available* Vehicle Lateral Acceleration, as shown in Equation 14

\[
A_{Y_V}^* = \frac{F_{Y_V}^*}{mg} = \mu_y \left[ \cos \theta_b - \frac{v_x^{*2}}{gR} \sin \theta_b \right] \quad \text{Equation 14}
\]

\[
= \mu_y \left[ \cos \theta_b - A_C^* \sin \theta_b \right]
\]

Note that by normalizing these forces and assuming a particle model for the vehicle, the resulting Available and Required Vehicle Lateral Accelerations are no longer functions of
the vehicle parameters, but only the friction, cross-slope, and velocity. Combining Equation 12 and Equation 14 leads to

$$\mu_y [\cos \theta_b - A_y' \sin \theta_b] = A_y^* \cos \theta_b - \sin \theta_b$$  \hspace{1cm} \text{Equation 15}$$

and Equation 16

$$A_y' = A_y^* = \frac{\mu_y + \tan \theta_b}{1 + \mu_y \tan \theta_b}$$ \hspace{1cm} \text{Equation 16}$$

When the grade is zero, $\tan \theta_b \ll 1$, and $\mu_y \tan \theta_b \ll 1/2$, then

$$A_y' = \mu_y + \tan \theta_b$$ \hspace{1cm} \text{Equation 17}$$

**Longitudinal Friction, $\mu_x$, Estimation**

Similarly, consider the particle model of a vehicle moving on an inclined road, as shown in Figure 8. The vehicle operating weight, $mg$, is balanced by forces acting on the vehicle in the road plane, $F_{XV}$ and $F_{ZV}$.

![Figure 8. Longitudinal forces acting on a vehicle system.](image)

The tire braking force, and vehicle normal force are given by Equation 18 and Equation 19

$$F_{brk} = -ma_{XV} - mg \sin \theta_s$$ \hspace{1cm} \text{Equation 18}$$
\[ F_{Zv} = mg \cos \theta_s \]  

Equation 19

The Vehicle Longitudinal Acceleration is written as Equation 20.

\[ A_{Xv} = - \frac{F_{brk}}{mg} - \sin \theta_s \]  

Equation 20

Consider the limiting condition without any lateral force, in which the limit on the force generation capability of the vehicle is reached. For this case, the available vehicle longitudinal force, \( F_{Xv}^* \), is equal to the available traction. The force is written as Equation 21.

\[ F_{Xv}^* = \mu_x F_{Zv} = \mu_x mg \cos \theta_s \]  

Equation 21

This available vehicle longitudinal force is normalized by the vehicle operating weight to form the available normalized vehicle longitudinal force, as shown in Equation 22.

\[ A_{Xv}^* = - \frac{F_{Xv}^*}{mg} - \sin \theta_s = -\mu_x \cos \theta_s - \sin \theta_s \]  

Equation 22

When the cross-slope (banking) is zero and \( n_s \ll 1 \)

\[ A_{X}^* = A_{Xv}^* = -\mu_x - \tan \theta_s \]  

Equation 23

Since this study only deals with braking cases, not acceleration, the sign of the Available Vehicle Longitudinal Acceleration is changed from negative to positive for the convenience of analysis.

3.1.3 Summary of Performance Margin Results

The maximum deceleration that can be accomplished in the absence of cornering forces is \( \mu_x + \tan \theta_s \) and the maximum lateral acceleration that can be achieved in the
absence of longitudinal force is $\mu_y + \tan \theta_b$. These two points on the Performance Envelope are each indicated in Figure 6 by a small grey dot. The equation defining this elliptical locus of points is then

$$\frac{(A_{XV})^2}{(\mu_x + \tan \theta_s)^2} + \frac{(A_{YV})^2}{(\mu_y + \tan \theta_b)^2} = 1$$

Equation 24

This is the equation that defines the Performance Envelope. That is, all points on the envelope $(A_{XV}^*, A_{YV}^*)$ must satisfy this equation which is a function of the Effective Friction ($\mu_x$ and $\mu_y$) and the road geometry (slope, $\tan \theta_s$, and cross-slope, $\tan \theta_b$). The minimum difference between this envelope and the current operating condition is the Performance Margin, represented in the Ground Plane, in terms of units of gravity. The equation for calculating the Performance Margin is given in Equation 7.

3.2 The Performance Margin for Vehicle Control System and its Practical Implementation

Several methods have been developed for measuring the capability of a vehicle [25, 27, 28, 92]. Typically, these methods represent a vehicle’s handling capability and are helpful for the design of a vehicle. However, these methods are not suitable for advanced vehicle control systems and estimation of an operating vehicle capability such as current or future handling characteristics [91]. The Performance Margin (PM) [91] is a simple, robust and widely applicable measure of vehicle capability; however, the estimation of its value for real-time applications using widely available vehicle sensors remains to be addressed. In this chapter, an estimator of the PM is developed using typical vehicle sensors and the concept of PM-based control is developed to demonstrate the PM’s application in a vehicle system. The control algorithm is simulated to show that the PM can be used as a feasible metric for a control system. In this section, the PM estimator for real-time applications is developed using typical vehicle sensor data.
3.2.1 Estimating the Performance Margin

Although the PM definition in Equation 7 is simple and robust, there are some limitations in its implementation as part of a vehicle control strategy. First, the search for the minimum distance between the current operating condition and the closest point on the Performance Envelope is computationally inefficient for real-time applications. Second, the estimation of the saturation limit of the tires at high slip angles and slip ratios must be addressed. Third, for the practical use of the PM, it needs to be calculated by using typical vehicle sensors. These three implementation issues are addressed in turn.

Defining the Estimated Performance Margin

It is clear that the Available Traction in the longitudinal direction will often differ from that in the lateral direction (the term “friction ellipse” derives from this fact). Consider the maximum available longitudinal force in the Road Plane, $\mu_x F_{ZV}$, and maximum available lateral force, $\mu_y F_{ZV}$, shown schematically in Figure 9 as the abscissa and ordinate intersection points with the Performance Envelope.

Consider a driving maneuver requiring longitudinal and lateral forces $(F_{XV}, F_{YV})$. The Available Traction is indicated in Figure 9 as a curved black line and represents the Performance Envelope. Next consider the intersection of the Performance Envelope and the extension line (dashed black line) of the resultant force vector $(\hat{F}_{XV}^*, \hat{F}_{YV}^*)$.

![Figure 9. The Performance Envelope.](image)
The estimated PM given in Equation 25 approximates PM under the assumption that the point on the Performance Envelope that is closest to the operating condition \((F_{Xv}, F_{Yv})\) is the point that lies at the intersection of the Performance Envelope and the extension line (dashed black line in Figure 9) of the resultant force vector \((\hat{F}_{Xv}^*, \hat{F}_{Yv}^*)\). This is exactly true when the longitudinal and lateral friction are identical.

\[
\hat{\rho}_M = \sqrt{\frac{(\hat{F}_{Xv}^* - F_{Xv})^2 + (\hat{F}_{Yv}^* - F_{Yv})^2}{(\hat{F}_{Xv}^*)^2 + (\hat{F}_{Yv}^*)^2}}
\]

Equation 25

The point on the Performance Envelope, \((\hat{F}_{Xv}^*, \hat{F}_{Yv}^*)\), is calculated from the equation of an ellipse, as Equation 26 and Equation 27.

\[
\hat{F}_{Xv}^* = \frac{\mu_x \mu_y F_{Zv}}{\sqrt{\mu_y^2 F_{Xv}^2 + \mu_x^2 F_{Yv}^2}} F_{Xv}
\]

Equation 26

\[
\hat{F}_{Yv}^* = \frac{\mu_x \mu_y F_{Zv}}{\sqrt{\mu_y^2 F_{Xv}^2 + \mu_x^2 F_{Yv}^2}} F_{Yv}
\]

Equation 27

The estimated PM is then given by Equation 28.

\[
\hat{\rho}_M = 1 - \sqrt{\frac{\mu_y^2 F_{Xv}^2 + \mu_x^2 F_{Yv}^2}{\mu_x \mu_y F_{Zv}}}
\]

Equation 28

The value of zero means the required tractive force equals the available tractive force—in other words, the tires will lose traction and spin or plow due to tire saturation. The value of unity indicates that the operating condition is stable and controllable, which is consistent with the definitions of phase margin and gain margin.
For vehicle handling capabilities, the tires can be grouped as the front set and rear set of tires unlike the “g-g” diagram. The front tire set can be used for analyzing the controllability and the rear tire set can be used for analyzing the stability. According to the original PM formulation of each tire set, the formulation actually uses variation of tire force, $\Delta F_X$ and $\Delta F_Y$, which is not captured the initial value of tire forces. However, in the practical vehicle dynamics, the initial forces are exerted to tires. For example, based on the simulation result, a sedan class vehicle has around 380 N and -380 N initial lateral forces at left and right front tires respectively in standstill situation because of a suspension system and tire characteristic. In the steady-state driving situation on a straight road with less than 10 km/h vehicle speed for the same vehicle system, the left and right rear tires have -870 N and 807 N as an initial lateral force. In the case of an intelligent tire, generally strain sensors are attached to the inner liner of the tire to directly measure and estimate the absolute forces, which include the initial force [96]. Thus, in the case of using the PM for these kind of systems, it needs to generalize the PM formulation that incorporates the initial value. Grouping the front and rear set of tires, each PM can be written as

\[
PM_f = 1 - \frac{\sqrt{\mu_x^2 (F_{X_1} + F_{X_2})^2 + \mu_y^2 (F_{Y_1} + F_{Y_2})^2}}{\mu_x \mu_y (F_{Z_1} + F_{Z_2})}
\]

\[
PM_r = 1 - \frac{\sqrt{\mu_x^2 (F_{X_3} + F_{X_4})^2 + \mu_y^2 (F_{Y_3} + F_{Y_4})^2}}{\mu_x \mu_y (F_{Z_3} + F_{Z_4})}
\]

Equation 29

Equation 30

**Compensation for the Performance Margin Value Rise in the Saturation Condition**

The compensation factor is defined to correct the PM value when its value indicates that a vehicle regains its stability despite the fact that the tires are actually saturated. This effect occurs because $F_{X}$ and $F_{Y}$ are decreased when tires are saturated. Consequently, the original PM indicates that a vehicle recovers stability even though tires lose traction. Figure 10 shows the result of the simulation which a sedan vehicle rounds the 90 degree turn with a radius of 50 m at 85 km/h (The corner starts at 100 m station). As shown in the
result of the vehicle lateral offset, the vehicle runs off the road during the cornering because of losing traction. As a result, the original PM value reaches zero at 122 m station (In this simulation, the original PM was inverted, data values were turned upside down in order to more easily match the PM values of the modified PM. Therefore, in here, the original PM value of zero means that a vehicle loses traction.). After the value reaches zero, the value increases up to 0.169, although the vehicle is still in the losing traction situation. As shown in the slip angle result, the vehicle still achieves higher value of a slip angle, whereas the PM value increases. This occurs because the tire forces, $F_{x\nu}$ and $F_{y\nu}$, decrease as a slip angle increases in a slippage condition. This effect increases the PM value during a slippage situation.
Figure 10. The simulation result of 50 m radius turn.

