EVALUATION OF MACHINE VISION COLLECTED PAVEMENT MARKING QUALITY DATA FOR USE IN TRANSPORTATION ASSET MANAGEMENT

A Thesis

by

ADAM REECE STACY

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Chair of Committee,	H. Gene Hawkins, Jr.
Committee Members,	Paul Carlson
	Dezhen Song
Head of Department,	Robin Autenrieth

August 2019

Major Subject: Civil Engineering

ABSTRACT

Transportation departments are tasked with managing numerous assets that are part of the roadway infrastructure. One of the most challenging pieces of transportation asset management is pavement markings. There are several characteristics of pavement markings that make them difficult to incorporate into an asset management system including the volume of markings on the roadway and the lack of easy, standardized data collection methods.

Machine vision technology has potential applications in transportation asset management and could alleviate some of the problems currently faced in managing pavement markings as an asset. Advanced driver assistance systems (ADAS) incorporating machine vision cameras have the ability to assign quality ratings to individual pavement markings, and vehicles equipped with machine vision have the capability to collect large amounts of data without direct input from the vehicle operator. The large amount of data collected by ADAS machine vision cameras is readily stored and easily processable for asset management decision-making.

In order for the machine vision data to be useful in pavement marking asset management, the reliability of the quality scores and their relationship to established pavement marking evaluation characteristics needed to be investigated. The purpose of this research was to explore the repeatability of the quality scores assigned by the machine vision camera under different collection conditions. Along with determining the

correlation between the machine vision quality scores and the defined pavement marking characteristics retroreflectivity, luminance, and contrast.

The results of the analysis were that the ADAS machine vision quality scores were determined to be mostly reliable under each individual condition but not across the different collection conditions. An acceptable relationship between the current pavement marking evaluation characteristics and the machine vision quality scores was not able to be conclusively established using several different regression approaches as a result of the correlation analysis. From the analysis that was done as a part of this research, it is recommended that further data collection efforts be conducted under various conditions in order to expand on both the repeatability and correlation analysis that was performed.

DEDICATION

This thesis is dedicated to my family and friends for their continued support, encouragement, and prayers.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Hawkins, and my committee members, Dr. Carlson and Dr. Song, for their guidance and support throughout the course of this research.

Thanks also go to my friends and peers and the department faculty and staff for making my time at Texas A&M University a great experience.

Finally, thanks to my family for their encouragement and support throughout this process and for laying the foundation on which all my education has been built.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a thesis committee consisting of Dr. Gene Hawkins, advisor, and Dr. Paul Carlson of the Department of Civil Engineering and Dr. Dezhen Song of the Department of Computer Science and Engineering.

The data analyzed for the Closed Course Correlation Analysis was provided by Mr. Adam Pike of TTI.

All work for the thesis was completed independently by the student.

Funding Sources

No outside funding was received for the research and compilation of this document.

NOMENCLATURE

ADAS	Advanced Driver Assistance Systems
AASHTO	American Association of State Highway and Transportation Officials
DOT	Department of Transportation
GIS	Geographic Information Systems
NHTSA	National Highway Traffic Safety Administration
TTI	Texas A&M Transportation Institute
TAM	Transportation Asset Management

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Departments of Transportation (DOTs) are tasked with the responsibility of managing and maintaining an extensive infrastructure network consisting of pavements, structures, traffic control devices, and other elements. In order to manage these assets effectively, a considerable amount of resources must be employed for asset inventory and condition assessment. With emerging vehicle technologies, such as automated and connected vehicles, sensor systems can be used to gather information about the roadway infrastructure. Applying these readily available sensor technologies to transportation asset management makes it possible to generate infrastructure inventory and condition assessment data. Equipping DOT fleet vehicles with onboard sensor equipment is relatively inexpensive and would allow for the creation of a continuously updated database containing infrastructure data without having to conduct specific data collection operations. This leads to greater understanding of current and future infrastructure conditions and improved transportation asset management practices.

A major area of innovation in transportation over the last decade plus has been the incorporation of automation into the driving task. SAE defines six levels of driving automation ranging from Level 0 to Level 5 described in Table 1 (*1*).

Table 1 SAE Automation Levels

0	No Automation	Zero autonomy; the driver performs all driving tasks.
1	Driver Assistance	Vehicle is controlled by the driver, but some driving assist features may be included in the vehicle design.
2	Partial Automation	Vehicle has combined automated functions, like acceleration and steering, but the driver must remain engaged with the driving task and monitor the environment at all times.
3	Conditional Automation	Driver is a necessity but is not required to monitor the environment. The driver must be ready to take control of the vehicle at all times with notice.
4	High Automation	The vehicle is capable of performing all driving functions under certain conditions. The driver may have the option to control the vehicle.
5	Full Automation	The vehicle is capable of performing all driving functions under all conditions. The driver may have the option to control the vehicle.

Many vehicles on the road today have some level of automation and all new vehicles will at least meet the standard for Level 1-Driver Assistance after the NHTSA decision to require all new vehicles to have rear-view cameras by May of 2018 (*2*). Rear-view cameras are part of evolving technologies referred to as driver assistance technologies aimed at keeping drivers, passengers, and other transportation system users safe. Many different driver assistance technologies exist including emergency braking systems, collision warnings, lane departure warnings and lane keeping assistance, blind spot detection, adaptive cruise control, and the aforementioned rear-view video systems. The integration of all these technologies into an automated system is often referred to as Advanced Driver Assistance Systems (ADAS). ADAS relies on inputs from a variety of data sources including radar, LiDAR, cameras, computer/machine vision, or even other vehicles. These systems can be comprehensive including all of the available technologies or only a few options and can be built into the vehicle by the manufacturer or installed as add-ons. ADAS that include the use of machine vision offer the highest potential levels of automation along with the greatest capabilities for roadway data collection. Machine vision cameras are often used in the lane assist technologies to either warn the driver the vehicle is departing the lane or to diagnose the vehicle leaving its lane and then activate corrective measures to return the vehicle to its intended travel lane automatically. In order to perform lane assist functions, the machine vision cameras must be able to adequately see the lane markings on the roadway.

Pavement markings are one of the most prolific components of transportation infrastructure. With countless miles of lane markings to inspect and maintain, DOTs are in need of innovative solutions to monitor and catalog their resources. Using vehicles equipped with systems of onboard cameras and sensors to record the type, location, and quality of pavement markings can greatly improve the efficiency of data collection. In order for this data collection method to be widely implemented for pavement marking asset management, the precision of the pavement marking quality assessment data needs to be determined. Once the precision of the data is better understood, the information can be integrated into transportation asset management practices. The capabilities of the system can be fully realized as useful raw data is processed, analyzed, and presented in an effective manner to facilitate decision making for transportation departments.

This research seeks to investigate how Advanced Driver Assistance Systems (ADAS) technology (specifically cameras using machine vision) may be used for pavement marking condition assessment as a part of transportation asset management.

The machine vision camera used in the ADAS relies on lane markings to perform several of its functions, both passive and active, including lane departure warnings and lane keeping assistance. These functions cannot be completed by the ADAS if the lane markings are not of a sufficient quality; therefore, the camera sensor continuously assesses the quality of each lane marking in its field of vision. These quality values indicate the confidence the sensor has in its ability to perform necessary functions or provide valid measurements based on the detection of the lane markings. In order for this data to be useful for understanding pavement marking conditions and included in asset management, the precision, or closeness of agreement between multiple results, for these quality score measurements needs to be determined.

Along with the statistical analysis required to determine the precision of the ADAS machine vision pavement marking quality scores, this research seeks to perform application analysis for potential uses of the data. Several applications exist for pavement marking data collected with ADAS cameras using machine vision. Using camera equipped vehicles allows for continuous data collection over a large area of the transportation network. A direct application for this data is using the pavement marking quality scores in the asset management practices for pavement markings. This research seeks to determine the cost effectiveness and other benefits of collecting real time data for use in pavement marking asset management.

2. BACKGROUND

2.1 Pavement Marking Performance Measurement

Pavement markings provide guidance to road users by supplying information about the roadway path. Maintaining the functional quality of pavement markings is essential to providing desirable levels of operational safety (*3*). Pavement marking performance can be evaluated by measuring several characteristics of the pavement marking materials. These characteristics include the pavement marking retroreflectivity, contrast, and color. Durability is another aspect of pavement marking performance and is evaluated based on the overall percentage of marking material remaining as well as retained retroreflectivity (*4*).

The remaining marking material is often referred to as the presence condition of the pavement marking. Pavement marking presence is a more difficult characteristic to quantify as the most widely adopted evaluation method is expert observation. With advancements in technology, attempts have been made to evaluate pavement marking presence with image processing techniques. These techniques have proven successful in determining the presence condition of pavement markings at levels consistent with expert observation (*4*). Presence is not specifically evaluated or analyzed in this study but is assumed to be incorporated in the quality score assigned by the ADAS machine vision camera.

The most widely measured performance indicator is retroreflectivity, which is directly related to the nighttime visibility of pavement markings. Retroreflectivity is the occurrence of light hitting a surface and being reflected back to the light source. It is measured by the coefficient of R_L in units of millicandelas per square meter per lux ($mcd/m^2/lux$). The standard specifications for measuring retroreflectivity are designed to measure at a point 30 meters ahead of a vehicle to simulate the driver's observation of the road at night (*5*). Retroreflectivity can be measured using both handheld and mobile retroreflectometers which are produced in many different models by several manufacturers. The standard retroreflectivity measurement geometry is based on a European vehicle which has a headlamp height of 0.65 meters and a driver eye height of 1.2 meters (*5*). Figure 1 shows the standard retroreflectivity geometry.

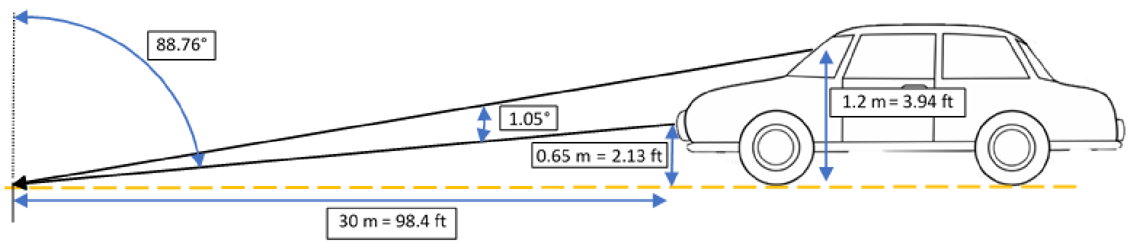

Figure 1. Standard 30-meter Retroreflectivity Measurement Geometry

Luminance is the brightness of a surface in a given direction per unit of area of the surface independent of viewing distance (*6*). Daytime luminance is represented by the luminance coefficient under diffuse illumination (Q_d) which is the quotient of the luminance of the pavement marking and the illuminance on the pavement marking expressed in $mcd/m^2/lux$ (*3*). Q_d determines the quality of the pavement marking for visibility in daylight or under roadway lighting where higher values for Q_d correspond to higher levels of lightness (*7*). The luminance coefficient under diffuse illumination is measured according to ASTM standard E2302 using a portable reflectometer with a co-viewing angle fixed at 2.29° and with the measurement geometry of the instrument based on a 30-meter viewing distance and 1.2-meter eye height (*7*).

Drivers are able to distinguish pavement markings from the pavement surface because of contrast. There are two types of contrast, color and luminance (*3*). The pavement marking color contrast is the degree of difference between the marking and pavement surface, while the luminance contrast is the ratio of luminance between the marking and pavement surface (*3*). The contrast ratio can be defined for both nighttime and daytime luminance using the coefficients R_L and Q_d in Equations 1 and 2. The higher the contrast ratio the more clearly the pavement marking can be distinguished.

$$CR = \frac{R_L(marking) - R_L(pavement)}{R_L(pavement)} \quad \text{(Equation 1)}$$

$$CR = \frac{Q_d(marking) - Q_d(pavement)}{Q_d(pavement)} \quad \text{(Equation 2)}$$

Color also plays an important role in communicating information about the roadway to drivers. The color of pavement marking materials is defined using the Yxy coordinates of the International Commission on Illumination where the Y coordinate refers to how light or dark the object is and the x,y plot the color on the chart (*3*). Color can be measured by using a colorimeter or spectrophotometer.

2.2 Precision

Two ASTM standards were reviewed in order to understand the precision for test methods. Precision refers to the closeness of agreement between independent test results under stipulated conditions (*8*). There are multiple concepts or categories for the precision of a test method including repeatability and reproducibility. For this test method, the repeatability is of main concern as it defines the precision under conditions where results are obtained with the same method on identical test items by the same operator using the same equipment in a short time interval (*8,9*). Reproducibility involves recreating the experimental results in another location with different operators and equipment on the same item, so it will not be examined in this study. This study only involves one ADAS machine vision system and the pavement marking materials are in fixed locations, so reproducibility is not an appropriate measure for this study. The repeatability can also be determined for a test method where a single repeatability experiment is conducted in multiple laboratories then the pooled repeatability standard deviation is used as the test method repeatability estimate (*8*). This approach is valuable as it provides an estimate of the magnitude of the variability that can be expected between results in other laboratories (*8,9*).

2.3 Asset Management

Asset management in transportation is continually growing in implementation and scope. The U.S. Department of Transportation's Asset Management Primer chooses to use the following working definition "Asset Management is a systematic process of maintaining, upgrading, and operating physical assets cost-effectively. It combines engineering principles with sound business practices and economic theory, and it provides tools to facilitate a more organized, logical approach to decision-making (*10*)." Asset management has been practiced for years within the transportation community and with increased demands being placed on an aging infrastructure system, is as important as ever. Traditionally pavement and bridge management systems have been the primary focus of asset management; however, advancements in technology and data practices are opening the door to including more highway assets in the asset management system. Applying current transportation asset management practices to pavement markings can be difficult for multiple reasons including issues with collecting inventory data, determining which attributes to consider when evaluating performance, and the conditions for which the asset should be evaluated. Currently pavement marking asset management relies on retroreflectivity measurements and visual inspections for evaluating the condition of the asset; however, data inventory collection with both of these methods can time consuming and costly (*11*, *12*). Sitzabee et al. developed a method for integrating pavement markings into asset management using collected retroreflectivity values and predictive degradation models for pavement markings along with GIS to assess the current and future conditions of pavement markings as a transportation asset (*11*). However, there are issues surrounding types of retroreflectometers and their measurements which have complicated a widespread acceptance of deterioration models for predicting performance and cost, which are key elements of asset management (*12*). Agencies recognize the value of pavement marking management, as over $1.5 billion was estimated to be spent in 2000 in the U.S. and Canada by state and local agencies, so continued efforts are needed to develop more effective ways to manage pavement markings as a transportation asset (*12*).

2.4 Lane Detection

Lane detection is a key problem in Advanced Driver Assistance Systems (ADAS) that attempt to warn drivers or assist in the driving process in potentially dangerous situations. Machine vision technology used in these systems must rely on the same visual cues as human drivers such as road boundaries, road color and texture, and lane marking color and type. Several sensing methods are used for lane understanding including vision (video camera), stereo imaging, LIDAR, RADAR, and Geographic Information Systems (GIS)/Global Positioning Systems (GPS)/Inertial Measurement Unit (IMU). Vision is the most prominent of the lane and road detection methods because markings are made for human vision, while LIDAR and GPS are important complements (*13*). Figure 2 shows a representation of a vision-based detection system *(14)*.

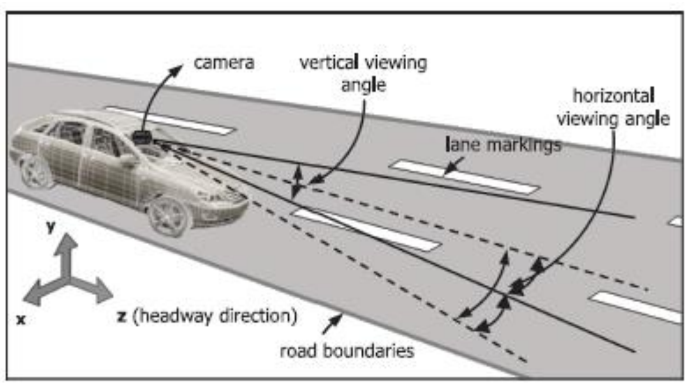

Figure 2. Vision-based Detection System

In recent years many approaches and algorithms have been developed to tackle the lane detection problem. Several reviews have been conducted in order to catalog the progress of road and lane detection. From these reviews it can be seen that most of the systems share commonalities that can be separated into functional elements of the detection process. Hillel et al. identified a generic system with the following modules: image cleaning, feature extraction, road/lane model fitting, temporal integration, image to world correspondence (*13*). Another survey of detection systems by Yenikaya et al. identified four basic steps: preprocessing, feature detection, fitting, and tracking (*14*). Lane markings are recognized in the feature detection and extraction step of the system. Several features of the road environment can be used for the detection of features such as lane markings. These include color, edges, and texture each of which are important to the human visual system along with machine vision systems. The image features of the lane markings are then extracted using various filters or statistical methods which fall into three classes: area-based, edge-based, and area-edge-combined methods (*14*). Many different techniques are used but the same set of assumptions underlies them all, the brightness change between the markings and road surface along with the narrow shape of the lane markings (*13*).

Detection systems need to be able to perform in various and rapidly changing environmental conditions in order to be acceptable. The combined effects of vehicle motion along with degraded lane markings, occlusion from shadows or other vehicles, and various lighting or weather conditions make developing lane detection systems a unique challenge as coverage for all conditions requires complex systems and considerable engineering effort (*13*). Further development is still needed in the robustness of state-of-the-art processing algorithms as the current algorithms used in vision-based lane detection systems rely on the use of many assumptions making them less adaptive than the human driver (*13*).

3. STUDY DESIGN

The experiment was conducted in order to investigate the repeatability of the pavement marking quality scores determined by the ADAS machine vision technology, and to establish if a correlation exists between the machine vision quality scores and current pavement marking evaluation characteristics. To determine the repeatability, appropriate samples were taken of lane markings in multiple configurations and conditions to ensure that the number of test results is a sufficiently large value. The repeatability is a measure of the precision of the test method not a parameter of the lane marking population (*8*). In order to investigate a correlation between the machine vision pavement marking quality scores and current pavement marking evaluation characteristics, a set of multiple pavement markings was fully defined for characteristics such as retroreflectivity, luminance, and color. Two scenarios were used for performing data collection on lane markings in this experiment. Open road data collection occurred on selected segments of local roadways in the Bryan/College Station area, while closed course data collection took place at a Texas A&M Transportation Institute (TTI) facility.

When designing the data collection methodology for the study. ASTM E177 and ASTM E691, which are standards for the use and determination of precision in a test method, were consulted. The study was designed based on ASTM E691, which deals with interlaboratory studies to determine the precision of a test method (*8, 9*). Since the pavement marking quality measurement being collected by the machine vision technology is an ordinal value and not in a traditional controlled laboratory setting the standard was not able to be directly applied; however, it did provide an adequate framework for designing the study. Borrowing from the language used in the ASTM standard, for this study, each lane marking was treated as a separate material and each lane position of the collection vehicle was a laboratory.

3.1 Open Road

The purpose of the open road experiment was to determine the repeatability of the quality scores provided by the machine vision technology under various operating conditions such as daytime and nighttime. The benefits of the open road environment are that it provides a representative simulation of the actual scenarios in which the machine vision technology is expected to operate and collect data. Collecting data on actual roadways also provides multiple lane configurations and pavement surfaces for the study.

For the open road data collection, three locations in the Bryan/College Station area were selected based on their different lane configurations. The multiple lane configurations allowed for more lane markings and lane routes to be included in the study following the recommendation of ASTM E691 which encourages involving more materials across more laboratories instead of a large number of results per material in a few laboratories (*9*). Figure 3 shows the locations with the lane markings numbered and the routes the test vehicle drove as letters.

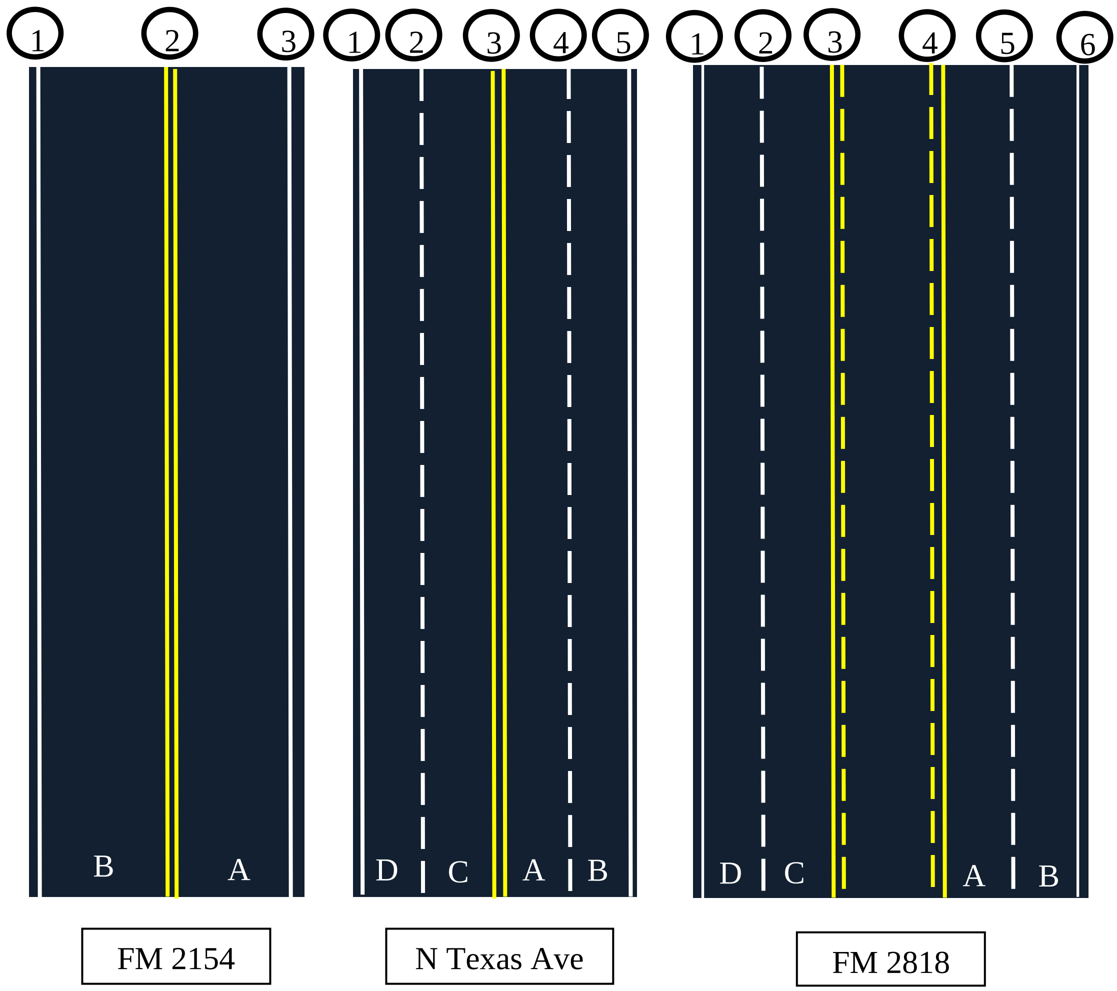

Figure 3. Open Road Collection Locations

The roadway sections are each between one and two miles long and were selected because of potential access to staging areas and turnaround locations. On FM 2154 the location was south of College Station from Greens Prairie Rd W to Hidden Springs Way. The N Texas Ave location was in Bryan from Wilhelm Dr to Arthur Davila Middle School. The third segment was on FM 2818 from La Brisa Dr in Bryan to F and B Road in College Station. These three sites were determined as adequate for the study because results were able to be obtained for 14 different pavement markings from

10 different observation lanes. The results from each route driven were obtained in the shortest practical period of time in order to preserve repeatability conditions (*9*).
The Mobileye system can observe and record data for two lane markings on each side of the vehicle; however, only the quality score data obtained on the lane markings when adjacent to the vehicle was analyzed.

Each lane route was driven 30 times to obtain results for the lane marking quality scores, this results in some of the markings being observed from multiple directions and positions. The number of times each route should be driven was determined with equation 3.

$$n \geq \left(\frac{t_{\alpha/2,df}}{\Delta} * \tilde{\sigma}\right)^2 \quad \textit{(Equation 3)}$$

$$n = sample\ size$$

$$\Delta = error\ bound$$

$$t_{\alpha/2,df} = t\ statistic\ for\ specified\ confidence\ level$$

$$\tilde{\sigma} = estimate\ of\ standard\ deviation$$

The equation was applied for a confidence interval about the mean quality score for a segment of lane markings. A 95 percent confidence level was chosen with an error bound of 0.25 and an estimate for the standard deviation of quality scores was determined to be 0.62 from previously collected data on another roadway segment. This method was chosen for the sample size calculation because even though the quality scores are interval data, they were averaged over a specified segment length converting them to a pseudo-continuous variable. The calculation of a sample size of 30 results for each lane marking also complies with the recommendation of the ASTM standards as a sufficiently large sample size for determining precision (*8*).

3.2 Closed Course

The purpose of the closed course testing was twofold, to investigate a correlation between the ADAS machine vision quality scores and the conventional pavement marking evaluation characteristics for various measurement conditions, and to determine the repeatability of the machine vision quality scores under different controlled conditions for pavement markings that are intentionally degraded. The closed course benefits include completely defined pavement markings which allows for a correlation to be established between the machine vision quality score and other pavement marking evaluation characteristics. Other closed course benefits include more easily controlled conditions and lack of outside interference from traffic or other sources when making multiple consecutive data collection runs for determining repeatability. Also degraded pavement markings on a closed course provide a designed sample for the repeatability and correlation analysis not available in the open road scenario.

The correlation portion of the closed course experiment used multiple pavement markings that were installed and characterized for another study at the TTI facility. These markings consisted of 7 levels of yellow and white preformed tape markings arranged in both solid line and skip line configurations. Each pavement marking was characterized in both daytime and nighttime lighting conditions. Data collected on the markings consisted of retroreflectivity, luminance, and color values. Machine vision quality scores were also obtained through the other study for the seven levels of yellow and white tape markings in daytime and nighttime conditions. However, since this data was from another study not designed for determining repeatability, there were not enough quality scores collected to meet the minimum sample size requirements for determining repeatability for all of the testing conditions and marking configurations. These markings had been removed from the TTI facility at the time of the data collection for this study so further data collection was not possible. Figure 4 shows an example of the pavement marking layout at the TTI facility which was used in the closed course experiment.

