Development and Assessment of a Driver Drowsiness Monitoring System

U.S. Department of Transportation
Federal Motor Carrier Safety Administration

December 2012

FOREWORD

This project developed a prototype integrated system that combines machine vision-based drowsy driver monitoring technology and analysis of operator/vehicle performance parameters to reliably assess driver drowsiness. The purpose of this system will be to reliably quantify commercial motor vehicle driver drowsiness and provide a real-time warning to the driver and/or a control output to the commercial motor vehicle or other systems as warranted.

The work performed under the project included:

- Survey of the literature associated with the detection and monitoring of bouts of fatigue and drowsiness.
- Preliminary focus group research to gather driver preferences for drowsiness feedback and warnings.
- Machine vision-based eye closure monitor trade study.
- Development of an integrated prototype Driver Drowsiness Monitoring System.
- On-road evaluation of the Driver Drowsiness Monitoring System.

NOTICE

Technical Report Documentation Page

1. Report No. **FMCSA-RRR-12-008**	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle **Development and Assessment of a Driver Drowsiness Monitoring System**		5. Report Date **December 2012** 6. Performing Organization Code
7. Author(s) **Darrell Bowman, Richard J. Hanowski, Andrew Alden, Santosh Gupta, Doug Wiegand, Stephanie Baker, Laura M. Stanley, and Walter Wierwille**		8. Performing Organization Report No.
9. Performing Organization Name and Address **Virginia Tech Transportation Institute 3500 Transportation Research Plaza Blacksburg, VA 24061**		10. Work Unit No. (TRAIS) 11. Contract or Grant No. **DTNH22-05-D-01019: Task No. 7**
12. Sponsoring Agency Name and Address **Department of Transportation Federal Motor Carrier Safety Administration Office of Analysis, Research and Technology 1200 New Jersey Ave., SE Washington, DC 20590**		13. Type of Report **Final Report** 14. Sponsoring Agency Code **FMCSA**

15. Supplementary Notes

This program was administered through the Federal Motor Carrier Safety Administration (FMCSA).
The FMCSA Program Manager is Robert Carroll.

16. Abstract

Commercial motor vehicle driver impairment due to drowsiness is known to be a major contributing factor in many crashes. This report details the steps taken to develop a prototype driver drowsiness monitoring system (DDMS). The first area of consideration was the basic design requirements that would pertain to all driver drowsiness monitors, such as the ideal functional specifications that designers and engineers would account for in the development of drowsy monitor designs. Next, the project reviewed salient driver-based and vehicle-based predictors of driver drowsiness based on a literature review and an analysis of data from two recent naturalistic commercial driving studies. The development of a prototype DDMS included the integration of a machine vision (MV) eye closure sensor and an MV lane position sensor. The operational performance of the prototype DDMS was assessed during a dynamic on-road evaluation under varying conditions of ambient illumination, eyewear, and skin complexion. This evaluation assessed the performance of the MV eye closure sensor, the MV lane position sensor, and the integrated prototype DDMS algorithms.

The key finding of the on-road evaluation is that the multiple sensors integrated approach is necessary.

The project provided seven recommendations to improve the operational performance of these sensors and topics for future DDMS development. As with any technology assessment, this evaluation was based on current state-of-the-art technology. As technology development efforts continue, performance of the sensors would be expected to improve. Therefore, the results presented here represent a single snapshot in time.

17. Key Words **CMV, commercial motor vehicle, drowsy, drowsiness, driver, driving, eye closure, fatigue, lane position, machine vision, PERCLOS**	18. Distribution Statement

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	**Unclassified**	**206**	**N/A**

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

SI* (MODERN METRIC) CONVERSION FACTORS

Table of APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yards	0.836	square meters	m^2
ac	acres	0.405	Hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME	1,000 L shall be shown in m^3	
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE	Temperature is in exact degrees	
°F	Fahrenheit	5 × (F-32) ÷ 9 or (F-32) ÷ 1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		Force and Pressure or Stress		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

Table of APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
Mm	millimeters	0.039	inches	in
M	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2,000 lb)	T
		TEMPERATURE	Temperature is in exact degrees	
°C	Celsius	1.8C + 32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		Force & Pressure Or Stress		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

* SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003, Section 508-accessible version September 2009.)

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ABBREVIATIONS AND ACRONYMS

AVECLOS	average time eyes are closed during a 1-minute interval
CDL	commercial driver's license
CMV	commercial motor vehicle
DAS	Data Acquisition System
DASS	divided attention steering simulator
DDMS	Driver Drowsiness Monitoring System
DDWS	Drowsy Driver Warning System
DVI	driver/vehicle interface
EEG	electroencephalography
EYEMEAS	sample average of the square of eye closure
Fc	foot candle
FOT	field operational test
G2PM	Generation 2 PERCLOS Monitor
KSS	Karolinska Sleepiness Scale
LED	light-emitting diode(s)
Ln	natural log
m	meter
mi/h	miles per hour
m/s	meters per second
MV	machine vision
OGFC	open grade friction course
ORD	observer rating of drowsiness
OSAS	Obstructive Sleep Apnea Syndrome

OSAHS	Obstructive Sleep Apnea/Hypopnea Syndrome
PERCLOS	proportion of time that the eyes are 80–100 percent closed
SD	standard deviation
STS	Socio-Technical Systems Model
TTC	time to collision

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EXECUTIVE SUMMARY

PURPOSE

Driver impairment due to drowsiness is known to be a major contributing factor in many motor vehicle crashes. For example, several sources indicate driver fatigue is the probable cause of approximately 30 percent of crashes (Folkard, 1997; Horne and Reyner, 1995; Kecklund and Åkerstedt, 1993; Lenne, Triggs, and Redman, 1997; Lynznicki, Doege, Davis, and Williams, 1998; National Transportation Safety Board, 1990). Fatigue is known to decrease a driver's attention level and reaction time. As such, fatigued drivers pay less attention to the driving environment and are less concerned with making errors, which decreases their likelihood of perceiving potential conflict situations. For example, Dinges (1995) found that the reaction time of fatigued drivers suffers by 5 percent to 25 percent, which interferes with their ability to properly avoid a crash situation with a timely evasive maneuver (e.g., steering to avoid a crash or allowing proper braking distance).

Given the impact of driver drowsiness on driving safety, there has been keen interest in developing a system that can monitor and quantify driver drowsiness, as well as provide a real-time warning to the driver and/or a control output to the vehicle or other systems as warranted. Numerous systems to detect and monitor driver drowsiness are available on the market; however, nearly all of these technologies rely on a single predictor of driver drowsiness (e.g., eye closures, lane position, or steering). One negative aspect of using only one predictor of drowsiness is that it is susceptible to periodic intervals in which data are unavailable due to failures of the single sensor or operation outside of the sensor's envelope of operation. When the single sensor does not work optimally, the system is less effective than it could be.

One measure seen in some drowsiness monitors is slow eye closures (i.e., percent closure [PERCLOS]). However, tests with some specific technologies have found periodic intervals of data loss in various conditions. For example, single-measure systems that are based on eye closure metrics may have data loss if the driver is wearing eyeglasses or there is high ambient illumination (Hanowski et al., 2008). If the driver is wearing sunglasses, or the driver's eyes are not within the system's field-of-regard because of normal visual scanning patterns (e.g., mirror checks), or the driver is performing a secondary task (e.g., looking down at the speedometer), then the system may misread those variables as valid eye closures (Wierwille et al., 2003).

Lane position, like slow eye closures, is another metric that has been used to identify drowsy driving. As with slow eye closures, lane position is not a completely robust measure. For example, lane position data loss can occur when the system fails to read the lane's edge markings due to weather, such as rain or snow covering; poor quality lane markings leading to insufficient contrast between the lane marking and the road; or inconsistent lane markings, such as merge lanes or intersections that confuse the visual system. Depending on how data loss is handled by the system, the result can be missed occurrences of drowsy driving and/or false alarms that indicate that the driver is drowsy when he/she is actually alert. Handling false alarms may be a difficult problem as too many false alarms may diminish the user's trust, confidence in, and acceptance of the technology (Bliss and Acton, 2003; Maltz and Shinar, 2004; Lees and Lee, 2007).

The objective of this research project was to develop a robust prototype system that combines drowsiness metrics to alleviate some of the issues associated with a single measure device. Based on literature review, it was determined that a machine vision (MV) eye monitoring technology, in combination with analysis of operator/vehicle performance parameters, would provide a strong combined metric to assess driver drowsiness reliably. The hypothesis of this research was that a multimeasure approach to detecting driver drowsiness would be superior to a single-measure approach. As noted, the problem with single-measure drowsiness detection systems is that when there is a loss of data, the system becomes unreliable. However, an approach that uses multiple distinct sensors provides not only a backup system, but also an integrated approach whereby both measures create a more robust drowsiness detection than either measure could alone. This report details the effort to test this hypothesis.

The steps taken for developing a prototype driver drowsiness monitoring system (DDMS) included:

Step 1: Exploring Design Fundamentals

This section of the report describes the basic design considerations, such as the ideal functional specifications designers and engineers are urged to account for in the development of drowsy monitor designs.

An ideal DDMS will operate successfully in a wide range of environmental conditions given varying quantities and qualities of sensor input. For example, such a system would be designed to provide valid and reliable detection of driver drowsiness given various environmental conditions (e.g., illumination levels), multiple operators, various physical characteristics of drivers (e.g., skin tone, use of eyeglasses, etc.), and common driver behaviors.

These functional specifications include:

- Accuracy,
- Ability to account for common driving behaviors,
- Reliability,
- Adaptability to various environmental conditions,
- Adaptability to various driver physical characteristics,
- Ability to detect a change in the vehicle operator,
- Ability to meet fundamental human interface needs,
- Non-encumbering design,
- Need for minimal calibration,
- Ability to gather data continuously in real time.

Step 2: Considering Salient Driver Drowsiness-Related Indicators

This section of the report considers the most salient driver-based and vehicle-based predictors of driver drowsiness based on a literature review and an analysis of data from two recent naturalistic commercial driving studies.

Key findings from the literature:

- Slow eye closures have shown promise in predicting the onset of driver drowsiness in both simulators (Skipper and Wierwille, 1986; Wierwille, Ellsworth, Wreggit, Fairbanks, and Kirn, 1994a) and over-the-road trucking operations (Dinges, Maislin, Krueger, Brewster, and Carroll, 2005).
- Measures of lane position have also been found to be a capable indicator of driver drowsiness (O'Hanlon and Kelley, 1977; Chatterjee, Cadotte, Stamatiadis, Sink, Venigalla, and Gaides, 1994; Wierwille, 1994; Tijerina, Glecker, Stoltzfus, Johnston, Goodman, and Wierwille, 1999).
- Heitmann, Guttkuhn, Aguirre, Trutschel, and Moore-Ede (2001) found that no single measure can sufficiently and reliably indicate driver alertness.
- A key finding of Wierwille (1999a) is that a simpler algorithm may be preferred to larger, more complex ones; hence, requiring fewer driver behavioral and physiological inputs.
- These key findings from the literature review indicate a multiple-sensors integrated approach is necessary for reliable monitoring of driver drowsiness. Furthermore, these findings suggest that slow eye closures and measures of lane position are strong candidates to integrate into an effective DDMS.

Step 3: Developing the Prototype DDMS

This section of the report describes the steps that were completed during the development of the prototype DDMS. These included:

- <u>Drowsiness predictive model derivation</u>: At the foundation of the system is the predictive model to ascertain the trends from the stimuli and to indicate when these trends exceed predetermined thresholds. This report discusses this straightforward mathematical model.
- <u>Driver input from focus groups</u>: Driver acceptance can limit the success of driver drowsiness monitoring devices. To obtain input from users, the team determined user requirements for the system and gathered user feedback on the preliminary concepts and proposals via focus groups.
- <u>Selection of an MV eye closure sensor</u>: The team needed to select the most capable sensors available to develop the prototype DDMS. To select these sensors, the team reviewed the commercially available eye closure monitor technology and selected two systems to be further examined using a systematic technology selection process. Details regarding the methodology and results of this selection process are described in section 4.4 of this report.

- System creation: The DDMS includes two primary MV technologies for detecting and monitoring driver drowsiness. The first technology is an MV eye closure sensor that uses machine vision to estimate the change in eye opening size over time from captured images of the driver's face. The second technology is an MV lane deviation sensor that estimates the vehicle's lane position, as well as other lane-related measures from captured images of the forward roadway. These technologies are evaluated both independently and in concert with one another as part of this study.

Step 4: Performing an On-Road Evaluation

This section of the report details the methodology and results of an on-road evaluation of the prototype DDMS using a sample of six individuals of varying demographic and physical characteristics. The evaluation focused on exercising the prototype system to determine its operational envelope (i.e., those operational conditions in which the system does and does not work effectively). The results of this on-road evaluation were used to assess the performance of the DDMS in terms of accuracy and sensitivity to the presented stimuli and determine the effectiveness of the multiple-sensors integrated approach.

Key Findings from the On-Road Evaluation of the DDMS Prototype:

The DDMS on-road evaluation was carried out in three parts: assessment of the eye closure sensor output, assessment of the lane deviation sensor output, and assessment of the integrated DDMS drowsiness algorithm.

- Assessment of the Eye Closure Sensor Input:
  - Overall, MV eye closure sensor performance was in line with expectations and worked most effectively (90-percent accuracy rate) during daytime operations without the presence of eyewear.
  - Using the shape criteria developed by Wierwille et al. (2003), 73 percent of the DDMS eye closure (PERCLOS) estimate algorithm's output were classified as either a "YES" (having the same shape as the manual PERCLOS estimate) or a "YES-BIASED" (having a similar shape as the manual PERCLOS with some discrepancies).
  - The false alarm analysis revealed that the MV PERCLOS estimate algorithms have a low propensity to generate false alarms for visual scanning tasks typical of commercial driving (e.g., visually scanning the side mirrors, looking down at the instrument panel).
  - The primary limitations of the MV eye closure sensor were uniform illumination across the face, the presence of eyewear, and head motions that were generated by vehicle ride or driving tasks. It is believed that future design iterations of the technology can improve upon these areas.
- Assessment of the Lane Deviation Sensor Input:
  - Overall, the MV lane position sensor performed well and worked in daytime conditions with an accuracy rate of 94 percent. In nighttime conditions, the accuracy rate was as high as 88 percent.

- Across all conditions (e.g., ambient illumination), the DDMS lane deviation estimate's correct classification ("YES" and "YES-BIASED") of lane deviations was 98 percent.
- The lane deviation sensor performed successfully during a false alarm task designed to evaluate whether intentional lane deviations (as indicated by turn signal use prior to the lane deviation maneuver) could be differentiated from unintentional lane deviations (as indicated by no turn signal use at the time of lane deviation). The lane deviation sensor performed correctly and was able to differentiate between intentional and unintentional lane deviations.
- The primary limitation of the MV lane position sensor was instances of a low contrast ratio between the lane's markings and the surrounding scene. It is believed this can be addressed by a technology improvement that can be made in future design iterations.

- Assessment of the Integrated DDMS Algorithm Output:
  - The sensitivity of the Integrated DDMS drowsiness algorithm was directly dependent on the output accuracies of the DDMS PERCLOS and lane deviation estimates. As stated, the accuracy of the DDMS PERCLOS estimate output was more effective without the presence of any eyewear, while the DDMS lane deviation was more reliable under higher levels of illumination.

CONCLUSIONS AND RECOMMENDATIONS

The key finding of this on-road evaluation is that a multiple-sensors integrated approach may provide a more robust approach to assessing driver drowsiness. Though there were limitations with each individual sensor, the combined approach performed successfully for 15 of the 17 functional specifications tested and performed moderately for the two remaining functional specification areas. It is believed that with further system improvements, an integrated DDMS would be effective across all necessary functional specifications.

Specific Recommendations

Recommendation 1

Develop an illumination system that provides an even illumination of the driver's face in *both* the lateral and vertical dimensions. Multiple infrared illuminators will need to be positioned away from the sensor in both the lateral and vertical dimensions to create a large array of illumination. By having more sources of illumination, the intensity of the individual infrared pods can be reduced to create a balanced illumination across the face. Therefore, the illumination system will require four or more infrared illuminators, positioned symmetrically on either side of the sensor, above, and below the driver's horizontal eye height. These additional infrared illuminators above the driver's eye height will reduce the shadows created by the driver's cheek structure.

Recommendation 2

Improve the MV eye closure sensor's ability to discern eye closures through eyewear lenses. It is recommended that future development work include several small investigations into the eyewear factors that limit the operational performance of the MV eye closure sensor. These may include, but are not limited to, reflections on the lenses, lens coatings that reduce infrared penetration, opaqueness of sunglasses, and eyewear frame materials (e.g., metal versus plastic frames, dark versus light frames, thin versus thick).

Recommendation 3

Improve the MV eye closure sensor's ability to adapt to head motions so that it includes work with the MV eye closure sensor manufacturer to improve software algorithms to adapt to head motions induced by vehicle ride, visual scanning patterns, or head nodding. Once these software improvements are available, they can be evaluated under similar conditions as the prototype DDMS in this evaluation.

Another possibility for improving the system's performance with head motions would be to move toward another type of sensor that uses more robust facial landmarks to create a face model for locating the eyes.

Recommendation 4

Update MV lane position sensors with advanced camera technology that incorporates "back light compensation." The MV lane position sensor consists of a low-quality camera with few features to compensate for headlight blooming (i.e., the occurrence of video image whiteout due to exposure to excessively high levels of reflected light).

Recommendation 5

Update MV lane deviation algorithms to account for headlight blooming. The MV lane deviation algorithms can be updated to include functions that identify areas of the image where white-out, low-contrast conditions are likely to occur.

Recommendation 6

Provide guidance as to the pavement types that enhance the performance of optically-based lane deviation sensors. Based on the findings of this evaluation, pavement type has a potential effect on the operational performance of lane trackers. Further testing is needed to explore pavement effects on these types of optical trackers and to determine which pavement types accentuate or hinder the performance of these sensors.

Step 5: Exploring Future Research Needs

Finally, this report discusses and recommends future research needs, to include: 1) recommendations to improve the prototype DDMS; 2) drowsy driver threshold determination; 3) refinement of DDMS design, including the driver/vehicle interface; and 4) development of a driver inattention monitor. These research areas are intended to improve the application of the DDMS and to expand its capabilities to be an all-inclusive driver awareness monitor.

Concluding Thoughts

The authors believe that the results of this evaluation point to the importance of a multimeasure, integrated approach to detect driver drowsiness. In its prototype form, the DDMS has demonstrated the potential to monitor and predict driver drowsiness, and this system provides an excellent integrated platform to refine drowsiness monitoring and to expand into other areas of driver inattention (e.g., distraction).

As with any equipment assessment, this evaluation was made on technology that continually evolves, so these results represent a snapshot in time. The authors are aware of current development efforts for both the MV eye closure sensor and MV lane position sensor to address many of the issues found in this assessment. Therefore, this evaluation's conclusions may not apply to new developments with these individual sensors.

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1. INTRODUCTION

According to the National Safety Council's (2004) *Injury Facts* report, motor vehicle crashes account for more deaths and disabling injuries than any other type of unintentional injury. In addition, while deaths attributed to other types of injuries decreased by 3 percent from 2002 to 2003, deaths attributed to motor vehicle crashes increased by 2 percent. Of the motor vehicle related deaths, 44 percent were attributed to collisions between vehicles, and 29 percent were attributed to collisions between vehicles and a fixed object. Approximately 28 percent of all motor vehicle crashes were the result of rear-end collisions. Driver impairment due to drowsiness is known to be a major contributing factor in many of these crashes. For example, several sources indicate driver fatigue was the probable cause of approximately 30 percent of crashes (Folkard, 1997; National Transportation Safety Board, 1990), mainly during nighttime driving conditions or when the driver had not obtained adequate sleep during the previous 24 hours (Horne and Reyner, 1995; Kecklund and Åkerstedt, 1993; Lenne et al., 1997; Lynznicki et al., 1998).

Fatigue[1] is known to decrease a driver's attention level and reaction time (Chatterjee, Cadotte, Stamatiadis, Sink, Venigalla, and Gaides, 1994; Mitler, Miller, Lipsitz, Walsh, and Wylie, 1997; Williamson, Feyer, and Friswell, 1996). Fatigued drivers pay less attention to the driving environment than alert drivers and are less concerned with making errors, circumstances which decrease the likelihood that they will perceive potential conflict situations (Dinges, 1995). Even if he or she recognizes a potential conflict situation, a fatigued driver may not respond in a proper or timely manner to avoid a crash. Dinges (1995) states that fatigue "increases errors (of omission and commission) and the compensatory effort needed to avoid them." He found that the reaction time of fatigued drivers worsens by 5 percent to 25 percent, interfering with their ability to avoid a crash situation with a timely evasive maneuver (e.g., steering to avoid a crash or allowing proper braking distance).

Given the impact of driver drowsiness on driving safety, there has been keen interest in developing a system that can monitor and quantify driver drowsiness and provide a real-time warning to the driver and/or a control output to the vehicle or other systems as warranted. Numerous drowsy driver monitoring systems are available on the market; however, nearly all of these technologies rely on a single predictor of driver drowsiness (e.g., eye closures, lane position, or steering). A negative aspect to using only one predictor of drowsiness is that such monitoring systems are susceptible to periodic intervals in which data are unavailable due to failures of the single sensor or operation outside of the sensor's capabilities. When the single sensor does not work optimally, the system is less effective than it could be.

One measure seen in some drowsiness monitors is slow eye closures (i.e., percent closure [PERCLOS]). However, tests with some specific technologies have found periodic intervals of

[1] Many people use the terms *fatigue* and *drowsiness* interchangeably. For example, Dinges (1995) states that he uses the terms *fatigue* and *drowsiness* interchangeably to describe "the neurobiological processes regulating circadian rhythms and the drive to sleep." The present authors understand there is a difference between the terms, which is described in detail in section 3.2.

data loss in various conditions—the driver is wearing eyewear (e.g., prescription eyeglasses or sunglasses), the driver's eyes are not within the system's field-of-regard because of normal visual scanning patterns (e.g., mirror checks), or the driver is performing a secondary task (e.g., looking down at the speedometer)—that can be misread by the system as a valid eye closure (Wierwille et al., 2003).

Lane position is another metric that has been used to identify drowsy driving. Like slow eye closures, this is not a completely robust measure. For example, lane position data loss can occur when the system fails to read the lane's edge markings due to weather (e.g., rain or snow covering); poor quality lane markings leading to insufficient contrast between the lane marking and the road; or inconsistent lane markings (e.g., merge lanes or intersections) which, confuse the visual system. Depending on how data loss is handled by the system, the result can be missed occurrences of drowsy driving and/or false alarms indicating the driver is drowsy when he/she is actually alert. Too many false alarms can diminish users' trust, confidence and acceptance of the technology (Bliss and Acton, 2003; Maltz and Shinar, 2004; Lees and Lee, 2007).

The objective of this research project was to develop a robust prototype system that combines drowsiness metrics to alleviate some of the issues associated with a single measure device. Based on an information gathering task, it was determined that a machine vision-based (MV) eye monitoring technology, combined with analysis of operator/vehicle performance parameters, would provide a strong metric to reliably assess driver drowsiness. The hypothesis of this research was that a multimeasure approach to detecting driver drowsiness would be superior to a single-measure approach. As noted, the problem with single-measure drowsiness detection systems is that when there is a loss of data, the system becomes unreliable. For example, single-measure systems based on eye closure metrics may have data loss if the driver is wearing eyeglasses or there is high ambient illumination (Hanowski et al., 2008). However, a multimeasure approach that uses multiple distinct sensors can provide not only a backup system but also an integrated approach whereby both measures provide more robust drowsiness detection than could either measure alone. This report details the effort to test this hypothesis.

The steps necessary to develop the prototype drowsy driver monitoring system (DDMS) include:

- **DDMS Design Fundamentals**: Basic design considerations, such as the ideal functional specifications that designers and engineers are urged to account for in the development of an ideal DDMS.
- **Identifying Salient Indicators of Fatigue**: Salient predictors of driver drowsiness as gathered from a literature review and an analysis of data from two recent naturalistic driving studies.
- **Prototype DDMS Development**: These development steps include drowsiness predictive model derivation, driver input from focus groups, selection of an MV eye closure sensor, and system creation.
- **DDMS On-Road Evaluation**: The procedure used to determine the effectiveness of the prototype system once it was created and installed in an actual commercial road tractor.
- **Future Research Needs**: Results of the on-road evaluation and recommendations for future research needs.

2. DESIGN AND FUNCTIONAL SPECIFICATIONS

2.1 OVERVIEW

Previously, DDMS models have shown promise in the detection of drowsy driving behavior. However, the technology and complex warning algorithms that comprise these systems may be limited in their individual functional characteristics. The principle behind a DDMS is to detect physiological and/or performance indicators of driver drowsiness and then provide feedback (e.g., an alarm) to the driver regarding his or her state of drowsiness. The purpose of providing such information to the driver in an impaired state is to motivate him or her to take corrective action (e.g., pull over to take a nap).

To successfully perform its purpose, a DDMS would, ideally, meet certain design and functional criteria. The sections below describe the criteria that would constitute an ideal DDMS (Dinges, Mallis, Maislin, and Powell, 1998; Wierwille, 1999b).

2.2 IDEAL DESIGN AND FUNCTIONAL SPECIFICATIONS

2.2.1 Accuracy

First and foremost, the ideal DDMS would accurately measure what it is intended to measure. This corresponds to the scientific principle of *validity*.

Further, the DDMS would have an acceptable level of sensitivity to the variables it is measuring. The *sensitivity* of the system refers to the likelihood that the effect of a variable will be detected when that variable does, indeed, have an effect (Shaughnessy and Zechmeister, 1994). Sensitivity is increased to the extent that error variation (e.g., false positives/negatives) is reduced. A driver may accept a small percentage of errors, but too many errors will ultimately reduce the driver's trust of the system (Lees and Lee, 2007). This distrust can lead to annoyance and disregard of the system, which may ultimately lead to deactivation.

2.2.2 Ability to Account for Common Driving Behaviors

This criterion is closely related to the validity of the DDMS. Reasonable operator behaviors would be accounted for in the design of the system. For example, it would accommodate the need for drivers to check mirrors, look over their shoulders, shift gears, make seat adjustments, reach for items within the cab, or move into common driving postures (e.g., slouching, erect), etc. This is especially important for a DDMS that includes an eye-related measure. For instance, some currently available DDMS models will assume a driver's eyes are closed if the eyes cannot be detected, such as when the driver turns to check the vehicle's mirrors.

2.2.3 Reliability

The DDMS would be reliable in that it *consistently* measures what it is intended to measure. Furthermore, the hardware and software of the system might require minimal maintenance. If the DDMS is often inconsistent and requires regular calibration or maintenance (beyond expectations), drivers may be less likely to trust and, therefore, use the system.

2.2.4 Adaptability to Various Environmental Conditions

An ideal DDMS would operate correctly in a variety of environmental conditions, both internal to the cab (e.g., temperature, ambient lighting, high noise levels, etc.) and external to the cab (e.g., time of day, adverse weather conditions, changing overhead lighting luminosities, dense or sparse ambient traffic, varying highway geometry, etc.). This corresponds to the scientific principle of *generalizability*.

2.2.5 Adaptability to Various Driver Physical Characteristics

Design for a wide variety of operator physical characteristics is critical for the system to be successful. The system might accommodate the widest range of physical characteristics of the operator, including demographic features (e.g., age and gender); physical features (e.g., face size, body height and size, eye color, skin color, and facial features); transient features (e.g., if the driver wears a hat); and visual needs (e.g., corrected or uncorrected visual impairments, use of eyeglasses, sunglasses, and/or contact lenses). This criterion also corresponds to the scientific principle of *generalizability*.

2.2.6 Ability to Detect a Change in the Vehicle Operator

Somewhat related to the above is the system's ability to detect and account for multiple drivers, as commercial vehicles are frequently operated by several individuals. The system would have the capability to self-calibrate and configure as needed to allow sharing the vehicle equipped with the DDMS. Hence, the system will ideally have the capability to identify a change in operator and adjust accordingly to detect changes in operators' physical characteristics.

2.2.7 Ability to Meet Fundamental Human Interface Needs

To be effective, the system's information and, if appropriate, warning would be noticed, heard, understood, and accepted by the driver (Wickens, Gordon, and Liu, 1998), creating a user-centered approach to interface design. The system would support the driver, not hinder or create potentially hazardous situations. The information would maintain a balance of driver attention and resource allocation. Allocations among distraction and attentional demands needed to operate the vehicle safely are critical.

The success of an information/warning system will depend on the driver interface and how well the algorithm fits the driver's capabilities and preferences. The driver would understand that the information/warning is not intended to serve as an "alarm clock," but rather as an indication of high likelihood of a hypovigilant state.

2.2.8 Non-Encumbering Design

Related to the interface needs specified above, the DDMS would not obstruct the operator's field of view or access to necessary controls and displays needed to operate the vehicle. Interaction with the system would be kept to a minimum, both for safety purposes and driver acceptance of the system. The system should not be overly distracting or require the driver to remove his/her hand(s) from the wheel for an extended period of time. In terms of driver acceptance, the greater the encumbrance of the system to the driver, the less likely the driver will be to accept the system. Ideally, such a system would require only limited, if any, intervention by the driver.

2.2.9 Need for Minimal Calibration

While calibration based upon individuals' needs may be inevitable, ongoing calibration would ideally be kept to a minimum. Closely related to nonencumbering features, any additional intervention required may lead to lack of acceptance. The calibration process should be simple and quick to implement, as drivers may be less likely to deal with system calibration complexities.

2.2.10 Ability to Gather Data Continuously in Real Time

For the DDMS to serve its intended purpose, the system would operate in real time, thus having an acceptably short delay in updating status information and issuing warnings. Noticeable delays will reduce the intended protection afforded by the system. Furthermore, it is clear that the system needs to have the ability to monitor driving continuously without major interruptions. Since drowsy driving can occur at any point during a drive, the system would be able to monitor the driver's condition throughout the entire driving session.

2.2.11 Cost-effectiveness

Once the system is well defined and found to adequately meet all design and functional specifications, it should be made economically viable. Generally, costs can be reduced once a viable prototype is developed. Ultimately, the benefits of the system would outweigh its costs, or the system will be dismissed by its potential consumers.

2.2.12 Summary

The design and functional criteria described above are important not only for the scientific evaluation of the DDMS, but also to keep the driver safe and obtain/maintain user acceptance.

With these general design and functional specifications considered, the next step to develop the prototype DDMS was to gather information to guide which fatigue-related indicators will be addressed by the system. Previous and current DDMS models have relied primarily on their ability to detect a single driver behavioral characteristic (such as ocular movements or steering) or vehicle-based measures (such as lane position/line crossing). (See appendix A for a summary of models currently on the market.)