For the modified PM, the correction factor, $\rho_{pm}$, is defined to compensate this influence. As shown in Figure 11, to perceive this improper effect through a general tire forces curve, it can be divided into two regions, A and B, by maximum force as a boundary. To discriminate between regions A and B for longitudinal and lateral tire force cases respectively, $\rho_{pm}$ is defined with Heaviside function, as shown in Equation 31. According to the definition of the equation, its value is unity if both longitudinal and lateral tire force
are in region A. If one of them is in region B, its value is 0 to make the modified PM value zero in the saturation condition.

Figure 11. General tire force curve.

\[ \rho_{pm} = H \left( \frac{\partial F_{xy}}{\partial S_x} \frac{\partial F_{yx}}{\partial \alpha} \right) \]  
Equation 31

Finally, to derive the proper PM value in tire saturation condition, the modified PM can be expressed as Equation 32.

\[ \bar{PM} = \rho_{pm} \left( 1 - \sqrt{\frac{\mu_y^2 F_{xy}^2 + \mu_x^2 F_{yx}^2}{\mu_x \mu_y F_{zy}}} \right) \]  
Equation 32

**Performance Margin Estimation for Applications to the Vehicle System**

In this section, the tire force estimator is proposed for the estimation of the PM using the basic vehicle sensor data. In reality, the tire forces are affected by the driver’s maneuvers and road characteristics. It also depends on the vehicle’s subsystems such as suspension dynamics, tire characteristics, and chassis characteristics. Because of the complexity and difficulty involved in actual vehicle dynamics, it is hard to estimate exact force values. However, this section proposes a simply designed real-time tire force estimator for the practical use of the PM. Although an intelligent tire, which can provide
the direct measuring and estimating of tire forces, have recently been an active area of research, there are still limitations for practical use. For the practical use of the PM, it needs to be calculated by using a widespread sensor such as Inertial Measurement Unit (IMU). Therefore, throughout this section it is assumed that the PM Estimator uses the basic vehicle sensor data such as vehicle acceleration, speed, rotational rate, and steering wheel angle. Also, the slope and the cross-slope considered in this work is assumed to be of reasonable magnitude, less than 5 % [97]. In addition, the vehicle system is assumed to be a front-wheel drive system.

The longitudinal and lateral tire forces can be estimated by using longitudinal and lateral accelerations and speeds, yaw angular speed, and steering wheel angle. The estimation is based on the equilibrium equation of forces and moments on the vehicle, as shown in Equation 33 to Equation 35.

\[
m(a_{xv} - v_{yv} \omega_{zv}) = F_{xvf} \cos \delta - F_{yvf} \sin \delta + mg \sin \theta_s + F_{aero} + F_{rolling} \quad \text{Equation 33}
\]

\[
m(a_{yv} - v_{xv} \omega_{zv}) = F_{xvf} \sin \delta - F_{yvf} \cos \delta + F_{yvr} - mg \sin \theta_b \quad \text{Equation 34}
\]

\[
I_{zv} \dot{\omega}_{zv} = \left( F_{xvf} \sin \delta + F_{yvf} \cos \delta \right) L_1 - F_{yvr} L_2 \quad \text{Equation 35}
\]

From Equation 33 to Equation 35, the longitudinal combined force of front tire set, \( F_{xvf} \), and the lateral combined force of front and rear tire set, \( F_{yvf} \) and \( F_{yvr} \), can be calculated as follows

\[
F_{xvf} = \frac{\lambda_1 + F_{yvf} \sin \delta}{\cos \delta} \quad \text{Equation 36}
\]
\[ F_{Yf} = \frac{\lambda_2 L_2 \cos \delta - \lambda_1 L \sin \delta + I_{Zv} \omega_{Zv} \cos \delta}{L} \]  
Equation 37

\[ F_{Yr} = \frac{\lambda_2 L_1 - I_{Zv} \omega_{Zv}}{L} \]  
Equation 38

where \( \lambda_1 \) and \( \lambda_2 \) are calculated as shown in Equation 39 and Equation 40.

\[
\lambda_1 = m(a_{Xv} - v_{Yv} \omega_{Zv}) - F_{aero} - F_{rolling} - mg \sin \theta_s
\]  
Equation 39

\[
\lambda_2 = m(a_{Yv} - v_{Xv} \omega_{Zv}) + mg \sin \theta_b
\]  
Equation 40

Under the assumptions, \( F_{Yf} \) and \( F_{Yr} \) are accurate to \( O(\theta_b \theta_s) \) and \( O(\theta_b) \), less than 7 \% and 5 \% error, which are negligible for typical application of this work. \( O(\theta_b \theta_s) \) and \( O(\theta_b) \) are terms involving \( \sin \theta_b + \sin \theta_s \) and \( \sin \theta_b \) respectively.

The vertical force can be estimated by using longitudinal and lateral acceleration, roll angle, and angular speed. The estimation of the vertical forces on each tire can be derived as Equation 41 to Equation 44.

\[
F_{Zv1} = \varepsilon_1 \zeta_1 - \frac{m h}{T} a_{Yv} + F_{sus1}
\]  
Equation 41

\[
F_{Zv2} = \varepsilon_1 \zeta_2 + \frac{m h}{T} a_{Yv} + F_{sus2}
\]  
Equation 42

\[
F_{Zv3} = \varepsilon_2 \zeta_1 - \frac{m h}{T} a_{Yv} + F_{sus3}
\]  
Equation 43

\[
F_{Zv4} = \varepsilon_2 \zeta_2 + \frac{m h}{T} a_{Yv} + F_{sus4}
\]  
Equation 44

where \( \varepsilon_1, \varepsilon_2, \zeta_1, \zeta_2 \), and the suspension force, \( F_{sus} \), are calculated as follows
\[
\varepsilon_1 = \frac{mgL_2 \cos \theta_s - ma_{Xy}h + mgh \sin \theta_s}{L}
\]  
Equation 45

\[
\varepsilon_2 = \frac{mgL_1 \cos \theta_s + ma_{Xy}h - mgh \sin \theta_s}{L}
\]  
Equation 46

\[
\zeta_1 = \frac{\cos \theta_b T/2 - h \sin \theta_b}{T}
\]  
Equation 47

\[
\zeta_2 = \frac{\cos \theta_b T/2 + h \sin \theta_b}{T}
\]  
Equation 48

\[
F_{sus_{left}} = K_{sus}(T/2) \sin \phi + C_{sus}(T/2) \dot{\phi} \cos \phi
\]  
Equation 49

\[
F_{sus_{right}} = -K_{sus}(T/2) \sin \phi - C_{sus}(T/2) \dot{\phi} \cos \phi
\]  
Equation 50

### 3.3 Simulation Results

#### 3.3.1 Simulation Results of PM for Geometric Road Design

Results are simulated for a flat road surface (free of slope and cross-slope) and for various grades and slopes that might normally be encountered. The slope and the cross-slope considered in this work is assumed to be of reasonable magnitude, less than 5\%. In addition, the vehicle system is assumed to be a front-wheel drive system. These simulations show the robustness of the estimation process; that is, the linearized equations closely capture the effects of grade and cross-slope. Specifically, the longitudinal friction \(\mu_x\) is estimated from the straight-line braking scenario that includes several road slopes, 0 to 5\%. Similarly, the 45.72 m (150 ft) constant radius test with 0 to 5\% cross-slope is used to determine the lateral friction \(\mu_y\). As shown in Figure 12, the results that are estimated from the linearized Equation 17 and Equation 23 are within 5.1\% of the actual simulation results.
These estimated Effective Friction coefficients are then used to create Performance Envelopes as shown in Figure 13, in which four plots are shown corresponding to four different road geometry cases. The ‘x’ shown in each plot corresponds to an operating condition in which the driver is quickly decelerating the vehicle on a curve, specifically $(A_X, A_Y) = (0.5, 0.3)$. The geometry and corresponding Performance Margin are described in Table 4.
Figure 13. Performance Envelopes and Performance Margin with four different road geometry cases.

Table 4. The four different road geometry cases and corresponding Performance Margin

<table>
<thead>
<tr>
<th>Case</th>
<th>Grade (%)</th>
<th>Cross-Slope (%)</th>
<th>Performance Margin</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.25</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>0</td>
<td>0.29</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>5</td>
<td>0.28</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>5</td>
<td>0.31</td>
</tr>
</tbody>
</table>

As shown in Figure 14, the result demonstrates how road geometry could affect Performance Margin.
3.3.2 Simulation Results of PM for Vehicle Control System

In this section, the simulations are implemented to validate and evaluate the proposed method. First, to demonstrate that the proposed PM improves measuring of vehicle performance, the simulation is conducted to compare the modified PM with the original PM. Next, the proposed PM Estimator is implemented and compared with real values to validate its usability. Finally, the prediction control algorithm based on the PM value is suggested and implemented to demonstrate the PM’s application in vehicle control systems.