Figure 4. Pavement Marking Layout for Closed Course Correlation Analysis

Additional machine vision data was collected on another set of markings in the closed course conditions for the repeatability analysis. The machine vision data was collected in as close to the same conditions and method as the open road data as possible. There were six painted white solid pavement markings used for the closed course experiment. Some of these markings had been intentionally degraded when placed at the TTI facility in order to simulate markings of varying quality. An example of the marking layout is shown in Figure 5.

Figure 5. Layout of Closed Course Pavement Markings for Repeatability Analysis

The markings were arranged in 3 sets of parallel lines at the TTI facility. The data collection vehicle was driven between each set of parallel markings in both directions. Driving through the markings in both directions allowed for the markings to be observed from both sides of the collection vehicle which served as multiple observation positions in the repeatability analysis. Along with observing each line from both sides of the collection vehicle, observing the markings in different travel directions was important because pavement markings characteristics can be direction dependent. Pavement marking evaluation characteristics, such as retroreflectivity and luminance, may not have the same value when measured in different directions due to variations in the marking application process or external influences. Retroreflectivity values change for different measurement directions because of the variation in the embedment and distribution of the glass beads that occurs in the paint marking construction process. A sufficiently large sample of quality scores was collected from this second set of closed course pavement markings for the repeatability analysis.

An important difference between the open road and closed course portions of the study is the type of pavement on which the lane markings are observed. The open road portion of the study consisted of asphalt pavement surfaces while the closed course markings were applied to a concrete pavement surface. Pavement type plays an important role in the visibility of lane markings due to the contrast between the pavement surface and the lane marking. Lighter colored pavement surfaces, such as concrete, have less contrast with white lane markings than a darker surface such as asphalt does. This difference in contrast could affect the quality scores assigned to the lane markings in each portion of the study as it is reasonable to assume that a lane marking on a dark surface would be more easily detected by the machine vision than a marking on a light surface.

Table 2 shows a summary of the attributes measured along with the sample size for the open and closed course scenarios.

Table 2. Data Collection Summary

Scenario	Analysis Type	Pavement Markings	Attributes Evaluated	Sample Size
Open Road	Repeatability Analysis	14 Lane Markings	Quality Score	30 observations per marking
Closed Course	Repeatability Analysis	6 Lane Markings	Quality Score	30 observations per marking
	Correlation Analysis	7 Lane Markings	Cap Y Luminance	At least 20 measurements per marking
			Qd Luminance	At least 14 measurements per marking
			Retroreflectivity	At least 14 measurements per marking
			Quality Score	18 observations per marking

4. DATA COLLECTION

4.1 Open Road Data Collection

The data collected in the open road portion of this study was for use in the repeatability analysis. The data of interest for the pavement markings in the open road scenario was the quality score that was assigned to the lane marking segments by the Mobileye machine vision system. The machine vision camera assigns the lane markings a quality that is an integer from zero to three (0-3), with zero being the lowest quality and three being the highest. In a sense, the machine vision quality score is akin to the confidence level that the machine vision camera has that it can detect the lane marking.

4.1.1 Data Collection Equipment

All of the data for the open road portion of the study was collected using a TTI fleet vehicle equipped with the Mobileye machine vision sensor technology. The data collection system consists of a single machine vision camera mounted to the inside of the windshield below the rear-view mirror and an in-vehicle data unit located underneath the rear seat. The in-vehicle data unit has wi-fi connectivity and is responsible for recording and pushing the data to a cloud server where it is stored. The data collection vehicle, the position of the machine vision camera, and the in-vehicle data unit are shown in Figure 6 through Figure 9. The data collection system does not require any input from the driver of the vehicle during the data collection process.

Figure 6. Data Collection Truck

Figure 7. Machine Vision Camera Position on Data Collection Truck

Figure 8. Installed Machine Vision Camera

Figure 9. Machine Vision In-Vehicle Data Unit

Understanding the geometry of the machine vision camera is important to be able to compare the machine vision quality scores to the other pavement marking characteristics such as retroreflectivity. The camera is positioned in the middle of the data collection vehicle at a height of about 64 inches from the ground. The headlamps of the data collection vehicle are located at a height of 39 inches from the pavement. According the user guide the Mobileye camera has an object maximum detection range of 80 meters (262 feet) and a view field of 40 degrees by 30 degrees (width x height) (*15*). However, the actual look ahead distance associated with the quality score assigned to the pavement markings by the machine vision camera is not explicitly stated. From another study it was determined that the sweet spot for the Mobileye machine vison camera to evaluate pavement markings is 30 to 40 feet in front of the vehicle (*16*). The distance at which the machine vision camera evaluates the lane marking and assigns the quality score is important in calculating the observation angle and entrance angle for comparison to the standard 30-meter geometry of the retroreflectometer used in this study. The angles were calculated using the 30 to 40-foot viewing distance discussed above. The observation angle was calculated to be between 2.94 and 3.89 degrees and the entrance angle was between 83.8 and 85.35 degrees. Figure 10 shows the viewing geometry of the data collection vehicle with the machine vision camera.

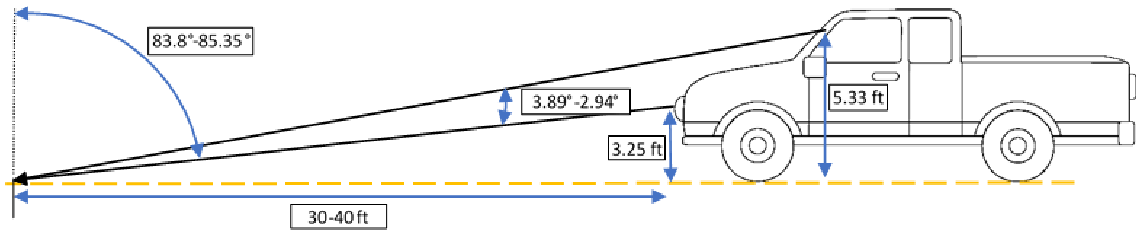

Figure 10. Data Collection Truck Viewing Geometry

The observation angle is a function of the distance between the headlamps and the machine vision camera along with the viewing distance. While the entrance angle is a function of the height of the headlamps and the viewing distance. A smaller observation angle increases the observed luminance as the light source (headlamps) and receptor (driver or machine vision camera) are closer together. A smaller entrance angle would also result in increased luminance as the light source and reflector are more in line with each other. The data collection vehicle has higher headlamps than the vehicle used to construct the standard 30-meter geometry along with a higher receptor height. When the geometry is calculated with the 30 to 40 foot viewing distance this results in a smaller entrance angle and a larger observation angle than the 30-meter geometry.

The Mobileye machine vision camera collects data for two lane markings on each side of the camera in the collection vehicle. The lane markings are named in the raw data files as far left, left, right, and far right. For this study only data collected on the adjacent lane markings (left and right) was analyzed. Data is recorded in tenth of second increments and is geolocated to an accuracy of less than one foot.

In the open road data collection, the ADAS machine vision sensor collected data for each lane marking and segment of roadway and recorded the data on the cloud server. The data collected included the pavement marking quality score, the type of pavement marking, and the position in relation to the collection vehicle. Other useful data collected about the test vehicle includes the time of day, speed, and geographic location.

4.1.2 Data Collection Conditions

In order to understand the full capabilities of the machine vision technology and usefulness of the data it collects; it was necessary to investigate the effects of different collection conditions on the consistency of the pavement marking quality scores. As mentioned previously, the open road setting allows for the experiment to be conducted in real world driving scenarios with other vehicles on the roadway and influence from the environment. It was desirable to perform data collection operations in a diverse set of conditions in order to determine if any effects exist on the pavement marking quality scores. Data was collected in four conditions: Bright overhead sun, Nighttime, Low Sun Angle, and Overcast. These conditions were selected based on the potential effects of light, glare, visibility, and shadows on the pavement markings. The low sun angle condition data was collected in late evening because of the orientation of the roadway segments to create potential for the scenario with the most extreme shadows on the roadway and glare for the camera. The purpose of collecting data in this condition was to determine if shadows on the lane markings and the camera pointing directly into or away from the sun have any effect on the consistency of the quality scores. As these conditions occur in a smaller window of time, it was difficult to collect an adequate sample size for analysis in a single session; therefore, it was necessary to split data collection over several days in order to drive a route the desired number of runs. The data collection efforts for this condition were carried out in consecutive days and started at the same time in order to minimize the effects of collecting in multiple sessions. Since the low angle sun and overcast conditions were more dependent on weather conditions and time, it was only feasible to perform data collection efforts at a single location instead of all three locations. This was due to the need to collect adequate sample sizes in a shorter amount of time. Low angle sun data was collected on N Texas Avenue because of the orientation of the roadway and the presence of trees close to the roadway to create shadows and glare conditions. Overcast data was collected on FM 2154 since it was one of the shorter sections and had a simple configuration with only one lane in each direction which allowed a sufficient sample size to be collected while overcast conditions persisted. The data for each condition was collected in the same window of time at each location in order to best replicate each condition for all of the locations. For the daytime condition, a bright overhead sun was desirable, so the data collection was performed in the middle of the day from 11:00 AM to 3:00 PM. The data for the nighttime condition was collected after darkness was fully reached from 10:00 PM to 2:00 AM. The low sun angle condition was collected in the evening before sunset from 6:00 PM to 8:00 PM. On the days this data was collected sunset was recorded to occur at 8:15 PM. The overcast condition was collected as long as the condition persisted.

4.1.3 Open Road Data Processing

The data collected by the ADAS machine vision camera was pushed to a cloud server where it is recorded in tenth of second increments. The server has a web interface that includes a model view showing what the machine vision detected and the raw data files available for download. The model view is shown in Figure 11 and the raw data format on the cloud server is shown in Figure 12. The model view shows the light condition the data was collected in (day or night), a visual representation of the lane markings as detected by the machine vision camera, the quality score of the lane markings, dimensions of the lane markings, and the distance from the machine vision camera to the lane markings. The raw data file shows all of the data collected on the lane markings along with the other data recorded about the data collection vehicle by the onboard system.

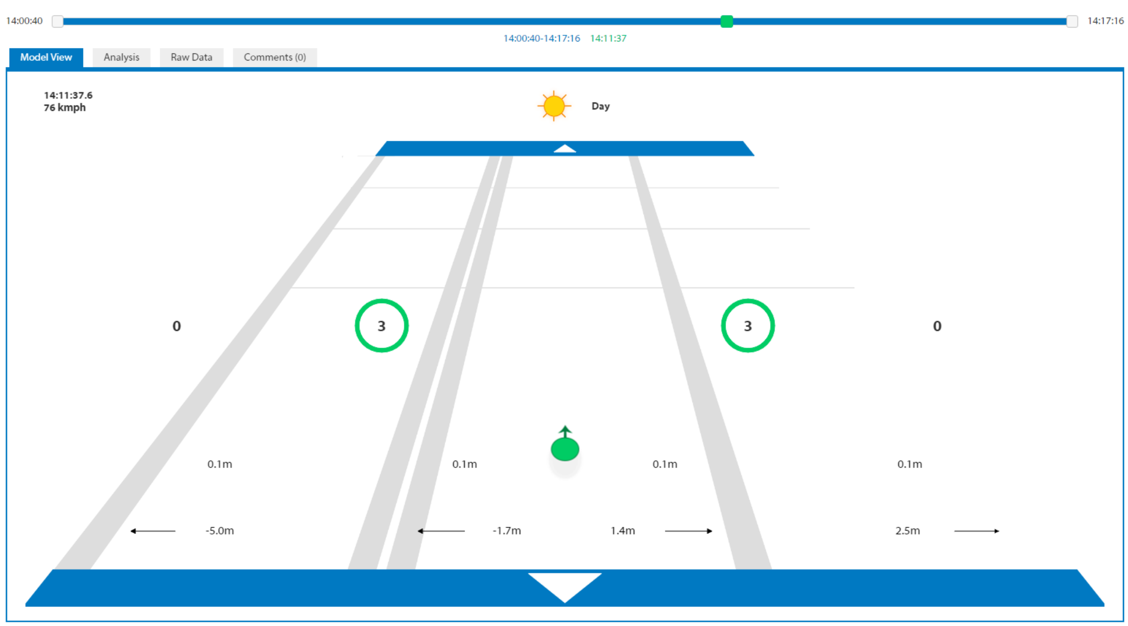

Figure 11. Model View Display of Machine Vision Data

Model View | Analysis | Raw Data | Comments (0)

Download CSV

left far mark wid...	left far quality	left far type	left ldw on	left mark width (...	left quality	left signal	left type	lkas left1
0.1080	0	1	false	0.1020	3	false	4	-1285.
0.1080	0	1	false	0.1020	3	false	4	-1286.
0.1080	0	1	false	0.1020	3	false	4	-1288.
0.1080	0	1	false	0.1020	3	false	4	-1289.
0.1080	0	1	false	0.1020	3	false	4	-1290.
0.1080	0	1	false	0.1020	3	false	4	-1291.
0.1080	0	1	false	0.1020	3	false	4	-1292.
0.1080	0	1	false	0.1020	3	false	4	-1293.
0.1080	0	1	false	0.1020	3	false	4	-1294.
0.1080	0	1	false	0.1020	3	false	4	-1292.
0.1080	0	1	false	0.1020	3	false	4	-1292.
0.1080	0	1	false	0.1020	3	false	4	-1291.
0.1080	0	1	false	0.1020	3	false	4	-1289.
0.1080	0	1	false	0.1020	3	false	4	-1290.
0.1080	0	1	false	0.1020	3	false	4	-1290.
0.1080	0	1	false	0.1020	3	false	4	-1292.

Figure 12. Raw Data Interface Sample

The data files are stored by each individual trip beginning with the turning on of the vehicle. In order to separate the data files into individual runs, the vehicle was turned off and back on after a section was traveled in each direction resulting in the creation of a new file for each data collection run. The ability of the ADAS machine vision system to record other vehicle functions, such as the activation of turn signals, was used to help mark the beginning and end of each roadway section. At the start of section, the left turn signal was activated then at the end of each section the right turn signal was activated. This allowed for easier separation of the raw data files into each collection section for analysis. Raw data files were able to be downloaded in the comma separated values format for use in the analysis portion of the study.

4.2 Closed Course Data Collection

There were two groups of closed course data collected for the purposes of this project. Closed course data was collected for both the repeatability analysis and the correlation analysis portions of the effort. For the repeatability analysis the quality score assigned by the Mobileye machine vision camera was collected for the closed course pavement markings. The correlation analysis required the quality score to be collected along with other characteristics of the pavement markings. These markings were fully characterized for retroreflectivity, luminance, and color. Table 3 shows the evaluation characteristics, by their variable name, that were collected or calculated from the collected values for each marking and used in the correlation analysis.

Table 3. Pavement Marking Characteristics

Marking Y	Luminance of the pavement marking	-	
Cap Y Contrast	Calculated contrast based on the luminance of the pavement marking and adjacent pavement surface	$CR = \frac{Y(marking) - Y(pavement)}{Y(pavement)}$	*Eq. 4*
Composite M1 Mk Luminance	Luminance of the pavement marking	-	
Luminance Ratio	Calculated ratio based on the average of the adjacent pavement surface luminance on both sides of the marking	$LR = \frac{Composite\ M1\ Mk\ Luminance}{\frac{1}{2} * (Pavment\ Luminance_{right} + Pavement\ Luminance_{left})}$	*Eq. 5*
Qd(LTL-XL) Marking	Luminance coefficient under diffuse illumination for the pavement marking	-	
Qd(LTL-XL) Contrast	Calculated contrast based on luminance coefficient under diffuse illumination of marking and adjacent pavement surface	$CR = \frac{Q_d(marking) - Q_d(pavement)}{Q_d(pavement)}$	*Eq. 6*
RL(LTL-X) Marking	Retroreflectivity of the pavement marking	-	
RL(LTL-X) Contrast	Calculated contrast based on retroreflectivity of the pavement marking and adjacent pavement surface	$CR = \frac{R_L(marking) - R_L(pavement)}{R_L(pavement)}$	*Eq. 7*

4.2.1 Data Collection Equipment

The closed course data collected for use in repeatability analysis was collected with the same equipment and method as the open road data. The closed course data collected for use in the correlation analysis included fully characterized pavement markings for retroreflectivity, luminance, and color along with the machine vision quality score. The data used in the correlation analysis was collected by other researchers in conjunction with another project.

Several different pieces of equipment were used to collect the pavement marking characteristic data. The retroreflectivity was measured with a 30-meter geometry using a handheld reflectometer. The device used to measure the retroreflectivity values was an LTL-X model reflectometer. Multiple luminance values were collected for each of the markings using different equipment and methods. The luminance coefficient under diffuse illumination (Qd) for the pavement markings were also collected using a handheld reflectometer, but with the LTL-XL model. The Marking Y and Composite M1 Mk luminance were the other luminance values collected for the markings. These luminance values for the pavement markings and adjacent pavement surface were measured using a CCD camera and a more traditional colorimeter. The color data is also measured with these devices in the form Y,x,y where Y is the luminance and x,y are the coordinates on the Hunter color chart. As with the open road data the Mobileye machine vision technology was used to collect pavement marking quality score data.

4.2.2 Data Collection Conditions

Each marking had its characteristics measured in daytime and nighttime conditions. The quality score data was collected in these same conditions driving through the pavement marking course in each direction. By collecting data in both directions any effects on the data due to glare or other factors can be observed along with providing another measurement location for calculating the repeatability.

4.2.3 Data Processing

The machine vision sensor used in the closed course data collection for the correlation analysis did not produce raw data files the same as for the open road data collection. The vehicle for this data collection was equipped with a separate video camera which was used in conjunction with the machine vision sensor to reduce the data and acquire quality scores for the pavement markings. A video viewing program was used to synchronize the video feeds from the camera and machine vision to determine quality scores over the length of the pavement markings. The data collected for the repeatability analysis did not require any additional processing as it was collected with the same equipment as the open road data.

5. DATA ANALYSIS AND RESULTS

5.1 Repeatability of Machine Vision Quality Scores

The fundamental precision statistic for characterizing the repeatability of the pavement marking quality scores is the repeatability standard deviation. Using the equation below the repeatability standard deviation was calculated for each lane marking in the study.

$$s_r = \sqrt{\textstyle\sum_1^p s^2 / p} \quad \textit{(Equation 8)}$$

$$s_r = the\ repeatability\ standard\ deviation$$

$$s = the\ cell\ standard\ deviation = \sqrt{\textstyle\sum_1^n (x - \bar{x})^2 / (n-1)} \quad \textit{(Equation 9)}$$

$$p = the\ number\ of\ laboratories$$

The pavement quality measurement being collected is not a continuous variable, but is a rapidly recorded integer value; however, for the purposes of this study the above equations and method are still able to be applied because of the way the way the data is recorded by the ADAS machine vision system.

The machine vision technology records a quality score more than ten times per second meaning there are a large number of results collected even on a short lane marking or roadway segment. Therefore, a segmented approach was used to analyze the data. In the segmented approach the quality score results were grouped into a defined distance and then averaged over each segment for use in the repeatability analysis. For the open road data collection, the pavement marking quality score results were grouped into 0.05-mile-long segments then averaged for analysis. In the closed course analysis, the observed pavement markings were each about 0.1 miles long, so they were divided in half for grouping the quality scores then averaged. The segment lengths were chosen based on the typical 0.1-mile distance used for aggregating pavement marking retroreflectivity values when reporting measurements collected with a mobile vehicle mounted retro-reflectometer. The segments used in the analysis are only half of the typical length for mobile retroreflectivity, but the machine vision camera is not directly measuring retroreflectivity, so it was decided that the 0.05-mile-long segment length would be acceptable to maintain a consistent segment length for the open road and closed course analysis.

The segmented approach required a substantial amount of data processing in order to transform the raw data into a useable format for analysis. Each data collection run had to be separated into individual lane markings then the data for each lane marking was binned into the 0.05-mile-long segments for the open road data and divided in half, which was roughly 0.05 miles, for the closed course data. Once the data was grouped into bins of the correct segment length the average and standard deviation of the pavement marking quality score from all of the data collection runs were calculated and assigned to the corresponding segment of each pavement marking. This process was repeated for all of the data collection locations and conditions. The result was fourteen open road lane markings each divided into 0.05-mile-long segments and six closed course pavement markings each divided into two segments.

The repeatability standard deviation was calculated according to Equation 8 for each segment of all the pavement markings in the study. When applying the formula to the collected data, the value p for the number of laboratories is equivalent to the number of positions the pavement marking is observed from by the machine vision camera. In order to calculate a true repeatability standard deviation, multiple laboratories must be used, or in this study multiple observation positions must be present. For the pavement markings that are only observed from one position, the repeatability standard deviation is equivalent to the sample standard deviation. In this study, the outside edge lane markings for each of the three open road locations and the two-way left-turn lane markings on FM 2818 are examples of lane markings only observed from one position. These lane markings were removed from the analysis results presented below.

5.1.1 Open Road Repeatability Analysis

The open road pavement markings analyzed for repeatability are shown in the figure below.

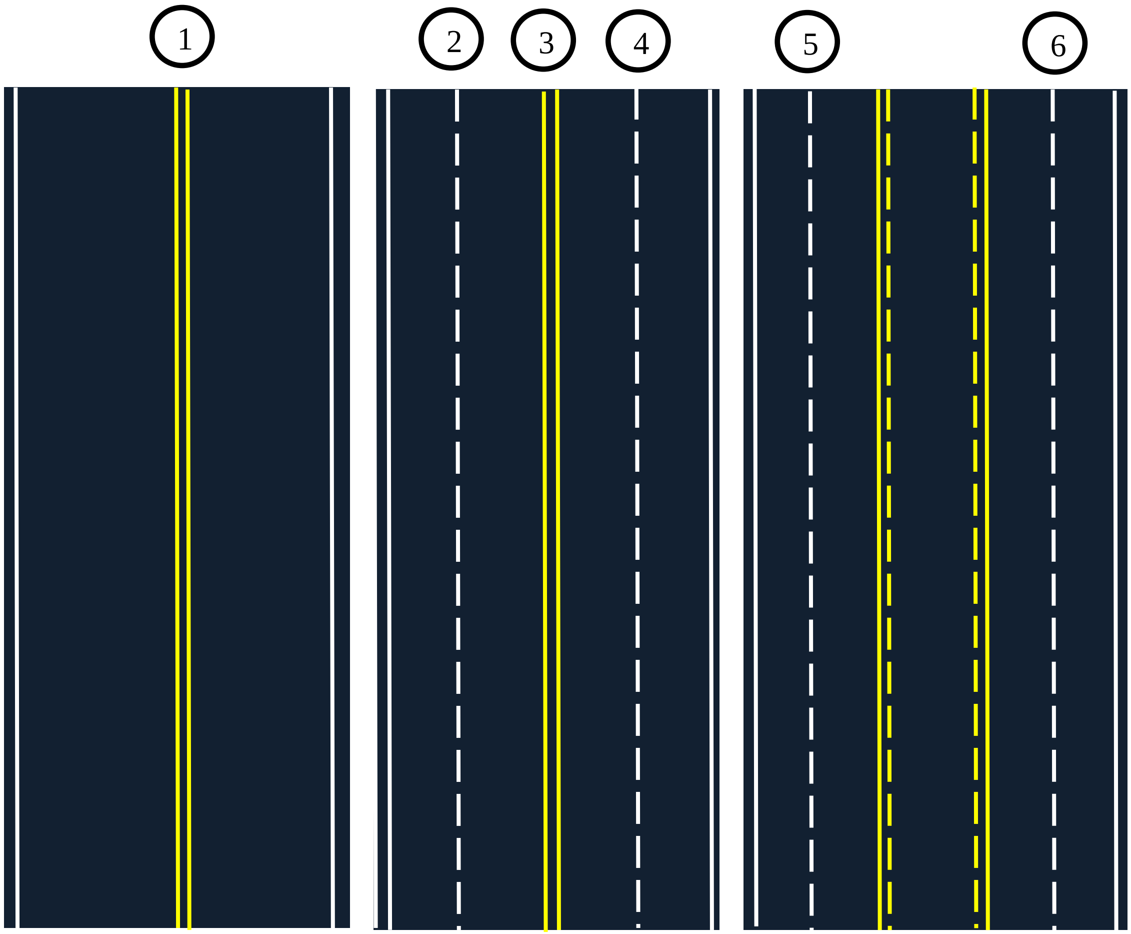

Figure 13. Open Road Pavement Markings with Repeatability Standard Deviation

Lane Marking 1 was the double yellow centerline marking on FM 2154 located outside of College Station, TX. The pavement marking was observed from two positions both on the left side of the data collection vehicle as the road segment was traveled in each direction. The road section was 0.80 miles long; therefore, it was divided 16 analysis segments each 0.05 miles long. For this location, data was collected in three observation conditions: day, night, and overcast. Since this marking was observed in different directions a comparison of the quality scores for each direction under each of the collection conditions was performed to see if there was a clear observable difference in the quality score assigned to the pavement marking based on the travel direction of the data collection vehicle. Figures 15 through 17 show the average quality score for each segment in each direction in the three collection conditions.