The following section provides an overview of information on salient driver drowsiness-related indicators. Once the "best" indicators of fatigue are identified, it is envisioned that the prototype DDMS will include cameras, electronics, a driver warning display, and an alarm that ultimately will be integrated into a single, unobtrusive unit. The DDMS of the future will ultimately be robust, inexpensive, and reliable to allow the driver sufficient time to mitigate or prevent fatigue-related crashes. The successful development and commercialization of such a system would be directed toward decreasing crashes and injuries, particularly those related to rear-end collisions and lane/road departures.

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3. SALIENT DRIVER DROWSINESS-RELATED INDICATORS

3.1 OVERVIEW

The effectiveness of a DDMS is dependent on the system's ability to attend to the stimuli in question and determine trends in the changes of those stimuli in order to predict the onset of drowsiness. To that end, this section will first investigate the current knowledge of driver drowsiness based on a literature review to find the most important indicators of the onset of drowsiness while driving.

Note that a DDMS is envisioned to be more than a fatigue detection/monitoring system; instead, the system uses three equally important phases: a detection phase, an alarm phase, and a countermeasure phase (Wierwille et al., 1996b). In the final analysis, the system would fail to perform its primary goal if fatigue is not effectively recognized. Therefore, the authors recommend that the development of a DDMS be centered on these three approach stages, the most critical of which is the detection phase.

The purpose of this literature review was to investigate what salient variables would best be included in this detection phase. Without adequate detection, the subsequent alarm and countermeasure strategies are of little value. This is not to say that proper warning and countermeasure phases are irrelevant. While this review provides a better understanding of what is needed to detect fatigue, it is again stressed that a systems perspective addressing each of the three stages is needed for the DDMS to work as a complete and effective unit.

Then, following the literature review, an analysis of data from two recent naturalistic commercial driving studies will be discussed. Overall, the information described in this section informed the selection of the most appropriate stimuli to monitor with the prototype system developed for this research project.

3.2 LITERATURE REVIEW

This portion of the report is a high-level review of research conducted on driver fatigue—namely, its measurement and detection. It is organized in terms of driver-based and vehicle-based approaches used to detect and monitor driver fatigue. Moreover, it serves as a guide to the technical specifications and needs for developing a robust DDMS. This review will assist in the development of a system that will effectively quantify driver drowsiness and provide real-time warnings to drivers.

3.2.1 Defining the Problem: Fatigue and Drowsiness

It is important to note that the terms *fatigue* and *drowsiness* are often used interchangeably in the literature. This work will use the terms interchangeably in the manner in which they are presented in the original literature sources. This is to ensure that the operational definitions and intentions of the original authors remain unchanged. However, a distinction between the terms is made at times, and this distinction is evident by comparing the definitions below.

Fatigue is defined as "a state of reduced physical or mental alertness which impairs performance" (Williamson et al., 1996, 709). Another definition provided by Dinges (1995) is "a neurobiological process directly related to the circadian pacemaker in the brain and to the biological sleep need of the individual." Dinges further states that fatigue is something all humans experience, noting that it cannot be prevented by any "known characteristics of personality, intelligence, education, training, skill, compensation, motivation, physical size, strength, attractiveness, or professionalism" (1995, 42).

Drowsiness is defined as the "inclination to sleep" (Stutts, Wilkins, and Vaughn, 1999) and is also commonly referred to as "sleepiness." As noted above, fatigue is a reduced state of mental or physical alertness that impairs performance. Fatigue can occur without the subject actually being drowsy; therefore, *fatigue* and *drowsiness* are not exactly synonymous. While fatigue is the result of physical or mental exertion, drowsiness may result from boredom, lack of sleep, hunger, or other factors.

Drowsiness is a natural occurrence in the human body that can affect individuals in different ways. The human body usually functions on a 24-hour circadian rhythm that is driven by light levels in the environment, as well as by specific physical states, such as body temperature, melatonin levels, etc. During a 24-hour period, the human body usually experiences two drowsiness-related lows: the first in the middle of the night between approximately 12 a.m. and 6 a.m. and the second in the afternoon between 2 p.m. and 4 p.m. (Dingus et al., 2002; Stutts et al., 1999; Williamson et al., 1996). An illustration of this phenomenon is shown in Figure 1.

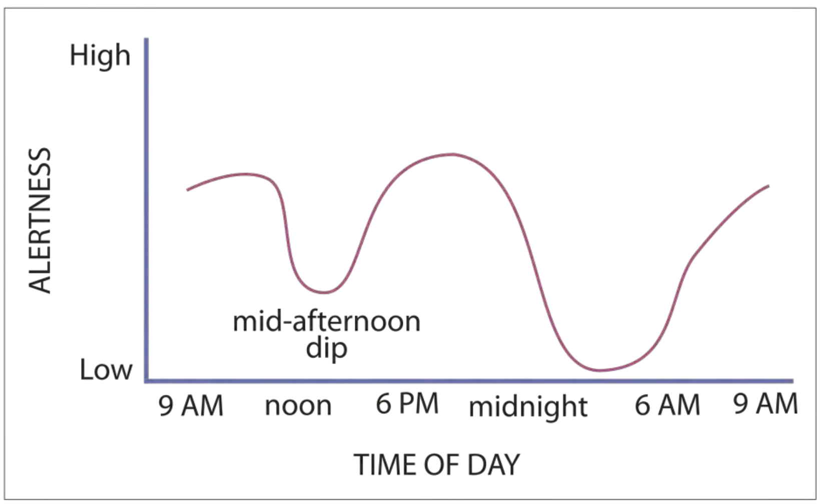

Figure 1. Human 24-Hour Circadian Rhythm

Source: National Sleep Foundation (2007)

3.2.2 Attempts to Measure Drowsiness

According to Knipling and Wierwille (1994), the full effects of drowsiness do not occur instantaneously. The period of onset of drowsiness can last for an hour or more and is often associated with a cumulative gradual decrease in performance coupled with measurable psycho-physiological signs. Over the past 2 decades, the trucking industry has seen a technological boom in on-board DDMS models designed to detect driver drowsiness and provide warnings when triggered. This technology has shown promise, but no system is found to be infallible in detecting fatigued and drowsy driving.

One issue is that quantification of driver fatigue is not straightforward. Unlike other impaired driver states, such as alcohol or drug intoxication, fatigue cannot be quickly or objectively measured with a breath test or urine sample. The detection process is more inexact. Also, as stated above, the onset of fatigue and drowsiness is a cumulative process, which may not be detected until there is a noticeable difference in driving performance or the driver's physical characteristics or mannerisms.

However, progress is being made in the area of quantification. Recent advances in fatigue monitoring technology have demonstrated the ability to detect potentially dangerous levels of fatigue through a range of different approaches. These approaches include monitoring brain activity via electroencephalography (EEG), eye movements, head movements, and facial features, as well as driver performance measures such as lane deviations and steering. Researchers are attempting to determine which of these salient indicators are most important so as to be able to measure drowsiness accurately and reliably through detection algorithms that can be implemented using technology.

3.2.2.1 Identifying Salient Indicators of Drowsiness

To make advances in fatigue-related transportation safety, a thorough understanding of variables associated with driver fatigue is of paramount importance. This literature review summarizes methodologies developed to measure fatigue-related changes in driver psycho-physiological states and driving behavior. These approaches include:

- Driver-based measures of a driver's current state of well-being ascertained by the physiological changes in ocular movements, EEG, pupil occlusion, etc.
- Vehicle-based measures of driving performance using variables such as speed, lateral lane position, time-to-line crossing, lane drift, steering movements, etc.
- A combination of person- and vehicle-based measures.

The following sections review the literature that pertains to how each of these measurement techniques relate to driver fatigue measurement. Before continuing, however, it is important to note several aspects of this research area that are not addressed in this review. First, several physiological methods for measuring fatigue—such as electrocardiogram, galvanic skin response, and electromyogram (Brookhuis and de Waard, 1993)—are not covered here because of their overly invasive nature and the relatively limited amount of research. While perhaps as invasive as the methods mentioned above, EEG is covered because of the sheer volume of research performed with this measure. Second, research investigating facial features and head movement as indicators of fatigue is not covered because there is so little research in this area, and so far, findings have been exploratory at best. Finally, it should be noted that this review covers studies that attempted to measure the effects of fatigue via simulation and on-road testing. Both of these driving scenarios have their advantages and disadvantages. However, a discussion of the merit or limitations of each is beyond the scope of this review. Here we provide a high-level review of only the most relevant research in driving-related fatigue measurement over the past several decades.

3.2.3 Driver-based Approaches

3.2.3.1 EEG Measures

It has been well documented that distinctive changes occur in EEG when an individual transitions from wake to sleep (Rechtschaffen and Kales, 1968). While numerous physiological indicators measure level of alertness, the EEG signal may be the most reliable and predictive means to measuring alertness levels (Erwin, Volow, and Gray, 1973; Volow and Erwin, 1973; Artaud, Planque, Lavergne, Cara, de Lepine, Tarrière, and Gueguen, 1994). Because of this, the EEG has been the standard for measuring alertness/drowsiness in the laboratory and, occasionally, in the field (e.g., Brookhuis, Louwerens, and O'Hanlon, 1986; Torsvall and Åkerstedt, 1987; Brookhuis, 1995; Wylie, Schultz, Miller, Mitler, and Mackie, 1996).

Simulator studies have shown a negative relationship between the EEG power of alpha and theta bands and alertness level of the driver (Åkerstedt, Kecklund, and Knuttsson, 1991). Increased alpha bands are generally regarded as the first sign of drowsiness, while an increase in theta bands is indicative of the early stages of sleep (Andreassi, 2000). In another driving simulator study, Lal and Craig (2000) found substantial increases in delta (indicating deep sleep; Andreassi, 2000) and theta activity, and smaller increases in alpha activity during transition to fatigue. A further finding by Petit, Chaput, Tarriere, LeCoz, and Planque (1990) demonstrated a strong correlation between steering wheel movement and the EEG power of alpha bands.

Although many studies have been conducted in this area, a reliable EEG-based fatigue detector has yet to be found. Lal, Craig, Boord, Kirkup, and Nguyen (2003) completed a simulation study in which they were able to detect fatigue and drowsiness using an EEG algorithm. However, this system needed further modifications to compensate for major artifacts in the EEG data, such as coughing, sneezing, vibration, and large body movements. The researchers therefore acknowledged that additional research is needed to produce a real-time, robust, and reliable fatigue detecting/alerting system (Lal et al., 2003).

Summary: Despite EEG being recognized as a powerful indicator of fatigue, its major drawback is the intrusiveness to drivers. EEG measurement requires the individual to wear a skullcap, which is connected to wires and may be uncomfortable and motion-limiting. Therefore, while EEG performs well under laboratory conditions, it is not considered feasible for measuring driver fatigue under natural driving conditions. Nonetheless, EEG monitoring technology of the future may become less intrusive and therefore more practical in the driving arena.

3.2.3.2 Ocular Measures

Building on EEG measures as a fatigue indicator, Åkerstedt et al. (1991) make the assumption that the two most critical indicators of sleepiness are EEG and oculomotor parameters. As noted, today's EEG technology does not afford an ideal opportunity to collect data in everyday driving situations. Fortunately, ocular movement/parameters research has demonstrated great promise in predicting a driver's state of drowsiness (Cleveland, 1999).

Various technologies have been developed to measure oculomotor parameters, most commonly in the form of eye closures, eye blinks, pupil responses, or other eye movements. Unfortunately, most of these devices have been tested in the laboratory and lack real-world driving exposure. For example, technologies developed to monitor ocular movement often use infrared light, which is directed at the eye and then reflected back from the eye and recorded using a video camera. This technique may work effectively in ideal low-light conditions, but may fail during daylight or well-lit road conditions (Wierwille et al., 2003).

Nonetheless, promising findings exist for using ocular measures as an indicator of fatigue. Specifically, two methods to measure ocular movement have provided the most consistent and promising results in gaining an understanding of eye behavior as it relates to fatigue; namely, slow eye closure and blinking behavior. Each of these is discussed below, based on seminal findings and recent research.

Percentage of Eye Closure: Percentage of eye closure (PERCLOS) is a mathematically defined proportion of a time interval in which the eyes are 80 percent to 100 percent closed (Wierwille, 1999b). PERCLOS is based on a measure of slow eye closure, not including eye blinks. While an eye blink is typically a very quick closing and reopening of the eyes, "slow eye closures" are relatively gradual eye movements in which the eyelids droop and close slowly. Alert individuals generally do not exhibit drooping facial features and slow eye closures, while eye blinks are common no matter what one's state of alertness. Hence, PERCLOS makes a distinction between the two (Wierwille, 1999b).

Research on slow eye closures as a measure of fatigue began in the mid-1970s, when researchers found that these eye movements provided a valid way to measure drowsiness levels in narcoleptic and normal subjects (Erwin, 1976; Erwin et al., 1973). During the mid-1980s, Skipper and Wierwille (1985, 1986) defined and tested a variety of measures of slow eye closure in a motion-based driving simulator. Their findings include moderate correlations between the various slow eye-closure measures and lane-related measures (e.g., range of $r = 0.50–0.60$ for lane deviation), with PERCLOS being superior to other slow eye-closure calculations (i.e., the sample mean of closure, termed AVECLOS, and the sample mean of the square of closure, termed EYEMEAS; Wierwille, 1999b).

With PERCLOS established, Wierwille and associates tested a variety of algorithms to detect fatigue while also measuring performance on non-driving- and driving-related tasks (Wierwille, Wreggit, and Knipling, 1994b). They found PERCLOS correlated well with non-driving task performance (e.g., solving arithmetic problems and letter searching tasks) as well as lane-related driving measures. A study by Pilutti and Ulsoy (1997) reported that the standard deviation of a vehicle's lateral position increases as the driver's state of alertness decreases and corresponds to PERCLOS.

A major finding relative to the PERCLOS measure includes an evaluation of six ocular measurement techniques that involved video-based scoring of slow eye closures by trained observers, which was conducted by Dinges et al. (1998) and Dinges and Grace (1998) to compare their potential for detecting drowsiness-induced hypovigilance. These include the following: PERCLOS, two EEG algorithms (Consolidated Research Incorporated's *EEG Algorithm and Head Positioning Monitoring Device* and Advanced Safety Concepts' *Proximity*

Array Sensing System), and two eye-blink monitors (MTI Research, Incorporated's *Alertness Monitor* and IM Systems, Incorporated's *Blinkometer*). All devices demonstrated potential in detecting drowsiness-induced hypovigilance in at least one of the subjects of the sample. However, only the PERCLOS-based system correlated highly with vigilance performance lapses in all participants across 42 hours of wakefulness.

PERCLOS has clearly demonstrated promise as a valid means to detect fatigue in the simulated environment. However, PERCLOS, with its complex fatigue detection algorithm, often fails to perform as it was intended in a naturalistic setting under current technology. As a result, a revised fatigue detection algorithm, AVECLOS, the percentage of time the eyes are estimated to be fully closed over a 1-minute interval, is thought to perform with greater accuracy in the naturalistic setting. It was noted by Barr, Howarth, Popkin, and Carroll (2005) that the correlation between PERCLOS and AVECLOS, which is based on the PERCLOS measure, has been validated (Pearson correlation coefficient of 0.95). The AVECLOS measure provides benefits over the PERCLOS measure in a naturalistic setting because its simpler algorithm can be processed using an automotive-grade processor rather than a higher-grade computer processor. However, these are computational considerations, not fundamental considerations. In fact, as noted above, Wierwille (1999b) presents data showing that PERCLOS has a higher correlation with lane-related measures than does AVECLOS.

It is important to note at this point that any algorithm developed for detecting fatigue must be tested on other data sets to ensure validity, as was done in Wierwille et al. (1994a). An algorithm may fit very well with one sample, but it may fail to replicate its results in another sample. Thus, establishing external validity is of paramount importance for the development of algorithms. Future research must include tests of external validity when developing algorithms to detect fatigue.

Summary: In summary, the evidence surrounding the validity of the PERCLOS measure as a fatigue indicator appears promising. For the most part, the research community agrees that PERCLOS is effective in detecting fatigue-induced lapses of attention during driving. In fact, PERCLOS has been deemed the "gold standard" of drowsiness measures (Knipling, 1998).

3.2.3.3 Eye Blinks

The spontaneous eye blink is also considered a suitable ocular indicator of fatigue (Stern, Boyer and Schroeder, 1994). This behavior can be measured in a noninvasive manner, recording blink rate via cameras and sensors (i.e., MV technology). Sirevaag and Stern (2000) have found the analysis of spontaneous blinks to have the potential to provide information about the central nervous system activation process and fatigue. In a laboratory study simulating sudden inversion of the sleep-wake cycle to mimic the cycles of some shift workers, researchers measured smooth pursuit (slow eye movements) and saccadic (rapid) eye movements of five participants as possible indicators of fatigue. The results suggested that saccadic performance, unlike smooth pursuit, seems to have increasing sensitivity to greater levels of sleepiness. Although this study was conducted with a small sample size, it encouraged further research on the topic of eye movements and, ultimately, blinking behavior (Porcu, Ferrara, Urbani, Bellatreccia, and Casagrande, 1998).

Åkerstedt, Peters, Anund, and Kecklund (2005) found that, with increased driving time and after working a night shift, there were increased subjective sleepiness levels, longer blink durations, and increased instances of lane drift. Another study found a relationship between the Karolinska Sleepiness Scale (KSS), a subjective measure of sleepiness, and the increased occurrence of slow eye movements (Åkerstedt and Gillberg, 1990). Additionally, Caffier, Erdmann and Ullsperger (2003) used a contact-free device (i.e., one that does not touch the eye) to capture spontaneous eye movements and found blink duration and reopening time changed reliably with increased drowsiness. They concluded that measurements of eye blink behaviors have the potential to be used in a continuous fashion to monitor the onset of sleepiness.

A literature review on blink rate as a measure of fatigue by Stern et al. (1994) found strong support for the notion that blink rate increases as a function of time on task. However, this review found that variables other than time on task are sensitive to task demands such fatigue effects as flurries of blinks, time with regard to information-processing demands, and blink closure duration. Galley, Reitter, and Andres (1999) measured saccades and blinks in 20 subjects during 40 6-hour trips on German highways. Fixation duration, saccadic velocity, blink rate, blink amplitude, eye closure velocity, and 19 additional parameters were measured and compared to subjective scores of fatigue and time on task. The research concluded that the subjective scores of fatigue could be better predicted by ocular motor and blink parameters than saccade parameters.

Individual Difference of Eye Blink Behaviors: Very little research has been conducted to understand distinct differences among individuals' eye blink behaviors as a result of fatigue. A study by Ingre, Åkerstedt, Peters, Anund, and Kecklund (2006) sought to address these individual differences and to develop subject-specific relationships between subjective sleepiness measured with KSS scores, blink duration, and lane drift. The results of this study indicated that a relationship exists between KSS, lane drift, and blink duration. Specifically, the researchers found that the effect is curvilinear with a steeper rise at high subjective sleepiness levels, especially for the standard deviation of the lateral position. However, it is important to note that large differences were found between individuals in their overall driving performance and blink duration independent of sleepiness levels and that "serious behavioral and physiological changes do not occur until relatively high levels of sleepiness are reached" (p. 50). Ingre et al. (2006) further expressed an interest in the presence of individual differences and warned against making statistical errors associated with group average estimates. For example, statistical methods to identify individual differences are not always employed on individualistic data sets; if these methods are practiced, they are often not mentioned in the research methods or results.

As noted by Ingre et al. (2006), individual differences are complex and the underlying principles behind them are not yet understood. It is clear that more research is needed to address these individual differences before an effective DDMS can be developed fully based on these aforementioned specifications. These findings imply that customizations based on individual differences are required. Rather than using averages among a group, individual differences will need to be understood and accounted for. To date, accurate individual variation estimates in eye blink behaviors appear to be unknown, potentially leading to poor reliability in detecting fatigue among individuals using eye blink as an indicator.

Adding to the complexities of individual differences is the lack of research on participants with sleep disorders, such as obstructive sleep apnea syndrome (OSAS). Previous studies have shown that drivers with OSAS perform poorly on driving simulation tasks and have an increased crash risk (George, Boudreau, and Smiley, 1996). Hakkanen, Summala, Partinen, Tiihonen, and Silvo (1999) addressed this by comparing professional bus drivers with mild to moderate OSAS to a control group, focusing on blink duration as a measure of sleepiness during on-road driving. This study's findings confirm those of Stern et al. (1994; discussed above); an increase in sleepiness is correlated with an increase in average duration of closure during blinks.

Summary: PERCLOS and AVECLOS measures have been found to be reliable indicators of drowsiness and performance deterioration due to drowsiness in both driving and nondriving tasks. Eye blink measures also show promise in detecting fatigue but do not appear as robust as the promise of the PERCLOS and AVECLOS measures. Confounding the issue of using eye blink behavior are individual differences, which may be problematic in providing robust measures of fatigue. At this time, it would seem that PERCLOS or AVECLOS would be a more suitable indicator of fatigue than eye blink behaviors.

3.2.4 Vehicle-based Approaches

For many years, researchers have studied the physical control of a vehicle that characterizes the driver's state of alertness. To date, two of the most promising approaches found are lane-related and steering measures. Using driving simulation, Skipper and Wierwille (1986) found that the standard deviation of lane position and the standard deviation of steering velocity (velocity as a measure of degrees of steering angle per second) were significant fatigue indicators as measured by slow eye closures. A review of the most relevant research on vehicle-based approaches in identifying salient fatigue indicators, specifically lane position/line-crossing and steering metrics, is presented in the following sections.

3.2.4.1 Lane Position/Line Crossing

Measures of lane position have shown compelling evidence that they are valid indicators of fatigue. Early driving fatigue research established that unintentionally drifting out of the lane while driving is an indicator of fatigue (O'Hanlon and Kelly, 1974). O'Hanlon and Kelly (1977) measured mean speed, standard deviation of speed, frequency of steering wheel movements, and lane drift frequency—determined by the number of times the left or right wheel crossed the lane line(s) per minute of driving—to determine whether any of these variables related to fatigue during a 4- to 5-hour drive. Of these metrics, lane drift frequency was determined to be the best indicator of fatigue.

Two early simulation studies investigating the effect of prolonged driving reported decrements in lane tracking and steering performance as driving time increased (Mast, Jones, and Heimstra, 1966; Dureman and Boden, 1972). Lane drift was also used as a measure of fatigue by Riemersma, Sanders, Wildervanck, and Gaillard (1977), who defined lane drift as the standard deviation of lane position. Again, the major findings from this study indicate that lane drift appears to be sensitive to fatigue effects, and this was shown to vary during different phases of the driving trip. Specifically, lane drift gradually increased during the beginning of the trip, decreased after the driver stopped for fuel, and reached a maximum near the end of the 8-hour drive. More recent studies (e.g., Wylie et al., 1996) found that steering wheel variability and lane tracking variability were greater for drowsy events than for non-drowsy events.

Wierwille et al. (1994a) studied simulator steering metrics and found that variations in lane-keeping, steering inputs, and speed maintenance were a function of fatigue. They also found that algorithms which include lane-related measures (mean square of lane position, variance of lateral position, standard deviation of lateral position relative to lane, proportion of time that any part of the vehicle crosses the lane boundary, mean square of the difference between the outside edge of the vehicle and the lane edge when the vehicle strays over the lane boundary, variance of the time derivative of lane position, and standard deviation of the time derivative of lane position) predict drowsiness better than algorithms that do not include lane-related measures. They concluded that constructing conditional criteria by using estimated PERCLOS outputs and the proportion of the time that any part of the vehicle strayed outside of the lane boundary was necessary to significantly improve the accuracy of detection of fatigue.

Research by Tijerina et al. (1999) was the first of its kind to evaluate the drowsy-driver detection algorithm of Wierwille, Lewin, and Fairbanks (1996a) using naturalistic driving data. Eight vehicles were instrumented with a system that enabled unobtrusive data collection. Their findings indicated that lane keeping is the key to drowsiness detection. It should be noted that these results are derived from a small sample size, and limitations of the lane tracking hardware should also be weighed when interpreting these results.

A recent study by Philip, Sagaspe, Moore, Tiallard, Charles, Guilleminault, and Bioulac (2005) tested sleep-deprived participants and a control group to determine the effects of sleep deprivation on naturalistic driving performance. Self-ratings of fatigue, reaction time, and the number of lane deviations were measured. Results from this study suggest an 8:1 likelihood of line crossing during conditions of sleep deprivation. Specifically, there were 535 lane deviations in the sleep-deprived condition and 66 lane deviations under normal sleep conditions. Similar findings were reported by Rimini-Doering, Manstetten, Altmueller, Ladstaetter, and Mahler (2001) in a simulator study in which 60 participants drove a scenario intended to induce fatigue and stress. Sixty-nine percent (n = 41) of the participants experienced sleep events lasting several seconds. Lane-tracking behavior showed decrements by a factor of 2–3 prior to simulated crash occurrences, leading the authors to conclude that lane-tracking capability shows merit in determining the state of the driver.

A study by Arnedt, Geddes, and MacLean (2005) involved simulated urban and highway driving during a period of prolonged wakefulness. Eleven males drove throughout the night without sleep and were tested at five different time periods: midnight, 2:30 a.m., 5 a.m., 7:30 a.m., and during the final 90 minutes of driving. Measurement variables included the following: physiological measures, such as EEG, electro-occulogram, and electromyogram; self-reported sleepiness measures, such as the Stanford Sleepiness Scale; and driver performance measures, including lane tracking, tracking variability, standard deviation of tracking, speed deviation, speed variability, standard deviation of speed, and the number of times the vehicle left the road. The results showed that as time progressed, the drivers' lane tracking and speed became more variable. Additionally, as the night went on, participants were more likely to drive off the road. These findings are consistent with previous studies that found that lateral position deviations increase with prolonged driving exposure (de Waard and Brookhuis, 1991; Dureman and Boden, 1972), and that fatigue leads to an increase in road departures (Chatterjee et al., 1994).

Verwey and Zaidel (2000) performed a study that included 26 sleep-deprived participants who drove a nighttime driving simulation lasting 135 minutes (2 hours, 13 minutes). Of the 26 participants, 6 drove off the road and 10 others left the pavement with 1 or 2 wheels. Dependent variables included driver performance measures, driver drowsiness measures, blinking, slow eye closure (frequency of eye closures lasting at least 1 second), self-rating of sleepiness, and a subjective measure of mental workload. It was found that the frequency of eye closures of duration greater than 1 second, events in which the frequency of time-to-line crossing was less than 0.5 seconds, and the number of earlier moderate lane crossing errors best predicted road departure errors. The best predictors of line-crossing errors were the frequency of events in which time-to-line crossing was less than 0.5 seconds, slow eye closure frequency, and the standard deviation of the lane position. Additionally, it was found that the frequency of events where time-to-line crossing was less than 0.5 seconds could be predicted by lane position, standard deviation of lane, steering frequency, and eye closure. The frequency of events where time-to-line crossing was less than 0.5 seconds was the most important predictor for severe driving errors resulting in a crash or road departure. This variable appears to be a more representative measure of degraded driving performance than conventional methods such as steering, speed, lane position, and standard deviation of lane position.

Summary: The literature on lane position/line crossing appears to provide strong evidence that lane keeping degrades as a function of fatigue-induced impairment. The findings from these studies show the following lane metrics as being representative measures of degraded driving performance as a result of fatigue:

- Lane keeping/lane tracking capability.
- Lane drift frequency (standard deviation of lane position).
- Line crossing.
- Time-to-lane crossing.

It is unclear which metric of lane tracking, position, crossing, etc. is the most appropriate measure. Nonetheless, lane-related behaviors demonstrate promise as a salient fatigue indicator.

3.2.4.2 Steering

Steering wheel inputs may indicate fatigue-induced impairment. During highway driving, a driver must continuously make small steering wheel movements to keep the vehicle in the center of the lane. Therefore, it is hypothesized that there is a relationship between the driver's alertness state and steering wheel behavior. Specifically, alert drivers will respond to lane deviations early with many small-amplitude steering movements to correct the car's trajectory, whereas fatigued drivers will respond slowly to lane deviations and make large steering wheel movements to correct for larger lane deviations (Thiffault and Bergeron, 2003). Most researchers agree that as fatigue-related impairment increases, a subsequent increase occurs in the variability of steering control. Beyond this general agreement, there is little consensus on what exact measure of steering is correlated with driver fatigue (Fairclough, 1997). Steering-related approaches are discussed below.

As mentioned above, some researchers believe studying micro-corrections of the steering wheel is a window into fatigue detection. For example, Petit et al. (1990) found that microcorrections lessen as driver impairment increases. Such research has led to the development of commercially available devices that claim to detect fatigue through steering movements. Examples include the steering attention monitor, which emits a warning sound when a predetermined “fatigue” threshold (which correlates with an absence of microsteering corrections) has been reached. The divided attention steering simulator (DASS) is another example of a device that attempts to detect fatigue through the use of standard deviations of steering error. A study by Philip et al. (2003) used the DASS and found steering error on a simulator could be used to measure fatigue.

A study by Paul, Boyle, Tippin, and Rizzo (2005) evaluated microsleeps as an indicator of driver performance impairment in drowsy drivers with sleep disorders. Microsleeps involve a brief unintended loss of attention lasting 3–14 seconds. Twenty-four drivers with obstructive sleep apnea/hypopnea syndrome (OSAHS) were tested to determine driving impairments when they were experiencing microsleeps, as compared to when they were not experiencing microsleeps. Steering variability (standard deviation of steering wheel angle), lane position variability (standard deviation of lane position), time-to-lane crossing, and acceleration and velocity measures were measured in a driving simulator. The results indicated that driver performance measures, steering variability, lane position variability, and minimum time-to-lane crossing are sound indicators of poorer driving control for drivers with OSAHS during microsleep episodes. Greater steering variation was found in drivers with OSAHS during microsleeps.

However, while Paul et al. (2005) and others (Moore-Ede, Guttkuhn, Heitmann, and Trutschel, 1999) believe that microsleeps are the basis for many crashes, there are at present no reliable overt indicators of microsleep. Consequently, there is no reliable method of detecting microsleep. If microsleep exists, it appears that the only way to ameliorate its effects would be to detect impending lane departures (using a lane departure warning system) or impending rear-end collisions (using a forward radar obstacle detection system) and warn the driver in the second or two that might be available prior to a crash-relevant conflict.

Filiatrault, Cooper, King, Siegmund, and Wong (1996) conducted a study on the efficiency of using vehicle-based data to predict lane departures as a result of driver fatigue. The study consisted of 17 long-haul truck drivers using a fully instrumented truck on a closed-circuit track. Drivers drove during two sessions: one when they were alert and another while sleep-deprived. Of the other measures collected (EEG, electrocardiogram, accelerator pedal angle and angular velocity, vehicle speed, vehicle lateral lane position, car-following distance, steering wheel angle, and angular velocity), micromovements in steering were found to be a reasonable predictor of lane departures as a result of fatigue. EEG was not found to be a reliable predictor.