Comparison of Modified PM with Original PM

Consider the vehicle traveling at 85 km/h and navigating a straight road of 100 m and a 90 degrees left turn with a radius of 50 m, as shown in Figure 15 without a slope and a cross-slope. Loss of traction will occur at around 120 m station in this condition. To validate the proposed method, the simulation is run, and the original and modified PM value at the front axles are evaluated for comparison.
As shown in Figure 16, when the vehicle lose the traction at the 122 m station, the value of the modified PM stays zero until its handling capability recovers the traction. Unlike the original PM, in which its value increases up to 0.17 while losing traction, the proposed PM indicates and distinguishes the saturation condition of the tires so that it can avoid a misjudgment.

**Simulation Result of Performance Margin Estimator**

To validate the proposed Performance Margin Estimator using vehicle sensor data, the simulations have been conducted with three differently designed roads. The first road is a 90 degree left turn with a radius of 50 m without a cross-slope and slope. The second road has the same left turn but with a slope such that the vehicle’s chassis is unloaded by a downslope during a 90 degree turn. The last road still has the left turn but with a 5 degree
cross-slope toward the outside of the road to make the vehicle maneuver an off-camber turn. Therefore, the cross-slope does not support the vehicle dynamics while the vehicles goes around the curve. These roads are designed to push the vehicle to its physical limit to evaluate the PM Estimator in severe situations.

Figure 17 shows the result of the simple left turn simulation. Although there is a noise around the 125 m station, the estimator calculates the PM value closely with the real value. The average of the absolute error between the estimated and real value is 0.0046. The maximum absolute error is 0.0771.

Figure 17. The left turn simulation result of estimated and real PM at front axle.

As shown in Figure 18(A) and (B), each calculation of the estimator shows a similar result to the real value. The average absolute errors are 0.0079 and 0.0075, respectively. The maximum absolute errors are 0.0938 and 0.0797, respectively. These results show that the estimator is valid and acceptable, even though the slope and cross-slope affect the vehicle’s dynamics.
Figure 18. A) The left turn with up and down slope simulation result of estimated and real PM at front axle, B) The left turn with cross-slope simulation result of estimated and real PM at front axle.

Figure 19 and Figure 20 shows the tire force estimation result of Figure 17 simulation. These forces are calculated by using sensor data such as acceleration, speed, rotational rate, and steering wheel angle. The average absolute error, maximum absolute error, and normalized root-mean-square error (NRMSE) of each tire force result are shown in Table 5. The estimator calculates the each tire forces closely with its real values, as shown in the results.
Figure 19. Real force and estimated force value in $F_{Xv}$ and $F_{Yv}$. 
Figure 20. Real force and estimated force value in $F_{Zv}$. 
Table 5. Average absolute error, maximum absolute error, and Normalized Root-Mean-Square Error (NRMSE) of tire force estimates

<table>
<thead>
<tr>
<th></th>
<th>Average Absolute Error</th>
<th>Maximum Absolute Error</th>
<th>NRMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_{X_{Vf}}$</td>
<td>61.62 N</td>
<td>253.39 N</td>
<td>11.09 %</td>
</tr>
<tr>
<td>$F_{Y_{Vf}}$</td>
<td>98.45 N</td>
<td>317.81 N</td>
<td>6.87 %</td>
</tr>
<tr>
<td>$F_{Y_{Vr}}$</td>
<td>81.67 N</td>
<td>251.37 N</td>
<td>6.34 %</td>
</tr>
<tr>
<td>$F_{Z_{V1}}$</td>
<td>277.86 N</td>
<td>1265.8 N</td>
<td>9.00 %</td>
</tr>
<tr>
<td>$F_{Z_{V2}}$</td>
<td>363.49 N</td>
<td>871.86 N</td>
<td>8.07 %</td>
</tr>
<tr>
<td>$F_{Z_{V3}}$</td>
<td>177.53 N</td>
<td>1498.7 N</td>
<td>7.86 %</td>
</tr>
<tr>
<td>$F_{Z_{V4}}$</td>
<td>190.70 N</td>
<td>1409.2 N</td>
<td>5.63 %</td>
</tr>
</tbody>
</table>

Application of the Performance Margin in Vehicle Control Systems

In this section, the concept of PM-based prediction control is introduced briefly to demonstrate the PM’s application in a vehicle’s control system. Also, the suggested algorithm is implemented to show that the PM can be used as a feasible metric for the system. The algorithm utilizes information about the upcoming local driving environment such as slope, cross-slope, and curvature. The local driving environment is measured in advance with a terrain measurement system developed and maintained by previous research studies introduced in Section 2. The algorithm continuously estimates the PM value for upcoming driving conditions and predicts future vehicle performance when it exceeds the defined threshold of the PM. If the PM value exceeds the threshold within the predicted future, the controller makes adjustments to driver commands to bring the PM back to a target value before the predicted situation occurs. By these processes, the proposed algorithm ensures that the vehicle maintains stability consistently. This algorithm is addressed in more detail in Section 4.2.3.

The simulation is run with the simple left turn scenario in the same way as Figure 15. The vehicle negotiates the curve at a constant 70 km/h. In this simulation, the target PM is set as 0.50. As shown in Figure 21, the simulation result without the proposed application shows that the PM value drops to near zero. Whereas the minimum PM value of the result with the proposed algorithm is 0.52, which is near to the target PM value, 0.50. The introduced algorithm calculates the $\Delta v_{X_{V}}$, which is -21.12 km/h, based on the target
PM. The vehicle speed is reduced by using this calculated result so that the PM value is regulated within the desired PM value.

![Graph](image.png)

Figure 21. The PM result comparison with and without 0.50 target PM algorithm.

### 3.4 Conclusion

Although several methods have been developed for measuring the performance capability of a vehicle, some require detailed knowledge of the forces acting at each tire contact patch, or do not account for both the vehicle dynamics and the road geometry. First, in this work, a redefined Performance Margin for geometric road design is developed as the additional performance capability available before the vehicle reaches the Performance Envelope (the upper limit of performance capability for a given operating condition). The Performance Margin accounts for both the environment and the dynamic response of the vehicle to this environment. Specifically, the Performance Envelope is estimated based on the Effective Friction (a function of vehicle dynamics and road surface properties) and the road geometry (slope and cross-slope). Next, the estimated PM has been defined to efficiently and suitably quantify vehicle handling capability for vehicle control system. The compensation factor has been defined to distinguish and compensate between saturated and unsaturated tires. These improvements and their effects are demonstrated with simulations of various scenarios. The estimator of the PM using the basic vehicle sensor data has been proposed for a practical application to vehicle system. The estimator has been validated with simulations spanning three different roads, which pushes the vehicle to its limit for evaluating the estimator in high-demand situations. Also, the concept of prediction control...
based on the PM has been introduced briefly and implemented to demonstrate the PM’s potential efficacy for application in vehicle systems. These simulation results show the feasibility of using the PM as the metric for handling capability in a vehicle control system. The application of the Performance Margin includes both geometric road design and vehicle control; both of which are crucial as transportation agencies and vehicle manufacturers prepare for the introduction of autonomous vehicles.
4. Vehicle Control System using Upcoming Driving Environment and the Performance Margin

This chapter is divided into two sections: developing the identification method to get upcoming local driving environment information and developing the predictive vehicle control system using driving environment and the PM.

4.1 Upcoming Driving Environment Identification Method using Preceding Vehicle Information

The objective of the research is to develop an algorithm for real time future terrain data estimation which utilizes the preceding vehicle dynamics information. Precise terrain information provides better prediction of future vehicle dynamics and improved performance of predictive-type control algorithms. The best way to get high-fidelity driving environment data is to measure a road profile using a terrain measurement system. However, the availability of this high-fidelity data is limited; it is impossible to measure every place all the time. Also, there is a possibility that the terrain may have undergone changes after the measurement because of road construction, for example. Therefore, an advanced vehicle control system should be able to accommodate unmeasured driving environment changes to achieve high performance and reliability.

This work begins by analyzing the response measurements of a preceding vehicle. It is assumed that the following and preceding vehicle are capable of Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) communication. By analyzing the response measurements of the preceding vehicle, the road information at the current position of the preceding vehicle (which is the upcoming road information for a following vehicle) is estimated at each sample time.

4.1.1 Methodology

In order to estimate the uncertainty in the road data from the response measurements of a preceding vehicle, the Disturbance Observer (DOB) is used. The DOB estimates the disturbance from the input and measurement output. Figure 22 shows a block
diagram of the DOB method. \( G_R(s) \) is a transfer function of actual plant dynamics model. \( G_A(s) \) is a transfer function of a mathematical analytical model (the nominal model). A disturbance, \( d \), is exerted on the plant so that the output \( y \) is affected by the disturbance. The actual output is

\[
y = G_R(s)(u + d) \quad \text{Equation 51}
\]

By inverse transfer function of analytical model, the estimated input can be described as

\[
\hat{u} = G_A^{-1}(s)y \quad \text{Equation 52}
\]

Subtracting the actual input, \( u \), from the estimated input, \( \hat{u} \), the effect of the disturbance and the model discrepancy, \( \hat{d} \), can be estimated as

\[
\hat{d} = Q(s)[G_A^{-1}(s)y - u] \quad \text{Equation 53}
\]

where \( Q(s) \) is a filter to make realizable. In practice, the inverse transfer function, \( G_A^{-1}(s) \), is not realizable by itself. However, \( Q(s)G_A^{-1}(s) \) can be made realizable by letting the relative order of \( Q(s) \) be equal or greater than that of \( G_A(s) \). As shown in Equation 54, \( Q(s) \), which satisfy above stated properties, has been suggested by [98].