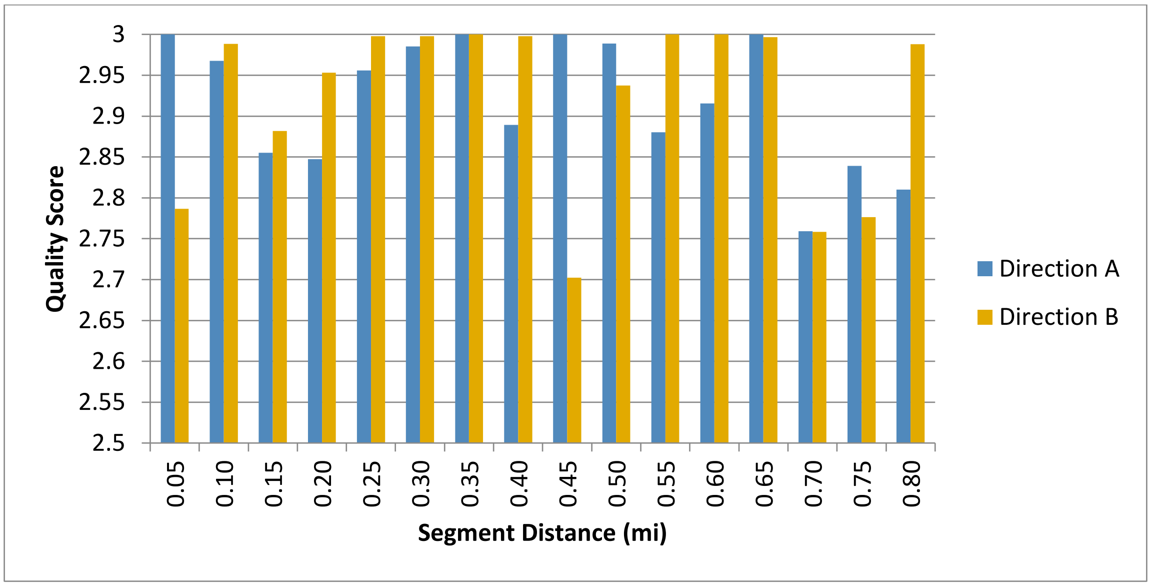

Figure 14. Daytime Quality Score by Direction

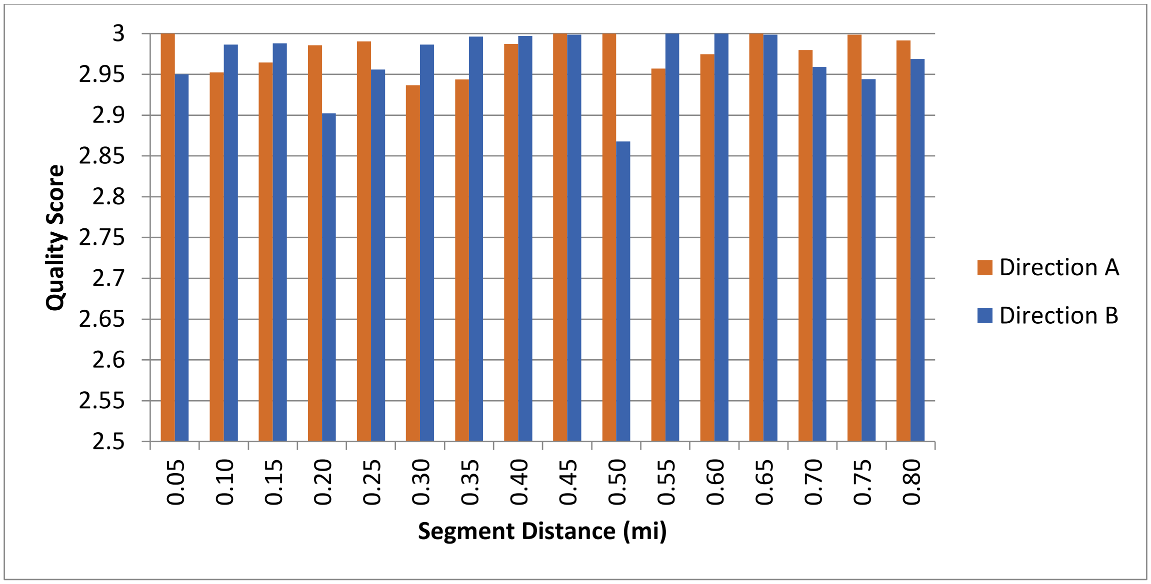

Figure 15. Nighttime Quality Score by Direction

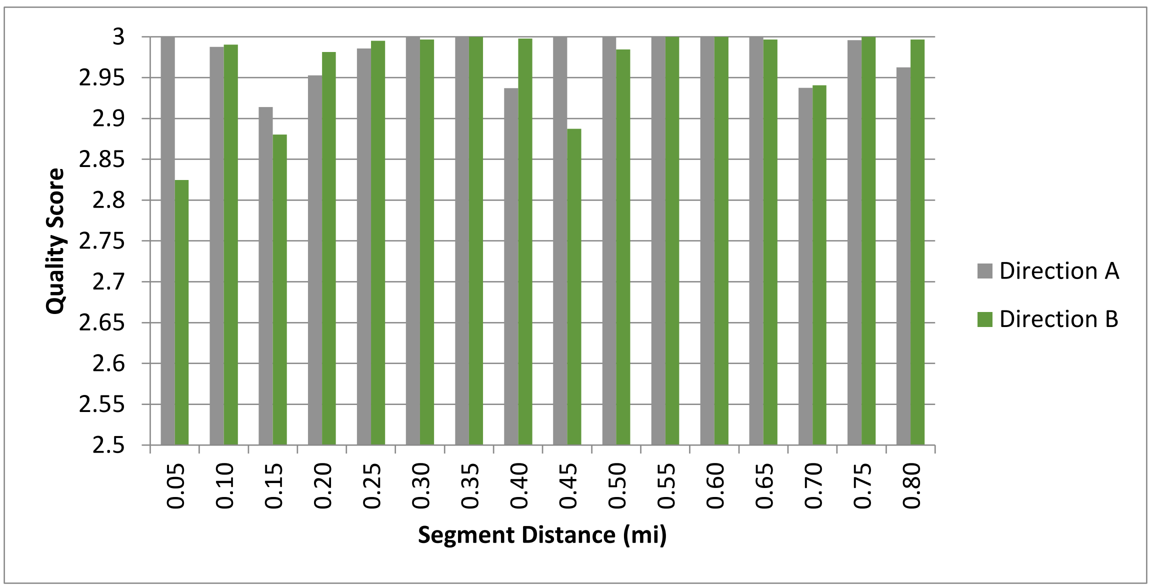

Figure 16. Overcast Quality Score by Direction

The comparison of the quality scores collected in each travel direction did not show a clear trend for a difference in quality score based one direction versus the other. This observation held true for all of the markings observed in different directions. Because of this both directions of data were combined for use in the repeatability analysis.

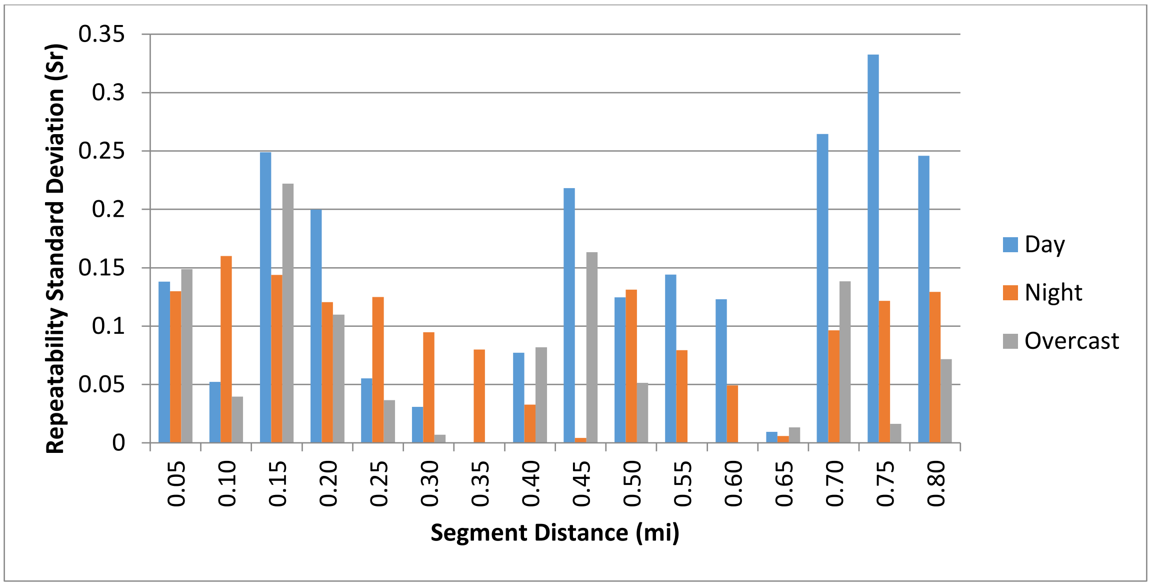

Figure 17. Lane Marking 1 FM 2154 Segment Repeatability Standard Deviation

The repeatability standard deviation is shown in Figure 17 for each segment under each of the three observation conditions. At this location, the repeatability standard deviation appears to vary for many of the analysis segments based on the condition the data was collected in day, night, or overcast. For the majority of the segments, the daytime collection condition resulted in a higher repeatability standard deviation than the other collection conditions. The relationship between the average quality score of each lane marking segment and the repeatability standard deviation for each segment is shown in Figure 18. The figure shows that for each of the observation conditions the repeatability standard deviation decreases as the average quality score increases.

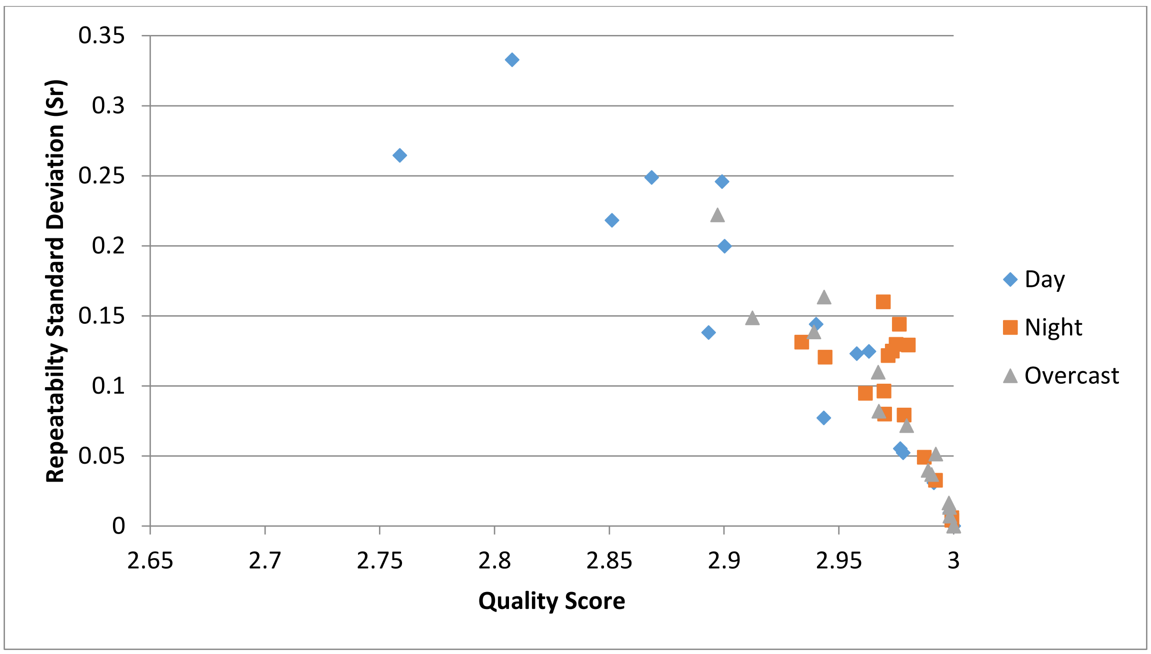

Figure 18. Lane Marking 1 Repeatability Standard Deviation vs. Average Quality Score

Lane marking 2 was the dashed white lane line for the southbound travel direction of N Texas Avenue in Bryan, TX. The pavement marking was observed from both the left and right sides of the data collection vehicle travelling in the same direction. The road section was 1.15 miles long and was divided into 23 analysis segments each

0.05 miles long. For this location data was collected in three observation conditions: day, night, and low angle sun.

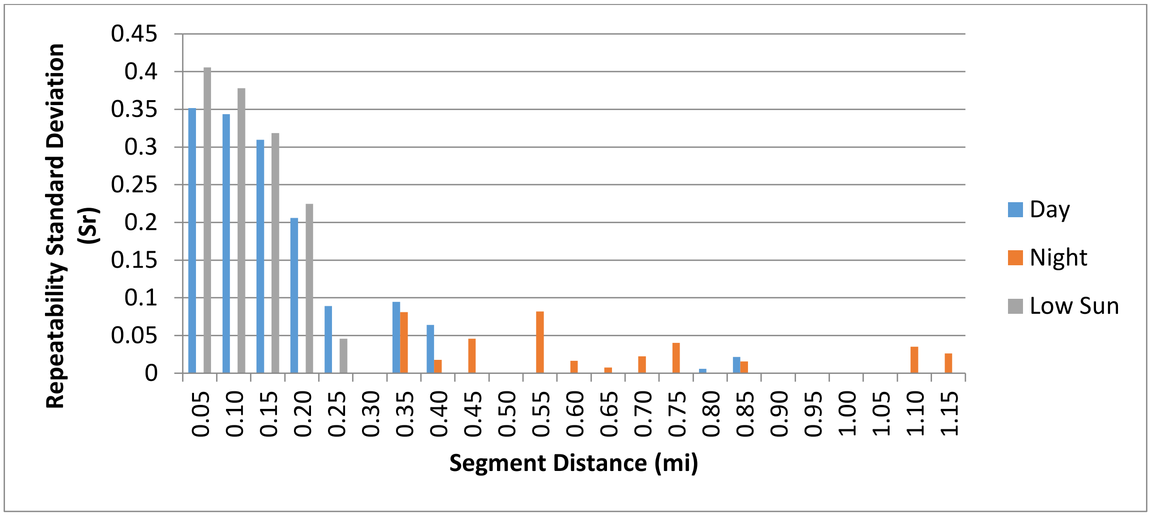

Figure 19. Lane Marking 2 N Texas Ave Segment Repeatability Standard Deviation

The repeatability standard deviation is shown in Figure 19 for each segment under each of the three observation conditions. At this location the repeatability standard deviations for the first segments are much higher than the end segments particularly in the day and low sun collection conditions. This could be due to the presence of shadows from trees close by the edge of the roadway at this location. For the segment with high repeatability standard deviations the low sun condition has a higher value in most instances. The lack of a bar for a condition indicates that the repeatability standard deviation is equal to zero, which means that the quality score was the same for each sample and observation position in that segment. The relationship between the average quality score of each lane marking segment and the repeatability standard deviation for each segment is shown in Figure 20. The figure shows that for each of the observation conditions the repeatability standard deviation decreases as the average quality score increases.

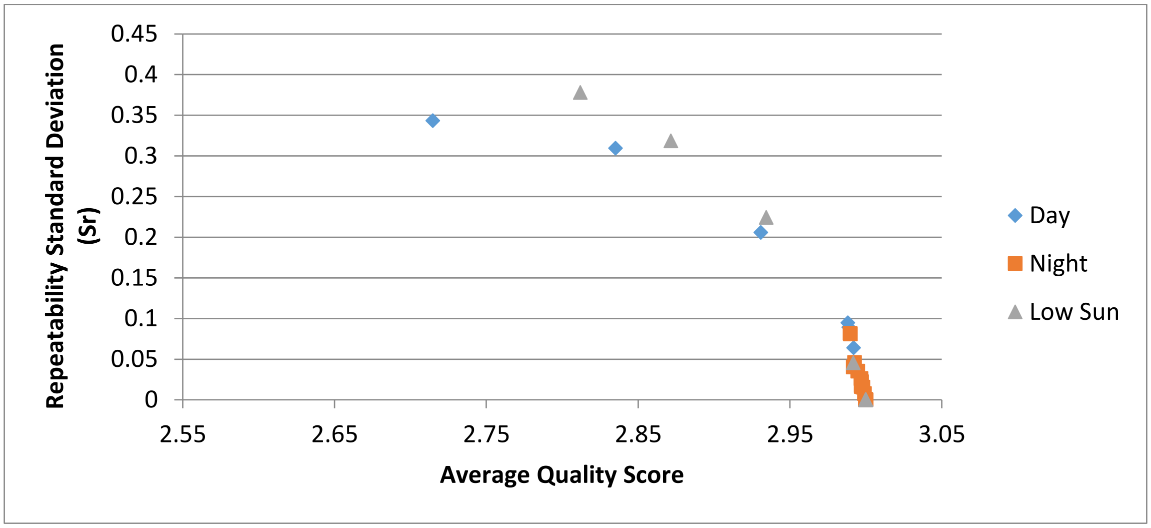

Figure 20. Lane Marking 2 Repeatability Standard Deviation vs. Average Quality Score

Lane marking 3 was the double yellow centerline marking on N Texas Avenue in Bryan, TX. The pavement marking was observed from two positions both on the left side of the data collection vehicle as the road segment was traveled in each direction. The road section was 1.15 miles long and was divided into 23 analysis segments each 0.05 miles long. For this location data was collected in three observation conditions: day, night, and low angle sun.

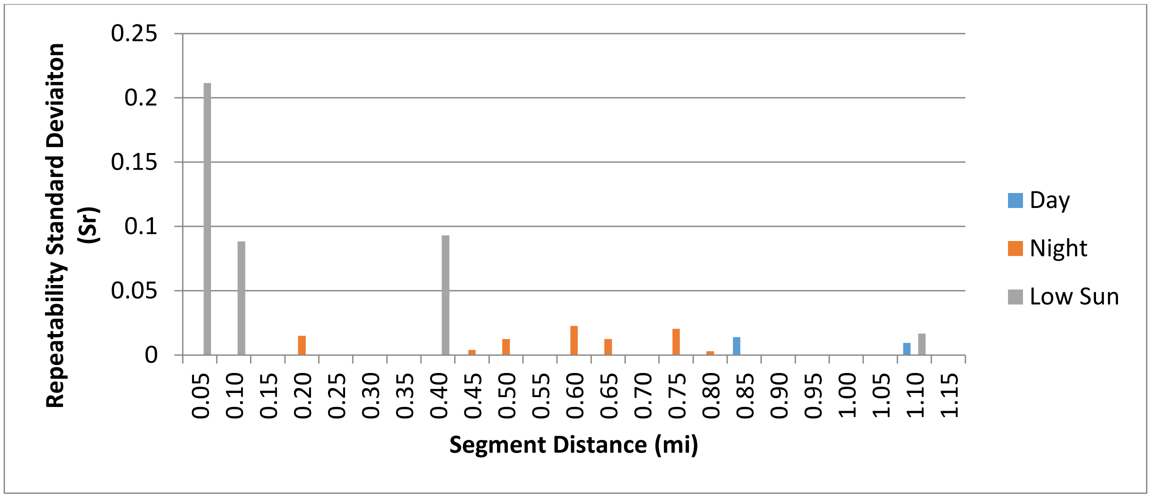

Figure 21. Lane Marking 3 N Texas Ave Segment Repeatability Standard Deviation

The repeatability standard deviation is shown in Figure 21 for each segment under each of the three observation conditions. This section had low repeatability standard deviations across all collection conditions and segments except for a few segments which had higher values in the low angle sun condition. The lack of a bar for a condition indicates that the repeatability standard deviation is equal to zero, which means that the quality score was the same for each sample and observation position in that segment. The relationship between the average quality score of each lane marking segment and the repeatability standard deviation for each segment is shown in Figure 22. The figure shows that for each of the observation conditions the repeatability standard deviation decreases as the average quality score increases.

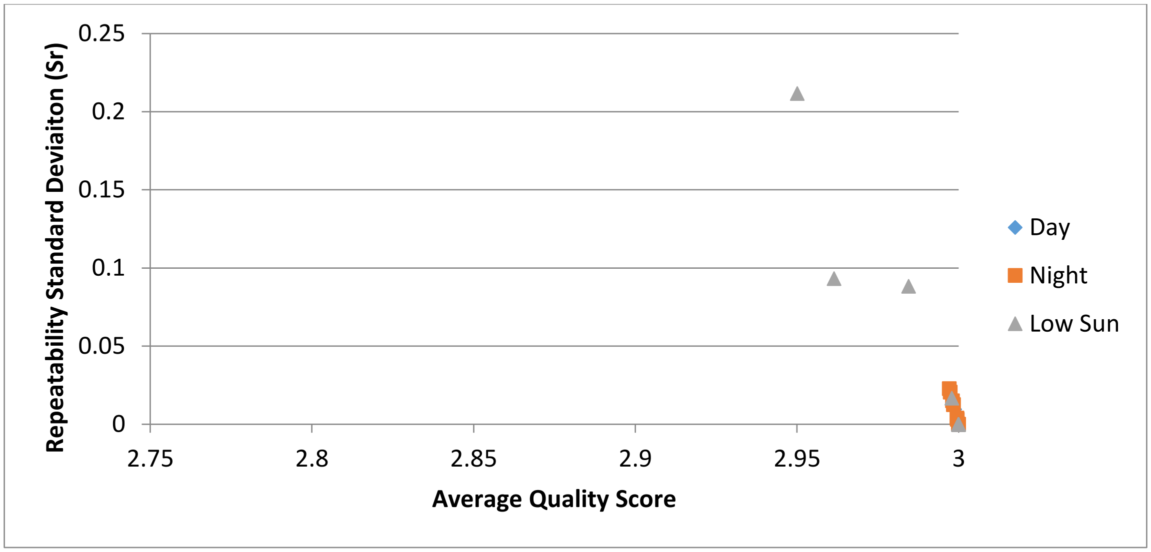

Figure 22. Lane Marking 3 Repeatability Standard Deviation vs Average Quality Score

Lane marking 4 was the dashed white lane line for the northbound travel direction of N Texas Avenue in Bryan, TX. The pavement marking was observed from both the left and right sides of the data collection vehicle travelling in the same direction. The road section was 1.15 miles long and was divided into 23 analysis segments each 0.05 miles long. For this location data was collected in three observation conditions: day, night, and low angle sun.

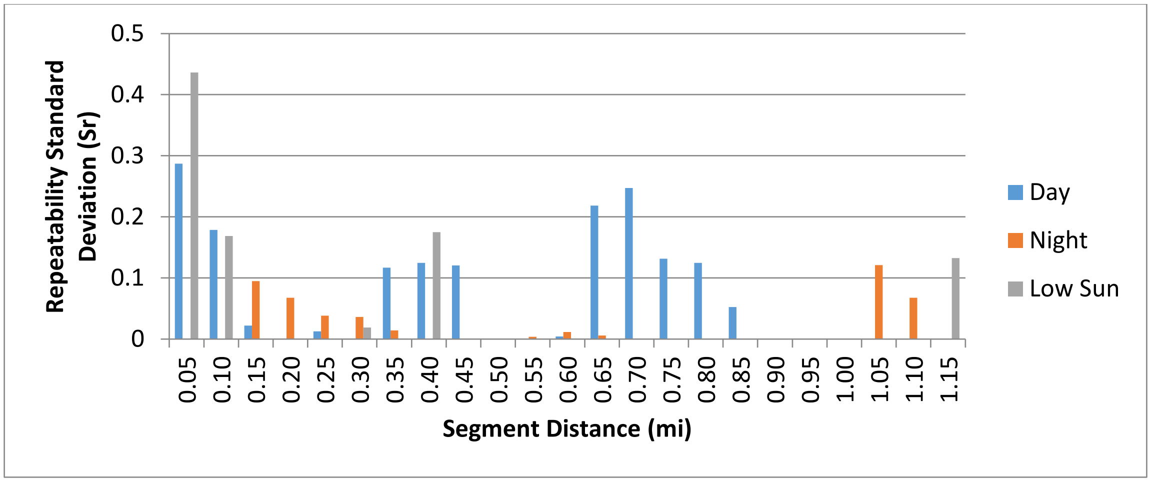

Figure 23. Lane Marking 4 N Texas Ave Segment Repeatability Standard Deviation

The repeatability standard deviation is shown in Figure 23 for each segment under each of the three observation conditions. This location shows a similar pattern to lane marking 2 where the segments at the beginning have higher repeatability standard deviations. It also shows the same trend as previous markings where the daytime condition results in the higher repeatability standard deviations. The lack of a bar for a condition indicates that the repeatability standard deviation is equal to zero, which means that the quality score was the same for each sample and observation position in that segment. The relationship between the average quality score of each lane marking segment and the repeatability standard deviation for each segment is shown in Figure 24. The figure shows that for each of the observation conditions the repeatability standard deviation decreases as the average quality score increases.

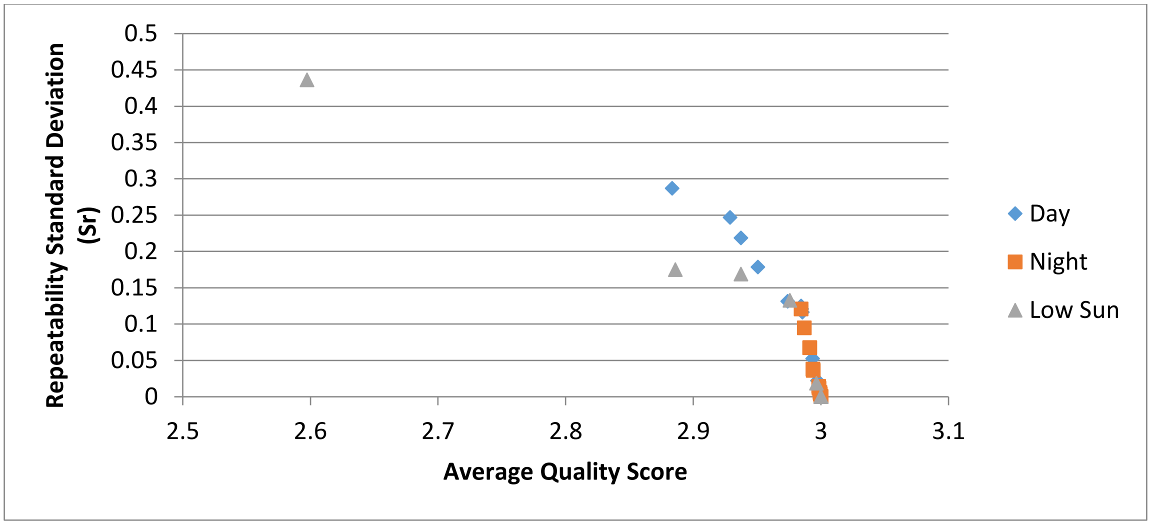

Figure 24. Lane Marking 4 Repeatability Standard Deviation vs. Average Quality Score

Lane marking 5 was the dashed white lane line for the southbound travel direction of FM 2818 in Bryan, TX. The pavement marking was observed from both the left and right sides of the data collection vehicle travelling in the same direction. The road section was 0.60 miles long and was divided into 12 analysis segments each 0.05 miles long. For this location data was collected in two observation conditions: day and night.