Another study by Fairclough (1997) investigated nine British police drivers under sleep-deprived conditions. The dependent variables included EEG, steering wheel variability and standard deviation, accelerator pedal standard deviation, mean speed, standard deviation of speed, and standard deviation of acceleration/deceleration. The researchers further developed fatigue detection variables (i.e., Y_1, Y_2, Y_3, and SSA) that combined the relationship between steering wheel movement and speed. The Y_1 variable quantified the underlying trend of steering change. The Y_2 and Y_3 variables quantified the number and magnitude of steering adjustments. The Y_3 variable also provided weights for higher magnitude steering adjustments. Finally, the SSA variable provided self-reported fatigue data using a nine-point rating scale. Results indicated that the variables, which focused on the number and magnitude of steering adjustments combined with speed, had a stronger predictive relationship with the self-reported fatigue measure than did the other steering measures.

Thiffault and Bergeron (2003) used monotonous driving scenarios to relate to driver fatigue. The aim of their study was to determine whether disruptions of monotony can assist in reducing the effects of driver fatigue. The study methodology was based upon the findings of Brookhuis (1995) and Wertheim (1978), who found that straight-line simulated driving is an appropriate task to measure vigilance. The researchers placed 56 male participants in two 40-minute scenarios: one was developed to mimic monotony, and the other aimed to disrupt monotony. Results indicated that participants had more frequent large steering wheel movements while driving in a monotonous environment. It was concluded that larger steering wheel movements implied greater decrements in alertness and vigilance. This study showed that the effects of fatigue can be measured by the standard deviation of lateral position, as well as the amplitude of steering wheel movement, frequency of larger steering wheel movements, and the standard deviation of steering wheel movements.

3.2.4.3 Individual Differences of Vehicle-Based Behaviors

O'Hanlon and Kelly (1977) investigated individual differences in lane drift and sleepiness and found a great deal of variance. Again, individual differences play a significant role in fatigue-related issues. Anecdotal and empirical evidence have shown that there are large individual differences in people's susceptibility to fatigue. Verwey and Zaidel (2000) attempted to predict driver behavior based upon a personality cluster classification. It was determined that those drivers who were classified as the "extraversion-boredom" personality type were more likely to go off the roadway because they had fallen asleep. Those classified as the "disinhibition-honesty" personality type did not fall asleep, but they were more likely to cross solid lane markings. Based on the driving performance variables collected, the researchers believe their results suggest that personality is a cluster of individual differences warranting further research for predicting fatigue-related driving behavior. This study used a very small sample size; so this work is considered exploratory and should be treated as such.

Peters (2003) performed a driving simulator experiment on 10 shift workers in which the participants drove for 2 hours in the morning under two different conditions: sleep-deprived and non-sleep-deprived. The dependent variables included road departures, lateral lane position, derived measures of time-to-line-crossing and steering behavior, KSS scores, and eye blink behavior. The overall mean correlation between KSS scores and corresponding measures of interest includes the following: lateral position was 0.52, time-to-line-crossing (right) was 0.49, and blink duration was 0.66. When analyzed on an individual level, the correlations were found to be higher. The researchers reported that their measures were moderately useful in detecting impaired driving behavior. Here again, the study bears witness to the effects of individual differences on fatigue and its effects. Again, caution must be exerted when interpreting results based on such a small sample size.

An important detail to consider with regard to steering is that it is considerably affected by such things as road type, road crown, curvature, environmental conditions (e.g., wind), and vehicle steering system characteristics. These items must be taken into account as confounds of steering is used as a measure of fatigue.

Summary: It appears evident that steering wheel movements provide some insight into drivers' level of fatigue. Most researchers who have studied steering behavior and driver fatigue agree that steering behavior has potential as a valid indicator of fatigue. However, there is little consensus regarding what specific metric of steering correlates best with fatigue. Overall, the findings from these studies support the notion that fatigue is correlated with steering behavior.

Again, it is important to take into account possible confounds (e.g., road type, road crown, crosswinds, and vehicle steering characteristics) when considering steering as an indicator of fatigue. While lane position is a product of steering input, it is the driver's task to keep the vehicle in the lane regardless of these confounds. For instance, an alert driver guiding a vehicle along a roadway may have to make frequent and high magnitude steering inputs to counter a crosswind, but the vehicle's change in lane position may not be indicative of these frequent steering corrections. However, as a driver becomes drowsy, lane-keeping behavior is quite likely to change because the driver is not sufficiently alert to counter the crosswinds. Consequently, lane-keeping behavior appears to be less sensitive to confounding factors while remaining sensitive to drowsiness.

3.2.5 Combination of Driver-based and Vehicle-based Approaches

As previously mentioned, several laboratory research studies have been conducted to evaluate a number of measures to assess driver alertness, including EEG, ocular measures, lane position, and steering. Heitmann et al. (2001) suggest no one measure can sufficiently and reliably indicate driver alertness; hence, the necessity for multiple measures. It is clear that further research is needed to understand more fully what metrics are necessary to capture drowsy driving in an effective, holistic fashion. Progress has been made toward obtaining a better understanding of driver-based and vehicle-based fatigue measurements independently, with each having their own unique strengths and limitations. However, relatively little research has been conducted in combining technology that uses both driver-based and vehicle-based fatigue metrics. It is believed that employing a systems approach, whereby several metrics are used to evaluate the situation, will be more effective in capturing drowsy driving as a complete phenomenon (Wierwille et al., 1994a; Wierwille, 1999a, 1999b).

One example of a multimeasure approach is the European Union's AWAKE (System for Effective Assessment of Driver Vigilance and Warning According to Traffic Risk Estimation) program (Boverie, 2004). The aim of the study is to incorporate eyelid movement, changes in steering grip, lane tracking, and accelerator and brake pedal use as a means to monitor driver vigilance. This ongoing research effort demonstrates promise but remains exploratory. Another example of using more than one metric to identify fatigue via technology is research by Grace et al. (1998). They developed a prototype drowsy driver detection system for heavy vehicles and determined that the most viable approach would not only measure psycho-physiological changes, such as PERCLOS, but would also include measurements of driver performance changes. These researchers suggested driver performance measures to include the following: steering wheel movements, lateral lane position information, longitudinal speed, lateral and/or longitudinal acceleration, and vehicle braking. Although this study did not reach a conclusion regarding the most reliable driver performance fatigue indicator, it remains that a combination approach is the recommended avenue to fatigue detection.

To supplement the need for a multimetric approach, some researchers have discussed the fundamental problem of using only ocular movement in the assessment of fatigue. The problem with using only eye behavior is that changes to a driver's state are likely to happen late in the process of fatigue. It is believed that the driver will have driven through a period of increased risk (because of his/her fatigued state) before significant eye closure effects will be realized. Further exacerbating the problem, Williamson and Chamberlain (2005) believe that in a situation in which late stages of fatigue are reached and signaled, the driver will have no other recovery option than to stop and sleep. An earlier warning may be more convenient for the driver and allow him or her to plan accordingly (e.g., having a caffeinated beverage with enough time for the caffeine to have an effect before drowsiness increases). Early detection may also be beneficial because the greater the driver's fatigue, the more difficult it is to overcome, leading to the need for a more substantial period of sleep (Williamson and Chamberlain, 2005). Under these circumstances, drivers may, in the long term, accept an early-detection feature more readily than a late-detection feature. On the other hand, drivers could consider an early warning to be a nuisance, which may lead to distrust and, ultimately, rejection of the system.

Further research supporting the need for a multivariable approach was implemented by Oron-Gilad and Hancock (2005). These researchers attempted to distinguish between fatigue caused by the demands of the driving task (i.e., characteristics of the driver and the road environment) and fatigue caused by driving while already sleep deprived. Their research determined that drivers can adopt coping strategies to deal with various road types (i.e., winding, two-lane straight, straight four-lane divided) and perceived level of fatigue. The researchers found that drivers were able to increase focus when critical elements of the roadway required attention. Because of these coping strategies, these authors caution against using a single or a limited number of performance measures to detect fatigue. Additionally, many individual differences were found among the participants, which included 10 professional military truck drivers and 17 university students. From the beginning of the drive, the student drivers tended to drive more poorly than the professional military truck drivers.

Summary: The approach that will probably be most successful in effectively detecting fatigue will include more than one measure or indicator. The combination that best predicts or indicates the onset of drowsiness and the corresponding impairment remains to be found.

3.2.6 Literature Review Summary

This literature review began with a brief summary of literature pertaining to the identification of salient fatigue indicators. The ongoing debate of reliable and valid fatigue measurement continues, although progress toward consensus is being made. Based on the information presented above, it seems two of the most promising measures of fatigue are the PERCLOS and lane position/line crossing variables. It is unclear which metric of lane measurement is the most appropriate (e.g., tracking, position, crossing, etc). Nonetheless, evidence suggests lane-related behaviors are salient fatigue indicators. It seems clear the research community agrees that steering wheel movements provide some insight into a driver's impaired state. However, as with lane-keeping measures, there is little consensus regarding what exact metric of steering correlates with fatigue.

Clearly, no single variable reliably predicts fatigue 100 percent of the time. Therefore, a multivariable approach will most likely provide a more reliable detection of fatigue. A particular metric may be more effective for a given driver while the other(s) may serve as a backup if the first fails to properly indicate fatigue in that individual. For example, if PERCLOS is determined to be the primary indicator of fatigue, then lane position could serve as an auxiliary to the eye closure warning algorithm if or when the latter fails to perform.

As discussed, most of the past research (but not all) is based on group average estimates. It is well known that there are no "average" humans; therefore, care must be taken in basing conclusions on the "average," which may lead to forming inaccurate conclusions. Human factors researchers understand that individual differences exist, but accounting for the differences when developing a robust fatigue monitoring system affords unique challenges. The magnitude of these differences with reference to the effects of fatigue on the driving population remains in an exploratory stage at best. More research is needed to understand more fully the differences among individuals. Again, not enough information is available to be able to rely solely on one performance metric for the whole driving population. Therefore, at this time, it appears that it would be most useful to have multiple performance metrics to determine a driver's state.

One of the primary design principles of this project is to develop a prototype system that effectively detects drowsiness across the widest possible user population. While individual differences will be considered in the design of the system, the system's performance will be optimized for the majority of users.

3.3 RATIONALE FOR USING EYE CLOSURES AND LANE POSITION AS PREDICTIVE MEASURES

Today, there are numerous drowsy driver monitoring systems available on the market. However, nearly all of these technologies rely on a single predictor of driver drowsiness (e.g., eye closures, lane position, steering). By using only one predictor of drowsiness, these drowsy monitors are susceptible to periodic intervals in which data are unavailable, rendering these systems ineffective. For slow eye closures, these periodic intervals of data loss include times the drivers are wearing incompatible eyewear (e.g., dark tinted sunglasses), the driver's eyes are not visible to the system because of normal visual scanning patterns, or the driver is completing a normal task (e.g., looking down at the speedometer) that is misread by the system as closing of the eyes. For lane position, periodic intervals of data loss occur when the system fails to read the lane's edge markings because of weather conditions such as rain or snow; poor quality lane markings; or mangled and inconsistent lane markings that confuse the detection system.

These periods of data loss may be mishandled by the system and may create false alarm events, leading to reduced user confidence and acceptance of these DDMS models.

To overcome the concern caused by data loss, there is interest in combining multiple predictors of driver drowsiness to provide a more robust model of detection. With two or more sources of predictive data, the model can continue to extract drowsiness information from the driver even as one of the two sources becomes unavailable. In line with this thinking, this project has the goal of developing a prototype integrated system that combines two separate predictive sources of driver drowsiness. To increase the reliability of these two separate predictive measures, the sources should be as independent as possible from one another (i.e., orthogonal). For this reason, the two drowsiness-related predictors chosen were eye closure (driver-based), and lane position (vehicle-based).

Slow eye closures have shown promise in predicting the onset of driver drowsiness in both simulators (Skipper and Wierwille, 1986; Wierwille et al., 1994b) and over-the-road trucking operations (Dinges et al., 2005). Of the numerous slow eye closure measures (e.g., PERCLOS, AVECLOS, and EYEMEAN), estimated PERCLOS values have been recognized by many in the fatigue research community as the most effective ocular measure to detect the onset of driver drowsiness (Dinges and Grace, 1998; Knipling, 1998). In fact, estimated PERCLOS value is the only ocular measure to be validated by the National Highway Traffic Safety Administration (NHTSA; Dinges, Mallis, Maislin, and Powell, 1998). Therefore, estimated PERCLOS value was chosen as the eye closure metric because of its proven efficacy at detecting the onset of driver drowsiness.

Measures of lane position have also been found to be a capable indicator of driver drowsiness (O'Hanlon and Kelley, 1977; Chatterjee et al., 1994; Wierwille, 1994; Tijerina et al., 1999). To further explore the power of lane position's relationship with driver drowsiness, the authors conducted a cursory analysis of data from two recent naturalistic commercial driving studies, the "Drowsy Driver Warning System Field Operational Test" (DDWS FOT) (Hanowski et al., 2008) and the "Naturalistic Data Collection" study. The purpose of this analysis was to examine the data in order to look for correlations between a drowsiness metric and driver performance metrics.

3.3.1 Drowsy Driver Warning System Field Operational Test

While specific details of the DDWS FOT methods can be found in Hanowski et al. (2008), this section will briefly summarize the key aspects of the study. The participants included 103 (102 males; 1 female) professional drivers who possessed a Class-A commercial driver's license (CDL). The drivers were volunteers and were selected based on the following qualifications:

- Engaged in night driving.
- Did not wear glasses while driving.
- Had a low risk of dropping out or leaving their current trucking company.
- Passed vision and hearing tests.

The DDWS FOT data set included several different types of variables: driver input/performance measures (e.g., lane position, headway), video (four camera views), actigraphy (wrist-worn Actigraphs, which measure sleep quantity), and questionnaires (pre-study, post-study, and focus groups). These variables were collected from 46 instrumented tractors that were driven an average of 13.72 weeks per participant. This data collection resulted in an extremely large data set that consisted of:

- Almost 48,000 driving-data hours covering 2.4 million miles (equivalent to almost 100 trips around the world or 800 coast-to-coast trips across the United States).
- More than one-quarter million data, video, and ASCII text files (279,600 files total).
- Approximately 12.4 terabytes of data from video and dynamic sensor files.
- A total of 397 load history files from 103 drivers who participated in the FOT.
- A total of 598 actigraphy data files and 356 data recording sheets from more than 8,000 days worth of actigraph data (or approximately 195,000 hours of activity/sleep data).
- Pre-participation, pre-study, post-study, and debriefing questionnaires from drivers.
- Fleet management surveys from each company.
- Focus group results collected from 14 drivers during two post-study focus group sessions.

The DDWS FOT data collection effort resulted in 915 safety-critical events (analysis of approximately 75 percent of the data set). These safety-critical events were:

- Identified as potential events, mostly through the use of an event trigger software program.
- Checked for validity by trained reductionists.
- Classified according to an established data directory.

For the purposes of this project, this data set was further reduced to include only safety-critical events that occurred when there was a high confidence of having valid lane-tracking data and where the vehicle speed was greater than 30 mi/h. This new data set included approximately 393 of the original 915 safety-critical events. For each of these safety-critical events, the data associated with the timeline illustrated in Figure 2 were used in the analyses. A 10-second gap was left between the event and the end of the E′-1 interval to avoid confounding or polluting the pre-event data of interest with data from the event itself. That is, for this analysis, the researchers were interested in the pre-event data that may be used to predict or prevent a possible event, not the event data per se. Note that some metrics were gathered over all three 1-minute timeframes (E′-3, E′-2, and E′-1), whereas others were only gathered for E′-1. These details are outlined in Table 1.

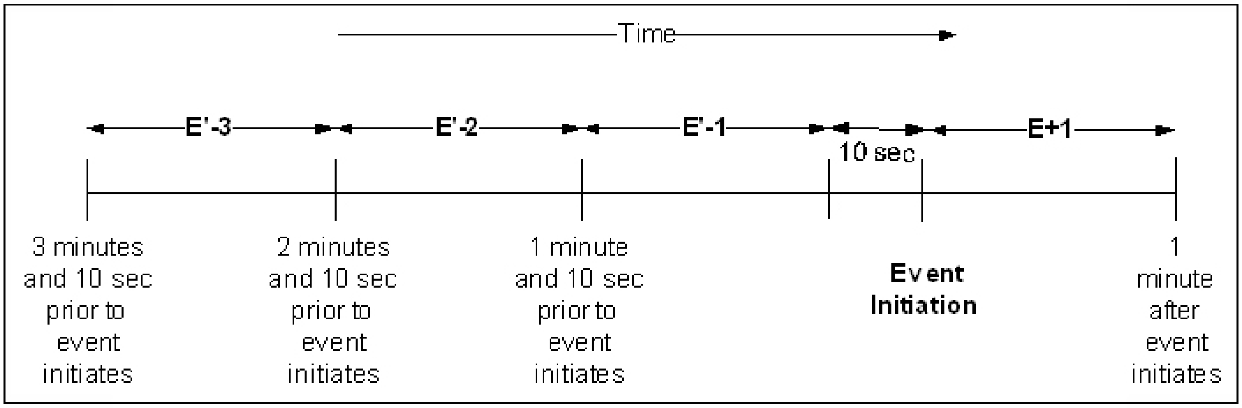

Figure 2. Data-Gathering Timeline Relative to Each Event

Table 1. Glossary of Metrics

Lane Keeping Metrics (all measured using MV lane position sensor Lane Tracker)	Definition
Lane Offset Standard Deviation (ft)	Standard deviation of the lane offset (distance outside the lane in feet) calculated over each of the three intervals separately, then averaged across the three values.
Lane Offset Variance (ft^2)	Variance of the lane offset (distance outside the lane in feet) calculated over each of the three intervals separately, then averaged across the three values.
Lane Offset MS (Mean Square, ft^2)	Mean Square (i.e., mean of the squared observations) of the lane offset (distance outside the lane in feet) calculated over each of the three intervals separately, then averaged across the three values.
Lane Offset RMS (Root Mean Square, ft)	Root Mean Square (i.e., square root of the mean of the squared observations) of the lane offset (distance outside the lane in feet) calculated over each of the three intervals separately, then averaged across the three values.
Gamma Standard Deviation (degrees)	Gamma (i.e., angle of vehicle heading relative to roadway heading) standard deviation calculated over each of the three intervals separately, then averaged across the three values.
Gamma Variance ($degrees^2$)	Gamma (i.e., angle of vehicle heading relative to roadway heading) variance calculated over each of the three intervals separately, then averaged across the three values.
Lane Departure (0–1.0)	The fraction of total interval time the vehicle is out of lane on either side, calculated over each of the three intervals separately, then averaged across the three values.

Longitudinal Metrics	Definition
Minimum Time to Collision	Those objects (i.e., leading vehicles or other substantive objects) that meet the following conditions will be referred to as *targets*: • Within 150 feet of the front of the primary vehicle. • Within an absolute azimuth angle ≤ 3 degrees. • With a closing rate ≤ primary vehicle's speed. For targets meeting the above criteria and the closing rate is > 0 (i.e., the primary vehicle is nearing the target), the minimum time to collision (TTC) value was determined for the each of the three intervals, then averaged that across the three values (measured by VORAD Radar).
Headway (ft)	Distance between the primary vehicle and the target at the point in time during which the minimum TTC was calculated (see above), averaged over the three values (measured by VORAD Radar).
Speed Change (mi/h)	Change in vehicle speed from the beginning of (E′-1) to the end of (E′-1). A negative vehicle speed change indicates slowing; a positive change indicates acceleration (measured with GPS Horizontal Speed).
Maximum Deceleration (ft/sec^2)	Largest value of deceleration over interval E′-1 (positive for deceleration; negative for acceleration).
Average Deceleration (ft/sec^2)	Velocity change over the E′-1 interval and divide by 60 s (positive for deceleration; negative for acceleration).
Driver Drowsiness Metrics	**Definition**
Observer Rating of Drowsiness (ORD, 0–100%)	Average of the driver drowsiness ratings of two trained evaluators over the E′-1 timeframe; initial ratings by the two raters that differed by more than 15 points were resolved by re-reviewing the segments together and achieving consensus.
PERCLOS1	Percent of time the driver's eye were 80–100% closed (based on slow closures, not blinks), averaged over the interval 1 minute prior to the event.
PERCLOS3	Percent of time the driver's eye were 80–100% closed (based on slow closures, not blinks), averaged over the interval 3 minutes prior to the event.
PERCLOS5	Percent of time the driver's eye were 80–100% closed (based on slow closures, not blinks), averaged over the interval 5 minutes prior to the event.

To ensure valid lane-tracking measures, each 1-minute interval of data (Figure 2) was omitted for all lane-tracking metrics where an intentional lane departure (e.g., where the driver used the directional indicators in the correct direction just prior to a lane change or the video indicated that the driver was avoiding an obvious obstacle along the roadside) was detected by analysts.

There were two phases of analyses. The first phase examined the relationship between the driver's PERCLOS values and the vehicle's kinematic data. The second phase examined the relationship between driver's observed rating of drowsiness (ORD), a subjective video-based rating performed by trained analysts (Wierwille and Ellsworth, 1994), and the vehicle's kinematic data.

Despite various statistical tests, the results from both phases of the Task2b analyses did not reveal any apparent significant relationship between the driver's level of drowsiness (as indicated by either PERCLOS or ORD) and the vehicle's kinematic measures. Although this finding was surprising, further investigation into the methodology of the DDWS FOT may have exposed some rationale for this unforeseen conclusion. The DDWS FOT study was constructed on the premise of evaluating a driver drowsiness monitor technology. The driver sample was aware of this fact and may have created fatigue countermeasures (e.g., ensuring adequate sleep was obtained) prior to participating in the study. Also, the technology being evaluated provided an alert to the driver when the level of drowsiness was excessive. These are just a few plausible explanations for why the analyses did not find a relationship between the level of fatigue and vehicle kinematic measures.

3.3.2 Naturalistic Data Collection Study

The Naturalistic Data Collection study is an ongoing follow-on study to the DDWS FOT. The intent of this study is to collect additional naturalistic driving from approximately 100 drivers in at least eight instrumented vehicles. However, this was not a driver drowsiness study, per se, as was the DDWS FOT. As such, the drivers in the "Naturalistic Data Collection" study did not participate in a pre-study that included a driver drowsiness information workshop or have a DDWS instrumented in their vehicles. According to a brief analysis of the more than 400 safety-critical events in the study data, 33 percent were triggered by a lane crossing. Of these lane crossings, 76 percent of the drivers were judged to have high levels of ORD as rated by trained analysts. This initial analysis of these data indicates a notable connection between lane-tracking and the level of observed drowsiness. Based on these data, lane position appears to have promising potential as a predictor of driver drowsiness.

While there are numerous means of measuring lane position (e.g., lateral lane position—or lane offset, standard deviation of lane position, line crossings, time-to-line crossings), it is still unclear in the literature which measure is the most appropriate. Therefore, the root of lane position—lane offset—was chosen as the secondary predictor. For this project, *lane offset* is defined as the instantaneous lateral lane position of the vehicle relative to the lane's edge lines. *Lane deviation* is defined as the portion of time that the Lane Offset value exceeds the width of the lane. As the algorithms mature, more complex measures of lane position can be substituted for this more basic predictive measure of lane offset.

According to Wierwille et al. (1994a), the accuracy of detecting drowsy driving can be improved by combining estimated PERCLOS values with the proportion of time that any part of the vehicle exceeds the lane edge lines. Therefore, both of these metrics will be incorporated into a mathematical model to provide a more robust predictive algorithm for detecting drowsy driving than either metric alone.

4. PROTOTYPE DRIVER DROWSINESS MONITORING SYSTEM DEVELOPMENT

4.1 OVERVIEW

With the preliminary design considerations established, the team began to develop a prototype DDMS. At the foundation of the system is the predictive model to ascertain the trends from the stimuli and indicate when these trends exceed predetermined thresholds. Section 4.2 discusses this straightforward mathematical model. Next, the team determined user requirements for the system and obtained user feedback on the preliminary concepts and proposals.

Driver acceptance of drowsiness monitoring devices has not been fully addressed in the research literature. However, it is intuitive that anything found to be restrictive (e.g., devices worn on the body) or requiring additional effort beyond normal driving may be unacceptable by drivers, as is the case with some drivers who are unwilling to wear a safety belt. Driver acceptance will further affect the success of DDMSs. Manufacturers of future drowsiness monitoring devices are urged to seek to increase social acceptance through the utilization of contact-free application methods. Section 4.3 will detail a focus group study that was completed in support of this project to address this issue.

With the understanding that MV was the technology choice and that the most salient indicators of driver drowsiness were PERCLOS and lane deviation, the team attempted to identify the most capable sensors available for the development of this prototype system. While the authors chose to use a proprietary MV lane position sensor system developed by their employers, the team needed to determine the best MV sensor for tracking eye closures. Commercially available MV eye closure monitors were identified, and a technology selection process was completed. Section 4.4 provides the details of this selection process. Finally, section 4.5 details the creation of the prototype DDMS and the steps completed prior to its on-road evaluation.

4.2 MODEL DERIVATION

This section of the report briefly explains the derivation of a preliminary mathematical model to predict driver drowsiness using relevant indicators as determined by the project’s literature review and analysis of “naturalistic data” from both the DDWS FOT and the “Naturalistic Data Collection” studies. Based on the literature review findings, eye closures and lane position were chosen as the most salient predictors of driver fatigue. The estimated metrics for these previously-mentioned measures include PERCLOS for eye closures and lane deviation for lane position. Lane deviation is derived from the measure lane offset, which is defined as the instantaneous distance between the vehicle’s centerline and the imaginary lane centerline in inches, as described in detail in section 4.5. The rationale for choosing both PERCLOS and lane deviation as predictors of driver drowsiness can be found in section 3.3.

From these measures, a simple mathematical model was derived to exercise the prototype DDMS. This preliminary algorithm uses a 3 × 3 look-up table (Table 2) to provide an associative array of drowsiness categories that correspond to the specified levels of PERCLOS and lane offset (green represents a rating of one, magenta represents a rating of two, and red represents a rating of three). Figure 3 shows that the algorithm is mathematically defined as:

$$X = (DDMS\ PERCLOS\_Category) + ln(Lane\ Deviation\_Category)$$

Figure 3. Equation to Determine Drowsiness

Where X is classified as one of the following drowsiness categories:

$X < 2$ Drowsiness Category 1 (depicted as green on the Driver/Vehicle Interface)

$2 \leq X < 3$ Drowsiness Category 2 (depicted as magenta on the Driver/Vehicle Interface)

$X \geq 3$ Drowsiness Category 3 (depicted as red on the Driver/Vehicle Interface)

By taking the natural logarithm of the lane deviation value, the algorithm is, in effect, exponentially increasing the power of the PERCLOS metric as the integrated drowsiness value increases. Thus, the computed values for the look-up table are shown in Table 3. The first value in the equation is associated with the PERCLOS category, and the second value is associated with the lane deviation category. Based on these calculations, the DDMS output to the driver vehicle interface (DVI) is depicted in Table 4. (Note: the use of magenta was due to a software limitation. While the color yellow was initially used as the indicator for Category 2, the resultant color was more red-amber, making differentiation from this color in Category 2 and the red of Category 3 very difficult.) Future human-machine interface development will need to investigate monitor technologies that allow for the use of colors (e.g., yellow) because of their standardized meanings for warnings. However, magenta was sufficient for the purposes of this project since the color only needed to indicate a change in state of the system for data reduction purposes.

The specific levels of the threshold criteria used to establish the categories of PERCLOS and lane deviation are intended to elicit a specific response from the drowsiness monitor. While these threshold criteria are founded on previous research (i.e., Wierwille et al., 2003) and expert judgment, future work ideally will determine appropriate levels for actual over-the-road commercial motor vehicle (CMV) driving. Section 6 of this report discusses this need in further detail. Therefore, the thresholds provided here are considered preliminary. It is recommended that future works use data from naturalistic bouts of drowsiness along with mathematical optimization techniques to derive revised threshold levels for PERCLOS and lane deviation.

Table 2. DDMS Integrated Drowsiness Metric Threshold Algorithm Matrix

	PERCLOS Category 1 ***X ≤ 0.125 (12.5%) of eye closures over a 3-min interval***	**PERCLOS Category 2** ***0.125 (12.5%)< X ≤ 0.25 (25%) of eye closures over a 3-min interval***	**PERCLOS Category 3** ***X >0.25 (25%) of eye closures over a 3-min interval***
Lane Deviation Category 1 ***Y ≤ 0.33 (33%) of lane deviation over a 1-min interval***	Low drowsiness	**Moderate drowsiness**	**Severe drowsiness**
Lane Deviation Category 2 ***0.33 (33%) < Y ≤ 0.66 (66%) of lane deviation over a 1-min interval***	Low drowsiness	**Moderate drowsiness**	**Severe drowsiness**
Lane Deviation Category 3 ***Y > 0.66 (66%) of lane deviation over a 1-min interval***	**Moderate drowsiness**	**Severe drowsiness**	**Severe drowsiness**

Table 3. Computed Values for the DDMS Integrated Drowsiness Metric Look Up Table

	PERCLOS Category 1 ***X ≤ 0.125 (12.5%) of eye closures over a 3-min interval***	**PERCLOS Category 2** ***0.125 (12.5%)< X ≤ 0.25 (25%) of eye closures over a 3-min interval***	**PERCLOS Category 3** ***X >0.25 (25%) of eye closures over a 3-min interval***
Lane Deviation Category 1 *Y ≤ 0.33 (33%) of lane deviation over a 1-min interval*	**1 + ln(1) = 1.0**	**2 + ln(1) = 2.0**	**3 + ln(1) = 3.0**
Lane Deviation Category 2 *0.33 (33%) < Y ≤ 0.66 (66%) of lane deviation over a 1-min interval*	**1 + ln(2) = 1.7**	**2 + ln(2) = 2.7**	**3 + ln(2) = 3.7**
Lane Deviation Category 3 *Y > 0.66 (66%) of lane deviation over a 1-min interval*	**1 + ln(3) = 2.1**	**2 + ln(3) = 3.1**	**3 + ln(3) = 4.1**

Table 4. DDMS Integrated Drowsiness Metric Output to the DVI

	PERCLOS Category 1 *X ≤ 0.125 (12.5%) of eye closures over a 3-min interval*	**PERCLOS Category 2** *0.125 (12.5%)< X ≤ 0.25 (25%) of eye closures over a 3-min interval*	**PERCLOS Category 3** *X >0.25 (25%) of eye closures over a 3-min interval*
Lane Deviation Category 1 *Y ≤ 0.33 (33%) of lane deviation over a 1-min interval*	**Green**	**Magenta**	**Red**
Lane Deviation Category 2 *0.33 (33%) < Y ≤ 0.66 (66%) of lane deviation over a 1-min interval*	**Green**	**Magenta**	**Red**
Lane Deviation Category 3 *Y > 0.66 (66%) of lane deviation over a 1-min interval*	**Magenta**	**Red**	**Red**

4.3 FOCUS GROUP

4.3.1 Overview

Obtaining user feedback is very important early in any system design cycle. In order to obtain this feedback, the authors conducted two focus groups with long-haul and regional CMV drivers as part of another project. The primary objective of the focus groups was to explore the myriad of factors that may influence CMV drivers' decision to pull over once they realize they are becoming too drowsy to drive. The focus groups were funded as part of the U.S. Department of Transportation's University Transportation Centers Program.