\[
Q(s) = \frac{1 + \sum_{k=1}^{N-r} a_k(\tau s)^k}{1 + \sum_{k=1}^{N} a_k(\tau s)^k} \quad \text{Equation 54}
\]

where \( r \) must be equal or greater than the relative order of the transfer function of the nominal model. \( N \) is order of \( Q(s) \) and \( 1/\tau \) is cut-off frequency of \( Q(s) \). The coefficients \( a_k \) are usually chosen as the coefficients of a Butterworth filter. As shown in the block diagram of DOB, if \( G_A(s) \) is closer to \( G_R(s) \), then more exact disturbance estimates are produced by the algorithm. Therefore, updated parameters are used to design the nominal transfer function \( G_A(s) \).
In case there is no upcoming road data for the controller, the input, $u$, is $0$ and the unknown road data can be estimated by calculating the disturbance, $d$ using the DOB. As shown in Equation 55, $G_R(s)$ is the transfer function with respect to vehicle vertical acceleration, $a_{Zv}$, and road height, $Z_{road}$. In order to estimate the unexpected road data that have undergone changes after the terrain measurement, the measured road height data, $Z_{road}$, is used as an input, $u$. The disturbance, $d$, herein is an unexpected road data.

$$G_R(s) = \frac{a_{Zv}}{Z_{road}}$$

Equation 55

### 4.1.2 Simulation Results

The simulation has been conducted to evaluate the proposed method. In this simulation, as shown in Figure 23, a quarter car model is used as transfer function $G_R(s)$.

$$\frac{a_{Zv}}{Z_{road}} = \frac{c_k k_t s^3 + k_k s^2}{m_u m_s s^4 + (m_u c_s + m_c c_s) s^3 + (m_u k_s + m_k k_t + m_s k_s) s^2 + c_k k_s + k_k k_t}$$

Equation 56

The measured road data is assumed as flat road, $Z_{road} = 0$ in order to estimate an unmeasured road profile. As shown in Figure 24, the unmeasured road data consist of 0.05 m height and 0.05 m depth road profile.
Figure 23. Quarter car model.

Figure 24. The road profile for the simulation.

As shown in Figure 25, the proposed method estimates a road profile by using DOB method. The proposed method is used to calculate the estimated road profile, and closely agrees with the real road profile. Although there is delay between the real road profile and the estimated road profile because of $Q(s)$ filter, it can be compensated before using for a following vehicle. This delay is left uncorrected in Figure 25 for improved visualization of the results.

Figure 25. Simulation result of estimated road.

Figure 26 shows the simulation result with three different height and depth road profiles. Each different height and depth profile are estimated using the DOB method and
the results closely align with the real profiles. Although the estimated results are not perfectly matched with its real profile, these results are encouraging. To validate the proposed method in the real world road, simulations have been conducted with real road measurement data. Figure 27 shows the real world road estimation result. Similarly, the estimated road profile closely agrees with the measured road profile.

![Simulation result of the estimated road with different height and depth road profile.]

Figure 26. Simulation result of the estimated road with different height and depth road profile.
4.2 Predictive Vehicle Control System

To avoid some of the problems found with reactive methods, predictive methods are attracting increasing interest in the field of robotics and vehicle research. Also, there are some commercialized vehicle control systems that are predictive in nature such as Collision Avoidance Systems and Lane-Keeping Systems. However, these vehicle control systems usually utilize limited information about the driving environment (e.g., road curvature, elevation changes, bank angle, and road roughness). This work proposes a predictive control system using upcoming driving environment information. The upcoming driving information, consisting of the pre-measured or estimated road data, is used for predicting future vehicle dynamics. By using the future vehicle dynamics information, the predictive controller enables a vehicle system to avoid the situations in which it loses stability and thereby improves the performance of the vehicle system. If the algorithm predicts situations in which the vehicle exceeds its handling capabilities, the predictive controller intervenes in driver commands. The intervention strategy maintains vehicle handling capabilities based on the results of the prediction. In this section, two types of control algorithms are introduced: the Speed Predictive Controller and the Performance Margin (PM) Predictive Controller. Vehicle speed and Performance Margin are used as metrics to identify when the controller intervenes. Each controller is used to make corrections to the driver’s throttle and brake commands to regulate the each metric, vehicle speed and PM, into an acceptable range.
This section is organized as follows. The limitation of a reactive vehicle control systems is addressed with simulation results in Section 4.2.1. The predictive controller based on vehicle speed is developed in Section 4.2.2. Section 4.2.3 presents the predictive vehicle controller based on PM values. In Section 4.2.4, the proposed algorithms are verified via a computer simulation.

### 4.2.1 Simulations of Reactive Vehicle Control System with Limited Driving Environment Information

Two kinds of simulations have been conducted to show the importance of the perception of driving environments and the necessity of reactive vehicle control system improvement. The first simulation is of an autonomous vehicle having fine longitudinal and lateral controllers. This simulated autonomous vehicle controller regards the road as ideally flat; the results show the importance of correctly perceiving the driving environment. The second simulation is conducted with an ESC system, which is a typical reactive controller. This simulation result demonstrates the limitation of an ESC system in certain circumstances.

The environment is one of the fundamental factors, along with the vehicle dynamics and the driver, to design and evaluate vehicle systems. Of particular interest for ground vehicles are the geometric properties the road [20]. Even if an autonomous vehicle has perfect cruise control and lane keeping systems, it can encounter unexpected insecure situations because of a lack of environment information. Figure 28 to Figure 30 show the simulation results of the autonomous vehicle having typical longitudinal and lateral controllers. However, this autonomous vehicle controller regards the environment information as an ideally flat road like a general vehicle controller. In the simulations, the target lateral offset from the centerline by the lateral controller is set to 0 m. Figure 28 is the simulation result of a 90 degrees turn with a radius of 50 m. The vehicle travels the curve at 75 km/h target speed. The simulation road of Figure 29 changes the vehicle dynamics to unload the chassis by a downslope during a 90 degrees turn with a 50 m radius. The target speed for the simulation is 65 km/h. Figure 30 simulation has a 90 degrees turn with a 50 m radius and a 10 degrees bank angle producing an off-camber turn in which vehicle goes around the curve at a 60 km/h target speed. Each of the scenario simulations
has two resultant graphs. The first one is an actual traveled lateral offset result of the vehicle. The second result is a result of the Performance Margin.

The results of each scenario simulation shows the limitations of an autonomous vehicle and ADAS caused by the lack of driving environment information. The lateral controller is not able to achieve precise tracking of the target lateral offset because of the driving environment effect. Moreover, each of the PM result shows that the vehicle loses traction during the cornering. As shown in the normal left turn simulation results, the vehicle deviates 5.8 m laterally. Also, the PM value reaches to zero. Figure 29 and Figure 30 show similar results; there are 3.9 m and 3.3 m lateral offset error respectively. Likewise, each of the PM value reaches to zero. These simulation results show that the perception of a local driving environment can be critical to advanced vehicle control. The advanced vehicle control system should be able to consider the driving environment to improve vehicle control performance and safety.

Figure 28. The left turn simulation results of an autonomous vehicle.
Figure 29. The left turn with up and down slope simulation results.

Figure 30. The left turn with cross-slope simulation results.
The current technologies are activated mostly based on the current vehicle state, rather than predicting a future state. Thus, even though a fine electromechanical device provides a high sensing capability and a computational power, the reactive type controller encounters difficulties in controlling a high-energy vehicle system because of the limitation of actuating powers. One highly valued vehicle controller is the Electronic Stability Control (ESC) system. The ESC system is a typical reactive control system. As shown in Figure 31, the same simulation of Figure 28 is conducted with ESC system on the autonomous vehicle.

Figure 31. 50 m radius turn simulation results with ESC and without ESC.
Figure 31 shows results similar to those in Figure 28. The maximum lateral offset is reduced by only 0.12 m (2%) by ESC system. Also, the PM value still reaches to zero. It means that ESC is insufficient and ineffective to get over the situation. As shown in the PM value and the brake pressure result of Figure 31, ESC system was activated after the PM reached zero because ESC system is reactive in nature. It is too late to recover stability of the vehicle after speed and acceleration have exceeded a certain threshold. In this case, a large actuating effort will be required to bring the vehicle back to a stable state. Consequently, ESC system was unavailing in this scenario. Likewise, other reactive systems such as Anti-Lock Braking Systems (ABS) and active rollover prevention system have similar limitations due to their reactive nature. Therefore, from this point of view, a predictive type approach is advantageous to resolve the limitations of a reactive system.

4.2.2 Development of the Speed Predictive Vehicle Control

Implementing terrain data into control systems is especially pertinent in preventing roadside departures, which annually constitutes over 15,000 deaths [99]. In a typical curved road departure scenario, the vehicle loses control when its velocity exceeds the maximum allowable cornering speed of the curve. As shown in Figure 32, the maximum allowable cornering speed can be affected by the road’s roughness. Therefore, incorporating precise terrain data into predictive controllers can improve their performance and thus reduce the number of roadside departures that occur.

There are three main parts in this work: a correction factor accounting for terrain roughness and a predictive speed control system with an optimized speed profile. All parts assist in reducing a vehicle's speed before entering a rough curve to avoid roadside departures. The correction factor is derived as a function of the road’s ISO Roughness index, which is determined a priori from existing measured terrain data. It is then used to generate an optimized speed profile for the vehicle to follow to maintain stability while negotiating the curve.

Maximum Allowable Cornering Speed

There exists a maximum allowable speed at which a vehicle can be kept on the road while traversing curved roads. This threshold depends on geometric parameters (bank angle, radius of curvature, and acceleration due to gravity) and the friction coefficient
between the road surface and tire. A force summation for a vehicle on a banked circular road yields Equation 57.

\[ v_{allow} = \sqrt{\frac{R_c g (\sin \theta_b + \mu \cos \theta_b)}{\cos \theta_b - \mu \sin \theta_b}} \]  

where \( v_{allow} \) represents the maximum allowable cornering speed, \( R_c \) is the radius of curvature, \( g \) is the acceleration due to gravity, \( \theta_b \) is the bank angle, and \( \mu \) is the friction coefficient.