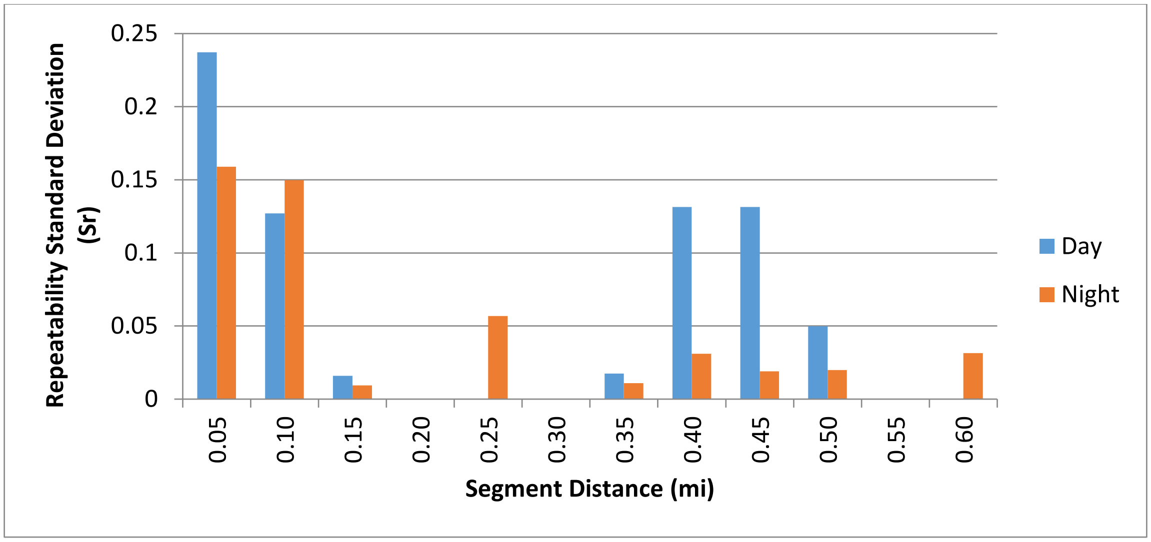

Figure 25. Lane Marking 5 FM 2818 Repeatability Standard Deviation

The repeatability standard deviation is shown in Figure 25 for each segment under each of the three observation conditions. Again, at this location, by observation, the data shows that the daytime collection condition repeatability standard deviation is usually higher than the nighttime values. The relationship between the average quality score of each lane marking segment and the repeatability standard deviation for each segment is shown in Figure 26. The figure shows that for each of the observation conditions the repeatability standard deviation decreases as the average quality score increases.

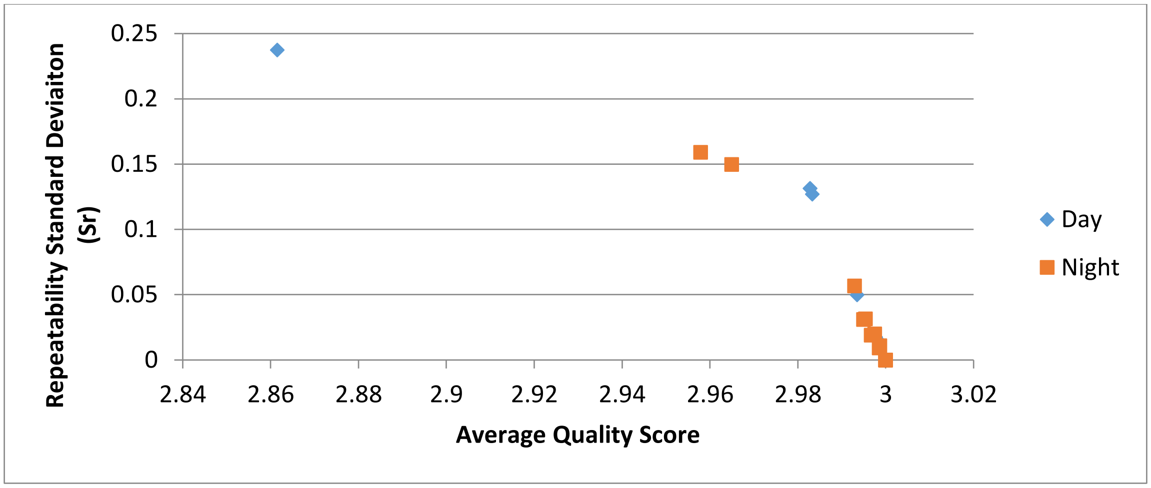

Figure 26. Lane Marking 5 Repeatability Standard Deviation vs. Average Quality Score

Lane marking 6 was the dashed white lane line for the northbound travel direction of FM 2818 in Bryan, TX. The pavement marking was observed from both the left and right sides of the data collection vehicle travelling in the same direction. The road section was 0.60 miles long and was divided into 12 analysis segments each 0.05 miles long. For this location data was collected in two observation conditions: day and night

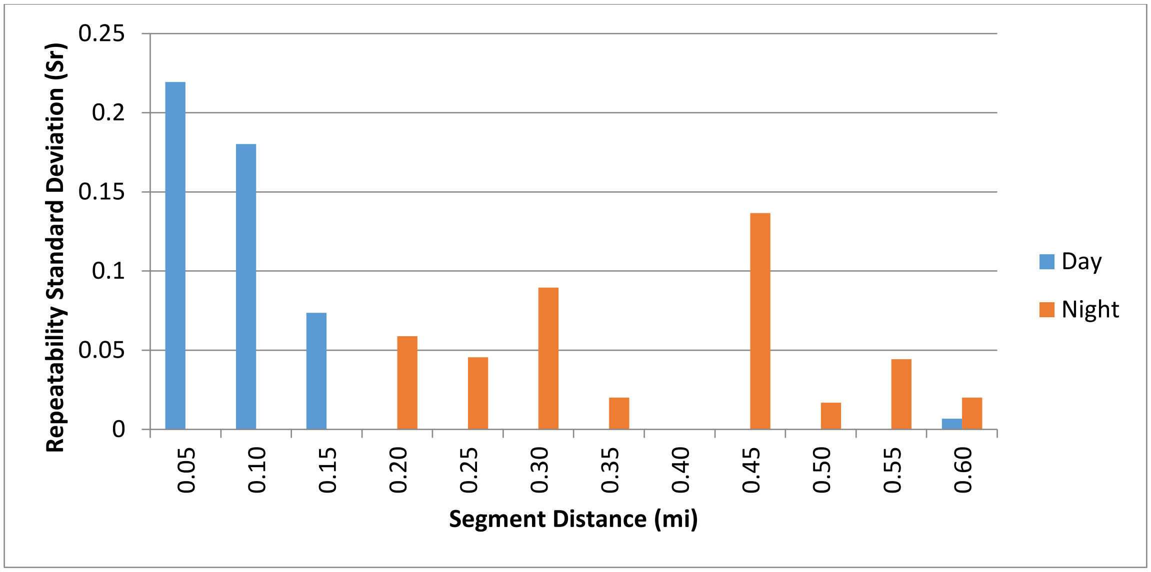

Figure 27. Lane Marking 6 FM 2818 Repeatability Standard Deviation

The repeatability standard deviation is shown in Figure 27 for each segment under each of the three observation conditions. This location is interesting as almost all of the segments only have repeatability standard deviations for one of the two collection conditions. The lack of a bar for a condition indicates that the repeatability standard deviation is equal to zero, which means that the quality score was the same for each sample and observation position in that segment. More segments have a repeatability standard deviation in the nighttime condition than the daytime condition which is different from previous lane markings where the daytime condition would often show the higher repeatability standard deviation. The relationship between the average quality score of each lane marking segment and the repeatability standard deviation for each segment is shown in Figure 28. The figure shows that for each of the observation conditions the repeatability standard deviation decreases as the average quality score increases.

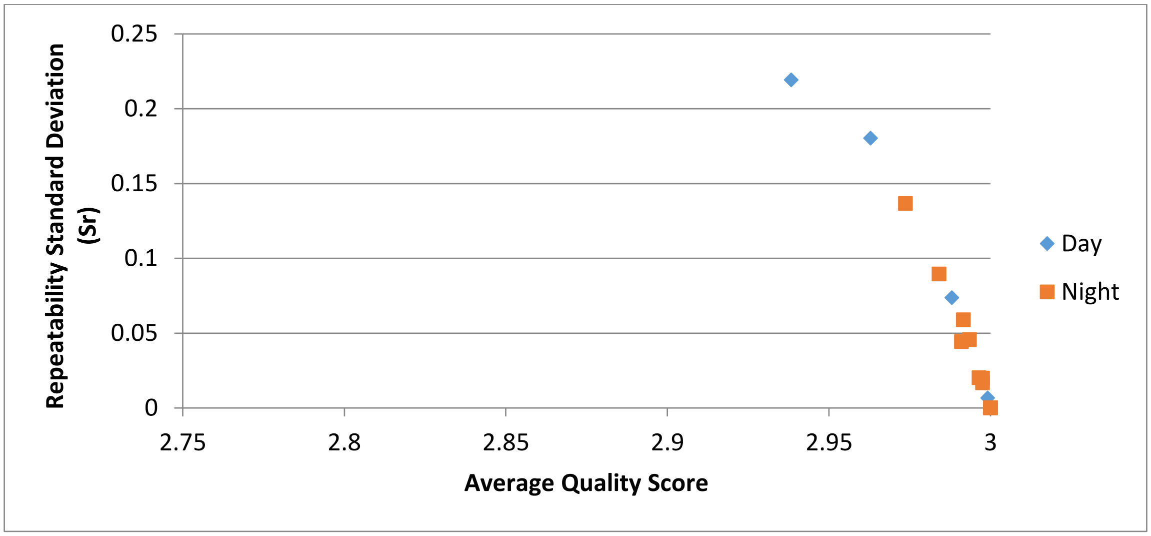

Figure 28. Lane Marking 6 Repeatability Standard Deviation vs. Average Quality Score

From analyzing the collection locations and segments individually it was observed that there appeared to be a difference in the repeatability standard deviations based on the data collection condition. Therefore, it was thought to be useful to compare the repeatability standard deviation and average quality score for all segments and conditions in order to see any potential effects the condition had on the collected values. From this it was observed that the different conditions all follow the same trend, that as the average quality score increases the repeatability standard deviation decreases. However, it was also observed that the different conditions appear to have very different ranges of average quality score and repeatability standard deviation. The daytime and low angle sun condition have the most spread in average quality score and also the highest repeatability standard deviations while the overcast and nighttime conditions are much more closely grouped and have lower repeatability standard deviations. This could be due to the more consistent light conditions present at night and in the overcast collection conditions than the low angle sun and daytime conditions where the light is more variable and can result in shadows or glare on the pavement markings and road surface. The results are shown in Figure 29.

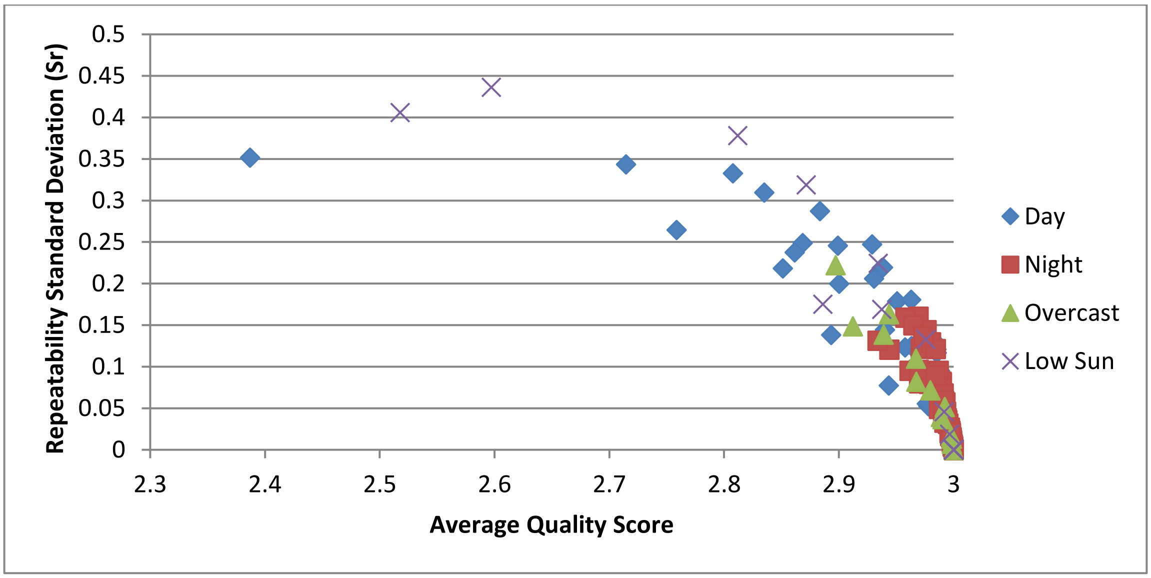

Figure 29. Repeatability Standard Deviation vs. Average Quality Score

As a result of these observations, further analysis was performed on the average quality score and repeatability standard deviation for each collection condition. The JMP software was used to create multiple comparisons between the different conditions to test for the effects of collection conditions on the quality score and repeatability standard deviation. All of the average quality scores and repeatability standard deviations for each segment and collection condition were combined into one data set for this analysis. The means of the average quality scores and repeatability standard deviations were compared using the Tukey's HSD test. This method compares the means of multiple groups and allows for the conclusion to be made whether the means are significantly different from each of the other groups. This test was performed for both the average quality score and the repeatability standard deviation. The results are shown in Figures 30 to Figure 33.

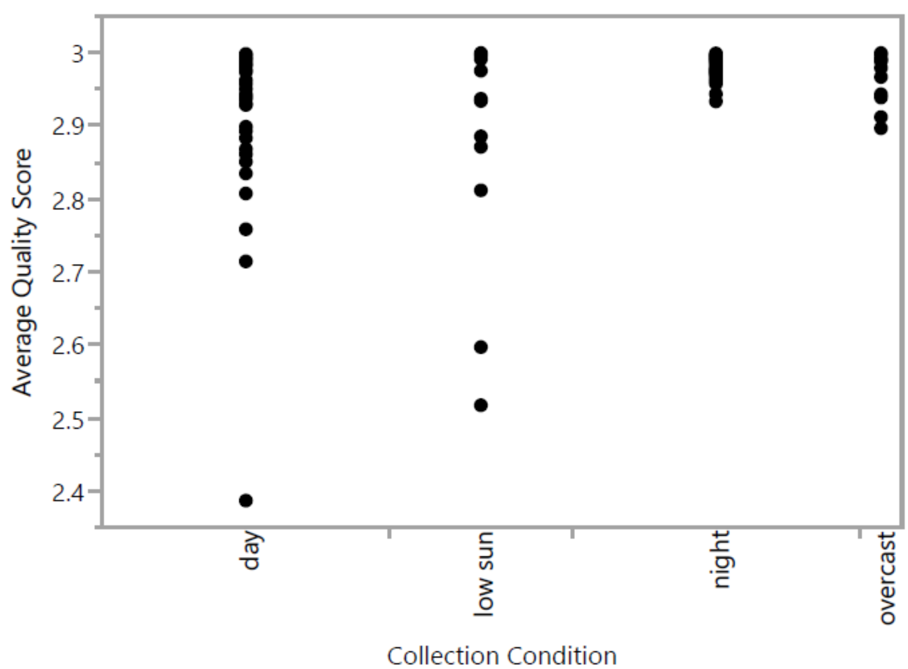

Figure 30. Average Quality Score by Collection Condition

HSD Threshold Matrix

Abs(Dif)-HSD

	night	low sun	overcast	day
night	-0.02120	-0.00930	-0.02185	0.00105
low sun	-0.00930	-0.02664	-0.03815	-0.01660
overcast	-0.02185	-0.03815	-0.05533	-0.03969
day	0.00105	-0.01660	-0.03969	-0.02120

Positive values show pairs of means that are significantly different.

Connecting Letters Report

Level			Mean
night	A		2.9933239
low sun	A	B	2.9785536
overcast	A	B	2.9732813
day		B	2.9710798

Levels not connected by same letter are significantly different.

Figure 31. Tukey's HSD Results for Average Quality Score

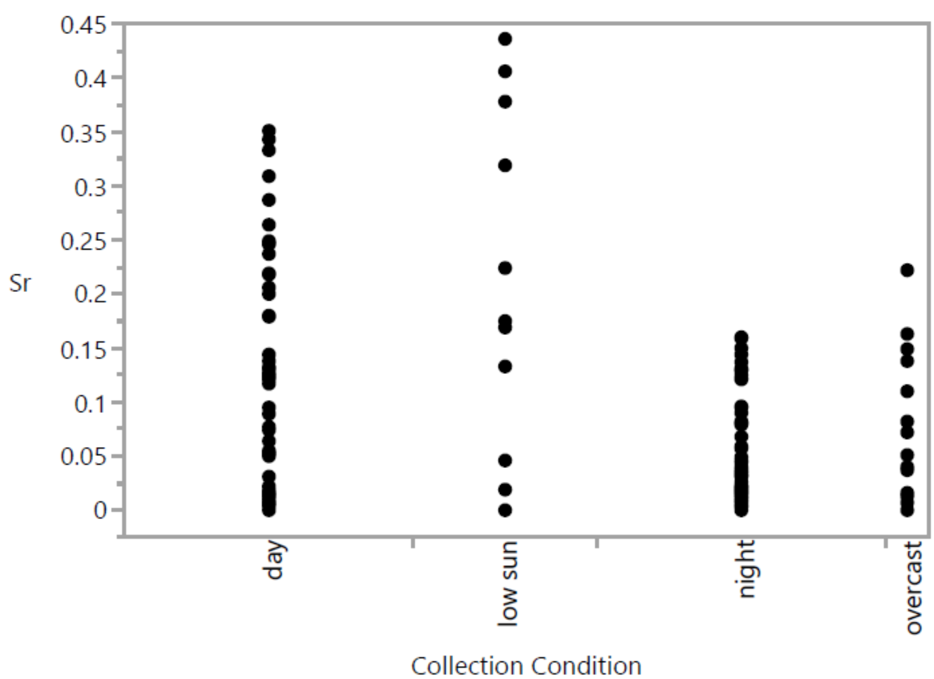

Figure 32. Repeatability Standard Deviation by Collection Condition

HSD Threshold Matrix

Abs(Dif)-HSD

	overcast	day	low sun	night
overcast	-0.07314	-0.04726	-0.02206	-0.01751
day	-0.04726	-0.02802	-0.00461	0.00172
low sun	-0.02206	-0.00461	-0.03522	-0.02930
night	-0.01751	0.00172	-0.02930	-0.02802

Positive values show pairs of means that are significantly different.

Connecting Letters Report

Level			Mean
overcast	A	B	0.06875000
day	A		0.06062385
low sun	A	B	0.03340580
night		B	0.03088073

Levels not connected by same letter are significantly different.

Figure 33. Tukey's HSD for Repeatability Standard Deviation

The results of the Tukey’s HSD test show that the means of the average quality scores for the lane markings and the repeatability standard deviations are significantly different between the daytime and nighttime collection conditions. All of the other comparisons between the different collection conditions do not indicate that there is a significant difference in the means for the average quality score or the repeatability standard deviation. The evidence of the means for the average quality score and repeatability standard deviation being different between the daytime and nighttime conditions could mean that the data collected by the ADAS machine vision camera is not repeatable across the different conditions. This could have implications on decision-making using ADAS machine vision data collected in different conditions.

5.1.2 Closed Course Repeatability Analysis

Along with the six open road lane markings, six more closed course pavement markings were analyzed for repeatability. Each of the closed course markings was a solid white lane marking. These markings were divided in half for analysis purposes resulting in 12 total segments from all six of the markings. The first half of each marking was designated as “a’ while the second half was labeled “b” for organizational and data presentation purposes. The repeatability standard deviation for each marking segment is shown in Figure 34.

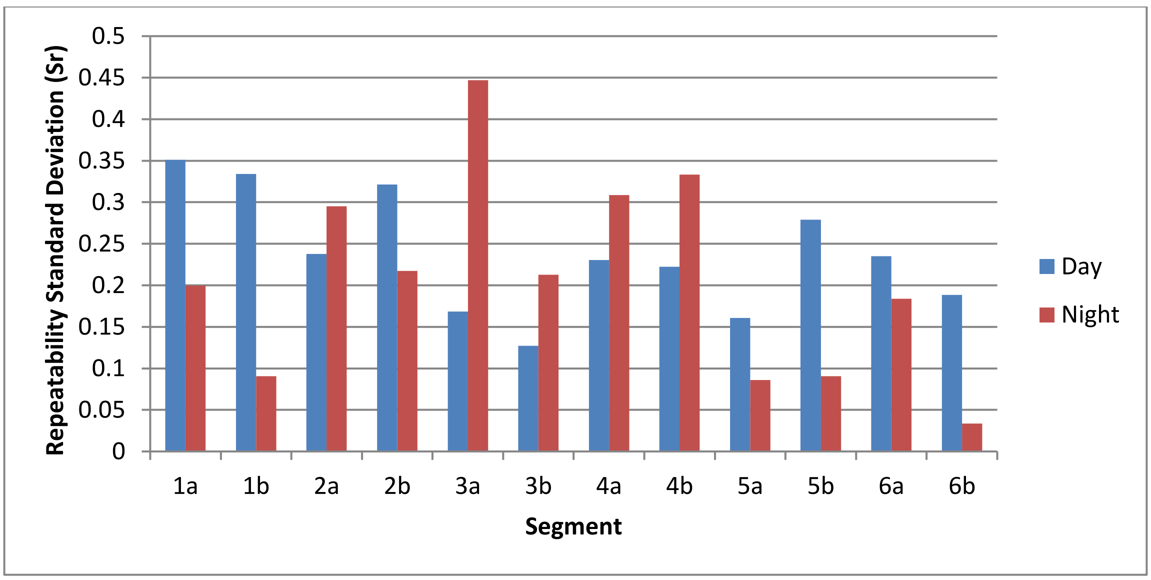

Figure 34. Closed Course Repeatability Standard Deviation by Segment

As a group the closed course pavement marking segments had lower average quality scores than the open road lane marking segments. This could be explained by a couple of different reasons. The first is that the closed course markings, being intentionally degraded, likely have lower retroreflectivity values than the open road markings. The second is that the closed course markings were applied to a concrete pavement surface which would have a lower contrast with the white lane markings than the asphalt pavement surface from the open road scenario. Both reasons could result in the closed course pavement markings being more difficult for the machine vision to detect, thus resulting in lower quality scores.

The relationship between the average quality score and the repeatability standard deviation was again plotted as it was for the open road data. The daytime data appears to exhibit close to the same relationship as the open road data where the repeatability standard deviation decreases as the average quality score increases; however, the nighttime data does not appear to follow this relationship as clearly as in the open road condition.

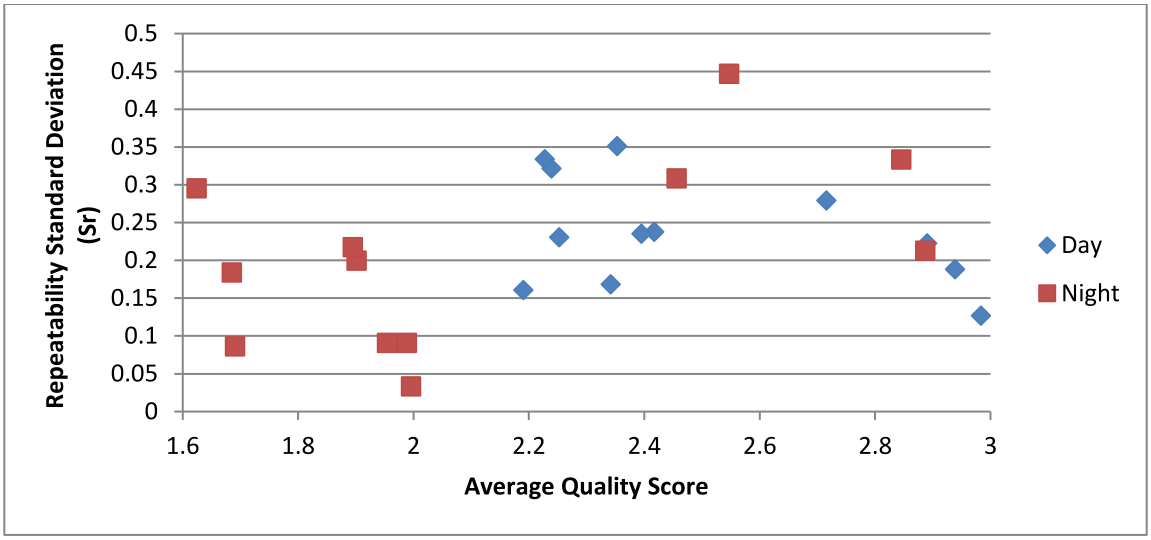

Figure 35. Closed Course Repeatability Standard Deviation vs. Average Quality Score

This difference in the relationship between the repeatability standard deviation and average quality score for the nighttime data could be a result of the lower average quality scores for the markings resulting in increased variability and higher S_r due to the presence of both lower and higher quality markings. The closed course nighttime average quality scores were consistently lower than the corresponding daytime average quality score for almost all of the closed course segments as shown in Figure 36.

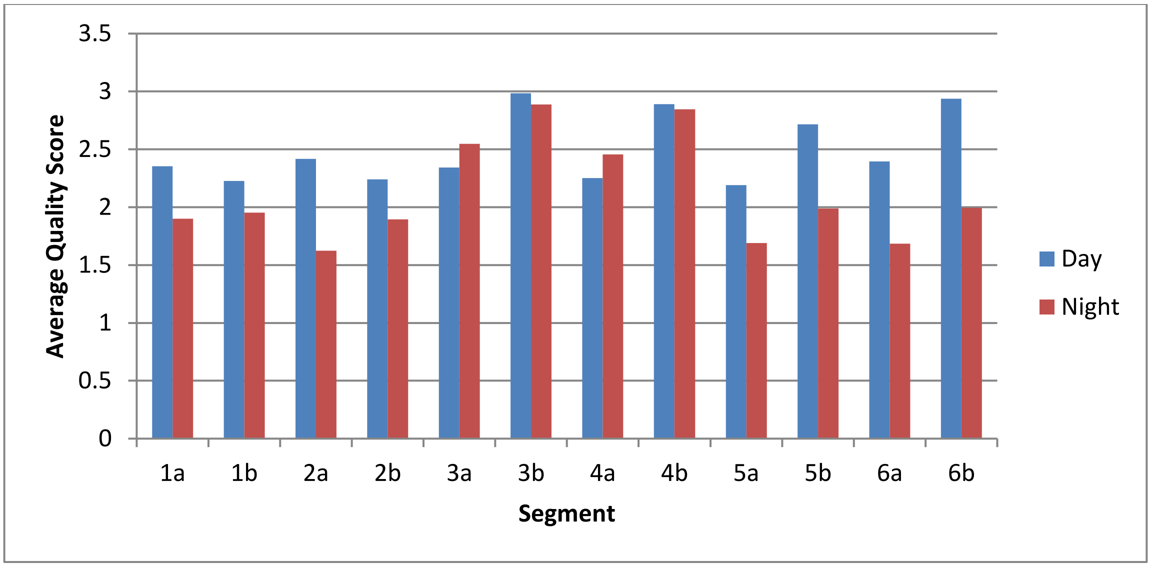

Figure 36. Closed Course Average Quality Score by Segment

The same comparison using the Tukey's HSD test performed on the open road data was also applied to the closed course data. For the closed course data, the means of the average quality score for the daytime and nighttime condition were significantly different just as they were for the open road data. However, the means of the repeatability standard deviations were not significantly different between the two collection conditions. The results of the JMP software outputs are shown Figures 37 through 40.