An adaptation of the Socio-technical Systems model (STS; Emery & Trist, 1960) was used to evaluate the barriers that deter CMV drivers from pulling over once they become sleepy. The STS model can be subdivided down into four subsystems: technology, driver, organizational design, and environment. These subsystems do not function independently but instead interact and influence each other. For example, the flexibility of a fleet's sleep hygiene policy (organizational design) impacts a driver's ability to rest as needed (driver). This focus-group study used the STS model as a framework to organize and explore the barriers that drivers feel impede them from pulling over when they are sleepy. Environmental barriers to pulling over (i.e., lack of truck parking, hours-of-service regulations, and parking tickets) were the most commonly mentioned.

Understanding these barriers and addressing them when possible will aid successful implementation of technology such as a DDMS. Recommendations for implementing a DDMS more effectively were also considered in the focus group study and include involving CMV drivers in testing the DDMS technology, educating drivers on how the technology works and the likelihood of false alarms, and providing outreach to trucking companies on the importance of scheduling drivers in such a way that they have time to rest.

4.3.2 Focus Group Recommendations

1. *Make the DDMS more sensitive to the signs of drowsiness during circadian sleepy periods and at the end of shifts.*

Several participants stated on exit questionnaires that they tend to feel drowsy at night (midnight to sun-up) and during the afternoon (12–4 p.m.). These periods roughly coincide with circadian sleepy periods. As stated earlier in this report, the human body ordinarily functions on a 24-hour circadian rhythm and most people experience two sleepy periods: the first during the middle of the night between approximately 12 a.m. and 6 a.m. and the second in the afternoon between 2:00 p.m. and 4 p.m. (Stutts et al., 1999). Some participants also said that they feel drowsy at the end of their shifts. These time periods (i.e., during circadian sleepy periods and at the end of shifts) could be preprogrammed into the DDMS so that it is more sensitive to the signs and signals of drowsiness during these periods when drivers are more likely to be drowsy.

2. Locate the DDMS in a place where it is not an annoyance to drivers and does not hamper their visibility.

During the focus groups, participants were given a demonstration. Participants were shown a potential prototype of the DDMS in an actual truck cab (as shown in Figure 4) and then asked to voice their concerns regarding the device. The primary complaint voiced by participants was with the location of the DDMS. Participants shared concerns about the location of the monitor, which is positioned directly in front of the driver. This location is currently necessary in order for the DDMS to detect eye closures accurately. Many of the participants did not want the monitor located directly in front of them because they felt that it would be distracting, irritating, or would hamper visibility during bad weather or while parking. As one participant said, “I’d rather it be out of sight and out of mind so that I can focus.”

Figure 4. Potential DDMS Location (Circled) for In-Cab Demonstration

3. Make the DDMS alert so annoying that drivers are forced to pull over and rest.

While safety was a very important concern voiced by the drivers, some participants said that they feel great pressure to keep driving even when they are tired. Most participants said if they are too tired to drive, they want to be forced to make the safe choice and pull over. As one driver said, "If I am tired and I've got to pull my truck off and I don't want to, I'm refusing to, but I need to, by all means, do something to get me off the road because I don't want to hurt me or somebody else." For this reason, many of the drivers said that the DDMS should annoy them so completely that they are compelled to stop.

In terms of the type of a preferable warning, participants said that they want an alert that is ongoing and increasingly loud or annoying. Audible alarms and horns were popular options, though other ideas included "flashing lights" and "a puff of air." One participant said that the system "[s]hould have an audible alert and then a visual alert."

4.3.3 Focus Group Conclusions

Developing a DDMS that meets the needs of the drivers who will use it is critical to successful implementation. Yet safety and logistical problems with some of the recommendations made by participants should be noted. For example, if the auditory alarm is annoying and loud, as suggested by the focus group participants, drivers might choose not to use the DDMS. Also, placing the DDMS sensor out of the drivers' line of vision may cause errors in detection. While these user comments are helpful, they were made with only partial information and understanding of how the actual system works. For this reason, more research needs to be done with system users once the prototype DDMS has been created.

These focus groups also revealed that there are many barriers (particularly organizational design issues) that deter CMVs driver from pulling over even when they feel sleepy. It is critical that key stakeholders (i.e., policymakers, trucking companies, drivers, etc.) consider how to overcome these barriers, because the DDMS can be successfully implemented only when the factors that may influence a drowsy CMV driver's decision to pull over are considered and, where possible, addressed. A more in-depth look at the results of these focus groups can be found in Baker, Bowman, Hickman, Nakata, and Hanowski (2007).

4.4 MACHINE VISION EYE CLOSURE SENSOR SELECTION

4.4.1 Overview

To provide the best choice for the DDMS project, the authors employed an analytical process that involves both quantitative and qualitative factors. After reviewing several decision-making tools, the Kepner-Tregoe Decision Matrix (Kepner and Tregoe, 1976) was found to embody all of the essential principles needed to inform an effective decision. This decision analysis method systematically assesses the viability of different alternatives using the following six steps:

- Prepare a decision statement having both an action and a result component.
- Establish strategic requirements (musts), operational objectives (wants), and restraints (limits).
- Generate alternatives.
- Assign a relative score for each alternative on an objective-by-objective basis.

- List adverse consequences for each top alternative and evaluate probability (high, medium, low) and severity (high, medium, low).
- Make a final, single choice between top alternatives.

The Kepner-Tregoe Decision Matrix is a step-by-step approach to make systematically good decisions and analyze potential risks and opportunities. It helps maximize critical thinking skills, set objectives, systematically organize and prioritize information, evaluate alternatives, and analyze the impact of the final decision (Value Based Management, 2006).

For the current project, a team of experts was assembled to complete a variant of the Kepner-Tregoe Decision Matrix, referred to as the Technology Selection Matrix (Appendix B). In order for the team to make a knowledgeable assessment of each alternative, a simple quasi-experiment was completed that exercised each system under varying conditions. The following sections detail the methods, results, and recommendations for the MV technology. The intent of this quasi-experiment was to test both MV eye closure monitoring systems under similar conditions that would be typical of actual use.

4.4.2 Method

Two studies were completed: a static study that tested the systems in an illumination-controlled environment and a dynamic study that involved using the systems under normal driving conditions for both daytime and nighttime illumination. Data were gathered using a Class-8 tractor instrumented with a data acquisition system (DAS) and the fatigue monitoring systems.

As with the previous drowsy driver detection study conducted by Wierwille et al. (2003), this experiment was an equipment evaluation quasi-experiment in which the driver drowsiness units are “deterministic” and, unlike typical human factors studies, will provide nearly identical outputs under similar conditions. Therefore, the driver drowsiness units need only be “exercised” over the range for which they are likely to be used (Wierwille et al., 2003).

4.4.3 Equipment

Four primary equipment items were used in this study:

- MV Eye Closure Monitoring System A.
- MV Eye Closure Monitoring System B.
- An instrumented tractor.
- A DAS. The next sections will detail these pieces of equipment.

4.4.3.1 Machine-vision-based Drowsy Monitoring Technology

Two soon-to-be commercially available driver drowsiness systems were selected for this study. Both systems were prototypes and employed the most recent sensor technology.

MV Eye Closure Monitoring System A: For the purposes of this study, the first system was defined as *MV System A*. This system uses an 18-degree field of view camera with eight near-infrared illuminators. This system’s image processing module can be remotely located; therefore, the image processing unit was located in the sleeper berth of the tractor for this study. *MV System A* uses computer vision algorithms to generate an "appearance model" of the driver's face. From this derived model, the computer determines whether the driver's eyes are open or fully closed. Based on the comparison of the current eye shape to the "appearance model," the output is a "0" for an open eye and a "1" for a fully closed eye. From this output, an AVECLOS measure is computed that estimates the percentage of time the eyes are fully closed over a 1-minute moving average. According to the developer, blinks are considered to be eye closures of less than 500 milliseconds and are discounted from the AVECLOS metric. For this study, all of the system's default settings were used.

MV Eye Closure Monitoring System B: For this study, the second system was defined as *MV System B*. *MV System B* measures the three-dimensional head pose and eyelid motion parameters of the driver. This system provides two fatigue metrics: microsleep event detection and a user-defined PERCLOS metric. The system has a 12 mm lens camera with an infrared-pass filter and two satellite near-infrared illuminators positioned approximately 24 cm symmetrically on both sides of the camera (as shown in Figure 5). The separate image processing unit can be remotely mounted. Because of the length of the cables provided with the system, it was mounted on top of the dash where a Citizens Band radio is typically located. *MV System B* also used computer vision to determine what percent the eyes were closed. This output was then used to calculate a PERCLOS metric. The original definition of PERCLOS is the mathematically defined proportion of a time interval that the eyes are 80–100 percent closed (Wierwille, 1999b). *MV System B* allows the user to define the eye opening threshold between 0 and 100 percent closed. According to the installation guide, this eye opening threshold should be increased:

- If the eye openings' signal, even with the eyes fully closed, does not reach the bottom of the graph.
- If squinting and glances down to the dashboard are interpreted as microsleep events.

This value should be decreased to fine tune the borderline between squinting and closed eyes. For this study, the system developer requested that this eye opening threshold be placed at 10 percent. The PERCLOS metric is continuously calculated over a moving time window that may be defined by the user. For this study, *MV System B*'s developer requested that the time window be set at 180 seconds (3 minutes); however, this time window may range from 10 seconds to 500 seconds.

Figure 5. *MV System B* Infrared-Illuminator Placement

4.4.3.2 Data Collection System

Both the static and dynamic studies used a truck tractor instrumented with a DAS. Since neither *MV System A* nor *MV System B* recorded data, an interface between the evaluated units and the DAS was created to allow the DAS to capture both video data and outputs from *MV System A* and *MV System B*. The video data included a four-way split screen view of the driver's face, the video input from either *MV System A* or *MV System B*, the forward roadway, and an over-the-shoulder view of the dash (Figure 6).

Figure 6. Quad View From DAS

For the static study, the tractor was positioned in a large vehicle bay where the space lighting consisted of four large metal halide lamps. These lamps were centrally controlled by a single switch and were allowed a minimum of 5 minutes to warm up before the start of any data collection. The primary purpose of the static study was to allow more individuals to participate, since a CDL would not be required. In addition, more independent variables could be introduced and controlled to determine their effects on the operation of the two units. These independent variables included: external illumination (mean: 79 lx [day conditions], 0 lx [night conditions]); eyewear (sunglasses, eyeglasses); and skin complexion (light skin tone, dark skin tone).

Varying levels of external illumination were included as a factor of interest because the operation of previous fatigue/drowsiness monitoring systems was limited to specific levels of illumination. Since bouts of drowsiness may occur throughout the 24-hour cycle, drowsiness monitors need to operate effectively under varying illuminance levels.

Various forms of eyewear were included as a factor of interest because of the prevalence of eyewear in commercial truck driving. According to estimates by Wierwille et al. (2003), roughly 36 percent of commercial drivers wore glasses during the Impact of Sleeper Berth Usage on Driver Fatigue study (Dingus et al., 2002), sponsored by the Federal Motor Carrier Safety Administration. Still, a high percent of drivers wear some form of sunglasses while driving. Therefore, all eye closure sensors need to effectively deal with this aspect of driving.

As stated in section 2.2.4, eye closure sensors need to account for the individual physical differences between drivers. Both *MV System A* and *MV System B* rely on the facial landmarks (i.e., edges of the mouth, corners of the eyes, eyebrows) to locate the driver's eyes. Therefore, those factors that may affect the eye closure sensor's ability to discern these facial features need to be examined. It can be hypothesized that varying skin complexions could reduce the gradient between these facial features and their surroundings. Therefore, varying skin complexion was included as a factor of interest.

Once the participants arrived, the experimenter (who was seated in the passenger seat) followed the instructions found in Appendix C. The participants were first asked to position themselves comfortably in the driver's seat. Since these individuals were not licensed commercial drivers, they were instructed to find a comfortable seat position in which they were able to depress the clutch to the floor. This was to ensure that the seat position chosen by the participant would allow him or her to effectively operate the vehicle. Following this, the participants were provided instruction on how to "exhibit" slow eye closures for the durations of 2 seconds, 5 seconds, and 10 seconds. After practicing each eye closure task, the experimenter reviewed the seven additional non-eye closure tasks:

- Looking straight forward for 10 seconds.
- Bouncing up and down in the seat (simulating speed bumps) while looking straightforward for 10 seconds.
- Looking down to the instrument panel and gazing at the speedometer.
- Looking up to the sun visor.

- Visually scanning by first looking into left mirror, scanning across the horizon through the windshield, and ending by looking into the right mirror.
- Horizontally scanning the environment, looking through the windshield from right to left (not including the mirrors).
- Rotating head through the entire range of neck motion both up and down and side-to-side with eyes remaining open. The participants were instructed to pick gaze points and fixate on those points as they visually scanned the arc of head motion.

These tasks were completed for four different conditions:

- Overhead lights on and no eyewear.
- Overhead lights on and either sunglasses or eyeglasses.
- Overhead lights off and no eyewear.
- Overhead lights off and eyeglasses. Those participants who did not wear eyeglasses only completed the first three conditions, since drivers typically do not wear sunglasses at night.

The dynamic study was conducted to determine the effects of actual driving conditions on the operation of the two units. The same route was driven both in the early afternoon (approximately 2 p.m.) and late evening (approximately 9:30 p.m.). The route consisted of stretches of lighted and unlighted divided highways, lighted parking areas, and rural two-lane roads. The duration of the route was approximately 45 minutes.

4.4.4 Participants

Three drivers with CDLs participated in the dynamic study, while 12 other participants who did not possess a CDL were involved in the static study. The participants' demographic profiles are depicted in Table 5 for the dynamic study and Table 6 for the static study.

Table 5. Dynamic MV Eye Closure Sensor Selection Study Subject Demographics

Dynamic Study	Age	Gender	Eyewear	Skin Tone
Subject 1	56	Male	Glasses	Light
Subject 2	30	Male	Sunglasses	Light
Subject 3	49	Male	Sunglasses	Light

Table 6. Static MV Eye Closure Sensor Selection Study Subject Demographics

Static Study	Age	Gender	Eyewear	Skin Tone
Subject 1	37	Female	Sunglasses	Light
Subject 2	30	Male	Glasses	Light
Subject 3	29	Male	Glasses	Dark
Subject 4	23	Female	Sunglasses	Light
Subject 5	36	Male	Sunglasses	Dark
Subject 6	70	Male	Glasses	Light
Subject 7	31	Male	Sunglasses	Light
Subject 8	29	Female	Glasses	Light
Subject 9	46	Male	Sunglasses	Light
Subject 10	22	Male	Sunglasses	Dark
Subject 11	28	Male	Sunglasses	Light
Subject 12	33	Female	Sunglasses	Light

4.4.5 Data Reduction

To compare the two different systems, a list of criteria was developed to standardize the evaluation process. These criteria are listed as "musts" and "wants" on the Technology Selection Matrix (appendix B). The data reduction for these two studies was tailored to answer these criteria.

The most essential criterion, *accurate tracking of eye closures*, was analyzed in a quantitative manner. The eye closure tracks produced by the two systems were compared to eye closure tracks manually created by trained data reductionists viewing the same segments of video. To keep the analysis focused solely on each system's ability to track just the eye closures, only data from the 2-second eye closure task were used. The 2-second eye closure task is purely an eye closure task with the driver's head remaining stationary. Therefore, the confounding effects of head droop were removed from the analysis.

MV System A produces an output for eye closures of either "0" for eyes open or "1" for eyes closed; therefore, the reductionists were instructed to do likewise for each frame of video during the 2-second eye closure. *MV System B* outputs eye closure as a percent of the fully open eye and then generates a binary list of "0s" and "1s" depending on whether the eye opening value is greater than or less than the user-defined eye opening threshold, ranging from 0–100. For this study, *MV System B*'s developer requested that this value be set to 10, meaning that an eye closure 0.9–1.0 was considered closed. With the intent to evaluate the advertised performance of the systems, the data reductionists were instructed to replicate this algorithm manually. Therefore, all eye closures deemed greater than 90 percent of the fully open eye were considered closed and given a value of "1." All other eye closures less than 90 percent were considered open and given a value of "0." There appeared to be a 3.6-second time lag between recording of the data and the video data for *MV System B* unit. Therefore, the data tracks were realigned by this

3.6-second value to account for this lag. According to *MV System B* developer, this time lag is expected and due to the necessary filtering within the image processing unit.

The systems' ability to operate with two other important criteria was also examined using this same quantitative analysis (e.g., different forms of eyewear and varying skin complexions). The remaining criteria were judged qualitatively based on the systems' output performance during specific conditions related to those criteria.

4.4.6 Results

In keeping with the criteria developed for the Technology Selection Matrix, the following section details the results found for the most pertinent "must" criteria and all the "want" criteria with an importance weighing seven or higher. The scores for the remaining criteria not found in the results section can be found in Appendix D. The criteria from the Technology Selection Matrix are listed in *italics* before each section presenting the results associated with that specific criterion.

4.4.6.1 Results Associated with the Following:

- Accurate tracking of eye closures.
- Satisfactory performance under both day and night operation.
- Works with no corrective eye wear.

The ability to track the driver's eye closure accurately is the basis for this study and the fundamental component of both systems that were evaluated. On average, both systems did a fairly good job of tracking eye closures during both high (simulating daytime lighting) and low (simulating nighttime lighting) illumination conditions (Figure 7). The accuracy for both systems declined once varying forms of eyewear were introduced for both high and low illumination conditions. *MV System B* achieved a higher level of accuracy in all four conditions.

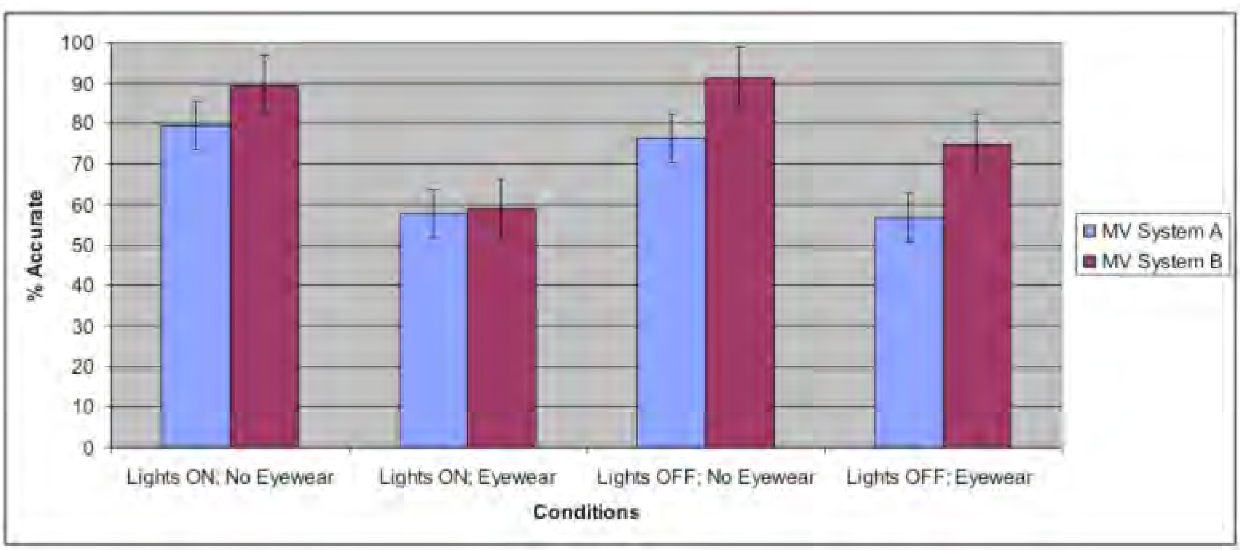

Figure 7. Overall Eye Tracking Accuracy

4.4.6.2 Results Associated with the Following:

- A “Failure to Track Eye Closure” indication.

Both systems do provide an indication when they have a failure to track eye closures. *MV System A* provides two indicators. The most obvious indicator is the green box that encircles the eye(s) in the video. If *MV System A* fails to track either eye then the indicator will not be present around that specific eye. If the system fails to track both eyes, then no green box will be present in the image. The second indicator of failure to track eye closure is the green word “Paused” near the bottom of the driver’s face image. This indicator provides a warning that the fatigue monitor has stopped computing the AVECLOS metric.

MV System B also provides an indication of a failure to track eye closures, but it is more subtle than *MV System A*. When *MV System B* is tracking the eyes, six red dots are displayed on the driver’s face image. These dots are positioned at the corners of the mouth and the corners of both eyes. They are used to create a face model that increases the system’s tracking confidence. An additional indicator is the vertical green lines to the outside of each eye. The length of these green lines indicates the magnitude of eye opening with a long line representing eyes open and a short line or dot representing eyes closed. Once *MV System B* fails to track the eye closures, all of these indicators (e.g., the red dots and green lines) disappear.

4.4.6.3 Results Associated with the Following:

- Adequate viewing angle to accommodate driver positions and ride motions.
- Capable of following/tracking head.
- Capable of maintaining eye track under normal driver ride motions.

The driver’s commercial vehicle environment presents an enormous challenge to achieving an adequate field of view sufficient to track the head and eyes. The first challenge is the variability presented by the driver’s selected seat position. Because of the cab air-ride seats, with approximately 9 in of horizontal travel and approximately 6 in of vertical travel, the range of seat positions available is greater than in other types of road vehicles (e.g., automobile, light-duty trucks). In addition, the physical size of the commercial driver population is quite diverse, with statures typically ranging from 142 cm (56 in) to 201 cm (79 in). Also, driver postures vary, with some sitting more erect to maintain vigilance and others slouching down in the seat to find a more comfortable posture. All of these factors combine to create the system’s need for a large viewing window to be able find the driver’s eyes. For this study, an effort was made to keep the field of view consistent between systems. In doing so, both systems were able to achieve an adequate field of view for nearly all participants. Two shorter participants sat lower in their seats, causing the bottom third of their face to be below the field of view of both systems. Without the full face, both systems appeared to experience some problems with maintaining confidence in tracking eye closures.

Because of the commercial vehicle’s heavy suspension systems, drivers are exposed to greater bouncing than they would experience in other types of road vehicles (e.g., automobiles, light-duty trucks). Although the static study had a task to simulate speed bumps, most participants bounced more than is typical for highway riding. Therefore, the ride motions were evaluated during the dynamic study. The greatest jouncing occurred as the vehicle traveled across bridges or changes in pavement. Both systems were able to track the eye closures during the majority of the rides with only the most extreme jouncing causing the systems to lose tracking of eye closures. *MV System A* requires that the head be stationary. Once the head moves, the "appearance model" is invalid and a new model is generated. When the system senses that the head is directed forward, the system pauses and the time component of the AVECLOS metric is halted. *MV System B* is more resilient during ride motions and appears to recapture the eyes sooner after losing them.

4.4.6.4 Results Associated with the Following:

- Does not present unacceptable risks to drivers.

It is anticipated that neither system would present unacceptable risks to drivers. However, several participants made spontaneous comments that were worth noting. During the dynamic study at night, one of the three drivers commented that *MV System B* near-infrared light-emitting diodes (LEDs) were visible and distracting. Also, a participant driving a daytime route during a dynamic study evaluating *MV System A* commented that his eyes had a slight burning sensation towards the end of the 45-minute drive. This may be the result of increased LED output to overcome the daylight conditions.

4.4.6.5 Results Associated with the Following:

- Works with a sample of externally-worn eyewear with no glare present.
- Works with glasses with glare present.
- Works with sunglasses.

Neither system performed well when participants wore eyewear (e.g., sunglasses or eyeglasses). While there was no appreciable difference between the two systems for eye tracking accuracy with sunglasses, *MV System B* appeared to have lower accuracies when the subjects wore sunglasses (Figure 8). However, when participants wore regular eyeglasses, *MV System B* had notably better eye-tracking accuracy as compared to *MV System A*.

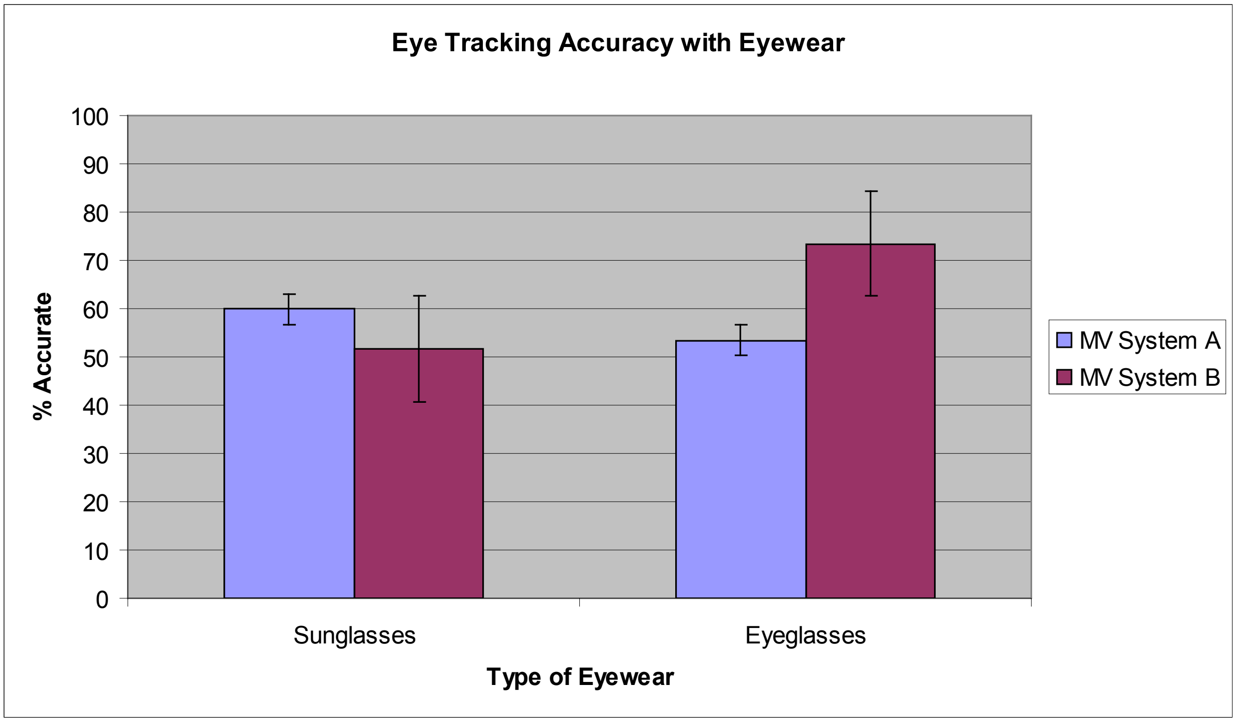

Figure 8. Eye Tracking Accuracy With Different Forms of Eyewear

4.4.6.6 Results Associated with the Following:

- Works with contact lenses.

Only one participant during the static study wore contact lenses. Therefore, it is difficult to say with certainty that the systems perform well with contacts, but this participant's data indicated that the performances of both systems were not affected by the presence of contacts (Figure 9). In fact, this participant's accuracy percentages (83 percent for *MV System A*, 97 percent for *MV System B*), calculated for the 2-second eye closure task, were higher than the group average (79 percent for *MV System A*, 89 percent for *MV System B*). Thus, it can be speculated (based on one participant) that contact lens use does not present problems for either system.

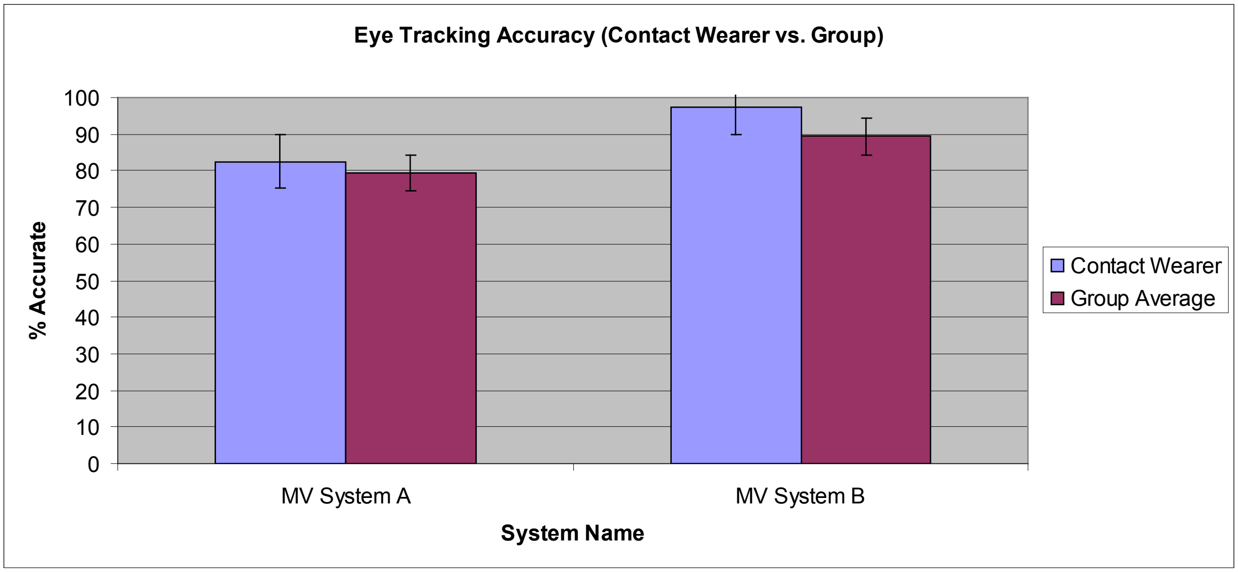

Figure 9. Eye Tracking Accuracy of Contact Wearer Versus Group Average

4.4.6.7 Results Associated with the Following:

- Calculation of PERCLOS (or acceptable surrogate).