Equation 57 does not account for road roughness or other terrain characteristics aside from the friction coefficient, \( \mu \). Thus, a dimensionless correction factor \( \rho \) is introduced to create an “effective” friction coefficient. It is defined as the friction coefficient of a flat road and each ISO class normalized with respect to the friction coefficient of a flat road, \( \mu_{flat} \).

\[ \rho = \frac{\mu_i}{\mu_{flat}}, \quad i = flat, A, B, C, D, E \]  

Equation 58

The coefficient of friction is the ratio of the maximum possible force in the horizontal plane to the force in the vertical direction. A standard constant-radius simulation was used to obtain each \( \mu_i \). A vehicle travels around a 45.72 m (150 ft) radius circle with lateral acceleration \( a_{Yv} \). The coefficient of friction is estimated by increasing the lateral acceleration until the moment that it slips, at which point the maximum force in the horizontal plane is \( max(m a_{Yv}) \). This simulation was then repeated using each ISO classification, returning the coefficient of friction for that particular surface. Because \( \mu_i \) can vary based on different measurement systems, it is recommended to hold \( \rho \) constant to approximate \( \mu_i \) when it is unknown. Given this, the corrected (effective) friction factor can be written as

\[ \mu_{eff} = \rho \mu_{flat} \]  

Equation 59
The correction factor versus ISO roughness is plotted in Figure 32. Note that for relatively smooth roads (ISO classes A and B) there is negligible effect on the friction estimate. However, on rough roads (ISO class E and beyond) there is a greater than 10% decrease in the limit performance, as measured by effective friction.

![Figure 32. Correction factor $\rho$ plotted as a function of ISO Roughness.](image)

Inserting the effective friction coefficient, Equation 59, into Equation 57 gives

$$v_{allow} = \sqrt{\frac{Rcg \left( \sin \theta_b + \mu_{eff} \cos \theta_b \right)}{\cos \theta_b - \mu_{eff} \sin \theta_b}}$$

Equation 60

which is the maximum allowable cornering speed, taking terrain effects into account.

**Predictive Vehicle Controller with Optimized Speed Profile**

The objective of the controller is to control throttle and brake commands to maintain a safe vehicle speed by predicting vehicle future states when navigating upcoming terrain. For example, the future 20 seconds are predicted at every time step based on a non-linear vehicle model, the driver commands, and the upcoming terrain data. Throttle and brake commands are controlled to ensure that future vehicle speeds will not exceed the maximum allowable speed. Figure 33 shows the strategy overview of the speed predictive control.
A sudden change of a vehicle’s reference speed for a cruise control can cause instability of a control system. Moreover, ride quality and vehicle dynamics should be considered when reducing a vehicle’s speed. Therefore, it is important to generate an optimal speed profile to maintain stability and ride quality while reducing a vehicle speed. In this study, a finite-horizon linear quadratic regulator is used for generating the optimized speed profile. The cost function for the optimal problem is given as follows.

\[ J = \int_{t_0}^{T} x(t)^T Q(x(t)) + u(t)^T R(u(t)) + x(T)^T M x(T) \]  

Equation 61

Q and R are the state weighting matrix and the control effort weighting matrix, respectively. M is the terminal state cost weighting matrix. This finite-horizon LQR controller, \( u(t) \), is given by

\[ u(t) = -R^{-1}B^T P x \]  

Equation 62

where \( P(t) \) solves the Riccati equation as shown in Equation 63.

\[ \dot{P} = -PA - A^T P + PBR^{-1}B^T P - Q \]  

Equation 63

The boundary condition for the Riccati equation is

\[ P(T) = M \]  

Equation 64
In this algorithm, the state vector is defined as

\[ x = [x_1, x_2] = \begin{bmatrix} v_{Xv} - v_{allow} \\ a_{Xv} \end{bmatrix} \quad \text{Equation 65} \]

The input \( u \) is

\[ u = \begin{bmatrix} T_e \\ \dot{T}_e \end{bmatrix} \quad \text{Equation 66} \]

where \( T_e \) is the engine torque. Equation 65 and Equation 66 lead to the matrices for the state-variable form as follows.

\[ A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \text{Equation 67} \]

where \( r_{eff} \) is the tire effective rolling radius. \( m \) is the vehicle mass. Therefore, in Equation 61, \( T \) is selected as the prediction time (20 sec in this work). \( x_1 \) is used as the optimized speed profile in the predictive vehicle controller.

To track the optimized speed profile, the upper and lower level controller of a standard cruise control system are used. The upper controller determines the desired acceleration, \( a_{Xv_{des}} \). The lower controller determines the driver command input required to track the desired acceleration [2]. Typically, PI control using error in vehicle speed is used as the upper level controller as shown in Equation 68.

\[ a_{Xv_{des}}(t) = -k_p(v_{Xv} - v_{osp}) - k_i \int_0^t (v_{Xv} - v_{osp}) \, dt \quad \text{Equation 68} \]

where \( v_{osp} \) is the desired vehicle speed calculated by the optimized speed profile generator. A simplified powertrain model is implemented in the lower level controller. Specifically, the torque converter is assumed to be locked, the transmission is in a steady state, and the
longitudinal tire slip is negligible. The net torque of the engine $\tau_{net}$ and the brake torque $\tau_{brk}$ can be modeled as [3, 9, 11]

$$\tau_{net} = \frac{J_e}{R_g r_{eff}} a_{X_{des}} + R_g (c_a R^2 r_{eff}^2 \omega_e^2 + r_{eff} R_x + \tau_{brk} + r_{eff} m g \sin \theta_s) \quad \text{Equation 69}$$

where $J_e = I_e + I_t + (m r_{eff}^2 + I_\omega) R_g^2$ is the effective inertia reflected on the engine side. Here, $I_e$, $I_t$, and $I_\omega$ are the engine moment of inertia, the transmission shaft moment of inertia, and the wheel moment of inertia, respectively. $R_g$ and $\omega_e$ are the gear ratio and the engine angular speed. $R_x$ is the rolling resistance of the tires, $c_a$ is the aerodynamics drag coefficient, and $\theta_s$ is the road slope. Once the required torque is obtained from Equation 69, the throttle position and brake pressure are calculated to provide the desired torque by the inverse steady-state engine map and the brake model.

### 4.2.3 Development of the PM-based Predictive Vehicle Control

In this section, the Performance Margin based prediction control is introduced. The PM value is used as a metric for the control system. The algorithm utilizes information about the upcoming local driving environment such as slope, cross-slope, and curvature. The algorithm continuously estimates the PM value for upcoming driving conditions and predicts future vehicle performance when it exceeds the defined threshold of the PM. If the PM value exceeds the threshold within the predicted future, the controller makes adjustments to driver commands to bring the PM back to a target value before the predicted situation occurs. By these processes, the proposed algorithm ensures that the vehicle maintains stability consistently. The block diagram of this concept is shown in Figure 34.
Figure 34. Block diagram of the PM based prediction control.

In this algorithm, the PM estimator is used as explained in Section 3.2.1. Also, same sub functions, such as the Optimized Speed Profile Generator, the upper and lower level controller, are used in the control system. Since the PM value is used as a metric for this controller, an analytical relationship between the change in the PM and the change in the longitudinal vehicle speed is derived. If the PM value exceeds the target PM, $PM_{target}$, at any point in the predicted future, this Linear Chassis Model is taken into account. In this model, the changes in the PM metric, $ΔPM$, is used as an input ($PM_{target} - PM_f$). The output of the model is the target vehicle speed. This relationship allows for a connection from the desired changes in Performance Margin value through necessary changes in vehicle speed.

As shown in Equation 70, the first order perturbations are given by taking the PM equations and performing a Taylor Series approximation.

$$ΔPM_f = αΔF_{x_f} + βΔF_{y_f} + γΔF_{z_f} \quad \text{Equation 70}$$

where $α$, $β$, and $γ$ coefficients are defined as follows.
\[
\alpha \approx \frac{\partial PM_f}{\partial F_{XV_1}} = \frac{\partial PM_f}{\partial F_{XV_2}} = -\left[ \frac{\mu_x^2 (F_{XV_1} + F_{XV_2})^2 + \mu_y^2 (F_{YV_1} + F_{YV_2})^2}{\mu_x (F_{ZV_1} + F_{ZV_2})} \right]^{\frac{1}{2}} \frac{1}{\mu_y (F_{ZV_1} + F_{ZV_2})}
\]

\[
\beta \approx \frac{\partial PM_f}{\partial F_{YV_1}} = \frac{\partial PM_f}{\partial F_{YV_2}} = -\left[ \frac{\mu_x^2 (F_{XV_1} + F_{XV_2})^2 + \mu_y^2 (F_{YV_1} + F_{YV_2})^2}{\mu_y (F_{ZV_1} + F_{ZV_2})} \right]^{\frac{1}{2}} \frac{1}{\mu_x (F_{ZV_1} + F_{ZV_2})}
\]

\[
\gamma \approx \frac{\partial PM_f}{\partial F_{ZV_1}} = \frac{\partial PM_f}{\partial F_{ZV_2}} = \frac{PM_f}{F_{ZV_1} + F_{ZV_2}}
\]

As shown in Equation 74 to Equation 76, \(\Delta F_{XV}, \Delta F_{YV}, \) and \(\Delta F_{ZV}\) are defined as the difference between the desired forces and the current forces.

\[
\Delta F_{XV} = F_{XV_{des}} - F_{XV} = m (a_{XV_{des}} - a_{XV})
\]

\[
\Delta F_{YV} = F_{YV_{des}} - F_{YV} = m (a_{YV_{des}} - a_{YV})
\]

\[
\Delta F_{ZV} = F_{ZV_{des}} - F_{ZV} = m (a_{ZV_{des}} - a_{ZV})
\]

Using Equation 74 to Equation 76 and Equation 36 to Equation 44 in Section 3.2.1 gives the equations for change in forces in terms of \(\Delta a_{XV}, \Delta a_{YV}, \) and \(\Delta \dot{a}_{ZV}\).