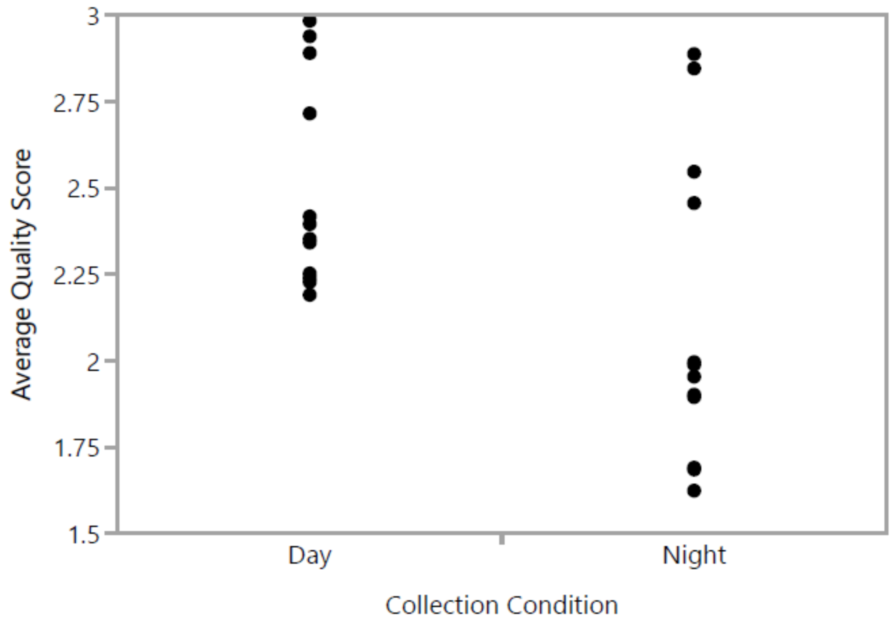

Figure 37. Closed Course Average Quality Score by Condition

HSD Threshold Matrix

Abs(Dif)-HSD

	Day	Night
Day	-0.32172	0.05119
Night	0.05119	-0.32172

Positive values show pairs of means that are significantly different.

Figure 38. Tukey's HSD Results for Closed Course Average Quality Score

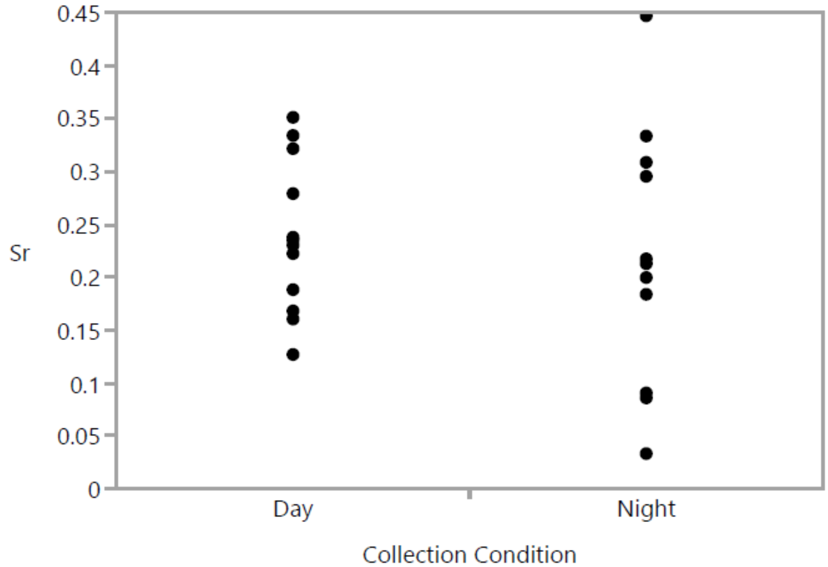

Figure 39. Closed Course Repeatability Standard Deviation by Condition

HSD Threshold Matrix

Abs(Dif)-HSD

	Day	Night
Day	-0.08483	-0.05514
Night	-0.05514	-0.08483

Positive values show pairs of means that are significantly different.

Figure 40. Tukey's HSD Results for Closed Course Repeatability Standard Deviation

5.1.3 Relationship between Quality Score and Retroreflectivity

Further investigation into the difference between the daytime and nighttime machine vision average quality scores was performed as a result of the closed course repeatability analysis and the comparison of the machine vision average quality scores collected in the different conditions. This analysis sought to understand the relationship between the average quality scores assigned by the ADAS machine vision camera and the measured retroreflectivity of the pavement markings. The measured retroreflectivity of the closed course pavement markings ranged from 14.14 mcd/m^2/lux to 1285.88 mcd/m^2/lux. For this analysis the average quality score for each individual data collection run was paired with the measured retroreflectivity for the pavement marking resulting a total of 597 paired observations. A box-and-whisker plot was then constructed to compare the mean and range of the measured retroreflectivity values that were assigned each quality score value by the machine vision.

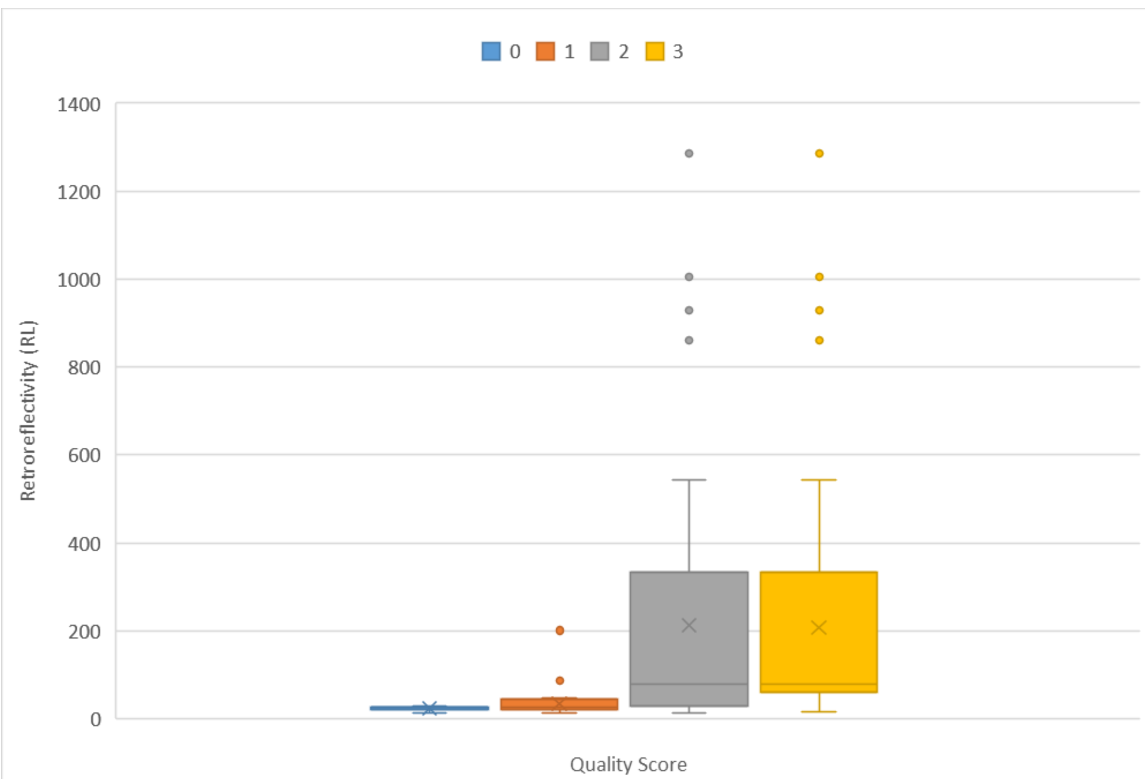

Figure 41. Box-and-Whisker Plot Retroreflectivity vs. Quality Score

The box-and-whisker plot in Figure 41 shows that the markings assigned a quality score of 0 and 1 have much lower retroreflectivity values that the markings assigned quality scores of 2 or 3. The plot indicates that the quality score of 0 or 1 was only assigned by the machine vision camera if the retroreflectivity was below about 200 mcd/m^2/lux, but the two highest retroreflectivity values assigned a quality score of 1 were outliers. The quality scores of 2 and 3 were assigned for a much larger range of retroreflectivity values including the range of retroreflectivity values that were given a 0 or 1 quality score. However, the average retroreflectivity value for the markings assigned a quality score of 2 or 3 is higher than the maximum retroreflectivity value assigned a quality score of 1. The plot appears to indicate that there is some relationship between the measured pavement marking retroreflectivity and the machine vision quality score. The relationship appears to be that a pavement marking with a retroreflectivity value greater that 200 mcd/m^2/lux will not receive a quality score of 0 or 1, but that a pavement marking with a retroreflectivity of less than 200 mcd/m^2/lux can receive a quality of 2 or 3.

Another chart comparing the retroreflectivity for each closed course pavement marking with its average quality score for all the data collection runs was also created to observe any potential relationships. Figure 42 shows the results of this chart where each point represents each of the different closed course pavement markings measured for retroreflectivity and assigned a machine vision quality score in both the northbound and southbound direction.

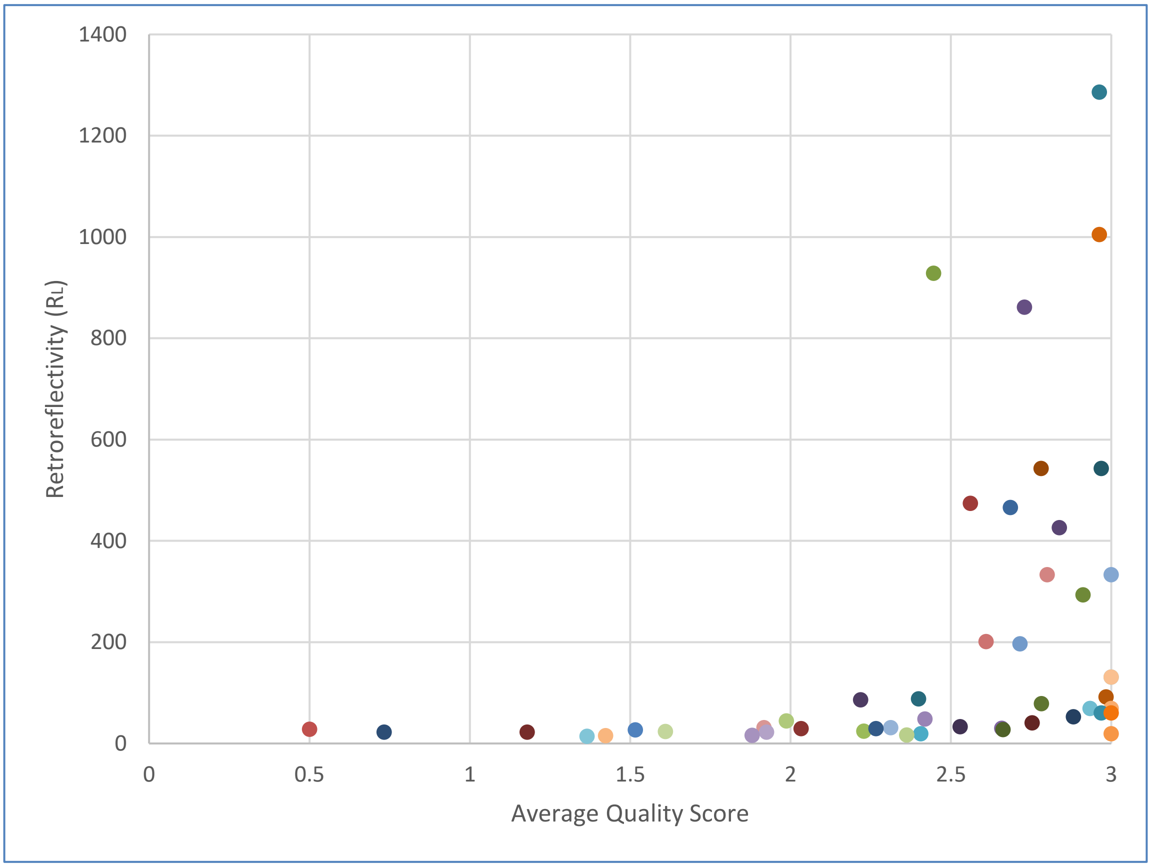

Figure 42. Retroreflectivity vs. Average Quality Score

The same relationship from the box-and-whisker plot can also be seen in this chart as the retroreflectivity values greater than 200 mcd/m^2/lux only received high quality scores (2 or 3) while the lower retroreflectivity values had averages across the entire range of the quality scores (0-3).

When the relationship between retroreflectivity and pavement marking is considered along with the previous analysis showing that the average of the daytime quality scores was significantly different, and higher, than the nighttime quality scores the conclusion could be made that presence of pavement markings with low retroreflectivity values is the reason for the lower nighttime quality scores. The higher average quality score in the daytime could also indicate that in the daytime condition the machine vision is not as dependent on the brightness of the marking measured by values such as Q_d, R_L, or Cap Y, but it could be more dependent on presence or contrast between the marking and the pavement surface. While in the nighttime condition, the machine vision is more reliant on the retroreflectivity of the marking in order to determine presence and assign a quality score; therefore, since the pavement markings had varying retroreflectivity values the result was lower average quality scores for the data collected in the nighttime condition.

5.1.4 Repeatability Analysis Conclusions

Between the open road and closed course data twelve pavement markings divided into 121 segments were analyzed for repeatability under four data collection conditions. For both the open road and closed course data it was found that the repeatability standard deviation and average quality score were significantly different between the daytime and nighttime collection conditions. There was not a significant difference when comparing to the low angle sun and overcast collection conditions. These results indicate that the data collected by the ADAS machine vision camera may not be repeatable under different collection conditions. As a result, the decision-making process should take this into account when using data collected under different conditions.

5.2 Correlation between Pavement Marking Characteristics and Quality Score

In order to understand the usefulness of the quality scores assigned by the machine vision system it was necessary understand how the quality score relates to known pavement marking characteristics such as retroreflectivity, luminance, and contrast. The relationship between the machine vision quality scores and the current pavement marking performance evaluation characteristics was established using the closed course data collected by TTI. While the values for retroreflectivity and luminance were directly collected using equipment and methods described in the data collection section, the values for contrast needed to be calculated. Contrast was calculated using the ratio between the pavement markings and pavement surface for all of the retroreflectivity and luminance values collected by the different methods and devices outlined in the data collection section.

Regression analysis was performed to investigate the correlation between the machine vision quality score and the current measured pavement marking evaluation characteristics. For the analysis, the pavement marking characteristics considered as explanatory variables included the collected retroreflectivity and luminance values along with the calculated contrast ratios, while the machine vision quality score was considered as the response variable. The regression analysis was performed using JMP software, which is an SAS product with enhanced analysis capabilities and features.

5.2.1 Simple Regression Models

The first step in building the regression models was to plot the machine vision quality score against each of the explanatory variables to determine which could be most useful in fitting an appropriate model. This step also allows the observation of any curved relationship or if a transformation could potentially be needed in fitting an appropriate model. As a part of this step the data was analyzed to determine if any outliers or influential points existed that could affect the validity of the fit models. Outliers and influential points were checked by calculating the studentized residuals and Cook's D. From this initial analysis it appeared that one of the materials used in the measurements produced outliers for each of the evaluation characteristics and for multiple degrees of regression polynomials in both the day and night collection conditions. However, because of the design of the experiment which used different materials, some of which were intentionally degraded, in order to obtain a representative sample of marking condition measurements, these data points were not removed as their appearance as outliers does not necessarily indicate an error in measurement, sampling, or data recording occurred.

After determining the validity of the data, the regression models created for each explanatory variable were analyzed to determine which of the variables appeared to correlate the most with the average marking quality score and if any variable transformations should be made. The average marking quality score for each marking was plotted against each of the eight explanatory variables for the day and night collection conditions. For each of the bivariate plots a linear, quadratic, and cubic regression equation was fit in order to observe any potential relationship between the individual explanatory variables and the average marking quality score. To determine which of the regression models most closely fit the data the coefficient of determination (R^2) was examined. The R^2 value is the proportion of the overall variability of the response that is explained by the model and indicates a close fit of the data to the estimated line, thus, it is a measure of the strength of the relationship. The residuals from the fit regression models were analyzed in order to validate the model assumptions and investigate the need for variable transformations. This analysis was performed by plotting the residuals against the explanatory variables and the model predicted response variable. From these plots the spread and shape of the residuals was examined to determine if the model assumptions were valid or if an appropriate variable transformation could be made to remedy any failing assumptions and fit a better model.

As a result of this analysis it was determined that none of the explanatory variables exhibit a linear relationship with the average making quality score in either the daytime or nighttime condition. The most appropriate fit for the daytime condition was a cubic regression with Marking Cap Y as the explanatory variable. The R^2 value was 0.72 and the fit line is shown in Figure 43.

$$Average\ Quality\ Score = -0.0000619x^3 + 0.00522575x^2 - 0.144011x + 3.72304$$

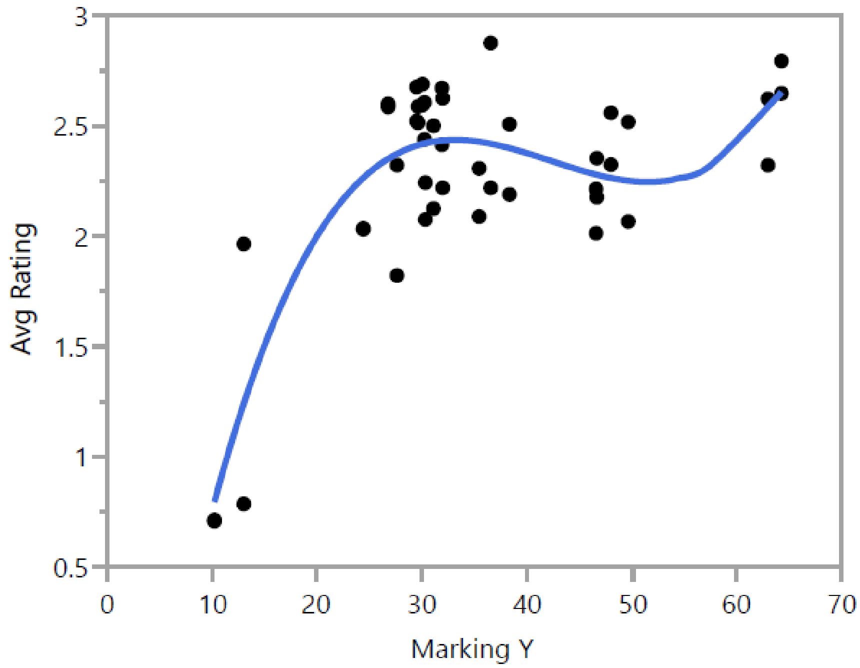

Figure 43. Daytime Average Marking Quality Score vs. Marking Y

For the daytime condition, the other variable most highly correlated when fit with a cubic regression was Cap Y Contrast which is expected as this variable is dependent on the Marking Y value. For the nighttime condition, the most appropriate fit was again a cubic regression this time with Cap Y Contrast as the explanatory variable. The R^2 value was 0.57 and the fit curve is shown below. This R^2 value is very low but was included to convey the lack of a good regression fit based on a single explanatory variable for the nighttime condition.

$$Average\ Quality\ Score = 0.0380291x^3 - 0.49435x^2 + 2.13915x - 0.281797$$

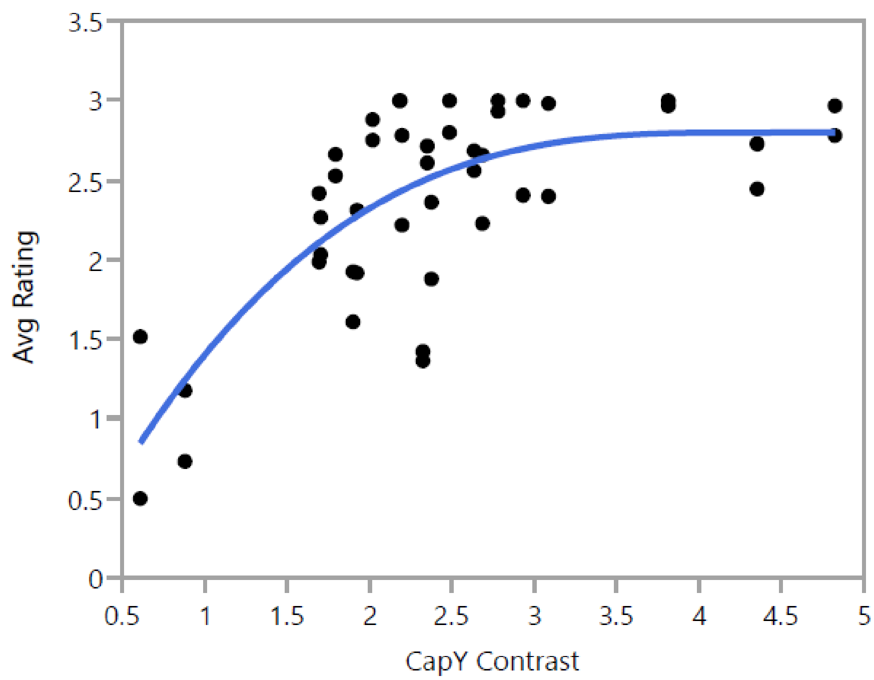

Figure 44. Nighttime Average Quality Score vs. Cap Y Contrast

For the nighttime condition, the other variable most closely correlated was Marking Y which is expected since Cap Y Contrast is related to the Marking Y value. The explanatory variables with the lowest correlation to the average marking quality score in both the daytime and nighttime conditions for all of the regression curves fit were the variables related to measuring the Q_d and R_L values. It is possible that the retroreflectivity measurements taken with the retroreflectometer are not as highly correlated with the quality scores given by the machine vision because the of the differences in viewing geometry between the retroreflectometer and the machine vision camera.

Along with observing the best fit regression models, the results for each explanatory variable were analyzed for potential transformations by the process previously described. For both the daytime and conditions none of the linear fit models clearly indicated that a logarithmic transformation would be appropriate. In order to fully investigate the potential for transforming the data, a reciprocal transformation was applied to the explanatory variables in both the daytime and nighttime conditions. For the daytime condition, none of the reciprocal transformed fits resulted in an improved model over the cubic regression for Marking Cap Y. In the nighttime condition the reciprocal transformation of the variable Composite M1 Mk Luminance did result in an improved correlation with an R^2 value equal to 0.62; however, the residuals were unclear as to whether the model fit is entirely appropriate. The fit curve is shown in Figure 45.

$$Average\ Quality\ Score = 3.0597877 - 0.646328 * \frac{1}{Composite\ M1\ Mk\ Luminance}$$

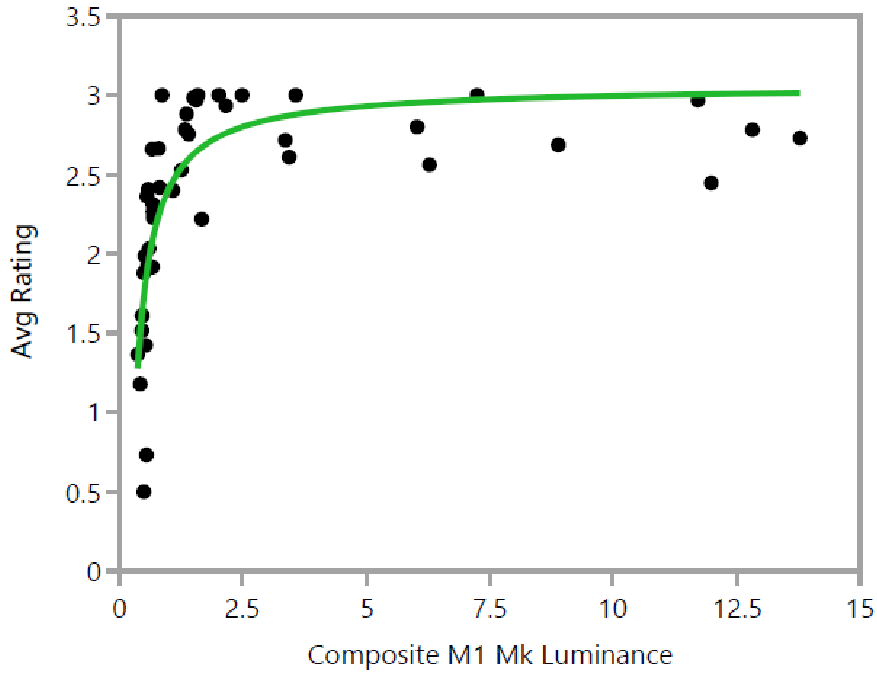

Figure 45. Reciprocal Transformation Average Marking Quality Score vs. Composite M1 Mk Luminance

The residuals, which were used to determine if the model fit assumptions were met or if a variable transformation was appropriate, were often unclear and difficult to use for drawing conclusions about regression models when only one explanatory variable was considered. Therefore, multiple linear regression models were constructed to investigate if a relationship existed between the average marking quality rating and a set of the explanatory variables.