MV System A uses computer vision algorithms to generate an "appearance model" of the driver's face. From this derived model, the computer determines whether the driver's eyes are open or fully closed. Based on the comparison of the current eye shape with the "appearance model," the output is a "0" for an open eye and a "1" for a fully closed eye. This output is used to compute an AVECLOS estimate, which estimates the percentage of time that the eyes are fully closed over a 1-minute moving average. Figure 10 illustrates a typical AVECLOS trace for the entire static trial. The eye closure task times are represented by the dashed line with the length of the eye closure labeled between these dashed lines. Section A on this figure depicts the AVECLOS trace as relatively flat throughout the 5-second and 10-second eye closure tasks. This can be attributed to the system's tendency to lose the eyes when the head moves. Section B on Figure 10 further supports this notion as the AVECLOS trace has a positive slope throughout the 2-second eye closure, which does not include the head drooping during the task. Section C, the central portion of the trace, is flat because the subject was wearing sunglasses and the system's detection paused throughout all eye closure tasks. The *MV System A* holds the last AVECLOS value until it resumes the AVECLOS calculation. Section D is similar to section A with the system's detection suffering when the head is drooped during the 5-second and 10-second eye closure tasks. Also, these traces indicate that the AVECLOS metric may be slow to respond to eye closures. Finally, section E of this figure provides the best example of *MV System A* performance during the 2-second eye closure under very low ambient illumination. Again, this trace is based on a 1-minute moving average that is standard for the unit and is not user-defined.

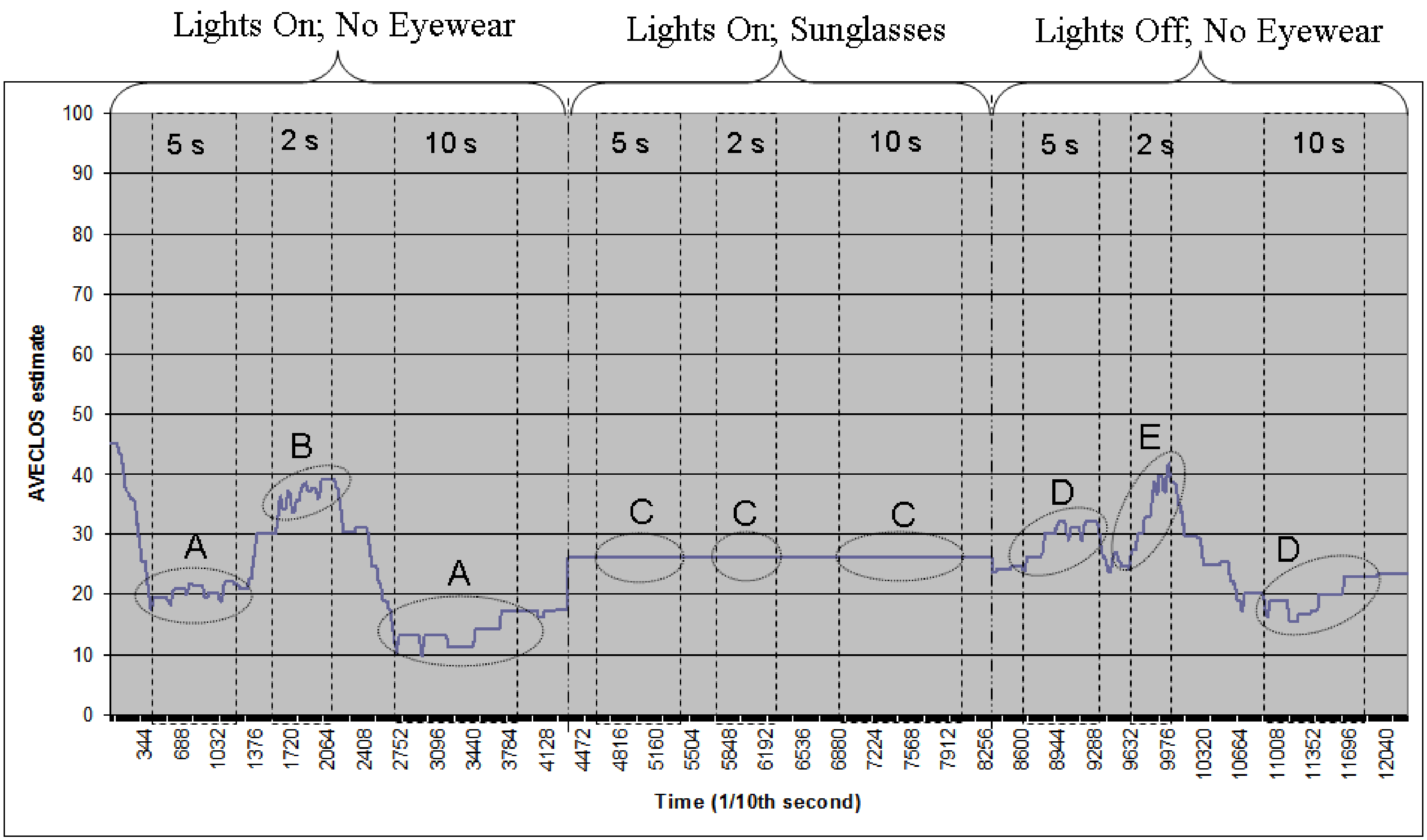

Figure 10. ***MV System A*** **AVECLOS Trace for Subject 1's Entire Static Study Trial**

MV System B computes a PERCLOS estimate continuously over a moving time window that can be defined by the user. For this study, the developer of *MV System B* requested that the time window be set at 180 seconds (3 minutes); however, this time window can range from 10 seconds to 500 seconds. Figure 11 illustrates a typical PERCLOS trace for the entire static trial. The eye closure task times are represented by the dashed line with the eye closure length labeled in seconds between these dashed lines. Section A of this figure, 5-second and 10-second eye closure tasks, illustrates how *MV System B* is better able to maintain detection of the eyes during a head droop. Section B depicts *MV System B* responsive performance to 2-second eye closures with a nearly perfect PERCLOS trace inclination. As with *MV System A*, section C of the PERCLOS trace is flat because the subject was wearing sunglasses and the system's detection paused throughout all eye closure tasks. When *MV System B* pauses, it resets the PERCLOS value back to zero. This is not a favorable characteristic, the resetting of the PERCLOS estimate to zero when the eyes are lost may give a false indication of the level of drowsiness. Section D depicts *MV System B's* performance suffering under low ambient illumination for eye closures with the head drooping. Sections A and B illustrate that *MV System B's* estimation of PERCLOS, even though it is a 3-minute moving average, is more responsive to eye closures than the *MV System A* metric.

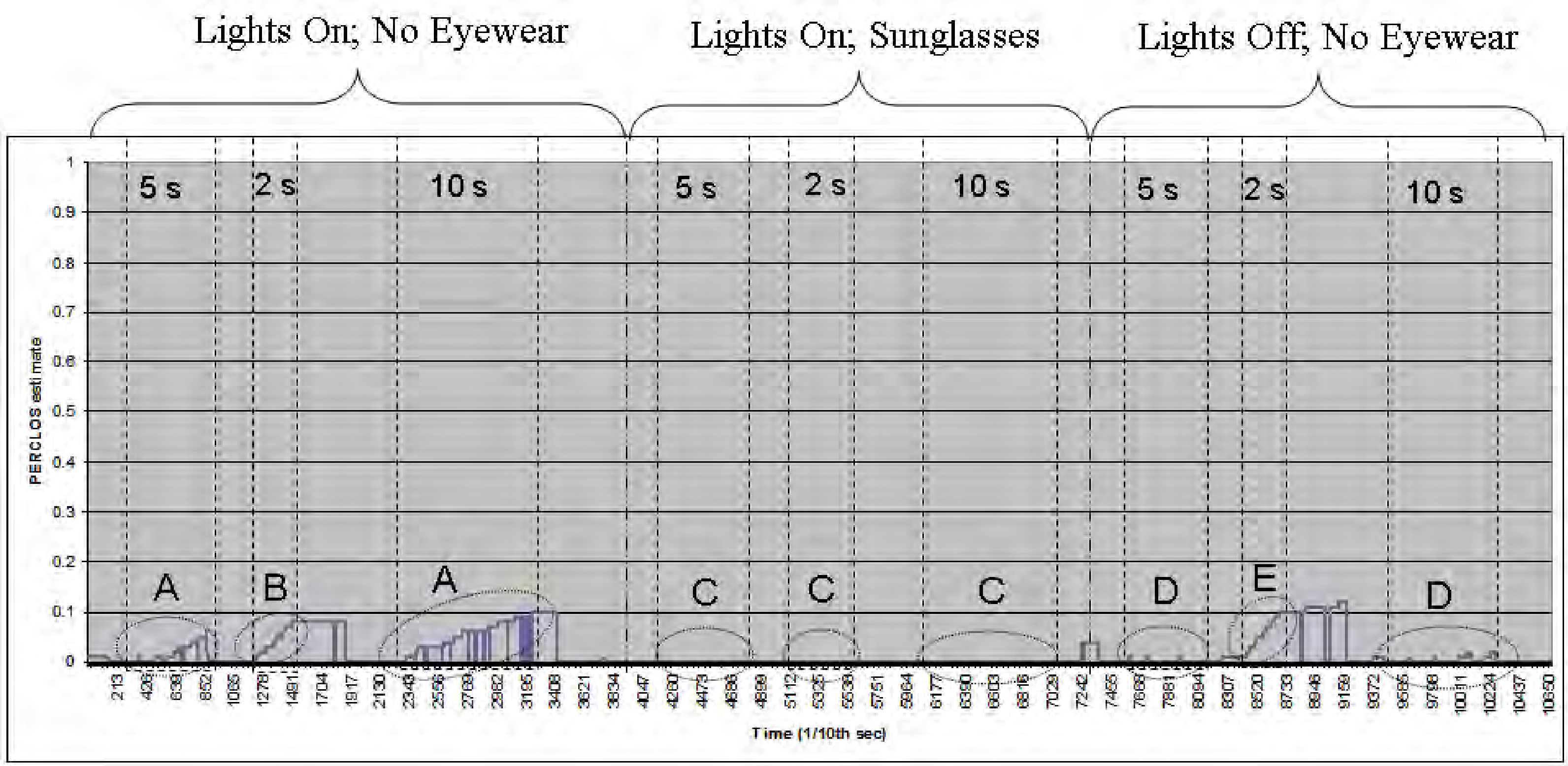

Figure 11. ***MV System B*****'s Trace for Subject 1's Entire Static Study Trial**

4.4.6.8 Results Associated with the Following:

- Capable of handling shadows on face (hats).

Because of the near-infrared LED emitters, the effect of shadows from hats was eliminated. This may become a larger issue if future implementations require a higher mounting position in the cab (e.g., near sun visor).

4.4.6.9 Results Associated with the Following:

- Sensitivity to gradual light changes.

Gradual light changes occurred during night driving adjacent to overhead street lighting or traveling through intersections. Typically, the average rate of change in lux ranges from 10–50 lx per second. These gradual light changes had minimal impact on the operation of both systems.

4.4.6.10 Results Associated with the Following:

- Sensitivity to rapid light changes.

Rapid light changes occurred during night driving in urban shopping centers with excessive overhead parking lot lighting or driving two-lane roadways with approaching headlights from oncoming traffic. Typically, the average rate of change in lux is greater than 50 lx per second. These rapid light changes had minimal impact on the operation of both systems.

4.4.6.11 Results Associated with the Following:

- Works with varying skin complexions.

The results of this study indicated a difference in eye tracking accuracy for both systems with subjects of varying skin complexions (Figure 12 and Figure 13). While *MV System B* provided a higher eye-tracking accuracy under both high and low levels of illumination, *MV System B* suffered with light skin complexions when the illumination was higher. The key area of difference between the systems was under low levels of illumination and with eyewear. *MV System B* had a notably higher eye-tracking accuracy when the lights were off. In addition, *MV System B* did much better than *MV System A* for eyewear under both illumination levels. Because of limited sample sizes, it is difficult to say whether or not the results would generalize to the entire population of heavy vehicle drivers.

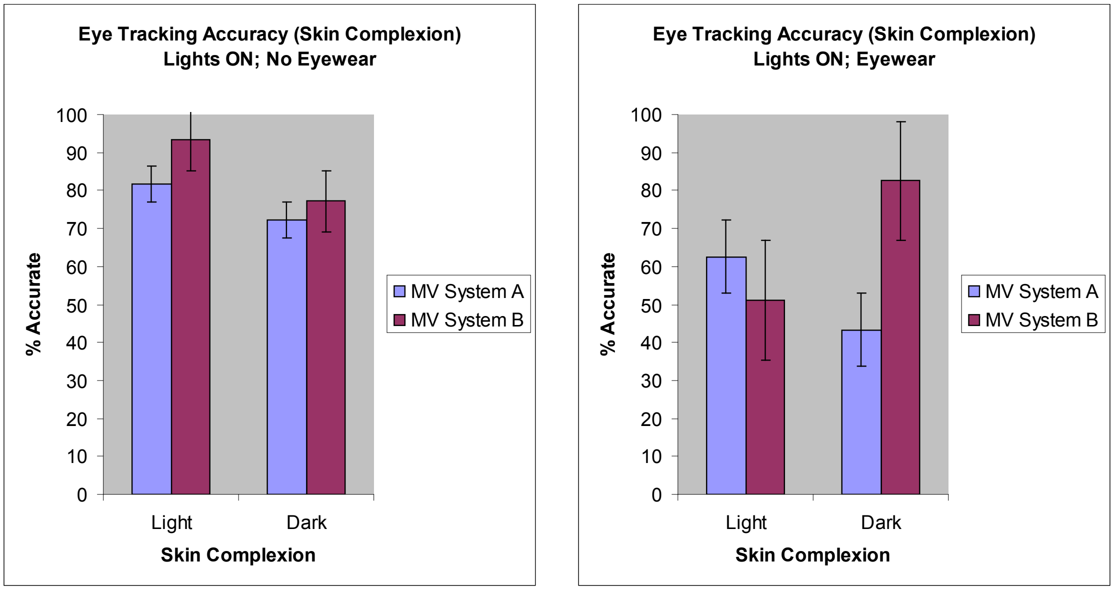

Figure 12. Eye Tracking Accuracy with Varying Skin Complexions (Lights ON)

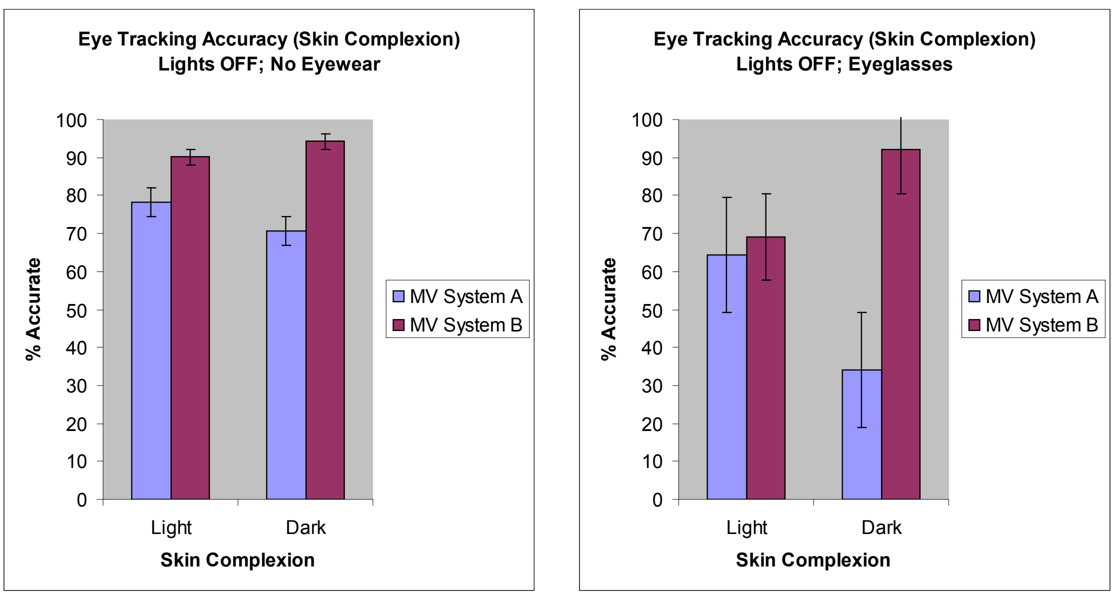

Figure 13. Eye Tracking Accuracy with Varying Skin Complexions (Lights OFF)

4.4.6.12 Results Associated with the Following:

- Other issues worth noting.

One issue observed during the dynamic study was the impact of the driver looking down to the instrument panel on the calculation of the estimated AVECLOS and PERCLOS values. As the subject glanced down, *MV System B* recorded a reduced eye opening, which would occasionally be included in the estimated PERCLOS calculation. Therefore, the PERCLOS level was influenced by this visual scanning pattern, and the estimated PERCLOS value erroneously increased. The manufacturer recommends that this issue be resolved by adjusting (in this case, increasing) the user-defined Eye Opening Threshold. However, this adjustment will alter the PERCLOS estimate from the original definition of PERCLOS as established by Wierwille (1999b).

MV System A was integrated into a single unit for both the camera and the near-infrared illuminators. The housing of *MV System A* had a smoke-colored plastic cover to protect these internal components. One issue noticed during the dynamic study was the debilitating effects of the sun's glare created on this plastic surface. This glare would cause the system to pause since the face was not recognizable. This glare problem was not experienced in *MV System B*.

4.4.7 MV Eye Closure Monitor Selection Conclusions/Recommendations

The purpose of this quasi-experiment was to exercise both systems under similar conditions typical of actual use. The results of these studies were then used to score the performance of each system against a standard set of criteria in the Technology Selection Matrix (Appendix B). While these systems are similar in many aspects of performance, they each possess unique strengths and weaknesses (Table 7). This evaluation represents a snapshot in time with specific criteria for the development of an integrated fatigue monitor system. Because the progress of these systems is ever-changing and fluid, the outcomes of tests with future systems may be different.

Table 7. Summary of Systems' Strengths and Weaknesses

	MV System A	*MV System B*
Strengths	• More obvious "failure to track eye closure" indicators • Handles gradual light changes • Handles rapid light changes	• Higher Eye-Tracking Accuracy • Calculates a PERCLOS metric • Greater range of tracking head motion • Responsive to eye closures • Handles gradual light changes • Handles rapid light changes • Less susceptible to varying skin complexions • Provides an eye point of regard estimate
Weaknesses	• More susceptible to skin tone differences • Less responsive to eye closures • Susceptible to veiling glare from sun	• More susceptible to use of sunglasses • More susceptible to false reading of eye closures through normal eye glances

The outcome of this systematic comparison can be found in Appendix D. Both systems meet all of the “must” criteria; therefore, the selection decision must be based on the individual scores from the “want” criteria.

The computed total scores indicated that *MV System B* achieved a higher rating. Therefore, the recommendation was to select *MV System B* as the machine-vision sensor for the project entitled “Development and Assessment of a Driver Drowsiness Monitoring System.” With the approval of the Task Order Manager, the authors acquired this system from the *MV System B* supplier to develop an integrated drowsy driver monitoring system.

4.5 SYSTEM CREATION

The functional specifications outlined in section 2.2 provided design guidance during the creation of the DDMS. In selecting the technology for the integrated system, the key requirement was the system’s ability to work unobtrusively for a wide range of operator characteristics and behaviors under varying environmental conditions. MV technology provided the greatest promise of meeting these design objectives. Wierwille (1999a) has stated that MV technology is the most promising noninvasive means to detect driver fatigue.

This technique to measure drowsiness typically includes a series of cameras that view the driver and driving environment. A forward-view camera reveals data about vehicle-based parameters, such as lane position and other lane-related measures from the roadway directly in front of the vehicle. Section 4.5.1 presents specific details about this technology. A driver-view camera allows for a high degree of accuracy in measuring head pose, eye gaze, and eyelid movement. Section 4.5.2 discusses this technology in more detail.

4.5.1 MV Lane Position Sensor

The lane tracking for this study was accomplished with a device referred to in this report as MV lane position sensor. The MV lane position sensor tracks lane markings on a roadway from a driver’s perspective (Figure 14). This device uses a monochrome camera and a computer running MV algorithms to find the lane line marking locations in real time. The MV lane position sensor designates values that are left and right of the lane’s centerline as positive (+) or negative (-), respectively.

MV lane position sensor has the ability to determine the location of lane lines (Figure 15), curvature of the road (Figure 16), and angular offset (gamma) of the vehicle relative to the lane centerline (Figure 16). Descriptions of the MV lane position sensor variables are presented in Table 8.

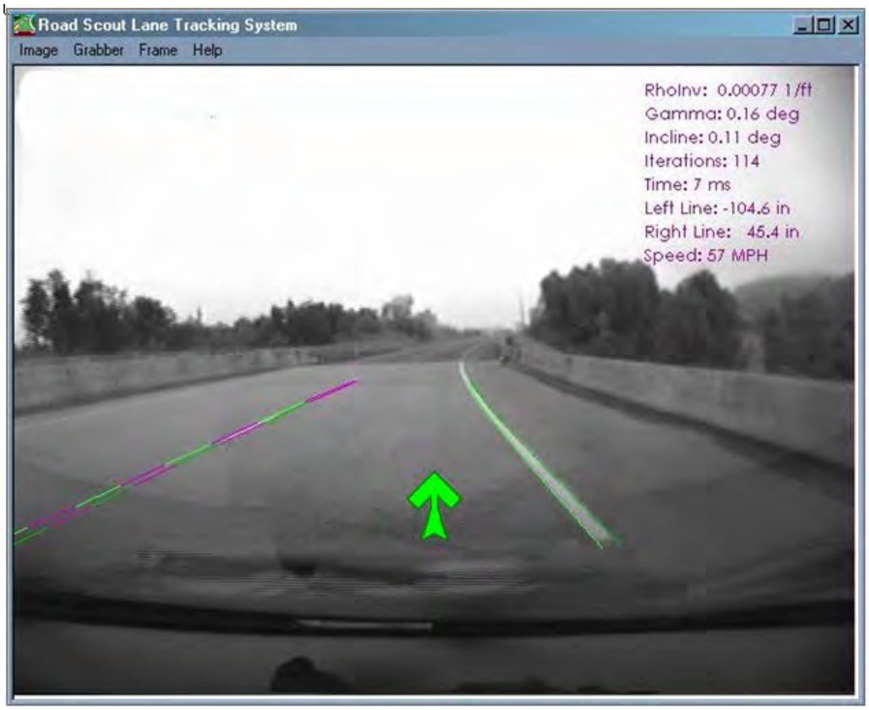

Figure 14. MV Lane Position Visual Perspective

Table 8. MV Lane Position Sensor Variables

Variable Name	Description
Rho Inverse	Inverse curvature of the roadway. Positive curvature is to the right (ft^{-1}).
Gamma	Angle between longitudinal centerline of vehicle and centerline of lane markings in radians at the camera position (Figure 17). Positive gamma means the vehicle is drifting to the right out of lane.
Incline	Change in the incline angle of the roadway in radians. Positive incline indicates that the roadway is changing to an upward slope. This value is intended for internal use for finding the edge lines correctly.
Time (Delta Frame)	The system is designed to run at 10 Hz. This value reports the actual time elapsed between the analyzed frames by MV Lane Position sensor in milliseconds.
Left and Right Lines (Lane Width)	Estimated width of roadway lane in inches.
Lane Offset	Distance between the center line of the vehicle and the imaginary centerline of the roadway lane in inches. This value is computed as –[(L1.d2) + (L2.d1)]/2. This equation assumes that the roadway centerline is at zero. See Figure 15 for details.
L1 Information	Bitwise information about the immediate left marking, including: Marking Type, Marking Shade, Left Dash, Right Dash, Threshold, L1 Probability, L1 Left Distance (in), and L1 Right Distance (in).
L2 Information	Bitwise information about the immediate left marking, including: L2 Probability, L2 Left Distance (in), and L2 Right Distance (in).

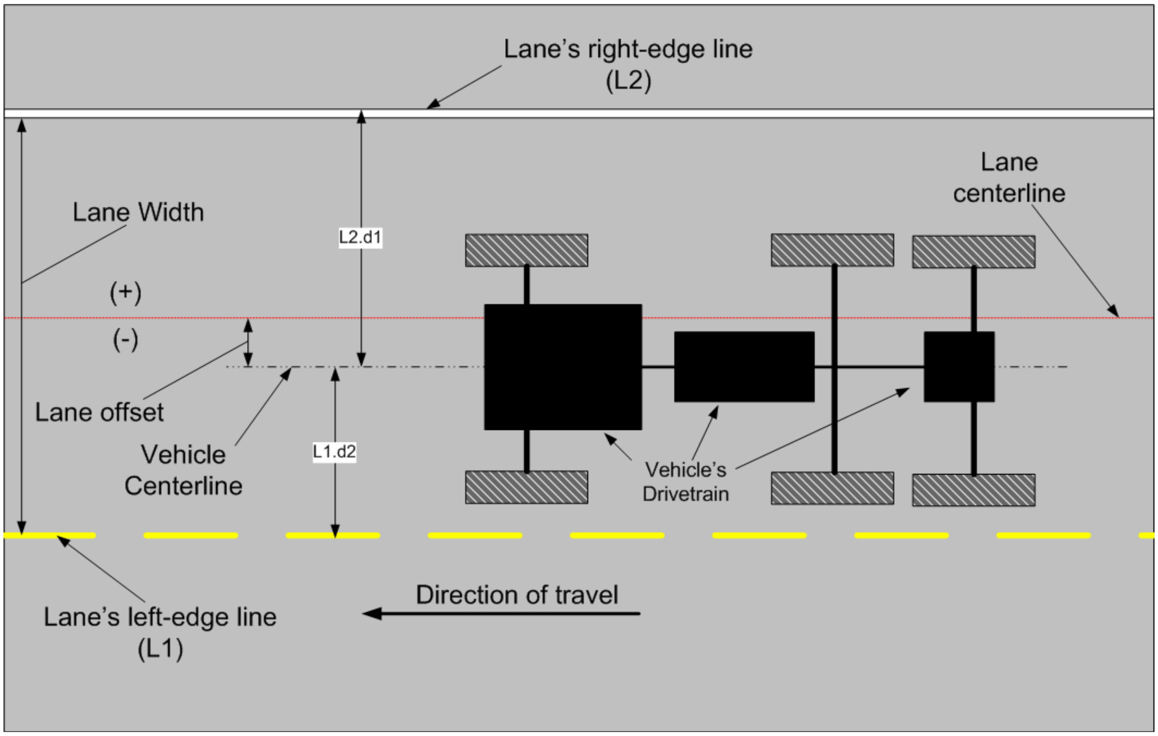

Figure 15. MV Lane Position Variables on Straight Roadway

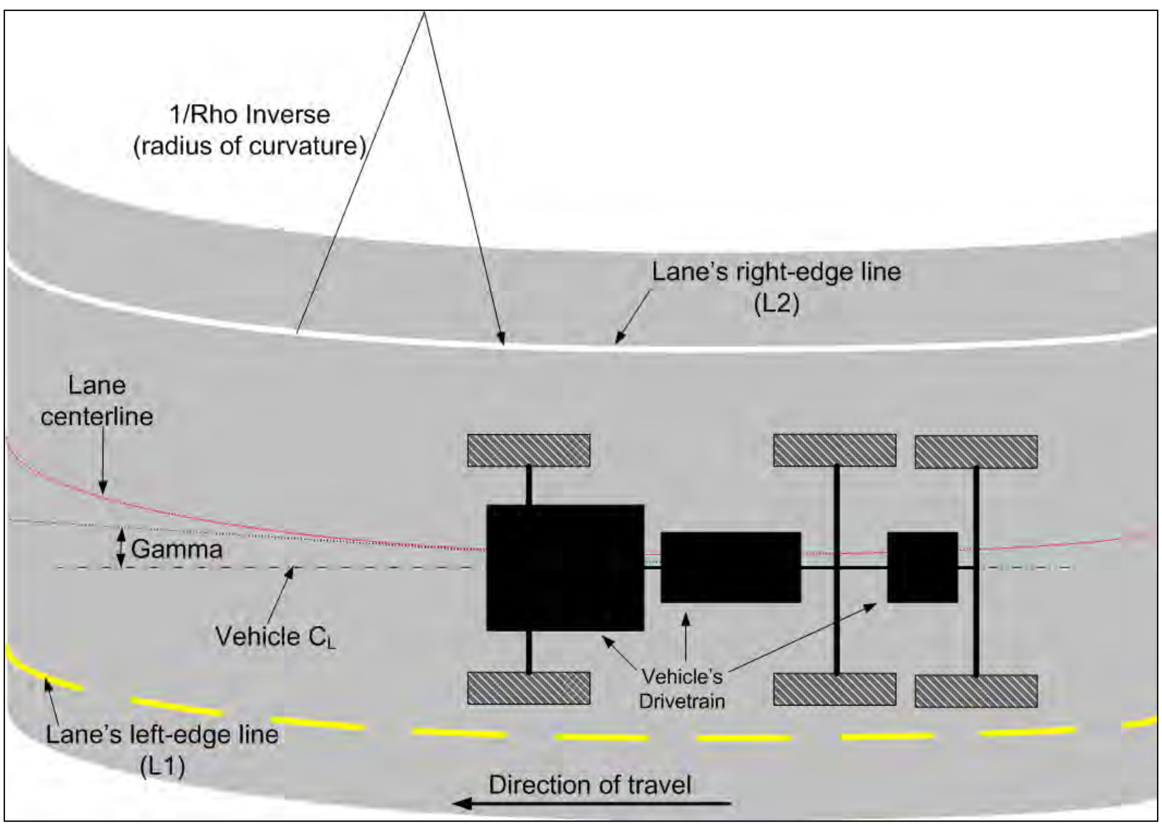

Figure 16. MV Lane Position Variables on Curved Roadway

This sensor determines if the lines are single, double, solid, or dashed. The sensor calibrates its angular position while in operation when necessary. The system also continuously monitors the camera properties so that if it is bumped or moved, the MV lane position sensor will automatically recalibrate itself.

4.5.2 MV Eye Closure Monitor

As stated, the second technology used by the DDMS is an MV eye closure sensor. In choosing an MV eye closure sensor, the authors conducted a trade study between two commercially available eye closure monitoring systems (i.e., *MV System A* and *MV System B*). In terms of accuracy of monitoring eye closures, this trade study found the performance of *MV System B* to be superior to *MV system A*, as detailed in section 4.4. The complete results may be found in Bowman, Wierwille, Alden, Blanco, and Hanowski (2007). *MV System B* measures the three-dimensional head pose and eyelid motion parameters of the driver. This system provides two fatigue metrics: microsleep event detection and a user-defined estimate of the PERCLOS metric. *MV System B* estimates the percentage of eye closure (Figure 17), and this output is used to calculate an estimate of the PERCLOS metric. According to Wierwille (1999b), the definition of PERCLOS is the mathematically defined proportion of a time interval that the eyes are 80–100 percent closed. *MV System B* allows the user to define the eye opening threshold between 0 and 100 percent closed. For the evaluation of the DDMS, this eye opening threshold was placed at 20 percent to be in-line with the originally-defined PERCLOS measure. The PERCLOS metric is continuously calculated over a shifting time window that can be defined by the user. For this evaluation, the PERCLOS estimate was computed over a 180-second (3-minute) time window; however, in general, this time window can range from 10 seconds to 500 seconds.