\[
\Delta F_{XV} = m \cos \delta \Delta a_{XV} + \frac{m L_2 \sin \delta}{L} \Delta a_{YV} + \frac{l_z \sin \delta}{L} \Delta \dot{a}_{ZV}
\]

Equation 77
\[
\Delta F_{Yv} = \frac{mL_2 \cos \delta}{L} \Delta a_{Xv} - m \sin \delta \Delta a_{Yv} + \frac{I_z \cos \delta}{L} \Delta \dot{a}_{Zv} \quad \text{Equation 78}
\]

\[
\Delta F_{Zv} = -\frac{mh}{L} \cos \theta_b \Delta a_{Xv} \quad \text{Equation 79}
\]

Substituting Equation 77, Equation 78, and Equation 79 into Equation 70 gives the equation relating changes in speed and acceleration terms to changes in PM value. In order to put this equation solely in terms of longitudinal terms, the lateral acceleration term and the rotational term are replaced with Equation 80 and Equation 81, since the vehicle is modeled as rotating about an instantaneous center for each station, as described by [100].

\[
\Delta a_{Yv} = \frac{\partial a_{Yv}}{\partial v_{Xv}} \Delta v_{Xv} = 2 \frac{v_{Yv}}{R} \Delta v_{Xv} \quad \text{Equation 80}
\]

\[
\Delta \dot{a}_{Zv} = \frac{1}{R} \Delta a_{Xv} \quad \text{Equation 81}
\]

The final equation relating changes in longitudinal speed and acceleration to changes in the PM is derived as follows.

\[
\Delta PM_f = \left[ m(\alpha \cos \delta - \beta \sin \delta - \gamma L \cos \theta_b) + \frac{I_z(\alpha \sin \delta + \beta \cos \delta)}{LR} \right] \Delta a_{Xv} + \left[ 2v_{Xv} mL_2(\alpha \sin \delta + \beta \cos \delta) \right] \Delta v_{Xv} \quad \text{Equation 82}
\]

By solving the differential equation in Equation 82, the target vehicle speed can be estimated to bring the PM value back to a target value, \( PM_{\text{target}} \).

### 4.2.4 Simulation Results

The pitch rate, which is a good indicator of ride quality, and vehicle’s longitudinal speed measure the success of the Optimized Speed Profile. Figure 35 presents the
simulation results of the Speed Predictive Control system with and without Optimized Speed Profile (OSP) to highlight the effects of the OSP system on the vehicle’s stability.

In this scenario, the reference speed was suddenly decreased from 90 km/h to 50 km/h at 20 sec, and increased back to the initial desired speed at 58 sec. Without OSP, the actual speed does not accurately conform to the desired speed profile. From inspection, it takes approximately 5 seconds for the vehicle to match the new desired speed and experiences slight velocity oscillations before stabilizing. Likewise, the vehicle fails to immediately jump to the initial desired speed at 58 sec; the velocity also oscillates and overshoots before reaching steady state. However, with OSP, the system produces a new desired and actual speed trajectory consisting of a smoother transition to and from 50 km/h. As a result, the actual speed closely aligns with the desired speed. In Figure 35, the vehicle stabilizes to 50 km/h around 30 sec and stabilizes back to the initial desired speed at around 70 sec, but the speed with OSP experiences less overshoot and oscillations, leading to a smoother ride (increased ride quality) and better stability. Figure 36 evaluates a more canonical handling metric, the pitch rate.
Figure 36. The simulation results of the pitch rate with and without OSP.

The velocity without OSP tries to suddenly drop the vehicle speed, consequently it experiences a decrease in ride quality. This ride quality loss is reflected in Figure 36. There are the sharp peaks in the pitch rate without OSP. With OSP, the pitch rate also deviates from zero at the same times at which the speeds change in Figure 35, but the magnitude of the pitch rate does not exceed 0.5 deg/s. Thus, the OSP is effective in providing a speed trajectory that helps prevent a loss in ride quality.

The Performance Margin (PM), which quantifies the vehicle’s handling capabilities, and the lateral offset are the metrics used to evaluate the Speed Predictive Control (SPC). Note that the SPC system encompasses the OSP system. The road used in the simulations consisted of a 1000 m straightaway followed by a 50 m radius left turn and another straight road. As seen in Figure 37, the vehicle deviates a fraction of a meter from the centerline of the road when the SPC system is used. Without SPC, the vehicle deviates by over 20 m. The PM without SPC drops to zero when the curve begins at Station 1000. This means that when the vehicle begins to drift, it loses control and continues to remain unstable until the curve ends at Station 1200.
Figure 37. Vehicle lateral offset from the path and the PM comparison with and without the Speed Predictive Control.

Next, the simulation of the PM based predictive control is implemented to validate and evaluate the proposed method. The simulation is run with the simple left turn scenario in the same way as Figure 15. The vehicle negotiates the curve at a constant 70 km/h. In this simulation, the target PM is set as 0.50. As shown in Figure 38, the simulation result without the proposed application shows that the PM value drops to near zero. Whereas the minimum PM value of the result with the proposed algorithm is 0.52, which is near to the target PM value, 0.50. The algorithm calculates the $\Delta v_{x,y}$, which is -21.12 km/h, based on the target PM. The vehicle speed is reduced by using this calculated result so that the PM value is regulated within the desired PM value.
Likewise, the simulations are conducted with 0.20, 0.40, and 0.60 target PM values. As shown in Figure 39, the minimum PM values of the simulation results each have 0.23, 0.43, and 0.60, respectively. Each vehicle speed has been changed to 61.52, 53.10, and 44.66 km/h by the estimated value, $\Delta v_x$. This simulation demonstrates the PM’s feasibility for using it as a metric for a vehicle control system.
5. Driving Simulator for Advanced Vehicle Control
System with Real-World Measurement System

Abstract

The performance of current Advanced Driver Assistance Systems (ADAS) is sensitive to the dynamics of the vehicle and the driving environment. In order to aid in the efficient development of such systems, driving simulators should emulate as closely as possible real-world scenarios with a range of vehicle dynamics and driving environments. The main objective of this work is to develop an integrated driving simulator which uses precise real-world driving environment data for advanced and computationally intensive vehicle control algorithms with a multi-user interface. The proposed driving simulator system consists of four subsystems: measured and synthetic terrain generation, vehicle dynamics, vehicle control, and visualization. The measured and synthetic terrain generation subsystem consists of the Vehicle Terrain Measurement System (VTMS) which acquires real world terrain data and the data processing algorithms which convert the acquired data into a usable format for the driving simulator. The vehicle dynamics subsystem consists of high-fidelity vehicle models and solvers that, along with the real-world driving environment data, are able to achieve high-fidelity driving simulation results. The vehicle control subsystem consists of advanced vehicle control algorithms such as predictive type control algorithms which demand more computational power than real-time controllers. The visualization subsystem converts the measured terrain data to a 3D geometry model for use in a virtual reality environment developed by a game engine to emulate a real-world scene with high-quality graphics. To demonstrate that the driving simulator works properly, the proposed predictive vehicle control algorithm is implemented in the driving simulator. The simulation results show the effect of the algorithm simultaneously operating the real-time controller and the predictive controller.
5.1 Introduction

In the field of modern automotive engineering, advanced vehicle control systems have been an active area of research, contributing to the development of ADAS and autonomous vehicle technologies. For developing and evaluating these advanced vehicle control systems, a driving simulation environment is necessary. Driving simulators can be used to implement and validate various vehicle control algorithms with flexibility and swiftness in adjusting simulation factors. Moreover, driving simulators are useful both in a repetitive simulation and in testing a dangerous conditions simulation, which are difficult in the real world. Due to these advantages, various types of driving simulators have been developed and enhanced in recent years. The steady progress has resulted in impressive contributions [101-120].

The recent vehicle control systems are sensitive to the dynamics of the vehicle and driving environment components such as road curvature, elevation, bank, friction, and terrain roughness [2, 20]. Thus, it is necessary that driving simulators are able to emulate as closely as possible real world scenarios in order to better understand, plan, and improve the advanced vehicle technologies. For high-fidelity simulation of an advanced vehicle control system, a driving simulator has to satisfy three essential requirements. First, a driving simulator has to be able to manage the sophisticated vehicle control algorithms with an enhanced computational capability in real-time without any conflict. Currently, various vehicle control systems are incorporated in automobiles such as a cruise control, Anti-Lock Braking System (ABS), and Electronic Stability Control (ESC). Moreover, autonomous vehicle systems and ADAS demanding more computational power are being developed. As a result, recent vehicle technologies require vehicle controllers with high computational power. Second, accurate and precise real-world driving environment data are required for a high-fidelity driving simulation environment. For a ground vehicle, the vehicle, driver, and environment (i.e. the geometric properties of the ground) are fundamental factors to understand the whole vehicle system [20]. In spite of the fact that the driving environment is one of the significant factors in vehicle systems, many driving simulators simplify or assume the driving environment as an ideally flat road surface. However, in the real-world vehicle dynamics rely heavily on the driving environment. The capabilities of advanced vehicle control systems in turn rely on the dynamics of the vehicle
and the driving environment. Thus, a driving simulator has to be able to generate and incorporate a synthetic driving environment that is as close as possible to the real world in order to get accurate simulation results. Last, the simulation environment should be able to include multiple interdependent driving agents interacting with each other in real time. Interaction of multiple vehicles is important in a driving simulation because many advanced vehicle technologies such as Vehicle to Vehicle (V2V) communication, adaptive cruise control, and Lane Keeping Systems are based on the vehicle’s interaction with other vehicles. Although currently there are many impressive driving simulators, few of them satisfy the aforementioned requirements for the advanced vehicle technologies. However, these driving simulators are high-cost systems with more than two high-performance computer systems [103, 117, 120].