5.2.2 Multiple Linear Regression Models

In a multiple linear regression model, more than one explanatory variable can be considered along with interaction between the explanatory variables when predicting the response variable. From the previous simple regression analysis, it was already determined which of the individual explanatory variables were most correlated with the average marking quality score, so it was expected that these variables would be included in the multiple regression model. The multiple regression models were constructed using the JMP software and all of the explanatory variables were considered for potential inclusion in the model. Since the multiple regression models being fit were exploratory in nature and purpose, the stepwise model construction method was used. This allowed for the inclusion of all the explanatory variables and the creation of multiple regression models including all combinations of the variables. Several model selection criteria were used in order to identify the best multiple regression model fit using the stepwise method. These criteria included the adjusted R^2, root mean square error (RMSE), Mallow's C_p, the predicted error sum of squares, and the Akaike's Information Criterion (AIC_c). Based on these criteria and the inclusion of all explanatory and their potential combinations in a multiple linear regression model, the models with the best fit were identified for both the day and night average marking quality scores. For the daytime condition, the best fit multiple linear regression model according to the stepwise process included the terms Marking Y, Qd (LTL-XL) Marking, and Luminance Ratio as explanatory variables. The prediction expression and model selection criteria are shown below.

$$1.742 + 0.034 * Marking\ Y - 0.012 * Qd(LTL - XL)Marking + 0.364 * Luminance\ Ratio$$

Adjusted R^2	**RMSE**	**C_p**	**PRESS**	**AIC_c**
0.599412	0.308312	8.7463	5.369	28.70717

For the nighttime condition, the best fit multiple linear regression model according to the stepwise process included the terms Marking Y, Qd (LTL-XL) Marking, and Qd (LTL-XL) Contrast as explanatory variables. The prediction expression and model selection criteria are shown below.

$$1.393 + 0.042 * Marking\ Y - 0.017 * Qd(LTL - XL)Marking + 0.785 * Qd(LTL - XL)Contrast$$

Adjusted R^2	**RMSE**	**C_p**	**PRESS**	**AIC_c**
0.42573	0.47839	1.7390	11.4694	67.3660

In order to investigate other potential multiple regression models that could better predict the average marking quality score, separate models were created including variable transformations again using the stepwise regression process. The variable transformations used were logarithmic transformation of the explanatory variables (LogX), logarithmic transformation of the explanatory and response variables (LogLog), and a reciprocal transformation of the explanatory variables (RecipX). The variables included in the best fit models along with their prediction equations and model selection criteria are shown below.

Day

- LogX:

$$3.946 + 0.768 * Log(Marking\ Y) - 1.037 * Log(Qd(LTL - XL)Marking) + 0.790 * Log(Luminance\ Ratio)$$

Adj R^2	**RMSE**	**C_p**	**PRESS**	**AIC_c**
0.799	0.218	4.99	2.37	-1.74

- LogLog:

$$Exp(2.667 + 0.506 * Log(Marking\ Y) + 0.543 * Log(RL(LTL - X)Marking) - 1.252 * Log(Qd(LTL - XL)Marking) - 0.580 * Log(RL(LTL - X)Contrast) + 0.846 * Log(Qd(LTL - XL)Contrast) + 0.453 * Log(Luminance\ Ratio))$$

Adj R^2	**RMSE**	**C_p**	**PRESS**	**AIC_c**
0.815	0.136	5.46	1.15	-38.08

- RecipX:

$$2.765 - 12.39 * \left(\frac{1}{Marking\ Y}\right) + 63.16 * \left(\frac{1}{Qd(LTL - XL)Marking}\right) - 1.23 * \left(\frac{1}{Luminance\ Ratio}\right)$$

Adj R^2	RMSE	C_p	PRESS	AIC_c
0.838	0.195	5.10	1.83	-11.35

Night

- LogX:

$$1.207 + 0.913 * Log(Marking\ Y) - 0.515 * Log(Qd(LTL - XL)Marking) + 0.248 * Log(Luminance\ Ratio)$$

Adj R^2	RMSE	C_p	PRESS	AIC_c
0.584	0.406	0.16	8.39	50.08

- LogLog:

$$Exp(-0.112 + 0.633 * Log(Marking\ Y) - 0.309 * Log(Qd(LTL - XL)Marking) + 0.104 * Log(Luminance\ Ratio))$$

Adj R^2	RMSE	C_p	PRESS	AIC_c
0.568	0.246	0.45	3.33	8.98

- RecipX:

$$3.348 - 14.67 * \left(\frac{1}{MarkingY}\right) - 0.450 * \left(\frac{1}{Composite\ M1\ Mk\ Luminance}\right)$$

Adj R^2	RMSE	C_p	PRESS	AIC_c
0.742	0.320	0.50	5.36	30.53

A few of the transformed multiple regression models appear to produce better fit models according to their adjusted R^2 value than the linear multiple regression models for both the day and night conditions. The best fit models for both the daytime and nighttime conditions use the reciprocal transformation of the explanatory variables which aligns with the previous results for the simple regression models when the reciprocal transformation produced a better fit model for the nighttime condition and a similar quality fit to the cubic regression for the daytime condition.

5.2.3 Correlation Analysis Conclusions

As a result of the correlation analysis it was found that none of the explanatory variables showed a clear linear correlation when compared individually with the average pavement marking quality score assigned by the Mobileye machine vision camera. Applying polynomial fits to the individual explanatory variables resulted in slightly better correlations as expected, but none of the models were overwhelmingly convincing as to their validity. Variable transformations were also investigated, and only reciprocal transformation resulted in comparable or better correlation for relating some of the variables to the average marking quality score. Multiple regression models were more successful in fitting the data as more explanatory variables were included in the analysis. Again, the reciprocal transformation produced the best fit models for both the daytime and nighttime conditions. Further study could be done on the relationship between known pavement marking evaluation characteristics and the pavement marking quality scores assigned by ADAS machine vision as more data becomes available. When performing further analysis, collecting more data from lower quality pavement markings would be useful in determining correlation. This analysis could include investigating the relationship between the pavement marking characteristics and the standard deviation of the marking quality scores instead of the average quality score. Other approaches to constructing regression models could also be explored by combining transformed and non-transformed explanatory variables or interaction terms in the models. As of now the results of the correlation analysis performed appear to be inconclusive in defining a clear model for predicting the average pavement marking quality score assigned by the ADAS machine vision camera based on the eight explanatory variables used in the analysis.

6. APPLICATION ANALYSIS

Some attempts have been made by organizations to include pavement markings in their transportation asset management systems. According to literature review and surveys conducted as a part of other research efforts, only a small percentage of agencies manage pavement markings with a dedicated system. An NCHRP synthesis study received responses where 20 to 25 percent of responding agencies identified a dedicated pavement marking management system or a workbook or spreadsheet (*12*), while in an AASHTO survey published by FHWA 21 of 39 states reported they inventory pavement markings and 26 of 39 monitor condition in some fashion (*17*). Akofio et al. identified from literature review that about 35 percent of the 64 agencies reviewed managed pavement markings. A target survey was sent out to agencies as a follow up to the literature review in order to get a more current state of practice and see if any agencies had expanded their asset management programs. The survey received 18 responses where 10 agencies indicated that they include pavement markings in their asset management efforts (*18*).

Often agencies lack required data to complete asset management systems because the data collection efforts required to create asset inventory and monitor asset condition can be quite challenging. In the studies and surveys mentioned above, visual inspection was the most commonly reported data collection method employed for both asset inventory and condition assessment (*12, 17*, *18*). The vast majority of reporting agencies assess pavement marking conditions at least on an annual basis and all responses indicate the frequency of condition surveys as being less than 5 years apart

(*12*, *17*, *18*). In addition to visual inspections, which provide qualitative evaluations of pavement markings, agencies may also take retroreflectivity measurements to evaluate asset performance.

Effective asset management depends on the type, amount, and quality of data available. For pavement markings, because of reliability and repeatability issues associated with different types of retroreflectometers, developing deterioration models for predicting performance or cost have not been widely accepted and used (*12*). This lack of reliable physical measurements along with the dependence on visual inspection affects the ability of agencies to fully implement an asset management plan for pavement markings. Machine vision data collection directly addresses the issues that currently exist in developing a widespread pavement marking asset management approach. The quality ratings provided by an ADAS machine vision system could be shown as reliable across various conditions with more investigation and data as shown in the data analysis section. The quality scores reliability and repeatability should not change with different operators since the data collection system does not require active input from the driver. Machine vision technology also provides continuous data for pavement marking quality. Pavement marking inventory and condition assessments can be updated real time for a large network of roadways by equipping only a small percentage of agency vehicles with this technology. Since the machine vision system does not require scheduled inventory or condition assessments of the pavement markings, like an approach based on visual inspection or using retroreflectometers, more efficient use of agency resources can be realized while also providing a greater percentage of asset inventory and more up to date condition assessments. Using machine vision technology for pavement marking data collection should improve on the numbers reported in the surveys mentioned previously where responses to Akofio's survey indicated a median value of 50 percent of pavement markings included in agency's asset management programs and in the AASHTO survey only 10 of the 39 responses indicated that all of their pavement marking assets were inventoried and less than 10 responses reported 100 percent coverage of condition monitored while the greatest number of responses indicated no coverage of condition monitored (*17,18*). An ADAS machine vision system also provides data on pavement markings not previously easily available when using only visual inspection and retroreflectometers such as GPS coordinates, marking width, and lane width.

Machine vision technology is easy to integrate and allows for the improvement of current information technology systems and data analysis tools used to support asset management. The most common currently used tools for analysis in pavement marking management are the Microsoft office suite (Excel and Access), Oracle database systems, or GIS interfaces (*12, 18*). The use of these programs indicates a simpler approach to managing pavement markings when compared with other advanced software management systems for bridges and pavements (*18*). Implementing machine vision technology for data collection and condition assessments allows for easy incorporation into a GIS or other map interface for data visualization because the data is geolocated automatically upon collection and hosted on a cloud-based server. Efforts have already been made to create an automatically updating map interface showing pavement marking inventory and conditions as shown in Figure 46.

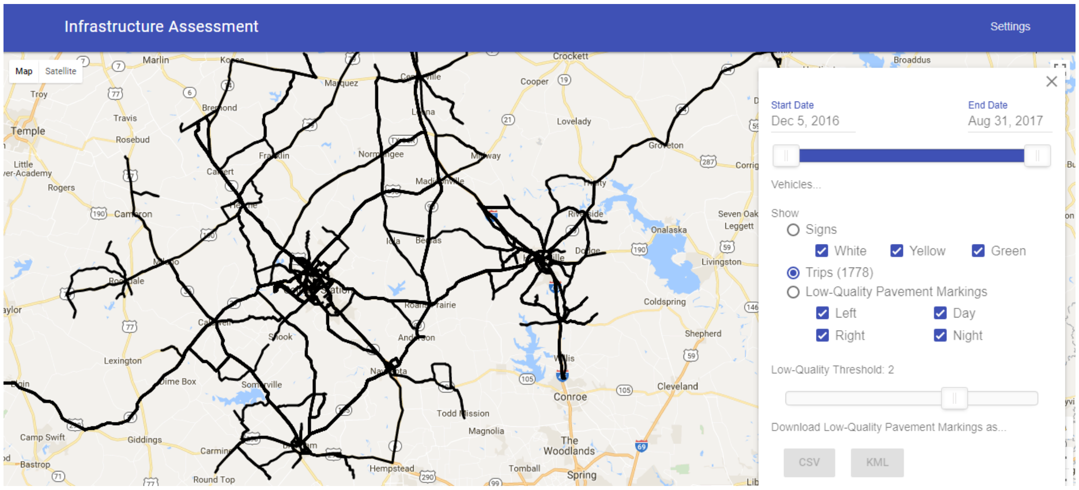

Figure 46. Example Pavement Marking Inventory Map

The pavement marking data could also be incorporated into a more widely used GIS interface with analysis tools which many agencies already use as a part of their transportation asset management programs for managing other infrastructure resources. When data is effectively integrated into a visual system, geographic information could be easily used to efficiently plan maintenance on multiple assets that are in close proximity.

One of the key elements of asset management is using inventory and quantitative condition data to inform the management decision making process for budget and maintenance of an asset. In the current state of pavement marking asset management practice, survey results indicate that the asset inventory and condition assessment are used to a degree in budgeting decisions but are not the primary drivers of budget processes. For both the AASHTO survey and the survey conducted by Markow, less than one-third of responses indicated an approach based on asset performance or asset inventory for funding allocation (*12*, *17*). Instead, most responses indicated using a method based on adjustments to previous budget, while a high percentage also responded that judgment and politics are involved (*12*). These trends in pavement marking asset management could be due to lacking asset inventory as discussed previously and the dependence on qualitative visual inspections. Machine vision technology would remedy these issues by increasing asset inventory and providing quantitative assessments of pavement marking conditions which can be used in budget and maintenance decision making as a part of the pavement marking asset management process.

When considering implementing machine vision technology into an already established pavement marking asset management system or using machine vision to create a new approach to managing pavement marking assets, it is important to understand the potential costs and benefits of such a system. Different approaches exist for evaluating asset management programs. Since asset management programs are often developed in stages one evaluation approach is to use a general scale to classify the maturity level of the system based on its capabilities. AASHTO uses the maturity scale shown in Table 4 as a general classification of transportation asset management system in order to understand the relative position of different processes and determine next steps to improve (*19*). This scale is most useful in understanding the potential span of improvement that is possible in asset management but is not necessarily an explicit definition of levels used to track improvement.

Table 4. AASHTO Transportation Asset Management Maturity Scale

Transportation Asset Management (TAM) Maturity Scale Level	Generalized Description
Initial	No effective support from strategy, processes, or tools. There can be lack of motivation to improve.
Awakening	Recognition of a need and basic data collection. There is often reliance on heroic effort of individuals.
Structured	Shared understanding, motivation, and coordination. Development of processes and tools.
Proficient	Expectations and accountability drawn from asset management strategy, processes, and tools
Best Practice	Asset management strategies, processes, and tools are routinely evaluated and improved.

Markow also applies a scale that evaluates the different aspects of an asset management system as listed in Table 5 by placing them into one of three general stages of maturity: basic infrastructure management, growing application of asset management, or state-of-the-art asset management (*20*). Each aspect of asset management has different criteria for being placed in the three general stages of maturity.

Table 5. Aspects of Infrastructure Asset Management Evaluated for Maturity

Aspect of Infrastructure Management
Overall Description of Agency Practice
Policy Guidance
Asset Life-Cycle Focus
Asset Performance and Costs
Impacts of Asset Performance
Resource Allocation, Budgeting, and Project Selection
Organization
Performance Measurement
IT and Data Collection and Processing

Implementing machine vision technology for pavement marking management as part of a transportation asset management system undoubtedly moves an asset management system up on either maturity scale. The machine vision technology and associated data processing systems, at minimum, would fall in the structured category on the AASHTO scale and if properly applied would result in a best practice maturity level. Using machine vision for pavement marking quality data collection falls in the IT and Data Collection and Processing aspect of infrastructure asset management in the scale outlined by Markow in NCHRP 371. The state-of-the-art asset management maturity level for the IT and Data Collection and Processing aspect describes multiple capabilities that should present in the asset management system. These capabilities include: a mix of technology used for data collection including automated measurement systems, data organized on an integrated platform accessible internally and potentially externally, data updated on an established schedule or criteria, and data coverage is high and cost effective. Using machine vision to collect pavement marking quality data and the associated data organization structure meets all of the capabilities required of an asset management system functioning at a state-of-the-art maturity level for the IT and Data Collection and Processing category. The more mature an asset management system is, the more benefits will be realized. When more assets are managed at a higher maturity level, as pavement markings would be with the utilization of machine vision technology, synergistic effects could also be realized, resulting in improved management of other transportation assets and the overall performance of the infrastructure management system.

Another method used to more quantitatively evaluate the costs and benefits of asset management systems and practices is to perform a benefit cost analysis. Benefit cost analysis can be performed for an entire transportation asset management system, the inclusion of a new asset to be managed, or for the implementation of a new technology, practice, or method for managing assets. Machine vision technology used for pavement marking asset management can be incorporated into an existing transportation asset management system that is already managing pavement markings using other methods, it can be used to add pavement markings into an infrastructure asset management system that is not currently managing pavement markings, or it can be used to create a stand-alone asset management system focused only on pavement markings. Ideally, for a benefit cost analysis two scenarios would be compared, in this case one asset management system would implement machine vision for managing pavement markings, while the other would not. The challenge in performing a benefit cost analysis for using machine vision technology for pavement marking asset management comes when attempting to quantify the benefits directly attributable to the machine vision technology. In an asset management system not currently managing pavement markings or managing pavement markings at low maturity level, implementing machine vision technology could have a synergistic effect resulting in potential benefits or costs for other assets being managed as the scope and maturity level of the asset management system increases. Also quantifying benefits for managing pavement markings using machine vision technology would be difficult as the performance of the machine vision system's outputs could be dependent on the maturity level of the asset management system in which the technology is implemented.

When taking these challenges into consideration the decision was made to do a cost comparison between using the repurposed ADAS machine vision system developed by TTI and costs reported in literature for pavement marking data collection. Finding costs for current pavement marking data collection methods proved to be difficult with the only costs coming from Akofio et al. and Sitzabee. In response to a survey sent out to numerous agencies by Akofio only one response indicated a cost for pavement marking data collection which was $4 per lane mile (*18*). The other cost for pavement marking data collection is specific to retroreflectivity data collection in North Carolina where a cost of $200,000 was reported by Sitzabee to collect data used in pavement marking asset management on approximately ten percent of the roadways (*11*). In 2013, North Carolina reported having 225,168 lane miles of roadway, so the cost to collect data on approximately 22,520 lane miles would be $8.88 per lane mile.

The costs for implementing machine vision technology for pavement marking quality data collection come from the pilot program where TTI installed ADAS machine vision units into TxDOT fleet vehicles and developed a hosting system for data storage. The costs for each component of the program are shown in Table 6.

Table 6. Machine Vision Component Costs

Component	Cost
Unit	$3,000/Unit
Install	$400/Unit
Cellular Data	$50/Unit
Hosting	$1,400/Month
Tech Services	$3,600/Month
Analysis and Development	$120/Hour

Four units were installed as a part of the program, and for this analysis costs were calculated over an operating period of only six months. The component and services cost assumptions come from a benefit cost analysis report prepared by TTI for the implementation of high-speed remote-sensing highway infrastructure technology on a large scale for TXDOT. The main assumptions made which affected the cost calculations were that the hosting and tech services components scaled linearly for the number of units being installed while the analysis and development hourly cost is not dependent on the number of units or timeframe. The benefit cost analysis performed by TTI assumed one hundred units would be implemented versus the four used for this cost comparison. These assumptions resulted in the total cost estimate shown in Table 7 for implementing and operating the machine vision technology over a six-month period.

Table 7. Total Cost Estimate for Machine Vision System

Component	Cost	Units	Months or Hours	Total Component Cost
Unit	$3,000/Unit	4	-	$ 12,000
Install	$400/Unit	4	-	$ 1,600
Cellular Data	$50/Unit/Month	4	6	$ 1,200
Hosting	$1,400/Month	4	6	$ 336
Tech Services	$3,600/Month	4	6	$ 864
Analysis and Development	$120/Hour	-	1040	$ 124,800
			Total Cost	**$140,800**

In order to compare the cost of using machine vision technology to collect pavement marking quality data to the current practices used for pavement marking quality data collection in asset management, the number of miles of roadway covered by the vehicles equipped with machine vision needed to be determined. A map showing the approximate coverage area of the four equipped vehicles was shown in Figure 47. The data file recorded for each trip made by a machine vision equipped vehicle contains the total distance traveled; these distances were recorded for a six-month period resulting in the total distances traveled shown in Table 8.

Table 8. Distance Traveled by Machine Vision Equipped Vehicles

Vehicle ID	Trips	Miles
TxDOT_4407K	440	12,153
TxDOT_4408K	39	465
TxDOT_4754K	747	6,908
TxDOT_5756K	888	9,700
	Total Miles	**29,226**

The machine vision equipped vehicles covered over 29,000 miles of road, assigning pavement marking quality scores for the markings on both sides of the vehicle resulting in almost 60,000 miles of pavement markings receiving quality assessment. When compared to the total implementation and operating cost of $140,800 the result is a cost of $4.82 per mile. This value is similar to the cost for pavement marking data collection of $4 per mile reported in the survey conducted by Akofio and is less than half of the $8.88 per lane mile cost for collecting pavement marking retroreflectivity data in North Carolina. The $4.82 per lane mile does not take into account any benefits that could result in cost savings in other ways by using machine vision technology for data collection and also assumes a high number of hours for the Analysis and Development component resulting in a most likely very conservative cost estimate over a six-month period.

There are several potential benefits that if included in a benefit cost analysis would lower the overall cost associated with the pavement marking data collection process. These benefits were not included in the cost comparison calculation above due to lack of data and information regarding specific maintenance and data collection practices for the area the pilot program was implemented. The benefits resulting in cost savings from implementing machine vision technology for pavement marking data collection can be placed into three main categories: human capital efficiency, maintenance efficiency, and equipment efficiency. One of the main anticipated benefits is improved efficiency for agency employees especially those tasked with pavement marking and roadway signage inspection and repair. These employees spend a significant portion of their time driving in order to perform visual inspections. Visual inspections must be performed at night which poses difficulties for personnel. With the implementation of machine vision data collection inspection efficiency is expected to increase, allowing for greater productivity from a large number of employees. Future savings could also be realized as the need for adding inspection focused employees would decrease with the adoption of more machine vision data collection methods. Another area expected to benefit from machine vision data collection is maintenance of pavement markings. Current pavement marking maintenance plans are often based on using cyclical schedules usually requiring restriping of markings every other year in order to ensure safety standards are properly met. This practice does not take into account the condition of the pavement markings. By using machine vision technology to collect quantifiable pavement marking quality data, the condition of the markings can be taken into account when making maintenance decisions allowing for longer periods between restriping versus the current practices. Even if striping efficiency only increases by a small percentage large cost savings will be realized because of the expansive network of pavement markings that must be maintained. The last main potential benefit area is increased equipment efficiency for agency fleet vehicles. With the implementation of machine vision technology, data collection for pavement markings and other roadway infrastructure such as signs can be performed by many types of agency vehicles instead of those dedicated to only inspections. This leads to reduced inspection vehicle usage which when coupled with increased inspection efficiency will result in fewer miles traveled by inspection vehicles. The benefit of fewer miles traveled is realized in vehicle operating cost savings and environmental cost savings. Fewer miles traveled means less maintenance and longer service times before replacement of inspection vehicles along with reduced emissions from inspection vehicles. There is still potential for other benefits outside of the three main categories when machine vision technology is implemented for data collection. Potential safety benefits from quantifiable pavement marking quality data are difficult to evaluate but could be realized by replacing deficient markings sooner because of machine vision collected data. Another final benefit is the data being collected. This data could be useful to companies researching and testing autonomous vehicles. The data could be used to create maps with optimal paths for autonomous vehicle travel based on the quality of pavement markings available to assist with navigation.

Machine vision technology provides a potentially reliable and cost-effective method for collecting pavement marking quality data. Implementing machine vision technology in transportation asset management will improve current practices allowing for more effective management of infrastructure resources. Benefits and cost savings will be realized by transportation agencies as a result of using machine vision technology for data collection and from the quantifiable pavement marking quality data that is collected.

7. CONCLUSIONS AND RECOMMENDATIONS

The potential of machine vision technology in transportation is evident. Whether the technology is applied to data collection and asset management or other uses such as navigation, it is a part of the future and the present. Using machine vision in transportation asset management specifically for pavement markings has numerous applications in data collection and analysis. If the machine vision technology is accurate, reliable, and fully understood many benefits could be realized. Being able to incorporate machine vision technology in pavement marking asset management provides potential cost savings, safety improvements, and the potential for a standardized quantitative evaluation method.

As a result of this study it was determined that the ADAS machine vision camera was mostly reliable under each individual data collection condition but was not necessarily reliable when comparing data between all of the data collection conditions. This would mean that when applying machine vision collected data to asset management decision-making, criteria would need to be established for evaluating the quality scores assigned to the markings by the machine vision based on what the collection conditions were. Also, from the study an acceptable correlation could not be established between current pavement marking evaluation characteristics and the machine vision quality scores. The pavement marking characteristics that were investigated for a correlation with the machine vision quality scores included retroreflectivity, luminance, and contrast. Not being able to relate the machine vision quality scores to established pavement marking evaluation characteristics means that exactly what the ADAS machine vision is evaluating is not fully understood. In order to fully rely on machine vision for data collection that could be used in pavement marking asset management decision-making, it is desirable that evaluation methods and criteria of the machine vision technology are more fully known and quantifiable. To achieve this level of understanding and confidence in the ADAS machine vision quality scores much more data must be collected under a wider variety of conditions so that the machine vision quality scores can be analyzed and understood on their own or another attempt must be made to establish a relationship between the ADAS machine vision quality scores and other pavement marking evaluation characteristics.

From this study it is recommended that further investigation be done into both the repeatability of the ADAS machine vision quality scores and the correlation of the quality scores to established pavement marking evaluation characteristics. Using machine vision repurposed from an ADAS system may not be the most effective method of evaluating pavement marking quality with machine vision technology. Machine vision has a wide range of capabilities outside of ADAS and can be tuned to specific functions such as pavement marking evaluation. Machine vision technology can allow for expansion of the current scope of most transportation asset management systems to include pavement markings by improving data collection and evaluation practices. Expansion beyond pavement markings is also possible for the use of machine vision technology in asset management to include signs and other transportation infrastructure. Other potential uses also exist for machine vision collected pavement marking data outside of asset management. This data could also be used for autonomous vehicle routing and mapping of quality pavement markings. The benefits of using machine vision technology for pavement marking evaluation and data collection warrant further study.

7.1 Limitations of the Work

This study provided valuable insights into the ability of a machine vision camera operating as part of an Advanced Driver Assistance System (ADAS) to be used for collecting pavement marking quality information. However, there are several limitations to the work and the conclusions drawn from it. One of the most significant limitations is that only one machine vision system was used for collecting the pavement marking quality data. By using only the Mobileye unit, the conclusions drawn from the results of the study are limited by the capabilities of this system. The quality score output from the Mobileye system is a limited measurement. There could be other proprietary background data available from the machine vision system that is not currently an available output but would offer more information as to how the machine vision camera is evaluating the pavement marking quality score. Since the time of the data collection in 2016 there may have been updates to the Mobileye system or other ADAS machine vision technologies with different capabilities that have emerged. The field of machine vision technology is much broader and has more capabilities than what is represented in this study. This should be considered when evaluating and applying the conclusions of this research.

Other limitations of the work include not collecting any pavement marking characteristic data for the lane markings in the open road scenario and not considering the color of the pavement markings in the correlation or repeatability analysis. By not collecting pavement marking characteristics for the open road scenario, correlation analysis could not be performed for the data collected in this scenario. Also, the pavement marking characteristics could not be compared with the data from the closed course markings which could have provided more insight to the effects of pavement type, retroreflectivity, and luminance on the machine vision quality scores. Color is an important characteristic that was not considered in any of the analysis. The difference in yellow and white markings and how they are evaluated by the machine vision camera is important to understand but is not investigated as a part of this research.