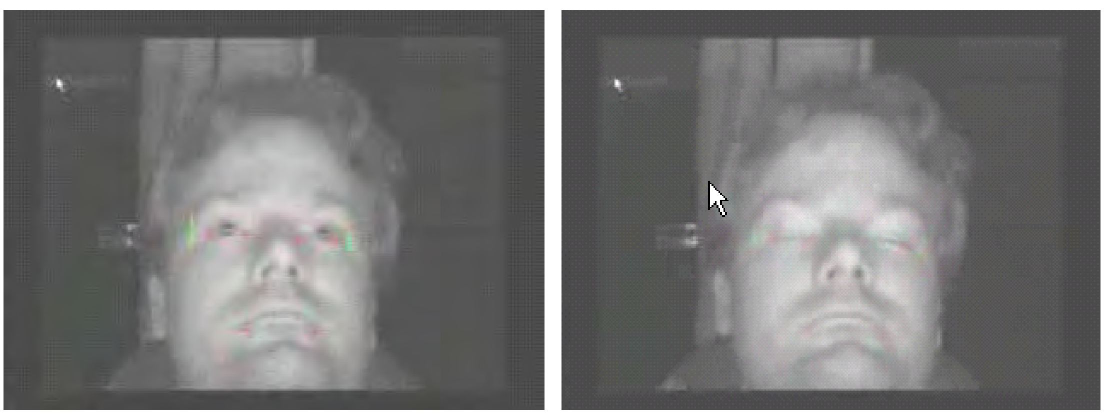

Figure 17. *MV System B* Display with Driver's Eyes Open and Closed

4.5.3 System Integration

The DDMS is an integration of MV-based drowsy driver monitoring and lane tracking technologies. Although the MV eye closure sensor system, *MV System B*, computed a PERCLOS estimate, there were issues associated with the manner in which the MV eye closure sensor system handled the loss of detection of the driver's eye locations. Basically, the MV eye closure sensor system's PERCLOS estimate would jump to zero if the eyes were not found (e.g., head turned to the side). Therefore, the authors generated a PERCLOS estimate using just the MV eye closure sensor's eye closure level output. As discussed in section 4.4 of this report, the MV eye closure sensor's ability to determine eye closure levels, once the eyes are located, is excellent.

The MV eye closure system provides an eye closure level value of 0 (open) or 1 (one or both eyes greater than 80 percent closed). The DDMS PERCLOS estimate (Figure 18) is computed from these values as:

$$\text{DDMS PERCLOS Estimate} = \frac{\text{number of “closed” eye samples}}{\text{3 min interval of all valid samples}}$$

Figure 18. Formula to determine the DDMS PERCLOS estimate

Eye blinks were ignored in the calculation of the DDMS PERCLOS estimate. To be valid, the data samples needed to satisfy the following criteria:

- Driver’s head and eyes were detected by the MV eye closure sensor system.
- Vehicle speed was greater than 3 meters per second (m/s, or 6.7 mi/h).

The first criterion, detection of the driver’s head and eyes, was to ensure that the PERCLOS estimate did not include samples when the driver was outside the viewing angle of the system for activities such as reaching for an object within the cab. The second criterion, vehicle speed greater than 3 m/s, was included to prevent the system from calculating the PERCLOS estimate while the vehicle is nearly stationary. This was done for two reasons. The first is, when the vehicle is stationary or nearly so, the risk of accident or injury from a drowsy driver is extremely low. The second reason is driver activities become more varied when the vehicle is stationary or nearly so. For this study, the speeds were kept low (i.e., 25 mi/h on straight sections and 15 mi/h on the turnarounds) for safety reasons. Therefore, the 6.7 mi/h speed threshold was also kept low to be reasonable for the study’s vehicle speeds. Future evaluations could consider raising this speed criterion as road speeds increase.

The lane deviation metric was defined as the proportion of a time interval the vehicle was outside the roadway lane as determined by the vehicle’s lane offset. Again, *lane offset* is defined as the distance between the vehicle’s centerline and the imaginary lane centerline in inches (Figure 15). This value (Figure 19) is computed as:

$$\textit{Lane offset} = \frac{-[(L1.d2) - (L2.d1)]}{2}$$

Figure 19. Formula for determining the lane deviation metric

The variable $L1.d2$ is the distance from the vehicle’s centerline to the outboard edge of the lane’s left edge line. The variable $L2.d1$ is the distance from the vehicle’s centerline to the outboard edge of the lane’s right edge line.

To ensure the correct lane offset value for the lane deviation algorithm, a 1997 Volvo VN Class-8 Tractor was placed on the roadway at the entrance of the Smart Road (described in section 4.5.5) with the right tire just outboard of the lane’s right edge marking (Figure 20). The centerline of the lane was determined by measuring the lane’s width from centerline of the right edge marking to the centerline of the left edge marking. This distance was 144 inches (365.76

cm); therefore, the centerline of the lane was 72 inches inboard of the centerline of the lane's right edge line marking. To determine the correct lane offset, the distance between the lane's centerline and the vehicle centerline were measured. This distance was 36 in (91.4 cm). Because both the lane width and vehicle suspension width are symmetrical, the 36-inch (91.4 cm) measurement is the appropriate value for both right and left lane departures. Since the Smart Road has a fairly consistent lane of 144 in, the 36-inch value was specific for the purposes of this study. It is known that lane widths vary across road types and road maintenance jurisdictions. To account for this variability under real-world operations, the DDMS algorithm will need to generate a varying lane width threshold in future refinements.

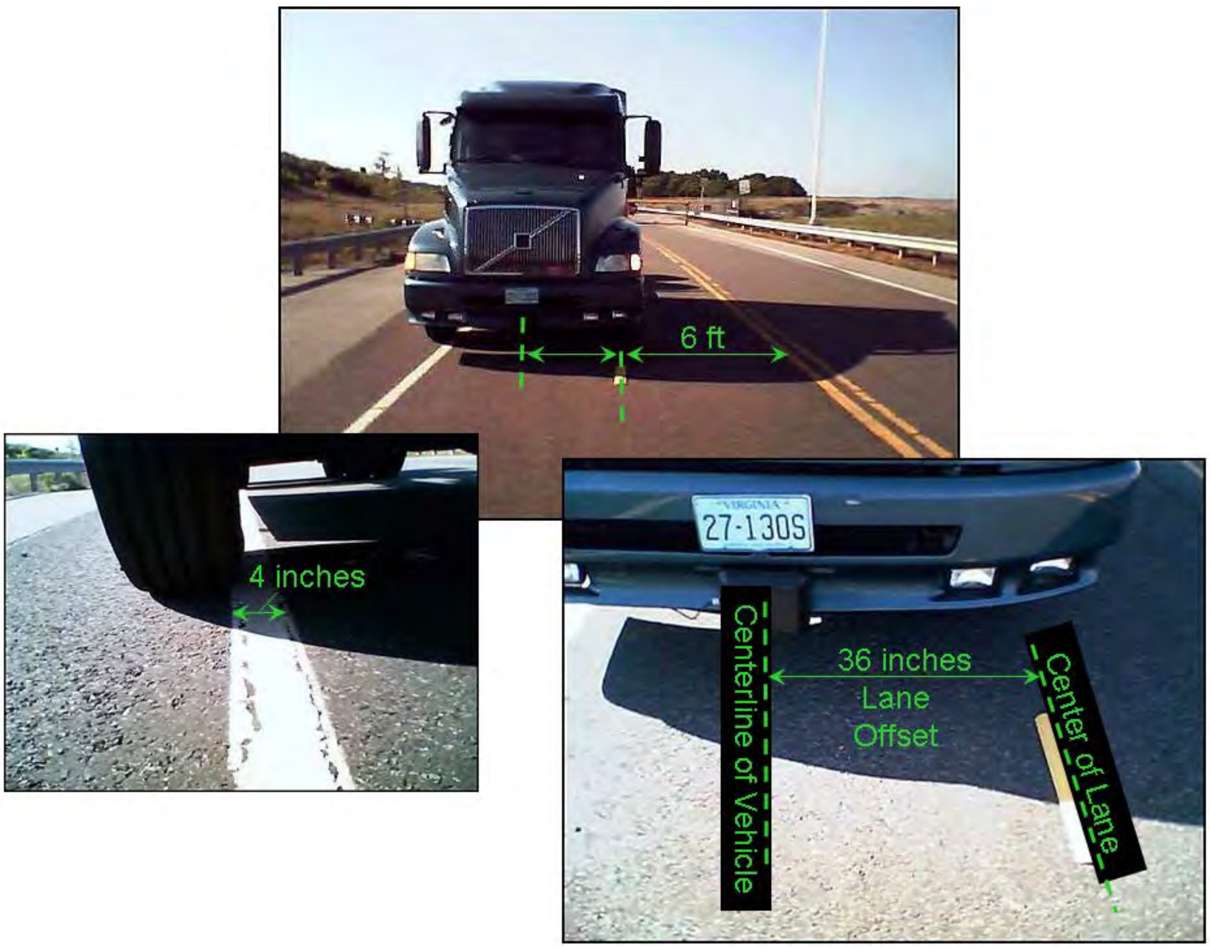

Figure 20. Confirmation Measurement for Appropriate Lane Offset

The DDMS lane deviation estimate (Figure **21**) is computed from these values as:

$$\text{DDMS Lane Deviation Estimate} = \frac{\text{sum of probability weighted out of lane samples}}{\text{1 min interval of sum of probability weighted valid values}}$$

Figure 21**. Formula for computing the DDMS lane deviation estimate**

To be considered *in lane* and *valid*, the data samples had to satisfy the following criteria:

- The lane position sensor detected the vehicle in lane (distance to both right and left markers > 36 in but both not > 108 in × maximum probability for right and left marker).
- The lane position sensor detected that the turn signals had not been activated.
- Vehicle speed was greater than 3 m/s (6.7 mi/h).

The detection of vehicle-in-lane was used as a criterion to ensure that the lane deviation estimate did not include samples when the vehicle was in areas other than an actual roadway (i.e., a parking lot). Once the vehicle was determined to be *in-lane*, the system verified that the turn signals were not activated. This was to ensure that the lane deviation estimate excluded samples of intentional lane change. The final criterion, vehicle speed, was included to prevent the system from calculating the lane deviation estimate while the vehicle was nearly stationary, as previously stated.

To be considered *out-of-lane* and *valid*, the data samples had to satisfy the following criteria:

- The lane position sensor detected that the vehicle's lane offset was outside of ±36 in multiplied by the marker probability.
- The lane position sensor detected that the turn signals had not been activated.
- Vehicle speed was greater than 3 m/s (6.7 mi/h).

The first criterion, detection of the vehicle's lane offset is outside of ±36 in, was used as a threshold to indicate the vehicle was departing a lane. The second criterion, that the left or right turn signal is not activated, ensured that lane deviation estimates did not include samples when the vehicle was departing the lane under intentional purposes. Again, vehicle speed greater than 3 m/s, was included to prevent the system from calculating the lane deviation estimate for reasons previously stated.

Figure 22 illustrates the data flow from calculation of eye closures and lane position metrics (equations 2 and 4) to DDMS algorithms to create an integrated drowsiness metric. Greater detail regarding the DDMS drowsiness model was presented in section 4.2 of this report. Once a threshold limit was exceeded, the system registered this change as a potential warning for the vehicle drivers. The minimum threshold limits for PERCLOS was set at the eye 80–100 percent closed for greater than or equal to 12.5 percent (0.125) during a 3-minute interval. The minimum threshold for lane deviation was set at the lane offsets exceeding 36 in (91.4 cm) outboard of either the lane's left or right edge lines for greater than or equal to 33 percent (0.33) of a 1-minute interval. In this study, a very basic human-machine interface provided system status and a visual warning when the DDMS model's criteria levels were reached. This display, referred to as DVI in Figure 22, depicts the individual criteria levels of either PERCLOS or lane deviation, as well as the collective criterion level of drowsiness. Therefore, if data for either PERCLOS or lane deviation are insufficient for computing drowsiness (depicted as a blue DVI indicator), the level of drowsiness is computed solely by the other valid metric.

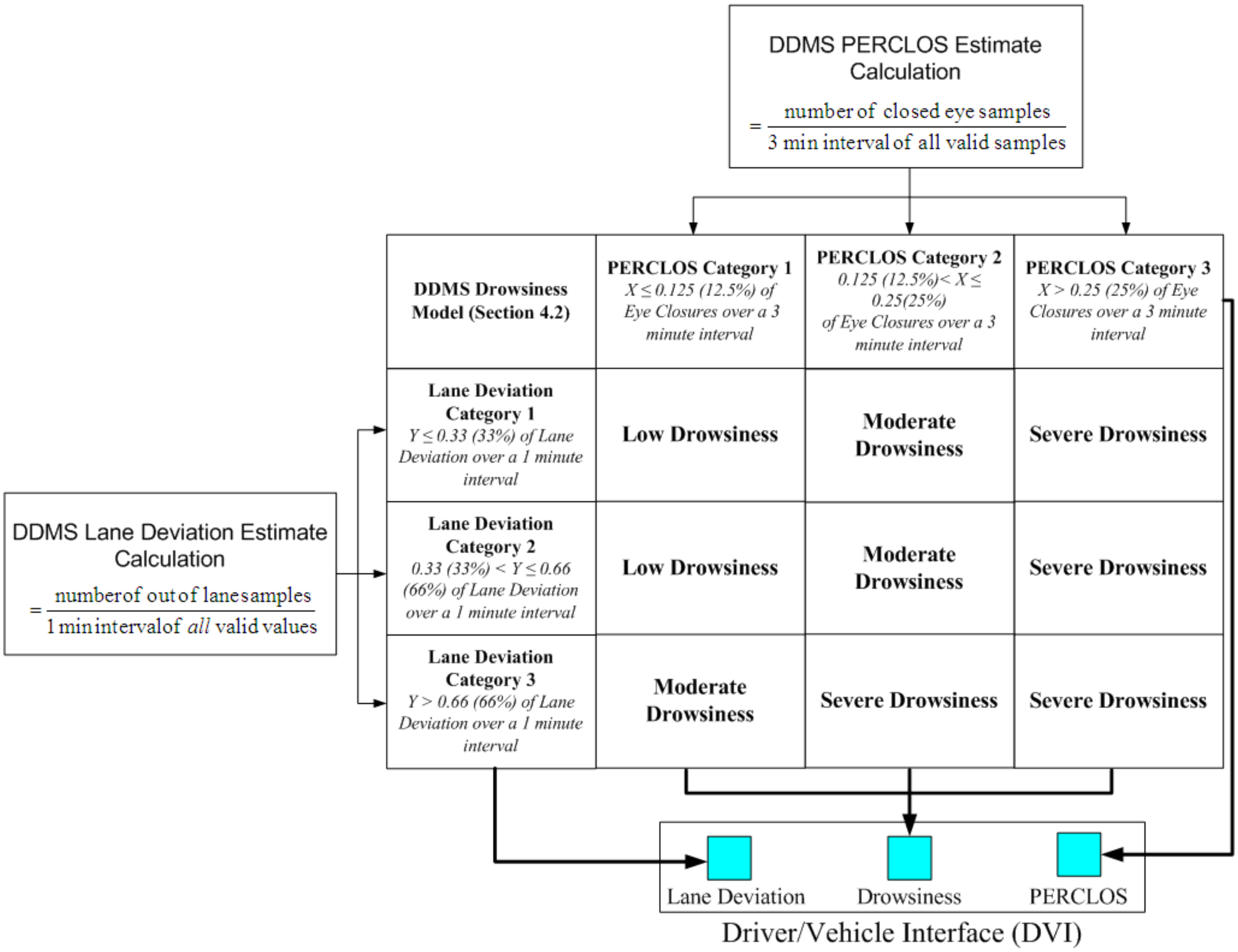

Figure 22. Illustration of the Prototype DDMS Drowsiness Model

4.5.4 Vehicle Installation

As mentioned, this on-road evaluation used a 1997 Volvo VN Class-8 Tractor instrumented with a DAS. The capture of the integrated data sources occurred through an interface connection between the DDMS and the DAS, which allowed the DAS to capture both video data and outputs from the DDMS (as shown in Figure 23). Note that Figure 23 is set up for the vehicle tests, which are further described in the next section. In particular, *MV System B* is set up for the passenger seat occupant, or pseudo-driver.

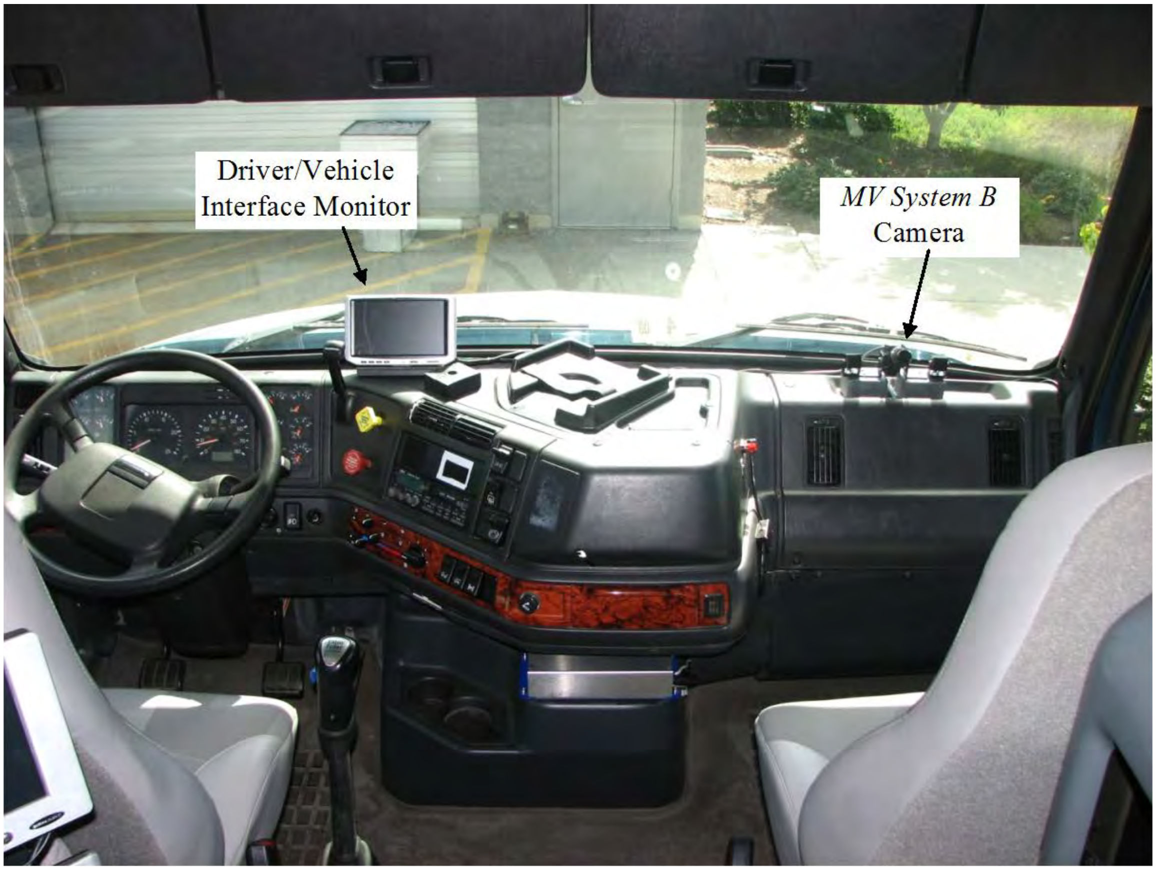

Figure 23. Prototype DDMS installed into the Vehicle Platform

The video data included a quad view (Figure 24) of the video input from *MV System B*, the forward roadway for the MV lane position sensor input, a view of the DVI output, and a split view of the lane-tracking cameras for the right and left sides of the tractor for output to conduct manual lane deviations. This video also displayed the driver's face for manual, relatively accurate PERCLOS calculations to generate the ground-truth measure. Mounted directly in front of the passenger seat was the *MV System B* camera and infrared-pods. To generate an integrated design, the infrared-pods were symmetrically mounted on either side of the camera at approximately 3.25 in (80 cm) from camera centerline.

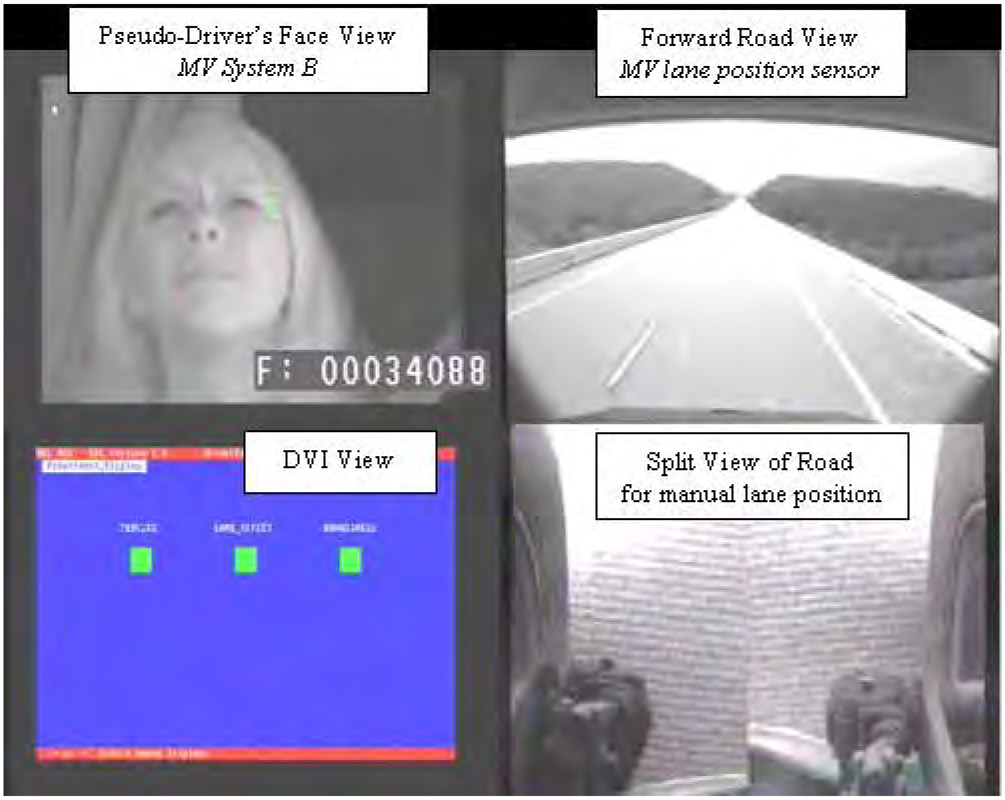

Figure 24. Quad View of Video from DAS

4.5.5 The Virginia Smart Road

The test facility for this study was the Virginia Smart Road (Figure 25) in Blacksburg, Virginia. The Smart Road is a 3.5-km (2.2-mile), two-lane test track with a fully functioning intersection. Turnarounds at either end allow for continuous driving. The closed course allows for high experimental control of driving conditions and helps ensure participant safety during testing. Additional information about the Smart Road may be found in Appendix E.

Figure 25. The Virginia Smart Road

5. DRIVER DROWSINESS MONITORING SYSTEM ON-ROAD EVALUATION

5.1 OVERVIEW

This part of the report details the method for conducting the DDMS evaluation. A discussion in section 5.2 highlights some of the challenges with the evaluation and describes operational factors that need to be considered. Section 5.3 discusses the methods that were used to conduct the evaluation. It is important to note that the evaluation is not to test human behavior and performance, but rather, the evaluation focuses on exercising a prototype system to determine its operational envelope (i.e., those operational conditions in which the system does and does not work effectively).

Because the prototype system is based on the combination of eye closure and lane position sensors, the evaluation approach involved having two participants simultaneously participate in each test session. Evaluation participants were all staff members of the authors' employer. One participant drove the tractor that was instrumented with the DDMS. This participant's role was to perform lane deviation maneuvers while driving the vehicle, which assessed the effectiveness of the lane position sensor. At the same time, other participants with varying physical facial features (e.g., skin complexion, eyewear) sat in the passenger seat (serving as pseudo-drivers) to perform eye closures to test the eye closure MV monitor. This two-participant approach served as an effective and efficient method that allowed multiple stimuli to be presented to the system simultaneously in a manner that was safe to the research participants.

The results of this on-road evaluation were used to assess performance, in terms of accuracy and sensitivity, of the DDMS to the presented stimuli. The method for analyzing the results was similar to that used for evaluating the Generation 2 PERCLOS Monitor (Wierwille et al., 2003). The output from the two systems (*MV System A* and *MV System B*) for measurement of PERCLOS and lane deviation were compared to a "ground-truth" plot that was manually derived by data reductionists. This comparison between the actual output and the ground-truth plot resulted in the output being classified as either "YES," meaning it was congruent with the ground-truth plot; "YES-BIASED," meaning it resembled the ground-truth plot but with some aberrations; or "NO," meaning it was incongruent with the ground-truth plot. These classifications were tallied and depicted as a function of type of tasks, type of skin complexion, type of eyewear, and the interactions of such factors.

This on-road evaluation took a comprehensive approach to "exercising" the prototype DDMS to determine its viability as a DDMS. These efforts are expected to serve as a foundation for future research in the area of driver drowsiness monitoring. Future research will need to include the complex issues of validity and optimization of driver drowsiness algorithms, driver warnings, and operational use.

There are a number of unique challenges involved with evaluating a prototype DDMS, and these, along with a brief description of the operationally relevant conditions, are presented in section 5.2. Following this discussion, the methods used for this evaluation are presented in section 5.3, as are details of the equipment used during the on-road evaluation that assessed the DDMS under near-real driving conditions. The results, discussion, and conclusions of the on-road evaluation are presented in section 5.4.

5.2 HOW SHOULD THE PROTOTYPE BE EVALUATED?

The prototype DDMS consists of two separate systems that provide an estimate of eye closure, called PERCLOS, and an estimate of lane crossings, called lane deviation. The purpose of this evaluation was to determine both how well these separate systems are able to calculate these estimates and the disparities between these estimates and the actual values of PERCLOS and lane deviation. As with any measurement system, the system's output was an estimate of the actual value of interest. This estimate contained multiple sources of errors (e.g., optical, omission, and computational) that created disparities between the estimate and the actual value. These disparities were assessed by comparing the DDMS estimates to "ground-truth" estimates in which error sources have been minimized. These "ground-truth" estimates were generated via meticulous manual review of the video data and provided the best estimate of the actual values. The differences computed between the DDMS estimates and the ground-truth estimates were considered to be indicative of the ability of the prototype DDMS to predict bouts of driver drowsiness.

The evaluation of the prototype DDMS is different from other experiments in human factors, as it focuses on sensor output validity rather than on human performance. More specifically, the authors evaluated equipment performance under varying conditions and not the influences that the apparatus had on the operators' performance. It was assumed that the DDMS performed similarly when presented with the same stimulus on separate occasions (Wierwille et al., 2003). For this reason, the DDMS was tested under operationally relevant conditions. The conditions included varying levels of environmental, operational, operator physical characteristics and behaviors, and system-specific factors typical of the normal operating environment.

5.2.1 Environmental Variables

The system would be expected to work in a variety of environmental conditions that are present both inside and outside of the cab. For example, the system would be expected to work in both daytime and nighttime conditions because drivers can become drowsy anytime, day or night. Thus, the system has to function effectively in all environmental conditions in which the driver may be drowsy.

5.2.1.1 Ambient Illumination as an Independent Variable

To test the prototype system in this regard, several ambient illumination conditions were tested: daytime (greater than 70 foot-candles [fc], 753.2 lx), nighttime (less than 0.05 fc, 0.5 lx), and artificial overhead lighting (between 0.06 fc, 0.6 lx and 4.5 fc, 753 lx). The daytime value is from the operational definition provided by Hanowski et al. (2004, 120), while the nighttime and artificial overhead lighting values are based on roadway illuminance measurements taken by Clark, Gibbons, and Hankey (2005, 5) during an evaluation of driver light adaptation levels. Because Clark et al., measured these illuminance readings at the driver's eye position and not outside the driver's side window, as proposed for this study, the illuminance values for this study have been scaled up by a factor of five to account for this position difference between setups.

Wierwille et al. (2003) found that there was roughly a factor of 10 between in-cab illuminance values and outside illuminance values.

5.2.2 Operational Variables

The DDMS must not be developed for a single individual but must operate reliably for different drivers. In many commercial operations, multiple drivers may operate a single vehicle via team or split-seat driving. Therefore, the DDMS must self-calibrate and work for all drivers. Consequently, this test plan included multiple participants to assess how well the DDMS handles individual differences.

5.2.3 Operator Physical Characteristics

The DDMS must work reliably for drivers who possess different physical characteristics. These different characteristics include:

- Physical features such as skin complexion.
- Transient features such as use of eyeglasses or sunglasses.

Again, this test plan included the effect of multiple drivers with varying physical traits.

5.2.3.1 Skin Complexion as an Independent Variable

MV System B relies on the facial landmarks (i.e., edges of the mouth, corners of the eyes, eyebrows) to locate the driver's eyes. Therefore, those individual physical factors that may affect the eye closure sensor's ability to discern these facial features need to be examined. It can be hypothesized that varying skin complexions could reduce the visual gradient between these facial features and their surround. Therefore, varying skin complexion was included as a factor of interest. The MV eye closure sensor selection testing (section 4.4) found skin complexion to be a notable factor in the performance of both eye closure sensors. Since *MV System B* is one of the MV technologies in the DDMS, the system's performance with varying skin complexions was considered important in this evaluation.

5.2.3.2 Eyewear as an Independent Variable

Various forms of eyewear were included as a factor of interest because of the prevalence of eyewear in the commercial truck driving community. Wierwille et al. (2003) estimate that roughly 36 percent of commercial drivers wore glasses at night during the Impact of Sleeper Berth Usage on Driver Fatigue study (Dingus et al., 2002). Therefore, all eye closure sensors need to effectively deal with this aspect of driving.