The main objective of this work is to develop an integrated driving simulator system using accurate and precise real-world measurement data for advanced high computational vehicle control systems with low-cost PC-based operation and multi-user interface. The overall structure for this chapter takes the form of six sections, including the introduction. The second section reviews the process by which terrain surfaces are measured and processed. The third section presents the system configuration of the proposed driving simulator. In the fourth section, measured and synthetic terrain generation systems are introduced. In the fifth section, the simulation result is presented to show the importance of considering real-world environment data in a driving simulator. Also, the fifth section analyzes the results of simulations to evaluate the performance of the driving simulator. Lastly, the sixth section concludes the chapter by summarizing the main results.

5.2 System Configuration

The driving simulator developed in this work is shown schematically in Figure 40. The measured and synthetic terrain generation subsystem consists of the Vehicle Terrain Measurement System (VTMS) and measured terrain data processing software packages addressed in Section 2.2.2. This subsystem provides gridded and characterized terrain data for the vehicle dynamics system and visualization subsystem. In the vehicle dynamics subsystem, the non-linear full vehicle dynamics model is used to generate high-fidelity simulation results. The vehicle dynamics subsystem uses driver commands as inputs
collected by the acquisition device such as the steering wheel, acceleration pedal, and brake pedal. This subsystem is able to import elements of the driving environment such as road path points, terrain roughness, bank angle, elevation, and curvature for the driving simulation. The user can choose the measured terrain data or define their own terrain data as the driving environments. Accordingly, the simulation of vehicle dynamics is affected by the driving environment. The vehicle dynamics subsystem is capable of using the dynamic models from CarSim©, a commercially available vehicle simulation software package. Various real-time vehicle control algorithms such as ADAS and autonomous vehicle control algorithms can be implemented in the vehicle control subsystem. Moreover, it is possible to run real-time predictive control algorithms requiring more processing power than reactive real-time controllers. The visual system consists of the Track Translator (code created by VTPL) and a virtual reality environment. Track Translator converts the final driving environment data to a 3D geometric model for use in the virtual reality environment. The virtual reality of the driving simulator is developed by a game engine, which is the same software used in the creation of video games to emulate a real-world scene with high-quality graphics (Figure 41).

Figure 40. The system configuration of the driving simulator.
Figure 41. The virtual reality of the driving simulator.

All of the subsystems of the driving simulator are operated independently on a single personal computer without conflict in real time. Each of the subsystems were developed by different software such as MATLAB, CarSim®, C#, and Unity. All of the subsystems are connected and integrated via User Datagram Protocol (UDP) with effective architecture to avoid conflict and interruption between each subsystem. In addition, interactive simulations of multiusers are practicable by using UDP and on-line gaming technology in the virtual reality system.

5.3 Synthetic Terrain Generation

After the measured and synthetic terrain generation system generates the finalized terrain data, the data has to be imported into the vehicle dynamics system and the visualization system in the proper format. Also, the data needs to be available for modification according to the various driving scenarios prescribed by the user. For example, to evaluate the robustness of a vehicle control algorithm in various road conditions, the driving scenarios should be simulated by the same path and elevation of the measured terrain data \((x, y, \text{ and } z)\) with different road roughness and friction factors. To accomplish this, Track Builder and Track Translator software packages have been developed in the VTPL to accomplish two tasks.

Track Builder has been developed to create completely synthetic terrain data (by defining path points, road bank angle, roughness, and friction) or to modify the measured terrain data and import the data into the vehicle dynamics system. Track Builder generates the track information files from the measured terrain data for the vehicle dynamics system.
The track files are imported automatically into the vehicle dynamics subsystem. Before importing the track files, Track Builder allows the user to modify the measured terrain data with custom xyz coordinates, right and left friction coefficients, and a road bank angle. In addition, synthetic roughness data can be generated based on International Organization for Standardization (ISO) 8608 standard [121]. Once given this desired track information, Track Builder interpolates the user prescribed data using the P-chip method and ploy structures to create a series of points. Consequently, the user is able to simulate real-world driving scenarios by modifying various parameters.

In this proposed system, the ISO 8608 standard is used as a criterion to generate synthetic road roughness profiles. ISO has proposed a road roughness classification based on the relationship between the PSD, $S_g(\Omega)$, and the spatial frequency, $\Omega$, for the elevation of the ground profile. The relationship can be expressed as

$$S_g(\Omega) = R_{ISO}(2\pi\Omega)^k$$

Equation 83

where $k$ is -2.0 for $\Omega \leq 1/2\pi$ cycles/m and -1.5 for $\Omega \geq 1/2\pi$ cycles/m. The range of values of $R_{ISO}$ for different road classes is given in Table 6. Also, the relationship is shown by the straight lines with different slopes on a log-log scale in Figure 42 [20, 121].

<table>
<thead>
<tr>
<th>Road Class</th>
<th>$R_{ISO}$ Range, $10^{-6}m^2$/cycles/m</th>
<th>Geometric Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (Very Good)</td>
<td>&lt;8</td>
<td>4</td>
</tr>
<tr>
<td>B (Good)</td>
<td>8–32</td>
<td>16</td>
</tr>
<tr>
<td>C (Average)</td>
<td>32–128</td>
<td>64</td>
</tr>
<tr>
<td>D (Poor)</td>
<td>128–512</td>
<td>256</td>
</tr>
<tr>
<td>E (Very Poor)</td>
<td>512–2048</td>
<td>1024</td>
</tr>
</tbody>
</table>
A fractal profile is one method for modeling terrain profiles [122-124]. In this work, the Weierstrass-Mandelbrot (W-M) function is used to generate a fractal profile that matches the PSD of different classes of road roughness in ISO 8608. The W-M function can represent a fractal surface profile, $z(u)$, that can be written as [125-130]

$$z(u) = L \left( \frac{G}{L} \right)^{D-1} \sum_{n=1}^{n_{\text{max}}} \cos \left( \frac{2\pi \gamma^n x}{L} \right) \frac{\gamma^{(2-D)n}}{\gamma^{(2-D)n}}$$

Equation 84

where $L$ is the sample length in the $u$ direction and $\gamma$ is a scaling parameter that determines the relative phase difference between fractal modes ($\gamma > 1$). In order to get the phases of different modes not to coincide at any given longitudinal $u$ position, $\gamma$ has to be chosen as a non-integer number; $\gamma$ is selected as 1.05 in this study. $n_{\text{max}}$ is related to the smallest characteristic length, $L_0$, and it is given by $n_{\text{max}} = \text{int} \left[ \log(L_x/L_0) / \log \gamma \right]$. $G$ and $D$ are the fractal roughness parameters and the fractal dimension of the surface profile ($1 < D < 2$), respectively. The PSD of the function given by Equation 84, $S(\Omega)$, can be approximated as [127]
\[ S(\Omega) = \frac{G^{2(D-1)}}{2 \ln \gamma} \Omega^{-(5-2D)} \]  
Equation 85

By matching the function of PSD proposed by ISO 8608, \( S_g(\Omega) \), and the function of PSD given by Equation 85, \( S(\Omega) \), the fractal parameters \( G \) and \( D \) generating the synthetic road roughness profile based on the value of \( R_{ISO} \) for the different road classes can be calculated as

\[ G = [2R_{ISO}(2\pi)^k \ln \gamma]^{\frac{1}{2D-2}} \]  
Equation 86

\[ D = \frac{k + 5}{2} \]  
Equation 87

By using the values of \( G \) and \( D \) calculated from Equation 86 and Equation 87, the synthetic road roughness height profile, \( z(u) \), which is given by Equation 84 can be generated based on ISO 8608. Figure 43 shows the result data generated with different ISO road roughness classifications. The PSD of the generated synthetic road roughness profiles closely matches the ideal PSD defined in ISO 8608.
Figure 43. PSD of generated synthetic road roughness compared to ideal PSD of ISO 8608, and generated synthetic road roughness profile based on ISO 8608.

Track Translator is an application developed to convert the measured terrain data to a 3D geometric model of a road surface for use in the driving simulator. To generate a 3D geometric model, three elements must be defined: geometric vertex, texture coordinate, and polygonal face. Measured terrain data is used to define these three elements for the 3D model according to the different factors such as vertex and texture resolution. Also, because many graphics software packages and hardware devices operate more efficiently on a triangle mesh, Track Translator triangulates the mesh faces of road models to improve the compatibility in 3D graphics software packages.
First, to create the 3D model of a road, the geometric vertices are defined from the uniformly spaced measured terrain data with a Curved Regular Grid (CRG) which has \( u \) and \( v \) path coordinates. The vertex consists of \( x \) and \( y \) position value with respect to \( uv \) coordinate, \( x_{uvij} \) and \( y_{uvij} \), and the terrain height, \( z_{ij} \), corresponding to \( u_i \) and \( v_j \). The geometric vertex is written in Equation 88

\[
V_{iv} = (x_{uvij}, y_{uvij}, z_{ij}) \quad \text{Equation 88}
\]

where, \( i_v \) is the geometric vertex index given by

\[
i_v = (i - 1)n + j \quad \text{Equation 89}
\]

and the matrix of geometric vertices, \( V \), is formulated as follows

\[
V = [V_1 \; V_2 \; \ldots \; V_{iv} \; \ldots \; V_{m \times n}] \quad \text{Equation 90}
\]

Before determining the texture coordinate, the values of texture coordinate elements are defined based on the texture resolution, \( r \). As shown in Figure 44B, the value of texture resolution, \( r \), defines the square mesh number used for one image texture in each axis. The value of the texture coordinate elements is between zero and one, which corresponds to the start and end point of each axis of the image texture, respectively. Equation 91 shows the list of the values of the texture coordinate elements.

\[
T = \begin{bmatrix}
0 & 1 & 2 & \ldots & r - 2 & r - 1 & 1
\end{bmatrix} \quad \text{Equation 91}
\]

By using the values of \( T \), the texture coordinate point is defined as

\[
VT_{ivt} = (T_{x_{ivt}}, T_{y_{ivt}})
\]

\[
VT_{ivt+1} = (T_{x_{ivt+1}}, T_{y_{ivt+1}}) \quad \text{Equation 92}
\]

\[
VT_{ivt+2} = (T_{x_{ivt+1}}, T_{y_{ivt+1}})
\]
\[ \mathbf{V T}_{i_{vt}+3} = (T_{x_{vt}+1}, T_{y_{vt}}) \]

where \( i_{vt} \) is a texture coordinate index (\( i_{vt} = 1, 5, 9, \ldots, 4r^2 - 3 \)). The texture coordinate index \( i_{vt} \) can be calculated from \( i \) and \( j \), as shown in Equation 93 and Equation 94.