As a part of future work related to research seeking to understand the repeatability of machine vision quality scores and establish a correlation between the quality scores and other pavement marking characteristics, it will be important to include multiple machine vision systems, collect pavement marking characteristics on open road lane markings, and investigate the effects of pavement marking color on the machine vision quality scores.

REFERENCES

1. SAE International. *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*. Recommended Practice J3016. Warrendale, PA, 2018.
2. National Highway Traffic Safety Administration, Department of Transportation. *Federal Motor Vehicle Safety Standard, Rearview Mirrors*. 49 CFR Parts 571 and 585. 2010
3. Zhang, Y., H. Ge, A. Pike, and P. Carlson. *Development of Field Performance Evaluation Tools and Program for Pavement Marking Materials: Technical Report*. Research Report No. 0-5548-1. Texas A&M Transportation Institute, Texas A&M University, College Station, Texas, 2011.
4. Zhang, Y, and H. Ge. Assessment of Presence Conditions of Pavement Markings with Image Processing. In Transportation Research Record: Journal of the Transportation Research Board, No. 2272, TRB, National Research Council, Washington, D.C., 2012, pp. 94-102.
5. ASTM International. *Standard Test Method for Measurement of Retroreflective Pavement Marking Materials with CEN-Prescribed Geometry Using a Portable Retroreflectometer*. Designation E1710-11. West Conshohocken, PA, 2011.
6. Wang, J.H., and Y. Cao. *Effects of Road Marking Luminance Contrast on Driving Safety*. Research Report No. FHWA-RIDOT-RTD-04-1. Rhode Island Department of Transportation, Providence, RI, 2004.

7. ASTM International. *Standard Test Method for Measurement of the Luminance Coefficient Under Diffuse Illumination of Pavement Marking Materials Using a Portable Reflectometer*. Designation E2302-03a. West Conshohocken, PA, 2016.
8. ASTM International. *Standard Practice for Use of the Terms Precision and Bias in ASTM Test Methods*. Designation E177-14. West Conshohocken, PA, 2014.
9. ASTM International. *Standard Practice for Conducting an Interlaboratory Study to Determine the Precision of a Test Method*. Designation E691-16. West Conshohocken, PA, 2016.
10. Asset Management Primer. Federal Highway Administration, Washington D.C., 1999.
11. Sitzabee, W.E., W. Rasdorf, J.E. Hummer, and H.A. Devine. Data Integration of Pavement Markings: A Case in Transportation Asset Management. *Journal of Computing in Civil Engineering*, Vol. 23, No. 5, 2009, pp. 288-298.
12. Markow, M.J. Current Asset Management Practices Applied to Pavement Markings. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2055*, TRB, National Research Council, Washington, D.C., 2008, pp. 78-86.
13. Hillel, A.B., R. Lerner, D. Levi, and G. Raz. Recent Progress in Road and Lane Detection – A Survey. *Machine Vision and Applications*, Vol. 25, No. 3, 2014, pp. 727-745.

14. Yenikaya, S., G. Yenikaya, and E. Duven. Keeping the Vehicle on the Road – A Survey on On-Road Lane Detection Systems. *ACM Computing Surveys*, Vol. 46, No. 1, 2013.

15. Autonomous Stuff. MobilEye Startup Guide. Version 1.4. 2015

16. Davies,

17. Hensing, D.J., and S. Rowshan. *Roadway Safety Hardware Asset Management Systems Case Studies*. Research Report No. FHWA-HRT-05-073. Office of Safety R&D Federal Highway Administration. Washington D.C., 2005.

18. Akofio-Sowah, M.A., R. Boadi, A. Amekudzi, and M. Meyer. Managing Ancillary Transportation Assets: The State of the Practice. *Journal of Infrastructure Systems,* Vol. 20, No. 1, 2014.

19. AASHTO. *Transportation Asset Management Guide: A Focus on Implementation.* Publication No. FHWA-HIF-13-047. FHWA, U.S. Department of Transportation, Washington D.C., 2001.

20. National Cooperative Highway Research Program. *Managing Selected Transportation Assets: Signals, Lighting, Signs, Pavement Markings, Culverts, and Sidewalks.* NCHRP 371. Transportation Research Board. Washington, D.C., 2007.

APPENDIX A

OPEN ROAD REPEATABILITY

Appendix A contains an example of the data used in the Open Road Repeatability analysis along with the summary data for each lane marking and observation condition, including calculated repeatability standard deviations.

		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	A21	A22	A23	A24	A25	A26	A27	A28	A29	A30
LEFT A	0.05	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.10	3	3	3	2.966667	3	3	3	3	2.896552	3	3	2.965517	3	2.933333	2.965517	3	2.966667	3	2.947368	3	3	3	3	2.793103	2.933333	3	2.965517	2.931034	3	2.758621
	0.15	3	3	3	3	3	3	2.344828	3	3	3	2.285714	3	3	2.714286	3	3	2.206897	3	2.236842	3	3	3	3	2.448276	3	3	3	3	2.655172	2.758621
	0.20	3	2.724138	3	2.678571	2.965517	3	2.666667	3	2.892857	3	2	2.827586	3	2.964286	2.964286	3	2.814815	3	2.714286	3	2.964286	2.678571	3	2.964286	2.931034	3	2.857143	2.964286	2	2.842105
	0.25	3	2.892857	3	2.678571	2.892857	3	3	3	3	3	2.892857	3	3	3	3	2.892857	3	3	3	3	2.892857	2.964286	2.962963	3	2.928571	3	3	2.962963	2.75	2.964286
	0.30	3	3	3	2.785714	3	3	3	3	3	3	3	2.947368	3	3	2.962963	3	3	3	3	3	3	3	2.965517	3	3	3	3	3	2.964286	2.928571
	0.35	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.40	2.931034	3	2.758621	2.931034	2.758621	3	2.62069	2.655172	2.821429	2.931034	2.785714	2.862069	2.785714	2.931034	2.928571	3	2.894737	3	2.931034	2.923077	2.821429	2.921053	2.965517	3	2.965517	3	2.758621	3	3	2.793103
	0.45	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.50	3	3	3	3	3	3	3	3	3	2.666667	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.55	2.766667	3	3	3	3	3	3	3	3	2.25	2.724138	2.7	2.758621	3	2.621622	3	3	2.714286	3	3	3	3	2.62069	3	3	2.357143	3	3	3	2.896552
	0.60	2.37037	3	3	3	3	3	3	3	3	3	2.666667	2.740741	2.703704	3	3	3	3	2.75	3	3	3	3	2.814815	3	3	3	3	3	3	2.423077
	0.65	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.70	2.8	2.793103	2.933333	3	3	3	3	2.25	2.8	2.827586	2.482759	2.655172	2.448276	2.9	2.384615	3	2.931034	3	2.966667	2.933333	2.413793	2.965517	2.413793	2.482759	2.7	2.448276	2.62069	2.758621	2.862069	3
	0.75	3	3	3	3	3	3	3	2.933333	3	3	2.897436	3	2.7	3	3	3	3	3	3	2.655172	2	2.833333	2.566667	2	3	2.586207	3	2	3	3
	0.80	3	3	3	3	3	3	3	3	3	2.904762	3	2.818182	3	3	3	2.785714	3	3	3	2	2.5625	2	2.764706	2	3	2	3	2.826087	2.642857	3
	0.85	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	0.90	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	0.95	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.00	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.05	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.10	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.15	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.20	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!

		B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20	B21	B22	B23	B24	B25	B26	B27	B28	B29	B30
LEFT B	0.05	2.775	2.9	2.9	2.925	2.975	2.875	2.394737	2.5	2.875	2.675	2.825	2.853659	2.775	2.925	2.575	2.9	2.974359	2.461538	3	2.55	2.780488	2.75	2.925	2.85	2.975	3	2.25	2.947368	2.658537	2.825
	0.10	3	3	3	3	3	2.833333	2.821429	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.15	3	3	2.321429	3	2.962963	2.464286	3	3	2.285714	3	2.482759	3	2.571429	3	2.888889	3	3	3	3	3	2.551724	3	3	3	2.964286	3	2.964286	3	3	3
	0.20	3	3	2.678571	3	3	3	3	3	2.551724	3	3	3	3	3	2.678571	3	3	3	3	3	3	3	3	3	3	2.928571	2.758621	3	3	3
	0.25	3	3	3	3	3	3	3	3	3	2.964286	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2.964286	3	3	3	3	3
	0.30	3	3	3	3	3	3	3	3	3	3	3	2.933333	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.35	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.40	3	2.931034	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.45	2.551724	2.035714	3	2.285714	2.586207	3	3	2.259259	2.5	2.703704	3	3	3	3	3	2.178571	2.947368	3	2.678571	2.37931	2.571429	2.5	3	2.555556	2.464286	3	2.392857	3	3	2.482759
	0.50	3	3	3	3	2.481481	3	3	3	2.75	3	3	3	3	3	3	2.444444	3	3	3	3	2.964286	3	3	3	3	3	3	3	3	2.481481
	0.55	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.60	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0.65	3	3	3	3	3	3	3	2.933333	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2.965517	3	3	3
	0.70	2.733333	3	3	3	2.896552	3	2.714286	2.551724	3	2.9	2.833333	3	2.551724	2.689655	2.105263	2.206897	2.206897	3	2.724138	3	3	2.35	3	2.862069	3	2.5	2.75	2.933333	2.241379	3
	0.75	3	2.965517	3	2.964286	2.178571	3	2	2.75	3	3	2.857143	3	3	3	2.178571	2.892857	2.285714	3	2.178571	3	3	2.642857	2.428571	3	3	2.964286	3	3	2	3
	0.80	3	3	3	3	2.695652	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2.944444	3
	0.85	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	0.90	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	0.95	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.00	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.05	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.10	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.15	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
	1.20	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!

Figure A-1. Example Data Collected for Open Road Repeatability Analysis

	A Day		B Day			
	mean	stdev	mean	stdev	avg mean	sr
0.05	3	0	2.786523	0.195365	2.893261	0.138144
0.10	2.967441	0.059357	2.988492	0.043823	2.977967	0.052171
0.15	2.855021	0.26804	2.881925	0.228023	2.868473	0.248837
0.20	2.847157	0.256489	2.953202	0.118212	2.90018	0.199701
0.25	2.955864	0.07772	2.997619	0.009061	2.976742	0.055329
0.30	2.985147	0.04194	2.997778	0.012172	2.991463	0.030879
0.35	3	0	3	0	3	0
0.40	2.889161	0.108429	2.997701	0.012591	2.943431	0.077186
0.45	3	0	2.702434	0.308657	2.851217	0.218253
0.50	2.988889	0.060858	2.93739	0.165315	2.963139	0.124565
0.55	2.880324	0.203782	3	0	2.940162	0.144095
0.60	2.915646	0.174071	3	0	2.957823	0.123086
0.65	3	0	2.996628	0.013509	2.998314	0.009552
0.70	2.759047	0.237744	2.758353	0.288653	2.7587	0.264426
0.75	2.839072	0.312593	2.776232	0.351572	2.807652	0.332654
0.80	2.81016	0.342981	2.988003	0.056139	2.899082	0.245751

	A Night		B Night			
	mean	stdev	mean	stdev	avg mean	sr
0.05	3	0	2.949877	0.183457	2.974939	0.129724
0.10	2.952279	0.21265	2.986328	0.07734	2.969304	0.160002
0.15	2.964718	0.199587	2.988092	0.039899	2.976405	0.143921
0.20	2.985846	0.064297	2.902069	0.157925	2.943958	0.12057
0.25	2.990517	0.027462	2.956048	0.174545	2.973282	0.12494
0.30	2.936673	0.113193	2.986328	0.07185	2.9615	0.094802
0.35	2.943746	0.110669	2.996094	0.022097	2.96992	0.079799
0.40	2.987084	0.043223	2.997159	0.016071	2.992122	0.032607
0.45	3	0	2.998494	0.005927	2.999247	0.004191
0.50	3	0	2.867692	0.185656	2.933846	0.131279
0.55	2.957	0.112066	3	0	2.9785	0.079243
0.60	2.974569	0.069449	3	0	2.987284	0.049108
0.65	3	0	2.998512	0.008418	2.999256	0.005952
0.70	2.979994	0.069288	2.959249	0.117285	2.969622	0.096324
0.75	2.99858	0.008035	2.944344	0.171714	2.971462	0.121553
0.80	2.991776	0.04652	2.96875	0.176777	2.980263	0.129256

	A Overcast		B Overcast			
	mean	stdev	mean	stdev	avg mean	sr
0.05	3	0	2.824697	0.210252	2.912349	0.148671
0.10	2.987482	0.030201	2.990287	0.047299	2.988884	0.039682
0.15	2.913793	0.227124	2.880419	0.216701	2.897106	0.221974
0.20	2.952865	0.117492	2.981481	0.10143	2.967173	0.109755
0.25	2.985539	0.049391	2.995232	0.015738	2.990386	0.036655
0.30	3	0	2.996736	0.009964	2.998368	0.007046
0.35	3	0	3	0	3	0
0.40	2.937189	0.1151	2.997778	0.012172	2.967484	0.081842
0.45	3	0	2.887288	0.230966	2.943644	0.163318
0.50	3	0	2.984436	0.07253	2.992218	0.051286
0.55	3	0	3	0	3	0
0.60	3	0	3	0	3	0
0.65	3	0	2.996552	0.018887	2.998276	0.013355
0.70	2.937597	0.156279	2.940561	0.117922	2.939079	0.138436
0.75	2.995838	0.023175	3	0	2.997919	0.016387
0.80	2.962404	0.100494	2.996818	0.012123	2.979611	0.071575

Figure A-2. Lane Marking 1 Summary Data

	C Day		D Day			
	mean	stdev	mean	stdev	avg means	sr
0.05	2.170661	0.268241	2.60345	0.418493	2.387056	0.351489
0.10	2.466378	0.477719	2.962957	0.087187	2.714667	0.343378
0.15	2.670226	0.437692	3	0	2.835113	0.309495
0.20	2.861472	0.291125	3	0	2.930736	0.205857
0.25	2.977679	0.126269	3	0	2.988839	0.089286
0.30	3	0	3	0	3	0
0.35	3	0	2.976293	0.134106	2.988147	0.094828
0.40	3	0	2.983994	0.090544	2.991997	0.064024
0.45	3	0	3	0	3	0
0.50	3	0	3	0	3	0
0.55	3	0	3	0	3	0
0.60	3	0	3	0	3	0
0.65	3	0	3	0	3	0
0.70	3	0	3	0	3	0
0.75	3	0	3	0	3	0
0.80	2.998494	0.008519	3	0	2.999247	0.006024
0.85	2.994612	0.030479	3	0	2.997306	0.021552
0.90	3	0	3	0	3	0
0.95	3	0	3	0	3	0
1.00	3	0	3	0	3	0
1.05	3	0	3	0	3	0
1.10	3	0	3	0	3	0
1.15	3	0	3	0	3	0

	C Night		D Night			
	mean	stdev	mean	stdev	avg means	sr
0.05	3	0	3	0	3	0
0.10	3	0	3	0	3	0
0.15	3	0	3	0	3	0
0.20	3	0	3	0	3	0
0.25	3	0	3	0	3	0
0.30	3	0	3	0	3	0
0.35	3	0	2.979472	0.114294	2.989736	0.080818
0.40	3	0	2.993768	0.025212	2.996884	0.017828
0.45	3	0	2.98503	0.064626	2.992515	0.045698
0.50	3	0	3	0	3	0
0.55	3	0	2.979211	0.115746	2.989606	0.081845
0.60	3	0	2.994067	0.022968	2.997033	0.016241
0.65	3	0	2.998045	0.010885	2.999022	0.007697
0.70	3	0	2.994307	0.031695	2.997154	0.022412
0.75	3	0	2.983382	0.056874	2.991691	0.040216
0.80	3	0	3	0	3	0
0.85	3	0	2.99609	0.02177	2.998045	0.015394
0.90	3	0	3	0	3	0
0.95	3	0	3	0	3	0
1.00	3	0	3	0	3	0
1.05	3	0	3	0	3	0
1.10	3	0	2.989247	0.049823	2.994624	0.03523
1.15	3	0	2.993326	0.03716	2.996663	0.026276

	C Low Sun	
	mean	stdev
0.05	2.517651	0.405722
0.10	2.811966	0.378186
0.15	2.871533	0.318649
0.20	2.934296	0.224473
0.25	2.991667	0.045644
0.30	3	0
0.35	3	0
0.40	3	0
0.45	3	0
0.50	3	0
0.55	3	0
0.60	3	0
0.65	3	0
0.70	3	0
0.75	3	0
0.80	3	0
0.85	3	0
0.90	3	0
0.95	3	0
1.00	3	0
1.05	3	0
1.10	3	0
1.15	3	0

Figure A-3. Lane Marking 2 Summary Data

	A Day		C Day			
	mean	stdev	mean	stdev	avg means	sr
0.05	3	0	3	0	3	0
0.10	3	0	3	0	3	0
0.15	3	0	3	0	3	0
0.20	3	0	3	0	3	0
0.25	3	0	3	0	3	0
0.30	3	0	3	0	3	0
0.35	3	0	3	0	3	0
0.40	3	0	3	0	3	0
0.45	3	0	3	0	3	0
0.50	3	0	3	0	3	0
0.55	3	0	3	0	3	0
0.60	3	0	3	0	3	0
0.65	3	0	3	0	3	0
0.70	3	0	3	0	3	0
0.75	3	0	3	0	3	0
0.80	3	0	3	0	3	0
0.85	3	0	2.996498	0.019811	2.998249	0.014009
0.90	3	0	3	0	3	0
0.95	3	0	3	0	3	0
1.00	3	0	3	0	3	0
1.05	3	0	3	0	3	0
1.10	2.997596	0.013598	3	0	2.998798	0.009615
1.15	3	0	3	0	3	0

	A Night		C Night			
	mean	stdev	mean	stdev	avg means	sr
0.05	3	0	3	0	3	0
0.10	3	0	3	0	3	0
0.15	3	0	3	0	3	0
0.20	3	0	2.996124	0.02123	2.998062	0.015012
0.25	3	0	3	0	3	0
0.30	3	0	3	0	3	0
0.35	3	0	3	0	3	0
0.40	3	0	3	0	3	0
0.45	3	0	2.99899	0.005533	2.999495	0.003912
0.50	2.996774	0.017668	3	0	2.998387	0.012493
0.55	3	0	3	0	3	0
0.60	3	0	2.994118	0.032219	2.997059	0.022782
0.65	3	0	2.996774	0.017668	2.998387	0.012493
0.70	3	0	3	0	3	0
0.75	3	0	2.994697	0.029046	2.997348	0.020539
0.80	3	0	2.999187	0.004453	2.999593	0.003149
0.85	3	0	3	0	3	0
0.90	3	0	3	0	3	0
0.95	3	0	3	0	3	0
1.00	3	0	3	0	3	0
1.05	3	0	3	0	3	0
1.10	3	0	3	0	3	0
1.15	3	0	3	0	3	0

	A Low Sun		C Low Sun			
	mean	stdev	mean	stdev	avg means	sr
0.05	2.900122	0.299248	3	0	2.950061	0.2116
0.10	2.968966	0.124938	3	0	2.984483	0.088344
0.15	3	0	3	0	3	0
0.20	3	0	3	0	3	0
0.25	3	0	3	0	3	0
0.30	3	0	3	0	3	0
0.35	3	0	3	0	3	0
0.40	2.923031	0.131782	3	0	2.961515	0.093184
0.45	3	0	3	0	3	0
0.50	3	0	3	0	3	0
0.55	3	0	3	0	3	0
0.60	3	0	3	0	3	0
0.65	3	0	3	0	3	0
0.70	3	0	3	0	3	0
0.75	3	0	3	0	3	0
0.80	3	0	3	0	3	0
0.85	3	0	3	0	3	0
0.90	3	0	3	0	3	0
0.95	3	0	3	0	3	0
1.00	3	0	3	0	3	0
1.05	3	0	3	0	3	0
1.10	2.995699	0.023558	3	0	2.997849	0.016658
1.15	3	0	3	0	3	0

Figure A-4. Lane Marking 3 Summary Data

	A Day		B Day			
	mean	stdev	mean	stdev	avg means	sr
0.05	2.767122	0.406105	3	0	2.8835609	0.28716
0.10	2.901506	0.252661	3	0	2.9507528	0.178658
0.15	2.99442	0.031567	3	0	2.9972098	0.022321
0.20	3	0	3	0	3	0
0.25	3	0	2.996774	0.017961	2.9983871	0.0127
0.30	3	0	3	0	3	0
0.35	2.970833	0.164992	3	0	2.9854167	0.116667
0.40	2.96875	0.176777	3	0	2.984375	0.125
0.45	2.969828	0.170681	3	0	2.9849138	0.12069
0.50	3	0	3	0	3	0
0.55	3	0	3	0	3	0
0.60	2.998922	0.006096	3	0	2.9994612	0.00431
0.65	2.890724	0.295816	2.983871	0.089803	2.9372976	0.2186
0.70	2.875	0.336011	2.982796	0.095789	2.9288978	0.247062
0.75	2.948008	0.186179	3	0	2.9740042	0.131649
0.80	2.96875	0.176777	3	0	2.984375	0.125
0.85	2.986842	0.074432	3	0	2.9934211	0.052632
0.90	3	0	3	0	3	0
0.95	3	0	3	0	3	0
1.00	3	0	3	0	3	0
1.05	3	0	3	0	3	0
1.10	3	0	3	0	3	0
1.15	3	0	3	0	3	0

	A Night		B Night			
	mean	stdev	mean	stdev	avg means	sr
0.05	3	0	3	0	3	0
0.10	3	0	3	0	3	0
0.15	2.975556	0.133888	2.998534	0.008164	2.9870446	0.094849
0.20	2.9825	0.095851	3	0	2.99125	0.067777
0.25	3	0	2.987748	0.053873	2.9938742	0.038094
0.30	3	0	2.98827	0.051114	2.9941349	0.036143
0.35	3	0	2.996416	0.019956	2.9982079	0.014111
0.40	3	0	3	0	3	0
0.45	3	0	3	0	3	0
0.50	3	0	3	0	3	0
0.55	3	0	2.999022	0.005443	2.9995112	0.003848
0.60	3	0	2.997067	0.016328	2.9985337	0.011545
0.65	3	0	2.998534	0.008164	2.9992669	0.005773
0.70	3	0	3	0	3	0
0.75	3	0	3	0	3	0
0.80	3	0	3	0	3	0
0.85	3	0	3	0	3	0
0.90	3	0	3	0	3	0
0.95	3	0	3	0	3	0
1.00	3	0	3	0	3	0
1.05	2.96875	0.171163	3	0	2.984375	0.121031
1.10	2.9825	0.095851	3	0	2.99125	0.067777
1.15	3	0	3	0	3	0

	A Low Sun	
	mean	stdev
0.05	2.597299	0.436176
0.10	2.937356	0.168906
0.15	3	0
0.20	3	0
0.25	3	0
0.30	2.996552	0.018887
0.35	3	0
0.40	2.885914	0.175264
0.45	3	0
0.50	3	0
0.55	3	0
0.60	3	0
0.65	3	0
0.70	3	0
0.75	3	0
0.80	3	0
0.85	3	0
0.90	3	0
0.95	3	0
1.00	3	0
1.05	3	0
1.10	3	0
1.15	2.975758	0.132781

Figure A-5. Lane Marking 4 Summary Data

	C Day		D Day			
	mean	stdev	mean	stdev	avg means	sr
0.05	2.737621	0.325311	2.985417	0.082496	2.861519	0.237311
0.10	2.96663	0.179705	3	0	2.983315	0.127071
0.15	2.995795	0.022646	3	0	2.997897	0.016013
0.20	3	0	3	0	3	0
0.25	3	0	3	0	3	0
0.30	3	0	3	0	3	0
0.35	2.995402	0.024759	3	0	2.997701	0.017508
0.40	2.965517	0.185695	3	0	2.982759	0.131306
0.45	2.965517	0.185695	3	0	2.982759	0.131306
0.50	2.98692	0.070436	3	0	2.99346	0.049806
0.55	3	0	3	0	3	0
0.60	3	0	3	0	3	0

	C Night		D Night			
	mean	stdev	mean	stdev	avg means	sr
0.05	2.980574	0.109888	2.935141	0.196248	2.957858	0.159042
0.10	2.984375	0.088388	2.945516	0.192487	2.964945	0.149773
0.15	3	0	2.997058	0.013127	2.998529	0.009282
0.20	3	0	3	0	3	0
0.25	3	0	2.985795	0.080353	2.992898	0.056818
0.30	3	0	3	0	3	0
0.35	3	0	2.997283	0.015372	2.998641	0.01087
0.40	3	0	2.98989	0.043949	2.994945	0.031077
0.45	2.997024	0.016836	2.996324	0.020797	2.996674	0.018921
0.50	3	0	2.995028	0.028124	2.997514	0.019886
0.55	3	0	3	0	3	0
0.60	3	0	2.990767	0.044663	2.995384	0.031581

Figure A-6. Lane Marking 5 Summary Data

	A Day		B Day			
	mean	stdev	mean	stdev	avg mean	sr
0.05	2.876689	0.310153	3	0	2.938345	0.219311
0.10	2.925806	0.255008	3	0	2.962903	0.180318
0.15	2.976054	0.104217	3	0	2.988027	0.073693
0.20	3	0	3	0	3	0
0.25	3	0	3	0	3	0
0.30	3	0	3	0	3	0
0.35	3	0	3	0	3	0
0.40	3	0	3	0	3	0
0.45	3	0	3	0	3	0
0.50	3	0	3	0	3	0
0.55	3	0	3	0	3	0
0.60	2.998246	0.009609	3	0	2.999123	0.006795

	A Night		B Night			
	mean	stdev	mean	stdev	avg mean	sr
0.05	3	0	3	0	3	0
0.10	3	0	3	0	3	0
0.15	3	0	3	0	3	0
0.20	3	0	2.983221	0.08335	2.99161	0.058938
0.25	2.999219	0.004419	2.98766	0.064342	2.993439	0.045604
0.30	2.987733	0.0611	2.980378	0.110999	2.984056	0.089594
0.35	2.995833	0.02357	2.997159	0.016071	2.996496	0.020172
0.40	3	0	3	0	3	0
0.45	3	0	2.947397	0.19317	2.973698	0.136592
0.50	3	0	2.995089	0.023809	2.997545	0.016836
0.55	2.995451	0.018908	2.986553	0.059754	2.991002	0.044317
0.60	3	0	2.995	0.028284	2.9975	0.02

Figure A-7. Lane Marking 6 Summary Data

APPENDIX B

CLOSED COURSE REPEATABILITY

Appendix B contains a summary of each of the closed course markings along with their calculated repeatability standard deviation used in the Closed Course Repeatability analysis.