Given how the prototype system was developed, the key sensor that needed to be tested with different individuals was the MV eye closure monitor, which provided the PERCLOS estimate. The lane position sensor measured the truck path relative to the lane and, therefore, testing multiple drivers with different physical characteristics was unnecessary. While there may be small variations resulting from different drivers, the tests performed should have accounted for any deviations likely to have occurred. Here again, it must be understood that the lane position sensor provides an estimate of ground-truth lane offset. However, errors were expected to be small.

5.2.4 Operator Behaviors

The system must also account for those individual driver behaviors that are formed through differences in training or habits. These driver behaviors include checking mirrors, movement within the cab, and other forms of variability of behaviors among drivers. This evaluation included numerous tasks that represented typical driving duties. As mentioned, the key sensor that needed to be tested with different individuals was the MV eye closure sensor.

5.2.5 System-Specific

Any DDMS will need to take into account those system-specific factors that relate to the interface between the driver and DDMS. Some of these system-specific factors include:

- The need for a system self-calibration feature to allow various drivers to use a single unit.
- The system's method for alerting the driver.
- The system's ability to identify internal faults.
- The system's ability to recognize when a driver makes a response to the system.

These system-specific factors were taken into account in the prototype design of the DDMS.

5.3 DYNAMIC ON-ROAD TEST PLAN

This section details the procedures used to exercise the prototype DDMS under normal driving conditions for varying levels of ambient illumination. It is important to reiterate that the primary purpose of this study was to evaluate a prototype system that integrated MV-based technologies to assess both driver and vehicle performance metrics in an on-road, dynamic situation.

5.3.1 On-road Test Procedures

The purpose of this dynamic on-road test was to use the Smart Road as a realistic environment to produce known levels of eye closures and lane deviations as input stimuli for the DDMS under varying levels of ambient illumination, skin complexions, and eyewear. To produce known inputs of eye closures and lane offsets safely, this study used two participants and one experimenter for each test session (Figure 26). One participant (the driver) was a professionally trained test driver whose task was to produce standardized lane deviations. The other participant (the pseudo-driver) was from a group who possessed the necessary physical characteristics (e.g., skin complexion and eyewear). The purpose of the pseudo-driver was to produce the prescribed eye closures as input to the *MV System B* portion of the DDMS. The experimenter sat between the two seats in the sleeper berth area to provide instructions to both participants. This approach allowed the driver to maintain eyes on the road and to focus solely on the lane deviation tasks. The second participant was positioned in the passenger seat with the *MV System B* components mounted on the dash directly in front of this seat. One participant served as the driver for all test sessions, while the pseudo-driver changed across test sessions to provide variability typical of the driver population.

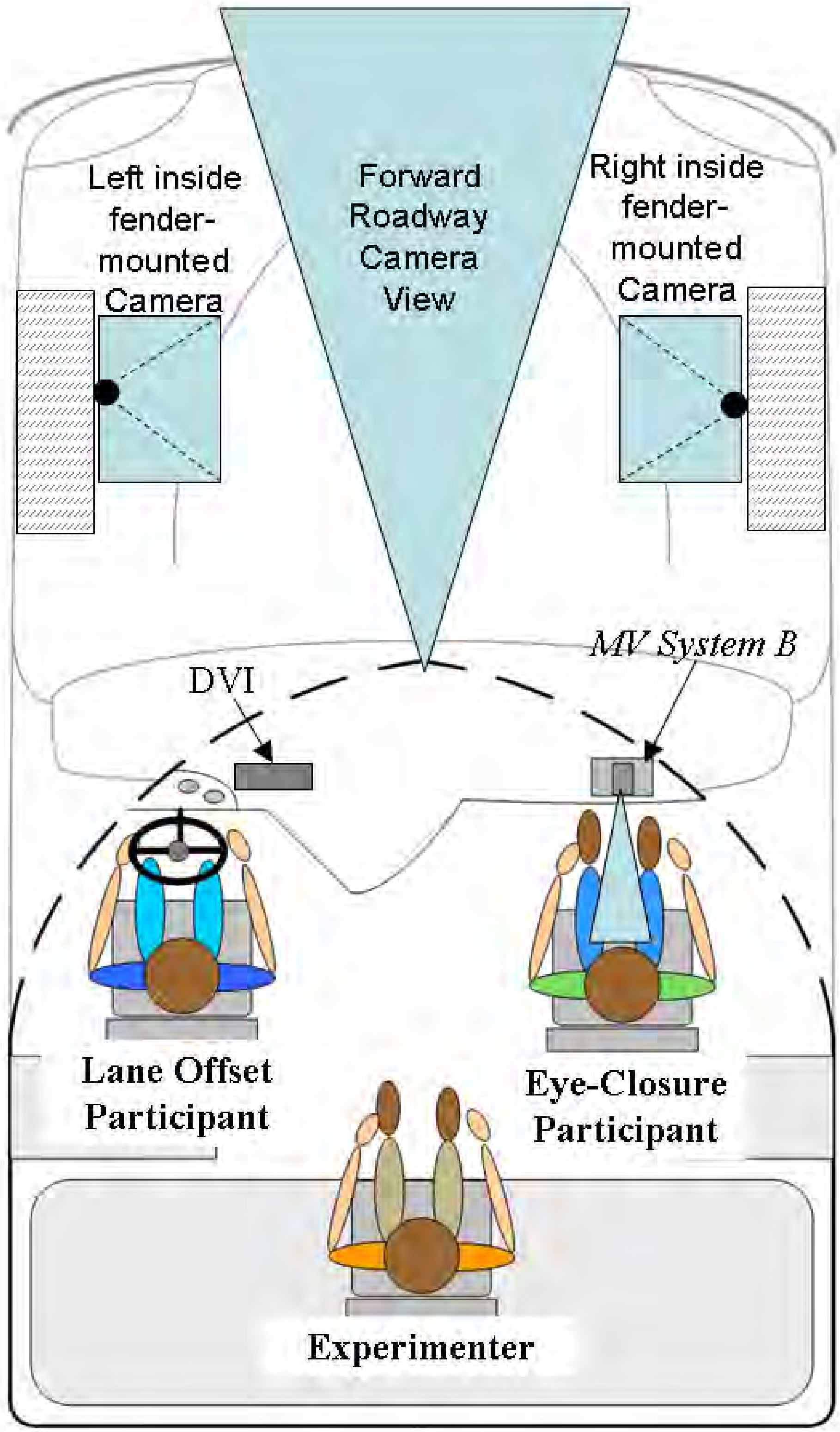

Figure 26. Top View of the Prototype DDMS On-Road Evaluation Vehicle Setup

Numerous test conditions were developed to exercise the DDMS under near-realistic dynamic driving situations (Table 9). Since the primary aim of the study was to determine the ability of the DDMS to monitor drowsiness-induced lane offsets and eye closures accurately, the purpose of these test conditions was to produce a controlled amount of stimulus for the DDMS sensors. For instance, the driver was asked, at specific times, to move the vehicle's right front tire across the right-side edge marking for a predetermined duration. The three durations of deviations were 10 seconds, 30 seconds, and 60 seconds. Feedback was provided to the driver by the test apparatus as to the time remaining in the lane deviation task. A similar procedure was used for eye closures. The pseudo-driver was asked at specific times to perform slow eye closures of varying durations (e.g., 2 seconds, 5 seconds, and 10 seconds). While these threshold criteria are based on previous research (Wierwille et al., 2003) and expert judgment, future work could determine appropriate levels for "true" naturalistic CMV driving. Depending on the exercise condition, the lane offset task and eye closure tasks were performed either separately or simultaneously.

To evaluate the propensity of the DDMS to generate false alarms from driving tasks typical of commercial trucking, three additional tasks were completed. These three false alarm tasks were:

- Looking down to the instrument panel.
- Checking both the left and right mirrors.
- Changing lanes using the turn signals.

The first two false alarm tasks were completed simultaneously by both the driver and pseudo-driver. By having both the driver and pseudo-driver complete these additional tasks simultaneously, the DDMS data may reflect any effects these tasks have on the integrated system. For instance, the driver completing the false alarm tasks may introduce variance to lane deviations indicating an effect, while at the same time, the PERCLOS estimation may be affected by the pseudo-driver completing these same false alarm tasks. The third false alarm task had the driver intentionally change lanes while using the vehicle's turn signals. The turn signals were activated at the beginning of the intentional lane change and were deactivated once the vehicle had fully crossed into the adjacent lane.

For comparison purposes, a baseline exercise condition was performed three times during each test run. During this baseline exercise, the driver was asked to maintain a lane position within the lane lines, and the pseudo-driver was asked to gaze in a forward direction with only normal eye blinks. This baseline exercise condition was performed for approximately 10 seconds each time.

Table 9. Types of Test Conditions

Exercise Condition	Corresponding Task Number	Pseudo-Driver Tasks	Eye Closures	Driver Tasks	Lane Deviation	Type of Condition
A	Tasks 1,9,&11	Look straight forward	Normal blinks	Normal driving	Maintain lane tracking	Baseline
B	Task 4	Eye closure	2-s	Normal driving	Maintain lane tracking	Low drowsiness
C	Task 2	Eye closure	5-s	Normal driving	Maintain lane tracking	Medium drowsiness
D	Task 7	Eye closure	10-s	Normal driving	Maintain lane tracking	High drowsiness
E	Task 12	Look straight forward	Normal blinks	10 s lane crossing	10 s lane crossing	Low lane deviation
F	Task 3	Look straight forward	Normal blinks	30 s lane crossing	30 s lane crossing	Moderate lane deviation
G	Task 5	Look straight forward	Normal blinks	60 s lane crossing	60 s lane crossing	High lane deviation
H	Task 10	Eye closure	2-s	10 s lane crossing	10 s lane crossing	Low PERCLOS
I	Task 8	Eye closure	5-s	30 s lane crossing	30 s lane crossing	Moderate PERCLOS
J	Task 13	Eye closure	10-s	60 s lane crossing	60 s lane crossing	High PERCLOS
K	Task 14	Look down at instrument panel	Normal blinks	Look down at instrument panel	Maintain lane tracking	False alarm
L	Task 6	Mirror check	Normal blinks	Mirror check	Maintain lane tracking	False alarm
M	Task 15	Look straight forward	Normal blinks	Change lanes using turn signal	Change lanes	False alarm

As can be seen in Table 10, the 15 exercise conditions required three loops (column 1) on the Smart Road to collect the necessary data. Three loops were necessary to provide the required length of roadway to perform the conditions under the lighted portion of the Smart Road. Table 10 provides greater detail as to the timing and order of the tasks. Specifically, each task is associated with the loop number and the section of road it occurred on. In addition, this table details the type of task and its purpose.

5.3.1.1 Road Loop

Three road loops were required to complete the 15 tasks listed by Table 10. A road loop refers to one complete cycle of the Smart Road (Figure 27), which is approximately 4.4 miles in length. As in Wierwille et al. (2003), the road loop did not have any significance as a performance variable; rather, it was used to track the progression of tasks.

5.3.1.2 Road Section

The second column of Table 10 (Road Section) refers to whether the task occurred on the downhill portion (Road Section 1) or the uphill portion (Road Section 2). Although road characteristics were not anticipated to have any influence on the performance of DDMS, the features of the roadway did impact the placement of the individual tasks within each road loop (e.g., for safety reasons, the lane deviation tasks were only completed on straight sections of roadway and not while traversing bridges).

5.3.1.3 Exercise Condition

The third column of Table 10 lists, in presented order, the 15 individual tasks that were completed by the driver and the pseudo-driver during the dynamic study. The following sections will provide more details about these 15 tasks.

5.3.1.4 Pseudo-Driver Tasks

As mentioned, the pseudo-driver tasks (column 4) provided stimuli for the MV eye closure monitor part of the DDMS. These tasks include three typical driving tasks (e.g., looking straight forward, looking down at the instrument panel, and checking the left and right mirrors) and three eye closure levels (e.g., 2 seconds, 5 seconds, and 10 seconds). These levels of eye closures were established in previous research to elicit adequate responses from the driver drowsiness monitors (Wierwille et al., 2003; Bowman et al., 2007).

Table 10. Order and Purpose of Test Conditions

Road Loop	Road Section	Exercise Condition	Pseudo-Driver Tasks	Driver Tasks	Purpose of Condition
1	1	Warm-up	Look straight forward	Maintain lane tracking	Warm-up
1	1	A (Task 1)	Look straight forward	Maintain lane tracking	Baseline
1	2	C (Task 2)	5 seconds	Maintain lane tracking	System detection accuracy
1	2	F (Task 3)	Look straight forward	30-second lane crossing	System detection accuracy
2	1	B (Task 4)	2 seconds	Maintain lane tracking	System detection accuracy
2	1	G (Task 5)	Look straight forward	60-second lane crossing	System detection accuracy
2	2	L (Task 6)	Mirror Check	Maintain lane tracking	False alarm
2	2	D (Task 7)	10 seconds	Maintain lane tracking	System detection accuracy
3	1	I (Task 8)	5 seconds	30-second lane crossing	System detection accuracy
3	1	A (Task 9)	Look straight forward	Maintain lane tracking	Baseline
3	1	H (Task 10)	2 seconds	10-second lane crossing	System detection accuracy
3	1	A (Task 11)	Look straight forward	Maintain lane tracking	Baseline
3	2	E (Task 12)	Look straight forward	10-second lane crossing	System detection accuracy
3	2	J (Task 13)	10 seconds	60-second lane crossing	System detection accuracy
3	2	K (Task 14)	Look down at instrument panel	Maintain lane tracking	False alarm check
3	2	M (Task 15)	Look straight forward	Changing lanes using turn signal	False alarm

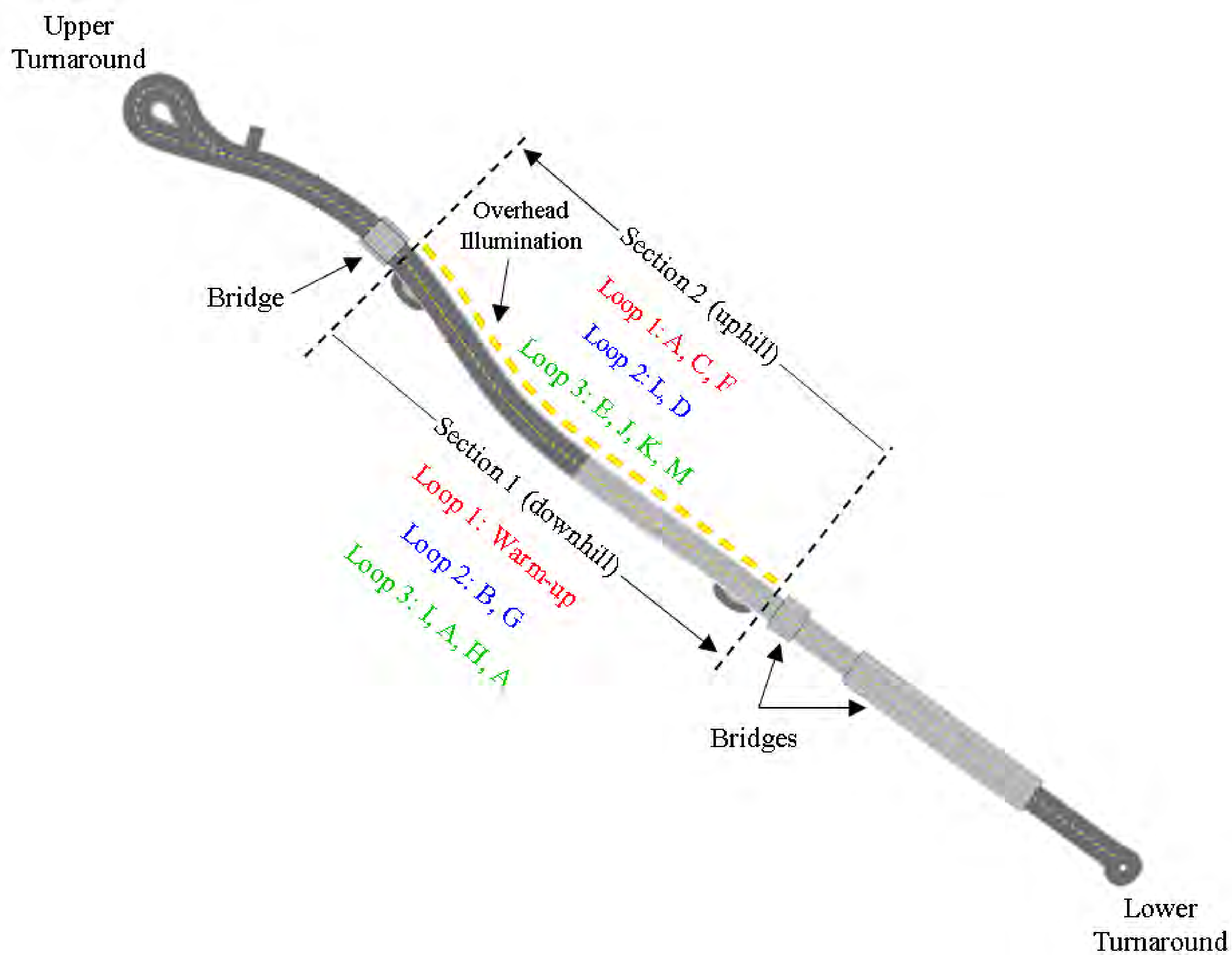

Figure 27. Schematic of the Smart Road and Test Condition Locations (*not to scale*)

5.3.1.5 Driver Tasks

The driver was involved in eight individual operating conditions (as shown in Table 9). The first operating condition served as the baseline condition in which the driver drove a straight section of the Smart Road. As stated previously, there were two false alarm driver tasks in which the driver imitated real-world driver naturalistic visual scanning behavior. These conditions included looking down at the instrument panel and then conducting a left and right mirror check. To ensure that the system received both the stimuli from the driving tasks and the eye closure tasks, the driver and pseudo-driver (in the passenger seat) completed their individual tasks simultaneously. The third false alarm task had the driver change lanes using the vehicle's turn signal. The remaining tasks were lane deviation tasks to assess the accuracy of the DDMS in monitoring drowsiness-induced lane deviations by having the driver intentionally perform edge line crossings with four different durations. A complete cycle of maneuvers involved the vehicle's right front tire crossing the lane's right edge line and returning back across to the inside of the lane's right edge line. The first edge line crossing duration was *zero*. In other words, the driver maintained lane tracking between the left and right lane edge lines, with the vehicle's right front tire not crossing the lane's right edge line. Next, there was a short edge line crossing duration of 10 seconds. With a test speed of 25 mi/h, the vehicle covered 37 ft per second; therefore, a 10-second edge line crossing covered 370 ft (Figure 28). The medium edge line crossing duration lasted for 30 seconds; a complete swerve cycle was completed in 1,110 ft (Figure 29). Finally, there was a long edge line crossing duration of 60 seconds that was completed in 2,220 ft (Figure 30). While previous research has shown that lane deviation is associated with the onset of driver drowsiness (Mast et al., 1966; O'Hanlon, Vermeeren, Uiterwijk, van Veggel, Swijgman, 1995; Wylie et al., 1996; and Arnedt et al., 2005), the specific lane edge line crossings used in this experiment were considered appropriate for eliciting an adequate response from the MV lane deviation sensor portion of the DDMS. For instance, the expected lane deviation values for a 10-second, 30-second, and 60-second lane deviation would be 17 percent, 50 percent, and 100 percent of a 1-minute interval, respectively. Therefore, the threshold levels of greater than 33 percent for Category 2 lane deviation and 66 percent for Category 3 lane deviation were believed to provide suitable limits for observing the effects of the different lane deviation durations.

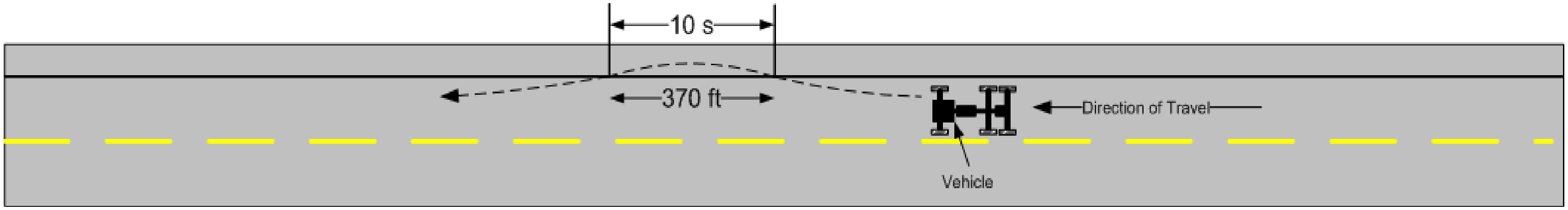

Figure 28. Schematic of the 10-Second Lane Deviation (*Not to Scale*)

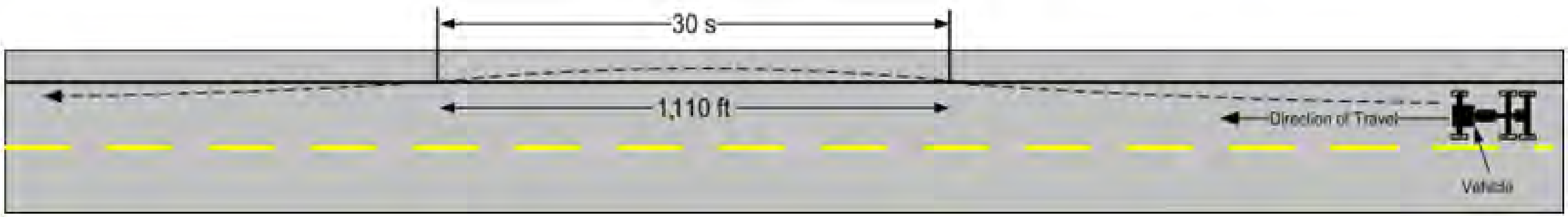

Figure 29. Schematic of the 30-Second Lane Deviation (*Not to Scale)*

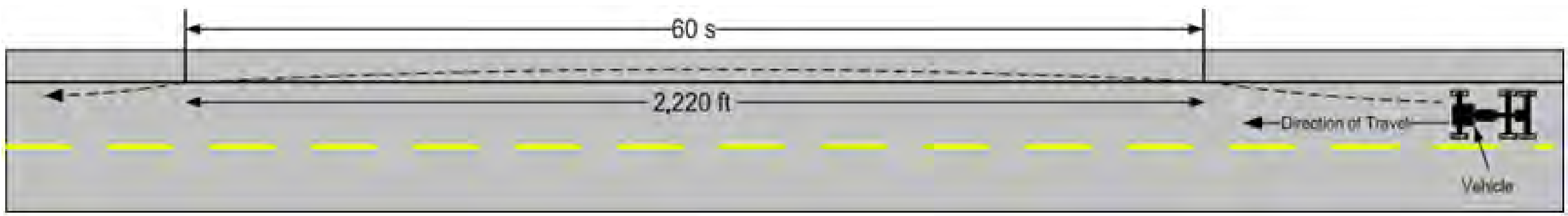

Figure 30. Schematic of the 60-Second Lane Deviation (*Not to Scale)*

5.3.1.6 *Purpose of Condition*

The last column in Table 10 indicates the purpose of each operating condition. As noted earlier, there were two primary purposes for this project. The first is to determine the detection accuracy of the DDMS when drowsiness-induced eye closures occur. For those tasks associated with determining this accuracy, the last column will have the text, "System Detection Accuracy." The second purpose of this project was to assess the performance of the DDMS under a variety of realistic driving conditions, including its propensity to generate false alarms when drowsiness-induced eye closures were not occurring. Those tasks that were associated with determining the propensity of the DDMS for false alarms are indicated in the last column by the text, "False Alarm Check."

These tests were conducted during three separate levels of ambient illumination: daytime (greater than 70 fc, 753.2 lx), nighttime (less than 0.05 fc, 0.5 lx), and artificial overhead lighting (between 0.06 fc, 0.6 lx and 4.5 fc, 753 lx). Approximately one-half mile of the Smart Road (see Sections 1 and 2 in Figure 27) is equipped with 10 overhead light poles, spaced 40 m (131.2 ft) apart. Affixed to each light pole is a 400-watt high-pressure sodium bulb with reflector and refractor that provided a light distribution that can classified as Type II (i.e., one-side edge mounting), medium spacing (i.e., spacing distance less than five times mounting height), and semi-cutoff glare control (i.e., medium control of lighting above 80 degree vertical angle) (Rea, 2000). The lighting system is considered to be typical of the overhead lighting present on U.S. roads. This roadway lighting system was used during the first nighttime driving session to observe any effects of overhead artificial lighting on the DDMS.

Other Smart Road important characteristics are shown section by section in Table 11 and illustrated in Figure 27. The anticipated speeds for the various sections are provided. Based on these speed estimates, a full loop was estimated to take just over 11 minutes or roughly five loops per hour for continuous testing (Wierwille et al., 2003).

Table 11.Smart Road Trip Time Characteristics

Description	Road Length (meters/miles)	Approximate Speed (mi/h)	Time to Traverse (min)
Upper Turnaround	623/0.387	15	1.55
End of Upper Turnaround to Small Bridge	1,968/1.223	25	2.94
Return Section	1,968/1.223	25	2.94
Small Bridge to End of Large Bridge	850/0.528	25	1.27
Return Section	850/0.528	25	1.27
End of Large Bridge to Beginning of Lower Turnaround	227/0.141	25	0.34
Return Section	227/0.141	25	0.34
Lower Turnaround	248/0.154	15	0.62
Approximate Loop Traverse Time	**–**	**–**	**11.27**

During the downhill portion of the first loop (Figure 27) on the Smart Road, both the driver and pseudo-driver became acclimated to the Volvo tractor (Section 1). After traversing the lower turnaround, the driver and pseudo-driver completed test conditions A, C, and F on the uphill portion of the Smart Road (Section 2). On the downhill portion of loop 2, test conditions B and D were completed; test conditions L and G were completed on the uphill portion (Section 2). On the third loop, test conditions I, A, H, and A were completed during the downhill portion; E, J, K, and M were completed on the uphill Section 2. Each section was balanced to encompass approximately 70 seconds of testing, covering 2,590 feet. This allowed the conditions to be completed under the lighted portion of the Smart Road, which is approximately 2,640 ft long.

5.3.1.7 Participants

Two types of participants were recruited for this evaluation, one commercial vehicle driver and nine pseudo-drivers. As mentioned earlier, the commercial vehicle driver was the only participant who drove the vehicle during the evaluation. This individual had been professionally trained as a commercial driver.

Nine pseudo-drivers also participated in this study, two preliminary subjects and seven subjects. Potential pseudo-drivers were scheduled to participate during one afternoon (2 p.m.–4 p.m.) and one evening session (9:30 p.m.–11:30 p.m.). Individuals who agreed to participate were given an informed consent form to review (Appendix F). The participants were provided with as much time as they needed to thoroughly read the informed consent form and have all questions answered. Once all questions were answered, both the participant and researcher signed two copies of the informed consent. One copy was for the participant, and one copy was kept for study records.

The pseudo-drivers involved in this evaluation varied in terms of vision acuity (e.g., no vision correction needed, prescription eyeglasses, non-prescription sunglasses) and skin complexion (e.g., light skin complexion—Caucasian; dark skin complexion—African American or Indian). The purpose of this diverse sample was to represent the types of personnel characteristics the DDMS would encounter in normal operations.

A description of each pseudo-driver involved in the evaluation is shown in Table 12. Data from Participant 3 could not be used during the analysis phase of the project because the participant exhibited extreme amounts of head drooping that prevented eye closure detection by both the MV eye closure sensor and data reductionists.

Table 12. Pseudo-Drivers' Physical Characteristics

Participant Number	Skin Complexion	Vision Acuity
Preliminary 1	Light	No Glasses
Preliminary 2	Light	Eyeglasses
1	Dark	No Glasses
2	Light	No Glasses
*3**	*Light*	*No Glasses*
4	Dark	No Glasses
5	Light	No Glasses/Glasses
6	Light	Eyeglasses
7	Dark	Eyeglasses

* Subject 3 data removed from analysis due to excessive head droop.

5.3.2 Participant Instructions

Prior to the actual test, the driver and experimenter became familiar with the features of the test tractor and the performance of the lane deviation tasks. Once the driver had demonstrated proficiency in the lane deviation tasks and had no questions about the driver tasks, the pseudo-drivers were scheduled. On the day of the test, the experimenter provided instructions to the pseudo-driver on how to "exhibit" slow eye closures for the durations indicated previously (2 seconds, 5 seconds, and 10 seconds). Once each pseudo-driver had successfully demonstrated the slow eye closures for the specified durations and had no eye closure related questions, he/she was taken by the experimenter to the instrumented tractor. Once in the tractor, the remaining tasks to be performed on the Smart Road were reviewed and practiced.

The testing progressed as outlined in Table 10. After the loops were completed, the participants were thanked for their participation and dismissed. Further details are presented in the appendices with regard to the informed consent (Appendix F), experimenter protocol (Appendix G), and participant instructions (Appendix H).

5.3.3 Data Reduction

As previously mentioned, the intent of this evaluation was to exercise the DDMS with realistic driving conditions under varying levels of ambient illumination. Therefore, this experiment introduced known stimulus inputs for both the timing and duration of eye closures and duration of lane deviations. To determine the performance of the DDMS, three separate elements needed to be assessed:

- The reliability of the eye closure sensor output.
- The reliability of the lane position sensor output.
- The sensitivity of the DDMS model algorithms to these data sources.

The accuracy of the MV eye closure sensor was assessed quantitatively. The eye closure tracks produced by the MV eye closure sensor were compared to eye closure tracks manually created by trained data reductionists viewing the same segments of video. *MV System B* outputs the eye closure as a percent of the fully open eye and then generates a binary list of “0s” and “1s,”depending on whether the eye opening value is greater than or less than the user-defined eye opening threshold, ranging from 0–100. For this assessment, the eye opening threshold was set at 20, meaning that an eye closure 0.8–1.0 was considered closed. All other eye closures less than 0.80 were considered open and given a value of “0.” As was found in the MV eye closure sensor selection study, *MV System B* has a 3.6-second time lag between recording of the data and the video data. Therefore, the data tracks were realigned by this 3.6-second value to account for this lag. According to *MV System B* developer, this time lag is expected and due to the necessary filtering within the image processing unit.

The accuracy of the MV lane position sensor was assessed in a similar manner. The lane deviation tracks produced by the MV lane position sensor were compared to the manually-derived lane deviation tracks.

The data reduction used to assess the reliability of both the algorithms for the DDMS PERCLOS estimate and the DDMS lane position estimate was similar to that which was used previously for an evaluation of the Generation 2 PERCLOS monitor (Wierwille et al., 2003). A ground-truth data stream was manually created by trained data reductionists from the actual video streams captured by the DAS.