\[
i_{vt} = 1 + 4r(x_{vt} - 1) + 4(y_{vt} - 1) \quad \text{Equation 93}
\]

\[
x_{vt} = \text{int} \left( \frac{i-1}{r} \right), \quad y_{vt} = \text{int} \left( \frac{j-1}{r} \right) \quad \text{Equation 94}
\]

Finally, the matrix of texture vertices, \( \mathbf{V T} \), is formulated as

\[
\mathbf{V T} =
\begin{bmatrix}
\mathbf{V T}_1 & \mathbf{V T}_2 & \mathbf{V T}_3 & \mathbf{V T}_4 & \cdots & \mathbf{V T}_{i_{vt}} & \cdots & \mathbf{V T}_{4r^2-3} & \mathbf{V T}_{4r^2-2} & \mathbf{V T}_{4r^2-1} & \mathbf{V T}_{4r^2}
\end{bmatrix} \quad \text{Equation 95}
\]

To define the face of a 3D road model consisting of the triangle mesh and the texture, the faces are defined as a list of geometric vertices and texture vertices. As shown in Equation 96 and Equation 97, the triangle mesh \( f_{v1} \) and \( f_{v2} \) are formulated from the geometric vertices given by Equation 90. Also, to add a texture on the defined face, the texture face \( f_{vt1} \) and \( f_{vt2} \) are determined from the texture vertices given by Equation 95. \( f_{v1} \) and \( f_{v2} \) are matched to \( f_{vt1} \) and \( f_{vt2} \) respectively, to create a final 3D road model with proper surface normal and coordinate matching between geometric and texture vertices.

\[
f_{v1}(V_{i_v}, V_{i_v+1}, V_{i_v+n+1}), \quad f_{vt1}(\mathbf{V T}_{i_{vt}}, \mathbf{V T}_{i_{vt}+1}, \mathbf{V T}_{i_{vt}+2}) \quad \text{Equation 96}
\]

\[
f_{v2}(V_{i_v+n+1}, V_{i_v+n}, V_{i_v}), \quad f_{vt2}(\mathbf{V T}_{i_{vt}+2}, \mathbf{V T}_{i_{vt}+3}, \mathbf{V T}_{i_{vt}}) \quad \text{Equation 97}
\]
Figure 44. A) Triangle mesh and B) texture coordinate of 3D road model translated from the measured terrain data.

Figure 45 shows the final translated 3D road model from the measured terrain data by Track Translator.

Figure 45. Translated 3D road model from the measured terrain data.

5.4 Simulation Result and Performance Evaluation

5.4.1 Simulation for Real-World Driving Environment

A simple driving maneuver is conducted to demonstrate two important aspects of the proposed system: the importance of including rough road surface data and that speed predictive control can be implemented in the driving simulator in real-time. The
Performance Margin (PM), a metric quantifying the limit handling capabilities, is used as the comparison index as shown in Equation 29 and Equation 30. The PM is defined as the ratio of required resultant tractive force to the maximum available tractive force at the front and rear axles, respectively. A PM value of zero means the required resultant tractive forces are equal to the maximum tractive force and a loss of handling capability ensues. To demonstrate the usefulness of the PM, consider two vehicles traveling at 49 km/h (shown as a solid line in Figure 46) and 70 km/h (shown as a dashed line), each navigating a 90 degree left turn with a radius of 50 m on a flat surface (the maximum allowable vehicle speed is 73.5 km/h). The simulation result of the vehicle traveling at 70 km/h shows that the PM value drops to nearly zero while the PM value of the vehicle traveling at 49 km/h does not go below 0.5.

![Figure 46. The PM result of the vehicles navigating the 50 m radius left turn.](image)

Consider the same simulation with different classes of ISO 8608 road roughness. In each simulation, the vehicle traverses a 100 m straight road at the constant vehicle speed prescribed between 10 to 60 km/h. After the results of the PM values are obtained for each simulation, the root-mean-square deviation (RMSD) is calculated to measure the differences between the PM of the ideally flat road simulation and the PM of the simulation of the road with the road roughness class A to E. As shown in Figure 47, the result demonstrates how a road roughness could affect vehicle dynamics, even with the same simulation scenario. For example, if the road has the road roughness class E and the vehicle travels at 50 km/h, the average PM difference between the flat road and the road with the
roughness class E is 0.112 which means that it can degrade 11.2% of the handling capability. This result means that the tires can momentarily lose traction which would be able to change whole vehicle dynamics just because of the road roughness effect.

![Figure 47. Simulation result of Performance Margin RMSD between the ideally flat road and the roads with different road roughness.](image)

This work also demonstrates the influence of the driving environment on the maximum allowable vehicle speed in a curve. To determine the maximum allowable vehicle speed, the 45.72 m (150 ft) constant radius test with -5 to 5% cross-slope and the different road roughness is simulated (The negative value of a cross-slope is a slope toward the outside of the road, which makes the vehicle maneuver an off-camber turn). During the constant radius test, the maximum allowable speed is estimated by increasing the vehicle speed until it is no longer able to remain on the circular path. Figure 48 shows how the cross-slope and the road roughness affect the maximum vehicle speed. The maximum vehicle speed in a curve decreases as the road roughness increases and the negative cross-slope increases. The maximum speed of the road with 5% cross-slope and the flat surface is 74.2 km/h. The maximum speed of the road with -5% cross-slope and ISO E roughness is 63.5 km/h.
5.4.2 Performance Evaluation of Advanced Vehicle Control Subsystem

In this section, a predictive vehicle control algorithm is implemented to validate the driving simulator. Speed predictive control is chosen because it requires more processing power than a real-time control algorithm (speed predictive control must control the vehicle dynamics in real-time and predict future vehicle states using a non-linear vehicle model and upcoming driving environment). The objective is to control throttle and brake commands to maintain a safe vehicle speed by predicting vehicle future states when navigating upcoming terrain. For example, the future 20 seconds are predicted at every time step based on a non-linear vehicle model, the driver commands, and the upcoming terrain data. Throttle and brake commands are controlled to ensure that future vehicle speeds will not exceed the allowable speed for the upcoming conditions. This control algorithm is addressed in more detail in Section 4.2.2.

To demonstrate that the algorithm works properly in the driving simulator, the simulation is implemented with and without the speed predictive control algorithm. Also, the simulation is conducted with the longitudinal vehicle controller to maintain the target longitudinal vehicle speed and the lateral controller to track the target lateral offset from the centerline of a road. In this simulation, the vehicle travels the 90 degrees curve with 50
m radius. The target longitudinal vehicle speed is 90 km/h and the target lateral offset is set to 0 m. If the speed predictive vehicle controller is activated, the target vehicle speed is set to 51.5 km/h, where the maximum allowable vehicle speed is 73.5 km/h.

Figure 49 shows the simulation results of the vehicle lateral offset and the PM with and without the predictive vehicle control algorithm. As shown in Figure 49A, the maximum lateral offset is reduced from 25.05 m to 0.36 m by the operation of the speed predictive control algorithm. Also, the operation of the algorithm increases the resulting minimum PM from 0 (an unstable condition) to 0.47, so that the vehicle could navigate the curve with enhanced handling capability. The effect of the algorithm simultaneously operating the real-time and the predictive controllers on PM is shown in Figure 49B.

Figure 49. Vehicle lateral offset from the path and Performance Margin comparison with and without the Speed Predictive Control (SPC).
5.5 Conclusion

This chapter describes the driving simulator system for an advanced vehicle controller with real-world measurement data. Synthetic road roughness profiles are generated based on ISO 8608. The visualization system converts the measured terrain data to a 3D geometry model to use in the virtual reality. The vehicle control system accomplishes the developed predictive vehicle control algorithms requiring more processing power than real-time controllers. The result of the simulation shows the effect of the algorithm simultaneously operating the real-time and the predictive controllers.
6. Conclusion

The objective of the research is to develop a predictive vehicle control system for improving vehicle safety and performance for autonomous vehicles and Advanced Driver Assistance Systems (ADAS). In order to improve the vehicle control system, the proposed system utilizes information about the upcoming local driving environment such as terrain roughness, elevation grade, bank angle, curvature, and friction. The local driving environment is measured in advance with a terrain measurement system to provide terrain data. Furthermore, in order to obtain the information of road conditions that is not able to be measured in advance, this work begins by analyzing the response measurements of a preceding vehicle. The response measurements of a preceding vehicle are acquired through Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) communication. The identification method analyzes the response measurements of a preceding vehicle to estimate road data. The estimated road data or the pre-measured road data is used as the upcoming driving environment information for the developed vehicle control system. The metric that objectively quantifies vehicle performance, the Performance Margin, is developed to accomplish the control objectives in an efficient manner. The metric is used as a control reference input and continuously estimated to predict current and future vehicle performance. Next, the predictive control algorithm is developed based on the upcoming driving environment and the performance metric. The developed system predicts future vehicle dynamics states using the upcoming driving environment and the Performance Margin. If the algorithm detects the risks of future vehicle dynamics, the control system intervenes between the driver’s input commands based on estimated future vehicle states. The developed control system maintains vehicle handling capabilities based on the results of the prediction by regulating the metric into an acceptable range. By these processes, the developed control system ensures that the vehicle maintains stability consistently, and improves vehicle performance for the near future even if there are undesirable and unexpected driving circumstances. To implement and evaluate the integrated systems of this work, the real-time driving simulator, which uses precise real-world driving environment data, has been developed for advanced high computational vehicle control
systems. The developed vehicle control system is implemented in the driving simulator, and the results show that the proposed system is a clear improvement on autonomous vehicle systems and ADAS.
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