	Day					
	NB		SB			
	Mean	Std dev	Mean	Std dev	Sr	avg means
1a	2.059476	0.244783	2.646009	0.431978	0.351087	2.352742468
1b	2.308895	0.410933	2.146169	0.232791	0.333959	2.22753238
2a	1.957661	0.161081	2.877147	0.295233	0.237813	2.417404239
2b	2.162268	0.368366	2.316532	0.266603	0.321535	2.239400049
3a	2.408266	0.167693	2.275202	0.168754	0.168224	2.341733871
3b	2.967742	0.179605	2.999022	0.005443	0.127058	2.983382209
4a	2.302419	0.187046	2.202621	0.26674	0.230366	2.252520161
4b	2.937256	0.174199	2.843093	0.261892	0.22241	2.890174179
5a	2.096774	0.180306	2.284274	0.137962	0.160536	2.190524194
5b	2.43304	0.394498	2.998045	0.010885	0.279058	2.715542522
6a	2.311492	0.259266	2.478831	0.208133	0.235094	2.39516129
6b	2.882698	0.265417	2.994589	0.021791	0.18831	2.938643346

	Night					
	NB		SB			
	Mean	Std dev	Mean	Std dev	Sr	avg means
1a	1.803226	0.282529	2	0	0.199778	1.901613
1b	2	0	1.907834	0.128328	0.090741	1.953917
2a	1.304839	0.374467	1.943164	0.185009	0.295342	1.624002
2b	1.886248	0.277868	1.903226	0.131555	0.217391	1.894737
3a	2.496976	0.492413	2.596774	0.396465	0.447021	2.546875
3b	2.855327	0.206966	2.918866	0.218572	0.212848	2.887097
4a	2.572581	0.308873	2.339718	0.308278	0.308576	2.456149
4b	2.899316	0.287095	2.791789	0.374071	0.333431	2.845552
5a	2	0	1.380952	0.121716	0.086066	1.690476
5b	2	0	1.976959	0.12829	0.090714	1.988479
6a	1.906452	0.208863	1.463902	0.155021	0.183923	1.685177
6b	1.991511	0.047265	2	0	0.033421	1.995756

Figure B-1. Closed Course Lane Marking Summary Data

APPENDIX C

CLOSED COURSE CORRELATION ANALYSIS

Appendix C contains the raw data for all of the markings in the day and night conditions used in the Closed Course Correlation analysis.

Section	Direction	SectionDirection	Avg Rating	Std Dev of Avg Rating	Color	Material	Marking Y	Marking x	Marking y	RL (LTL-X) Marking	Qd (LTL-XL) Marking	Composite M1 Mk Luminance	Composite M1 Mk Color Cx	Composite M1 Mk Color Cy	CapY Contrast	RL (LTL-X) Contrast	Qd (LTL-XL) Contrast	Luminance Ratio
1LDD	NB	1LDDNB	0.712988	0.83624	Yellow	AA	10.211667	0.34163333	0.3607	26.5625	91.125	2580.358	0.3167711	0.3701586	0.6103806	1.5686516	1.301785714	0.715116179
1LDD	SB	1LDDSB	0.707512	0.601392	Yellow	AA	10.211667	0.34163333	0.3607	28.1875	88.75	3092.213	0.31247	0.372174	0.6103806	1.6646161	1.347248577	0.830003527
1RDD	NB	1RDDNB	2.012975	0.368243	White	F	46.581667	0.31813333	0.33833333	24.095238	131.0909091	6603.512	0.3005658	0.3549184	2.6840488	1.4326898	1.83227446	1.914231511
1RDD	SB	1RDDSB	2.213363	0.217718	White	F	46.581667	0.31813333	0.33833333	29.857143	133.0909091	5829.371	0.295538	0.3503129	2.6840488	1.7752896	1.916230366	1.673946391
1WDD	NB	1WDDNB	2.352941	0.523352	White	F	46.655	0.31765	0.336525	19.538462	125.3846154	5397.188	0.3234415	0.3571842	2.9310507	1.1598174	1.783369803	1.678714244
1WDD	SB	1WDDSB	2.176471	0.498158	White	F	46.655	0.31765	0.336525	19.538462	128	3547.439	0.3221087	0.3530482	2.9310507	1.3439153	1.930394432	1.336359957
1YDD	NB	1YDDNB	0.785714	1.032441	Yellow	AA	13.0025	0.354475	0.370925	22.307692	85.46153846	2253.195	0.343617	0.3815416	0.8816749	1.5425532	1.299415205	0.803883639
1YDD	SB	1YDDSB	1.964286	0.237316	Yellow	AA	13.0025	0.354475	0.370925	22.307692	85.23076923	5384.884	0.3387183	0.3771008	0.8816749	1.5675676	1.346294046	1.850910979
2LDD	NB	2LDDNB	2.306817	0.214283	Yellow	D	35.423333	0.47048333	0.43108333	78.761905	119.6	6766.751	0.4152772	0.4353935	2.1970229	4.5006803	1.733333333	1.851895711
2LDD	SB	2LDDSB	2.088098	0.18647	Yellow	D	35.423333	0.47048333	0.43108333	86.333333	118.6363636	6764.904	0.4185826	0.4330259	2.1970229	4.9333333	1.751677852	1.556080953
2RDD	NB	2RDDNB	2.066441	0.205609	White	K	49.631667	0.3191	0.33911667	88.25	126.8	7744.495	0.3015269	0.3572684	3.0843086	5.1608187	1.783403657	2.20438877
2RDD	SB	2RDDSB	2.517618	0.258665	White	K	49.631667	0.3191	0.33911667	92.05	127.2	7191.51	0.3007592	0.3576624	3.0843086	5.3830409	1.86784141	1.86638188
3LDD	NB	3LDDNB	2.242381	0.267508	Yellow	G	30.311667	0.46651667	0.42853333	197.04762	95.36363636	5700.818	0.4058966	0.4351811	2.3497416	12.7953	1.725328947	1.763149312
3LDD	SB	3LDDSB	2.075232	0.216254	Yellow	G	30.311667	0.46651667	0.42853333	201.47619	93.09090909	5513.94	0.4011006	0.4301083	2.3497416	13.08287	1.706666667	1.656880478
3RDD	NB	3RDDNB	2.030561	0.187456	White	BB	24.4	0.31045	0.32866667	44.611111	131.5555556	5442.015	0.2919061	0.3511414	1.6948368	2.841472	2.200743494	1.591119868
3RDD	SB	3RDDSB	2.034673	0.232692	White	BB	24.4	0.31045	0.32866667	48.333333	119.2222222	5838.824	0.294846	0.3530234	1.6948368	3.0785563	2.185336049	1.768419153
3YDD	NB	3YDDNB	2.625	0.223607	Yellow	D	31.9475	0.46115	0.4272	68.909091	99.45454545	5065.433	0.426441	0.443687	2.7780435	5.0533333	1.683076923	2.705544303
3YDD	SB	3YDDSB	2.21875	0.256174	Yellow	D	31.9475	0.46115	0.4272	68.909091	102.0909091	5158.924	0.3677812	0.3953588	2.7780435	5.2638889	1.722392638	2.141708996
4LDD	NB	4LDDNB	2.507598	0.149841	Yellow	C	38.333333	0.48721667	0.4322	465.78947	136.1	8717.31	0.4588226	0.4369329	2.6342916	28.059607	2.167197452	2.806043224
4LDD	SB	4LDDSB	2.188974	0.254116	Yellow	C	38.333333	0.48721667	0.4322	474.42105	135.9	7390.184	0.4473546	0.4341005	2.6342916	28.579581	2.164012739	1.97691534
4RDD	NB	4RDDNB	2.321069	0.19273	White	A	62.946667	0.31798333	0.33823333	928.38095	249.3636364	16793.61	0.3031037	0.3616157	4.3496487	61.51922	3.85252809	5.206128767
4RDD	SB	4RDDSB	2.622561	0.217657	White	A	62.946667	0.31798333	0.33823333	861.28571	248.2727273	13810.29	0.3020548	0.3607877	4.3496487	57.07315	3.835674157	4.397424583
4WDD	NB	4WDDNB	2.558824	0.428746	White	K	48	0.318325	0.337025	60.444444	127.6666667	6357.974	0.3235091	0.359645	3.8102798	4.352	2.147663551	2.390752361
4WDD	SB	4WDDSB	2.323529	0.430885	White	K	48	0.318325	0.337025	60.444444	126.2222222	4474.604	0.3248345	0.3554766	3.8102798	4.7304348	2.281124498	1.804810336
5LDD	NB	5LDDNB	2.671066	0.188116	White	Paint	31.875	0.3407	0.35968333	31.4	97	6567.718	0.3229884	0.3797092	1.9242379	1.7532995	1.487028302	1.879811948
5LDD	SB	5LDDSB	2.413702	0.320214	White	Paint	31.875	0.3407	0.35968333	31.36	98.84615385	6597.112	0.3208107	0.381	1.9242379	1.751066	1.540767386	1.805635666
5RDD	NB	5RDDNB	2.438376	0.164668	White	Paint	30.23	0.32558333	0.34146667	23.52	87.61538462	6089.179	0.3101664	0.3626527	1.900461	1.3688889	1.420199501	1.932216083
5RDD	SB	5RDDSB	2.606245	0.157955	White	Paint	30.23	0.32558333	0.34146667	22.12	86.23076923	6582.973	0.3107103	0.365043	1.900461	1.2874074	1.387376238	1.836631732
5YDD	NB	5YDDNB	2.5	0.365148	Yellow	G	31.09	0.460175	0.427375	131.36364	90.36363636	4544.343	0.4190169	0.4422224	2.1840534	10.176056	1.80399274	1.878784158
5YDD	SB	5YDDSB	2.125	0.341565	Yellow	G	31.09	0.460175	0.427375	131.36364	91.36363636	4445.012	0.3678523	0.3958064	2.1840534	10.94697	1.86802974	2.00636302
6LDD	NB	6LDDNB	2.587322	0.13639	White	Paint	29.596667	0.35261167	0.37006667	53.04	80.92307692	5613.804	0.3305265	0.3896995	2.0193314	3.0022642	1.340127389	1.589440582
6LDD	SB	6LDDSB	2.513877	0.080122	White	Paint	29.596667	0.35261167	0.37006667	40.72	79.84615385	6170.225	0.3276109	0.3886161	2.0193314	2.3049057	1.322292994	1.613423033
6RDD	NB	6RDDNB	2.59957	0.310363	White	Paint	26.758333	0.32746667	0.34578333	27.24	77	5501.993	0.3084615	0.3708118	1.7940552	1.68	1.284980745	1.547865451
6RDD	SB	6RDDSB	2.584969	0.179812	White	Paint	26.758333	0.32746667	0.34578333	33.12	79.21428571	5375.335	0.3094451	0.3690255	1.7940552	2.0426432	1.321932881	1.752352448
6WDD	NB	6WDDNB	2.647059	0.293934	White	A	64.2325	0.3178	0.3368	543.09091	226.7272727	12286.25	0.3259476	0.361039	4.8204503	40.364865	3.909090909	5.541013535
6WDD	SB	6WDDSB	2.794118	0.309173	White	A	64.2325	0.3178	0.3368	543.09091	243.0909091	7481.352	0.3265119	0.3560296	4.8204503	44.58209	4.563139932	3.331519586
6YDD	NB	6YDDNB	2.875	0.223607	Yellow	C	36.53	0.479875	0.431175	333	124.8181818	6400.095	0.4527389	0.4467053	2.4841891	25.615385	2.27694859	3.148586994
6YDD	SB	6YDDSB	2.21875	0.363719	Yellow	C	36.53	0.479875	0.431175	333	127.8181818	3953.387	0.4227078	0.4077181	2.4841891	26.543478	2.46234676	1.644887596
7LDD	NB	7LDDNB	2.521534	0.302015	White	Paint	29.463333	0.35005	0.36735	16.64	52.46153846	3918.231	0.3289984	0.3855618	2.3747985	1.0203774	0.972895863	1.382770523
7LDD	SB	7LDDSB	2.676049	0.197692	White	Paint	29.463333	0.35005	0.36735	16.2	51	4085.177	0.3235559	0.3838105	2.3747985	0.9933962	0.945791726	1.560643462
7RDD	NB	7RDDNB	2.593872	0.302289	White	Paint	30.045	0.32578333	0.34218333	14.4	57.15384615	4169.964	0.3147798	0.3728409	2.3239655	0.9191489	1.073699422	1.383875882
7RDD	SB	7RDDSB	2.68918	0.197883	White	Paint	30.045	0.32578333	0.34218333	15.44	65.15384615	5071.949	0.3100629	0.3672117	2.3239655	0.9855319	1.223988439	1.957006391
7YDD	NB	7YDDNB	2.321429	1.067116	Yellow	BB	27.61	0.322925	0.34095	29.142857	136.5714286	4683.133	0.3276119	0.3610279	1.7048472	2.1702128	2.483116883	2.482250531
7YDD	SB	7YDDSB	1.821429	0.60787	Yellow	BB	27.61	0.322925	0.34095	29.142857	134.7142857	7452.811	0.3301617	0.3656223	1.7048472	2.372093	2.583561644	2.588148252
8ONLYDD	NB	8ONLYDDNB	1.911216	0.45892	White	Paint	#N/A	#N/A	#N/A	#N/A	#N/A	3722.336	0.2883837	0.3449163	#N/A	#N/A	#N/A	1.72222532
8ONLYDD	SB	8ONLYDDSB	1.62026	0.481742	White	Paint	#N/A	#N/A	#N/A	#N/A	#N/A	3535.906	0.2879814	0.3471958	#N/A	#N/A	#N/A	1.477929631
9LDD	NB	9LDDNB	2.495935	0.862527	White	Structured	#N/A	#N/A	#N/A	293.72727	202.5	12055.03	0.3076669	0.3662655	#N/A	13.459201	2.325358852	2.438356558
9LDD	SB	9LDDSB	2.555556	0.096225	White	Structured	#N/A	#N/A	#N/A	426.21212	207.1666667	4889.98	0.3496487	0.3890828	#N/A	19.529935	2.385796545	0.997208112
9RDD	NB	9RDDNB	2.248971	0.750002	White	Structured	#N/A	#N/A	#N/A	1005	192.25	2691.909	0.3283421	0.3753243	#N/A	42.605985	2.214011516	0.359160449
9RDD	SB	9RDDSB	2.560606	0.104973	White	Structured	#N/A	#N/A	#N/A	1285.8788	191.6666667	11164.75	0.3147542	0.3717721	#N/A	54.513565	2.200956938	2.349765045

Figure C-1. Daytime Correlation Analysis Raw Data

Section	Direction	SectionDirection	Avg of Avg Rating	Std dev of Avg Rating	Color	Material	Marking Y	Marking x	Marking y	RL (LTL-X) Marking	Qd (LTL-XL) Marking	Composite M1 Mk Luminance	Composite M1 Mk Color Cx	Composite M1 Mk Color Cy	CapY Contrast	RL (LTL-X) Contrast	Qd (LTL-XL) Contrast	Luminance Ratio
1LND	NB	1LNDNB	1.515971	0.859902	Yellow	AA	10.2116667	0.34163333	0.3607	26.5625	91.125	0.449532	0.4068173	0.4278198	0.6103806	1.5686516	1.301785714	1.271069589
1LND	SB	1LNDSB	0.5	0.516398	Yellow	AA	10.2116667	0.34163333	0.3607	28.1875	88.75	0.4888445	0.4099051	0.4311203	0.6103806	1.6646161	1.347248577	1.354993798
1RND	NB	1RNDNB	2.228609	0.369291	White	F	46.5816667	0.31813333	0.3383333	24.095238	131.0909091	0.6737899	0.4091183	0.4202611	2.6840488	1.4326898	1.83227446	2.155994871
1RND	SB	1RNDSB	2.658436	0.217704	White	F	46.5816667	0.31813333	0.3383333	29.857143	133.0909091	0.6540531	0.409692	0.4168809	2.6840488	1.7752896	1.916230366	1.587964642
1WND	NB	1WNDNB	2.40625	0.455293	White	F	46.655	0.31765	0.336525	19.538462	125.3846154	0.5779593	0.4097775	0.4260155	2.9310507	1.1598174	1.783369803	3.311461443
1WND	SB	1WNDSB	3	0	White	F	46.655	0.31765	0.336525	19.538462	128	0.8582862	0.4077874	0.4190924	2.9310507	1.3439153	1.930394432	3.067794414
1YND	NB	1YNDNB	0.733333	1.066815	Yellow	AA	13.0025	0.354475	0.370925	22.307692	85.46153846	0.541317	0.4313708	0.443958	0.8816749	1.5425532	1.299415205	2.095547865
1YND	SB	1YNDSB	1.178571	0.464391	Yellow	AA	13.0025	0.354475	0.370925	22.307692	85.23076923	0.4146714	0.4308802	0.443809	0.8816749	1.5675676	1.346294046	1.879168432
2LND	NB	2LNDNB	2.781958	0.22785	Yellow	D	35.4233333	0.47048333	0.4310833	78.761905	119.6	1.321505	0.4736177	0.4654773	2.1970229	4.5006803	1.733333333	3.715590675
2LND	SB	2LNDSB	2.218921	0.311339	Yellow	D	35.4233333	0.47048333	0.4310833	86.333333	118.6363636	1.662009	0.4819003	0.4628263	2.1970229	4.9333333	1.751677852	4.246876059
2RND	NB	2RNDNB	2.399134	0.267939	White	K	49.6316667	0.3191	0.3391167	88.25	126.8	1.074546	0.4022581	0.4230177	3.0843086	5.1608187	1.783403657	3.814447921
2RND	SB	2RNDSB	2.983205	0.041208	White	K	49.6316667	0.3191	0.3391167	92.05	127.2	1.496451	0.4059463	0.4195385	3.0843086	5.3830409	1.86784141	3.776655918
3LND	NB	3LNDNB	2.715384	0.240979	Yellow	G	30.3116667	0.46651667	0.4285333	197.04762	95.36363636	3.356826	0.4880576	0.4668988	2.3497416	12.7953	1.725328947	11.50592498
3LND	SB	3LNDSB	2.609718	0.288336	Yellow	G	30.3116667	0.46651667	0.4285333	201.47619	93.09090909	3.432306	0.4880968	0.4677967	2.3497416	13.08287	1.706666667	10.56706393
3RND	NB	3RNDNB	1.98706	0.357199	White	BB	24.4	0.31045	0.3286667	44.611111	131.5555556	0.5110642	0.3997904	0.4187356	1.6948368	2.841472	2.200743494	1.919131355
3RND	SB	3RNDSB	2.418531	0.43552	White	BB	24.4	0.31045	0.3286667	48.333333	119.2222222	0.806058	0.4018632	0.4162491	1.6948368	3.0785563	2.185336049	2.325178151
3YND	NB	3YNDNB	2.933333	0.258199	Yellow	D	31.9475	0.46115	0.4272	68.909091	99.45454545	2.149807	0.4742302	0.4627762	2.7780435	5.0533333	1.683076923	8.372021386
3YND	SB	3YNDSB	3	0	Yellow	D	31.9475	0.46115	0.4272	68.909091	102.0909091	1.582365	0.4754758	0.4607317	2.7780435	5.2638889	1.722392638	8.932743825
4LND	NB	4LNDNB	2.685332	0.203337	Yellow	C	38.3333333	0.48721667	0.4322	465.78947	136.1	8.885652	0.4990942	0.4666835	2.6342916	28.059607	2.167197452	28.21887795
4LND	SB	4LNDSB	2.560471	0.260504	Yellow	C	38.3333333	0.48721667	0.4322	474.42105	135.9	6.275712	0.500036	0.4667149	2.6342916	28.579581	2.164012739	16.37649505
4RND	NB	4RNDNB	2.446079	0.38152	White	A	62.9466667	0.31798333	0.3382333	928.38095	249.3636364	11.9841	0.4156517	0.4263643	4.3496487	61.51922	3.85252809	41.27756867
4RND	SB	4RNDSB	2.729141	0.272038	White	A	62.9466667	0.31798333	0.3382333	861.28571	248.2727273	13.7835	0.4184054	0.4250424	4.3496487	57.07315	3.835674157	35.81871497
4WND	NB	4WNDNB	2.96875	0.125	White	K	48	0.318325	0.337025	60.444444	127.6666667	1.548646	0.4010411	0.4198068	3.8102798	4.352	2.147663551	9.281134943
4WND	SB	4WNDSB	3	0	White	K	48	0.318325	0.337025	60.444444	126.2222222	2.009435	0.4011684	0.419714	3.8102798	4.7304348	2.281124498	9.047845039
5LND	NB	5LNDNB	2.3125	0.458063	White	Paint	31.875	0.3407	0.3596833	31.4	97	0.6664867	0.4274157	0.4285385	1.9242379	1.7532995	1.487028302	1.782584775
5LND	SB	5LNDSB	1.917109	0.185568	White	Paint	31.875	0.3407	0.3596833	31.36	98.84615385	0.6602609	0.4256894	0.4289289	1.9242379	1.751066	1.540767386	1.660630355
5RND	NB	5RNDNB	1.609931	0.252553	White	Paint	30.23	0.32558333	0.3414667	23.52	87.61538462	0.4577237	0.4219691	0.4243605	1.900461	1.3688889	1.420199501	1.429587111
5RND	SB	5RNDSB	1.924908	0.187611	White	Paint	30.23	0.32558333	0.3414667	22.12	86.23076923	0.5650537	0.4247916	0.4245265	1.900461	1.2874074	1.387376238	1.32284855
5YND	NB	5YNDNB	3	0	Yellow	G	31.09	0.460175	0.427375	131.36364	90.36363636	3.568069	0.4630106	0.4967968	2.1840534	10.176056	1.80399274	19.18045459
5YND	SB	5YNDSB	3	0	Yellow	G	31.09	0.460175	0.427375	131.36364	91.36363636	2.478183	0.4880293	0.4675807	2.1840534	10.94697	1.86802974	15.10839841
6LND	NB	6LNDNB	2.881665	0.193188	White	Paint	29.5966667	0.35261167	0.3700667	53.04	80.92307692	1.354424	0.4164217	0.4273468	2.0193314	3.0022642	1.340127389	3.764113961
6LND	SB	6LNDSB	2.752789	0.292159	White	Paint	29.5966667	0.35261167	0.3700667	40.72	79.84615385	1.3981	0.4120632	0.4276463	2.0193314	2.3049057	1.322292994	3.134193987
6RND	NB	6RNDNB	2.662919	0.382529	White	Paint	26.7583333	0.32746667	0.3457833	27.24	77	0.7884879	0.4111149	0.4212217	1.7940552	1.68	1.284980745	2.382276497
6RND	SB	6RNDSB	2.528395	0.398892	White	Paint	26.7583333	0.32746667	0.3457833	33.12	79.21428571	1.249056	0.4076713	0.4206043	1.7940552	2.0426432	1.321932881	2.746794103
6WND	NB	6WNDNB	2.96875	0.125	White	A	64.2325	0.3178	0.3368	543.09091	226.7272727	11.71396	0.4177966	0.4286889	4.8204503	40.364865	3.909090909	68.44605195
6WND	SB	6WNDSB	2.78125	0.256174	White	A	64.2325	0.3178	0.3368	543.09091	243.0909091	12.81983	0.4179248	0.4263071	4.8204503	44.58209	4.563139932	69.77708592
6YND	NB	6YNDNB	3	0	Yellow	C	36.53	0.479875	0.431175	333	124.8181818	7.239649	0.4994377	0.466287	2.4841891	25.615385	2.27694859	37.39923736
6YND	SB	6YNDSB	2.8	0.253546	Yellow	C	36.53	0.479875	0.431175	333	127.8181818	6.024119	0.5005425	0.4659278	2.4841891	26.543478	2.46234676	34.47740069
7LND	NB	7LNDNB	2.361784	0.528953	White	Paint	29.4633333	0.35005	0.36735	16.64	52.46153846	0.548721	0.4240282	0.4245309	2.3747985	1.0203774	0.972895863	1.532305571
7LND	SB	7LNDSB	1.880272	0.199214	White	Paint	29.4633333	0.35005	0.36735	16.2	51	0.4901594	0.422339	0.4243484	2.3747985	0.9933962	0.945791726	1.524716087
7RND	NB	7RNDNB	1.365532	0.834143	White	Paint	30.045	0.32578333	0.3421833	14.4	57.15384615	0.3624344	0.4127897	0.4253849	2.3239655	0.9191489	1.073699422	1.072178355
7RND	SB	7RNDSB	1.423574	0.721486	White	Paint	30.045	0.32578333	0.3421833	15.44	65.15384615	0.525175	0.4169841	0.4198146	2.3239655	0.9855319	1.223988439	1.370895536
7YND	NB	7YNDNB	2.266667	1.222799	Yellow	BB	27.61	0.322925	0.34095	29.142857	136.5714286	0.6713651	0.4028491	0.4192194	1.7048472	2.1702128	2.483116883	3.696020378
7YND	SB	7YNDSB	2.033333	0.58146	Yellow	BB	27.61	0.322925	0.34095	29.142857	134.7142857	0.5941023	0.4039021	0.4187648	1.7048472	2.372093	2.583561644	3.696769617
8ONLYND	NB	8ONLYNDI	2.176008	0.815346	White	Paint	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
8ONLYND	SB	8ONLYNDS	2.363335	0.414986	White	Paint	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
9LND	NB	9LNDNB	2.911392	0.12531	White	Structured	#N/A	#N/A	#N/A	293.72727	202.5	6.437537	0.4103611	0.4188881	#N/A	13.459201	2.325358852	9.501778317
9LND	SB	9LNDSB	2.837963	0.280656	White	Structured	#N/A	#N/A	#N/A	426.21212	207.1666667	9.786879	0.4052649	0.4212015	#N/A	19.529935	2.385796545	15.17110253
9RND	NB	9RNDNB	2.962963	0.052378	White	Structured	#N/A	#N/A	#N/A	1285.8788	191.6666667	21.51538	0.4084843	0.412733	#N/A	54.513565	2.200956938	40.00778757
9RND	SB	9RNDSB	2.962963	0.06415	White	Structured	#N/A	#N/A	#N/A	1005	192.25	17.35245	0.4050983	0.4181929	#N/A	42.605985	2.214011516	26.84852076

Figure C-2. Nighttime Correlation Analysis Raw Data