The video image of the pseudo-driver’s face during the eye closure tasks was used to track the closure of the pseudo-driver’s eyes manually. From this assessment, a 3-minute moving average PERCLOS value was computed. While estimated PERCLOS can be averaged over a wide range of time periods, a 3-minute average was chosen because it provides a good compromise between statistical instability and responsiveness to drowsiness changes (Wierwille et al., 2003, p. 190). Data reduction quality checks were completed by sampling the ground-truth PERCLOS data using two trained data reductionists providing independent assessments. If there was more than 1 percentage point average difference between these analysts’ tracks over the 3-minute interval, the analysts collectively reviewed and deliberated over the disparities between the independent tracks until they agreed on a resultant track, having less than 1 percentage point of disparity. These data quality checks were augmented by two senior researchers who completed 100 percent inspection of all the collected data. The manual tracks were then compared to the output of the DDMS PERCLOS estimate. This comparison was used to determine the eye closure monitor’s performance/accuracy during eye closure tasks.

For false alarms, it was not necessary to track eye closures because the pseudo-driver was alert and there were no intentional slow closures. For the eye closure monitor’s output to be considered accurate, the estimated PERCLOS output during a false alarm task should remain the same or decrease across the task time interval.

The PERCLOS ground-truth data were imported into a spreadsheet database and sorted by task. The estimated PERCLOS values were computed using data from a 3-minute moving window. Therefore, the estimated PERCLOS values for time (X) required 1,800 samples of data that occurred prior to time (X), as seen in Figure 31.

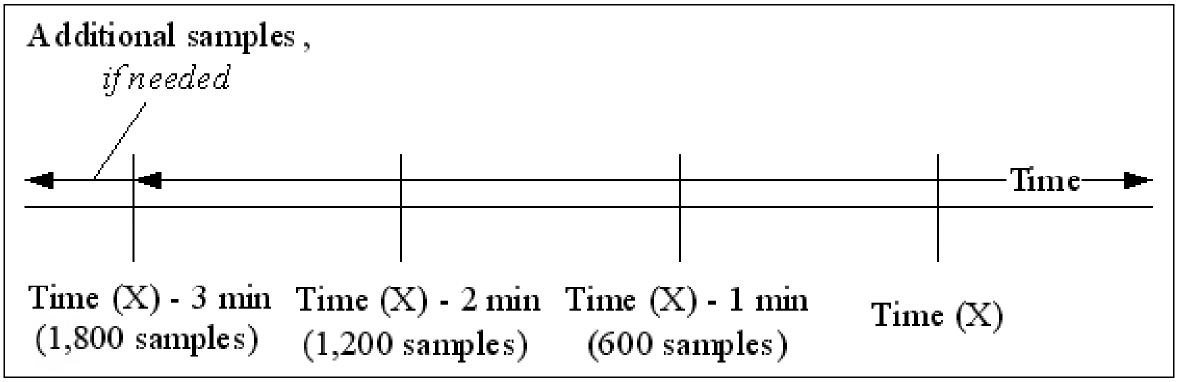

Figure 31. Estimated PERCLOS Timeline From "Ground-Truth" Data

Within these 1,800 samples of data, the number of blinks that occurred and the instances when the eyes could not be seen within the video were determined. To correspond to the DDMS PERCLOS algorithm, the instances of blinks and no view of the pseudo-driver's eyes were replaced with data still further back than the 1,800 samples. Therefore, the estimated PERCLOS value was computed solely from valid eye openings and eye closures.

During this operation, it was discovered that the data set lacked a full 3 minutes of valid data prior to the first eye closure task. Typically, only 2 minutes of valid data were present prior to the first eye closure task. Instead of removing this eye closure task from the analysis, it was decided to retain the task and apply the logic used for the false alarm tasks in Wierwille et al. (2003). According to this logic, the eyes could be reasonably considered open because the participants were alert during this timeframe, and eye blinks are not included in the DDMS PERCLOS estimate.

To assess the lane tracker's ability to provide reliable data to the DDMS algorithms, video data were captured by the two cameras mounted on the left and right fenders of the tractor. These captured images were used to track the lane position of the vehicle manually. As with the PERCLOS "ground-truth" data trace, the data were sampled using two analysts who reviewed the lane position data and provided an independent estimate of lane position. Again, the difference between estimates needed to be less than 1 percent to be considered a "ground truth" estimate. As with the PERCLOS "ground-truth," two senior researchers completed 100 percent verification of all reduced data. The manual "ground-truth" lane deviation was then compared to the DDMS lane deviation estimate. As with the PERCLOS data, this comparison was used to determine the performance/accuracy of the lane position sensor output.

5.4 DATA ANALYSIS, RESULTS, CONCLUSIONS, AND RECOMMENDATIONS

Analysis of the DDMS on-road evaluation was carried out in three parts:

- Assessment of the eye closure sensor output.
- Assessment of the lane position sensor output.
- Assessment of the DDMS' algorithms.

The intent of this evaluation was to exercise a prototype driver drowsiness monitor and determine its operational limits under varying conditions outlined in the functional specifications (section 2.2). As stated, this evaluation was not a traditional human factors experiment in which a full factorial study was completed. Instead, a small sample of participants was used to introduce varying levels of stimuli, such as eyewear, eye color, and skin complexion, and to observe the effects on the system's operational performance. While much can be learned about the operational limits of the system, this small sample size does not allow for traditional statistical analysis of the factors. Therefore, the results below are exploratory to test the hypothesis that the multiple-measure approach provides a more robust means of detecting and monitoring bouts of driver drowsiness than does a single-measure approach. Also, the results provide indications of the strengths and limitations of the prototype DDMS and areas that the authors recommend be addressed in future research. While the strengths will be carried forward into future development efforts, the limitations will be identified, and possible explanations will be discussed. Further, recommendations for remedying the limitations will be made.

Since the prototype DDMS is an integration of two separate MV sensors, it was necessary to evaluate both the inputs from the independent sensors (eye closure and lane position sensors), the performance of the DDMS algorithms from these inputs, and the outputs from the integrated system algorithm (prototype DDMS). Figure 32 illustrates where in the system schematic the assessments occurred. It is important to assess the system's operational performance at each of these points to understand the total system performance.

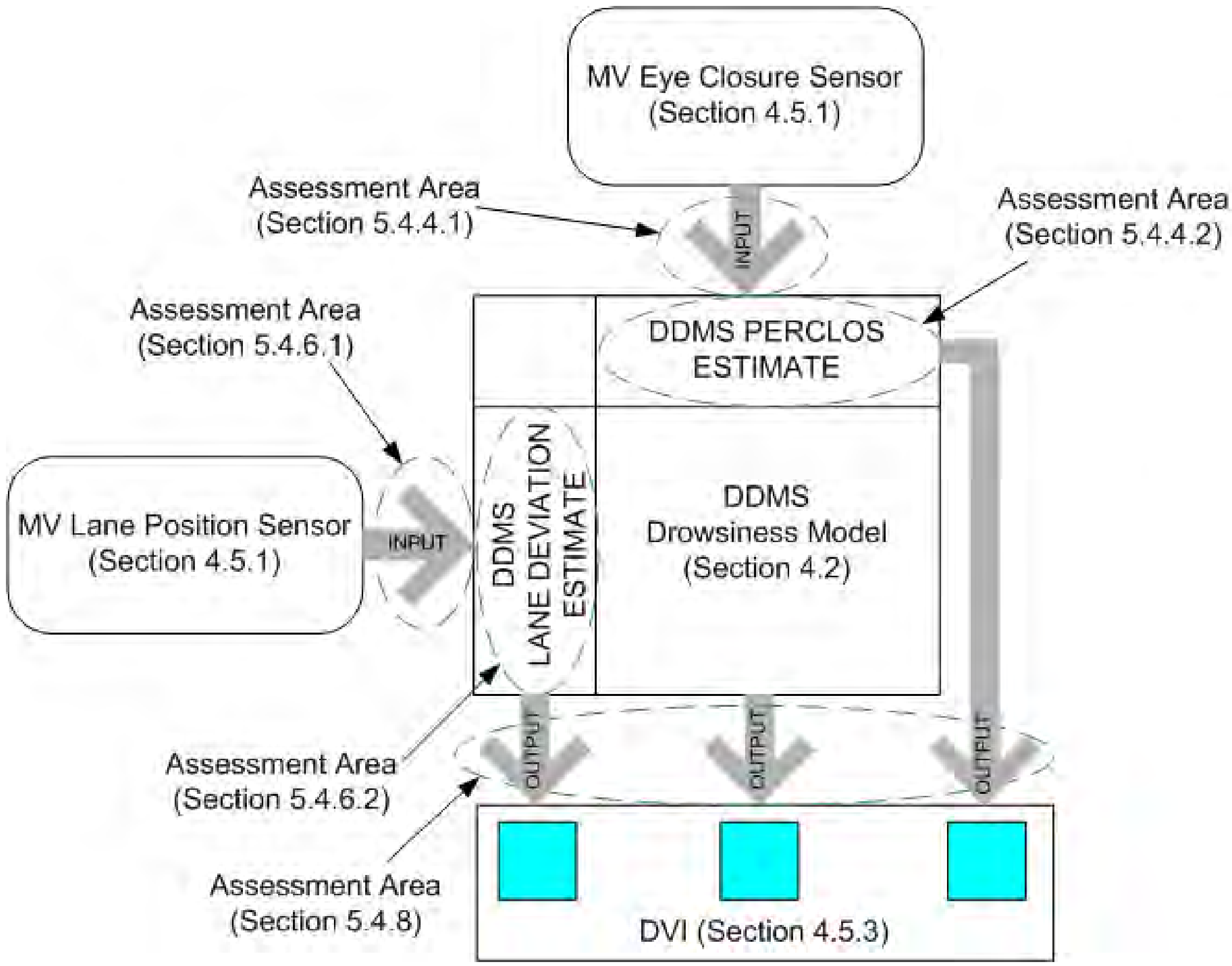

Figure 32. Prototype DDMS System Diagram Illustrating Operational Performance Assessment Areas

5.4.1 Results Summary

The analysis included data from six of the seven pseudo-drivers whose characteristics varied. One participant's data, Subject 3, was removed because of excessive head drooping during all 5-second and 10-second eye closure tasks. Subjects 6 and 7 required prescription eyeglasses, and the remaining four participants did not. Subjects 2, 5, and 6 were classified as having light skin complexion and three others (Subjects 1, 4, and 7) as having dark skin complexion. Subjects 1, 4, 6, and 7 had brown eyes, while the remaining two had blue eyes. In terms of environmental conditions, all of the DDMS data runs were conducted under similar illumination levels, defined as daytime (greater than 70 fc, 753.2 lx), nighttime (less than 0.05 fc, 0.5 lx), and nighttime with artificial overhead lighting (between 0.06 fc, 0.6 lx and 4.5 fc, 753 lx).

The first level of analysis occurred at the inputs of the MV eye closure sensor and the MV lane position sensor. The accuracies of the individual MV eye closure sensor and the MV lane position sensor were assessed by comparing their specific computed eye closure and lane deviation output tracks with manually-derived eye closure and manually-derived lane deviation tracks. The overall accuracy of the MV eye closure sensor was the highest (90 percent) during daytime illumination levels without the presence of any eyewear and the lowest (52 percent) during daytime illumination levels when sunglasses were worn by participants (Run 2). For nighttime illumination levels, the average accuracy of the MV eye closure sensor was 67 percent with artificial overhead lighting (Run 3) and 71 percent without artificial overhead lighting (Run 4). These average accuracies for the MV eye closure sensor were consistent with the average accuracies collected during the static MV eye closure sensor Selection Testing (section 4.4). The overall accuracy of the MV lane position sensor was highest (94 percent) during daytime illumination levels (Runs 1 and 2) and lowest (83 percent) under nighttime illumination levels with artificial overhead lighting (Run 3). MV lane position sensor's average accuracy during nighttime illumination levels without artificial overhead lighting was 88 percent.

The accuracies of the PERCLOS and lane deviation estimates was assessed using a shape scoring procedure similar to that used by Wierwille et al. (2003) to evaluate the Generation 2 PERCLOS Monitor (G2PM). Based on this assessment, the DDMS PERCLOS estimate appears to be most accurate during higher levels of ambient illumination and without the presence of eyewear. Conversely, the primary limitations for the DDMS PERCLOS estimate appear to be eyewear and lower levels of ambient illumination. The DDMS lane deviation estimate demonstrated high levels of accuracy for all run conditions (Runs 1, 2, and 4), except for nighttime illumination with artificial overhead lighting (Run 3). The primary limitation of the DDMS lane deviation is low contrast of the lane markers with surroundings, caused by the overhead lighting and headlight blooming.

The propensity of the DDMS to generate false alarms was also determined. Again, this analysis used a similar scoring procedure to that used by Wierwille et al. (2003). There were two false alarm tasks for the DDMS PERCLOS estimate. The first was to determine if visual scan patterns could produce an increase in the PERCLOS estimate (i.e., would instances of visually scanning the environment be misinterpreted by the DDMS as "eyes closed"?). For this task, the pseudo-driver was asked to complete a visual scan starting with the left mirror and ending the scan in the right mirror. The second false alarm task was to determine if looking down at the instrument panel would cause an increase in the PERCLOS estimate. Analysis of both of these tasks indicated that 100 percent of samples were below the 0.05 threshold; therefore, the DDMS PERCLOS estimate was deemed successful in avoiding false alarms based on scanning the driving environment. The MV eye closure sensor's accuracy was also examined during these false alarm tasks. The average accuracy of the MV eye closure sensor was 90 percent during the false alarm task that had the pseudo-driver complete a visual scan of the left and right mirrors (Task 6). The average accuracy of the MV eye closure sensor decreased to 82 percent when the pseudo-driver looked down at a target on the dash. The tendency of the DDMS lane deviation estimate to generate false alarms from maintaining the vehicle within the lane was assessed by analyzing the baseline conditions that had the driver maintain the vehicle's position within the lane. This same analysis was performed for a false alarm task that had the driver perform an intentional lane change using the vehicle's turn signals. As mentioned, the DDMS lane deviation algorithm is programmed to ignore instances of lane deviations when the turn signal is applied. For both of these false alarm tasks, analysis of the data indicated that 100 percent of the samples were below the 0.05 threshold; therefore, the DDMS lane deviation estimate was deemed successful in avoiding false alarms based on maintaining the vehicle's within-lane position or intentional lane changes. Analysis of the MV lane position sensor's accuracy during these false alarm tasks indicated that the MV lane position sensor is very proficient at determining the vehicle's lane position during instances the vehicle's position is maintained within the lane (97 percent) or when the vehicle is intentionally driven out of the lane using the turn signals.

Finally, the sensitivity of the DDMS algorithms to the presence of stimuli was assessed by operational definitions that characterized expected and unexpected changes in color for the DVI indicators in the DDMS. For 10-second eye closures, the greatest sensitivity occurred during Run 4 (nighttime without artificial illumination). The DDMS PERCLOS algorithms were least sensitive during Run 2 (daytime with sunglasses). For 60-second lane crossings, the sensitivity DDMS lane deviation Algorithm was consistently high (100 percent) across all run conditions.

The following sections provide greater detail associated with the summarized results.

5.4.2 Subject Demographics

Table 13 summarizes the demographic information for each participant involved in the on-road evaluation. The table includes descriptions of two preliminary subjects and seven regular subjects. Subject 3's data was removed because of excessive head drooping during all 5-second and 10-second eye closure tasks. The eye closure tasks involving intentional head drooping (i.e., where the participant was instructed to droop his/her head to mimic "nodding off") include tasks 2, 7, 8 and 13. This head drooping was considered excessive since only the top of the head was visible through the eye closure monitor. This extent of head drooping for this participant was not typical of the group and was therefore considered an outlier.

The remaining six regular participants included four males and two females. The ages of this participating group ranged from 22 to 36, with an average of 28.3 years old. Two of the participants (Subjects 6 and 7) wore prescription eyeglasses, while one participant (Subject 5) wore contact lenses. Subjects 6 and 7 wore their prescription eyeglasses during Run Condition 1. When asked, Subject 7 indicated he did not typically wear sunglasses to drive; therefore, he was excluded from Run 2. Subject 6 did occasionally wear photochromic lenses (commonly referred to as transition lenses because they change from clear to tinted as they are exposed to light), so he was asked to wear these during Run Condition 2 to determine if photochromic eyewear had an effect on the DDMS's eye closure sensor operation. The remaining participants did not require corrected vision for driving; therefore, these individuals completed Run 1 without eyewear and Run 2 with sunglasses. Subjects 6 and 7 wore their normal eyeglasses during Runs 3 and 4, while the remaining participants did not wear eyewear for either of these conditions. During data reduction, the Run 2 data for Subject 1 could not be reduced owing to the extreme opaqueness of his sunglasses, which made discernment of eye closures impossible for both the MV eye closure sensor and the data reductionists who performed manual coding of data. Therefore, Subject 1's data for Run 2 was excluded from the analysis.

5.4.3 Ambient Illumination

The DDMS was evaluated under three distinct levels of ambient illumination (Table 14). As defined in section 5.2, these ambient illumination conditions included: daytime (greater than 70 fc, 753.2 lx), nighttime (less than 0.05 fc, 0.5 lx), and artificial overhead lighting (between 0.06 fc, 0.6 lx and 4.5 fc, 753 lx). These illuminations were measured with a hand-held light meter pointed directly up while being held out the driver's side window. The daytime illuminance values for this measurement position exceeded the maximum thresholds of the meter. Therefore, the daytime reading out the driver's window fell within the daytime classification criterion. At night, the average illuminance values with and without artificial overhead lighting were 37.05 lx (with a standard deviation [SD] of 8.5 lx) and 0.005 lx (0.008 lx SD), respectively. For comparison purposes, another illuminance reading was performed with the hand-held meter positioned near the pseudo-driver's eye and pointed directly forward. The average daytime illuminance for this measurement position was 2,545 lx (784.5 lx SD). Also at this measurement position, the average illuminance values with and without artificial overhead lighting were 2.6 lx (0.6 lx SD) and 1.6 lx (0.6 lx SD), respectively.

Table 13. Pseudo-Drivers' Demographic and Illumination Data

Subject #	Gender	Age	Eye Color	No Eyewear	Sunglasses	Prescription Eyeglasses	Light Skin Complexion	Dark Skin Complexion
Preliminary 1	*M*	*25*	*Brown*			*X*	*X*	
Preliminary 2	*M*	*47*	*Hazel*	*X*	*X*		*X*	
1	M	36	Dark Brown	X	X			X
2	F	23	Blue	X	X		X	
3[*]	*F*	*23*	*Brown*	*X*	*X*		*X*	
4	M	22	Dark Brown	X	X			X
5	F	31	Blue	X	X		X	
6	M	31	Brown		X[†]	X	X	
7	M	27	Dark Brown			X		X

Table 14. Measured Illumination Data

Subject #	Daytime Illumination	Nighttime with Artificial Overhead Lighting	Nighttime without Artificial Lighting
Preliminary 1	*2,100*	*2.7 [50]*	*1.5 [0.01]*
Preliminary 2	*2,475*	*2.3 [38.2]*	*1.64 [0.00]*
1	1,860	2.87 [34.4]	1.44 [0.00]
2	3,360	2.10 [37.5]	1.7 [0.02]
3[†]	*2,710*	*2.11 [31.2]*	*1.34 [0.01]*
4	1,680	2.52 [53]	0.88 [0.01]
5	1,980	2.4 [33.3]	1.3 [0.00]
6	3,070	2.22 [36.4]	1.65 [0.00]
7	3,320	3.64 [27.7]	2.62 [0.00]
Average (excluding Preliminary 1, Preliminary 2, and Subject 3)	**2,545**	**2.625 [37.05]**	**1.60 [0.005]**

Note: Illumination measurements were taken at both the pseudo-driver's eye and from outside the driver's window for comparison purposes.

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[*] Subject 3 data removed from analysis due to excessive head droop.
[†] Photochromic prescription lenses.

5.4.4 Analysis of Eye Closure Tasks

Analysis of eye closure tasks was performed with data from six pseudo-drivers. Again, the eye closure tasks were completed under varying conditions for:

- Ambient illumination (i.e., daytime, nighttime with artificial overhead illumination, and nighttime without overhead illumination).
- Eyewear (i.e., no eyewear, sunglasses, and eyeglasses).
- Skin complexion (i.e., light and dark skin complexion). The accuracy of both the MV eye closure sensor and the DDMS PERCLOS estimate was assessed as a function of these varying conditions.

In accordance with Table 10, there were three "Eye Closure Only" tasks. Tasks 2, 4, and 7 were eye closure only tasks and involved a 5-second, 2-second, and 10-second eye closure duration, respectively. The 5-second and 10-second eye closure tasks had the pseudo-driver-subject droop the head forward. The drooping of the head was added to these longer eye closures to mimic nodding off in extremely drowsy states. The task intervals were extracted from the data and will be referenced as sample numbers in the results to follow.

5.4.4.1 MV Eye Closure Sensor Accuracy

As stated, the accuracy of the MV eye closure sensor was assessed by comparing its eye closure tracks to manually derived eye closure tracks. This accuracy was determined for all eye closures tasks across all run conditions. For comparison purposes, the accuracy of the MV eye closure sensor during the static MV eye closure sensor selection testing was compared to the data gathered during this dynamic on-road evaluation. The data were averaged over all subjects from both studies (with and without eyeglasses), under high and low ambient illumination levels.

5.4.4.2 MV Eye Closure Sensor Accuracy Results

The overall accuracy of the MV eye closure sensor during the on-road evaluation is illustrated in Figure 33. When the data are grouped by Run Condition, the MV eye closure sensor's performance is higher under higher ambient illumination without the presence of sunglasses (Run 1). The influence of prescription glasses can be seen in the results (as shown in Figure 34) when the data are separated between those who wear prescription eyeglasses and those who do not. The MV eye closure sensor has the greatest accuracy (90 percent) during daytime ambient illumination levels without the presence of any eyewear. Furthermore, the average accuracy levels increase by 10 percent for the remaining Run Conditions, as well as when the effects of eyewear are removed.

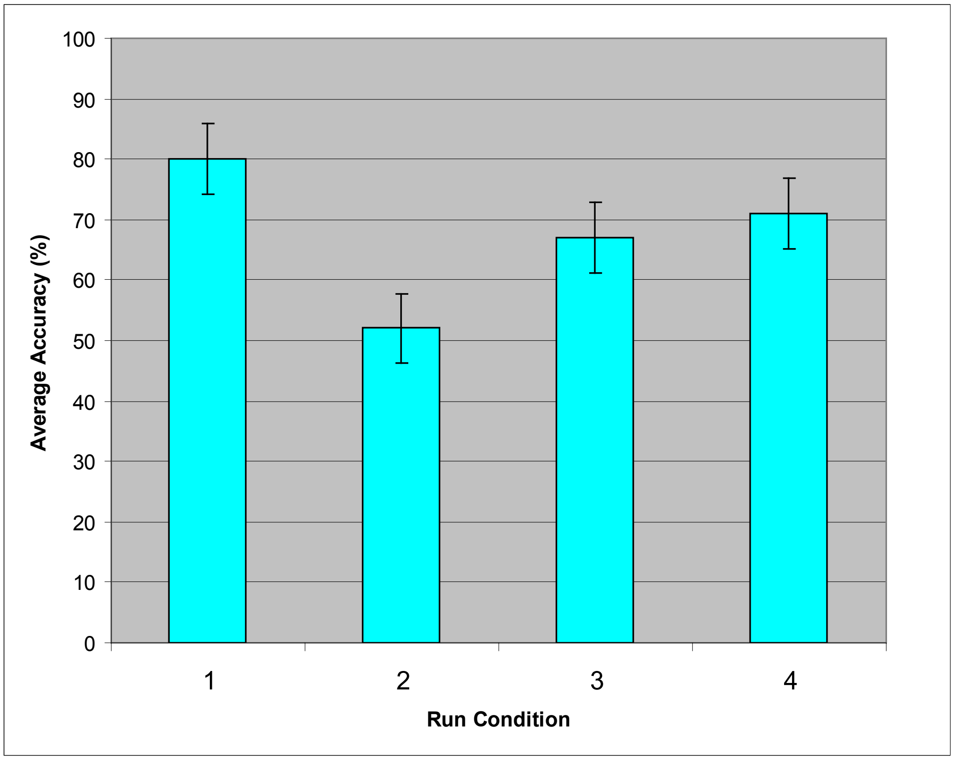


Figure 33. Overall MV Eye Closure Sensor Accuracy for On-Road Evaluation

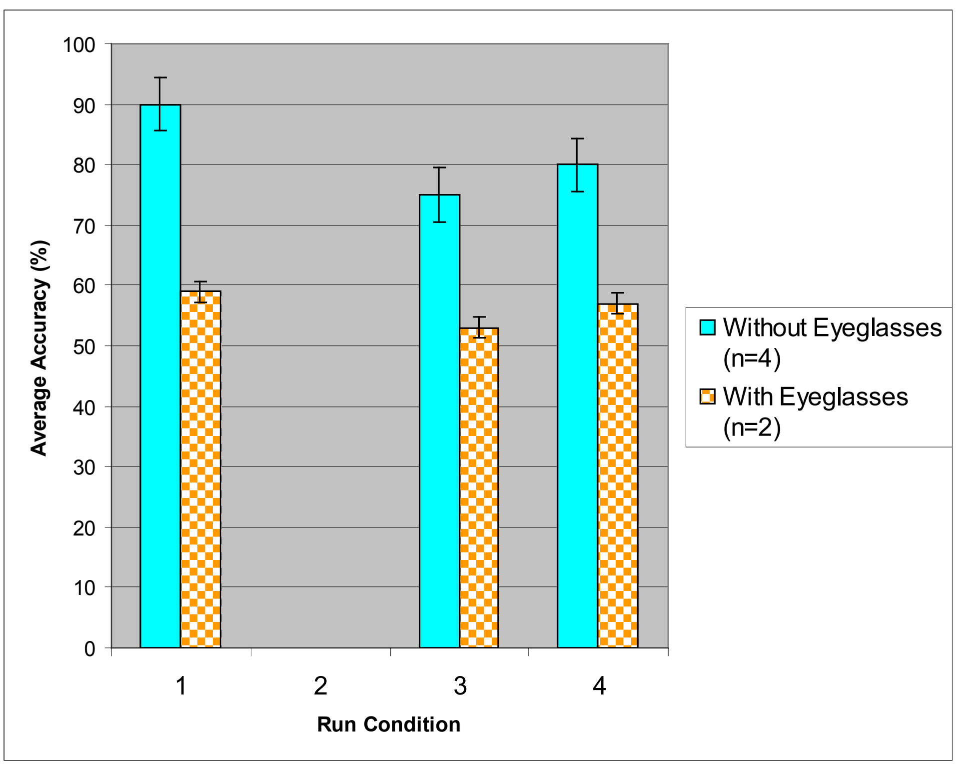


Figure 34. MV Eye Closure Sensor Accuracy With and Without the Presence of Eyeglasses

A comparison of the overall results between the static MV eye closure sensor Selection Evaluation (section 4.4) and the currently reported On-road Evaluation revealed that the accuracies of the MV eye closure sensor under both high and low levels of illumination were similar (Figure 35). From this comparison, the ability of the MV eye closure sensor to discern eye closures in both high and low ambient illumination (with and without eyeglasses) appears to transfer reasonably well from the controlled environment to actual driving conditions.

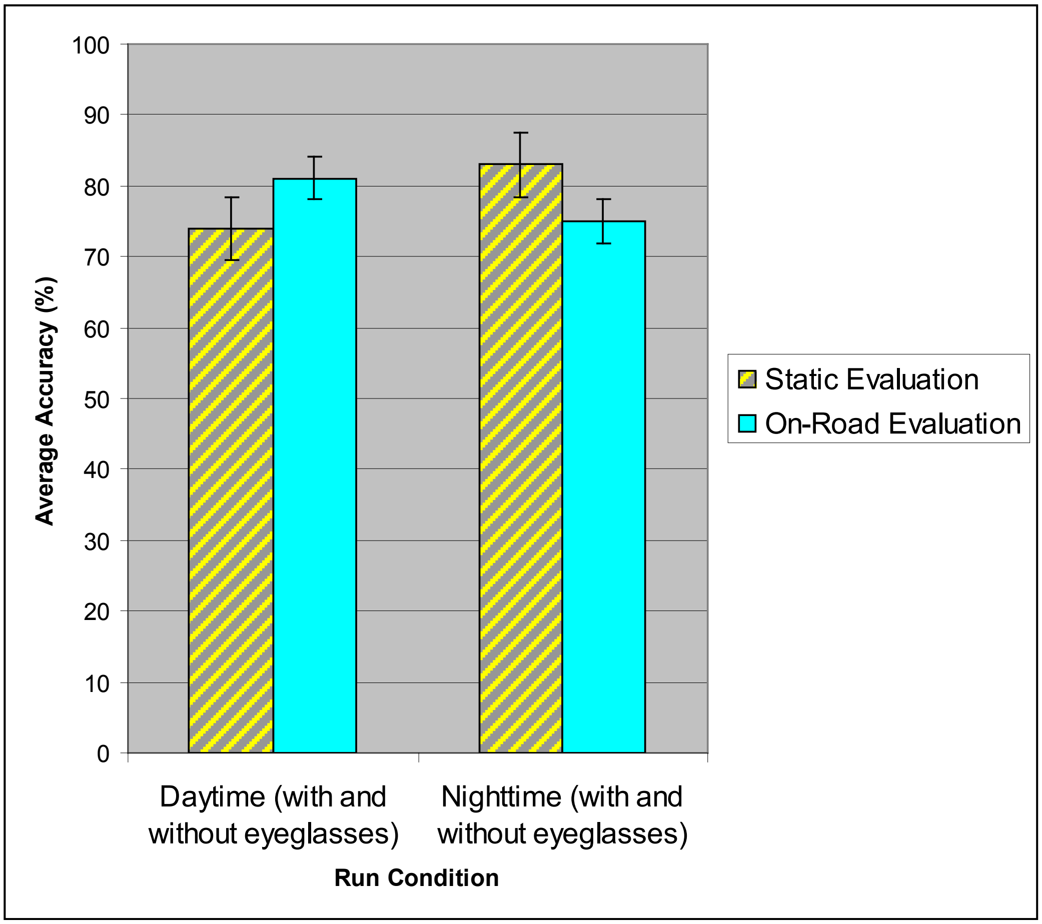


Figure 35. Comparison of MV Eye Closure Sensor Accuracies Between Static Sensor Selection Evaluation and On-Road Evaluation

Figure 36 further divides the MV eye closure sensor accuracy by subject across each run condition. Again, Subjects 1's Task 2 data could not be deduced because of the extreme opaqueness of the sunglasses being worn. Therefore, Subject 1's data for Run 2 were excluded from the analysis. Also, Subject 7 normally did not wear tinted eyewear to drive and was, therefore, excluded from Task 2.

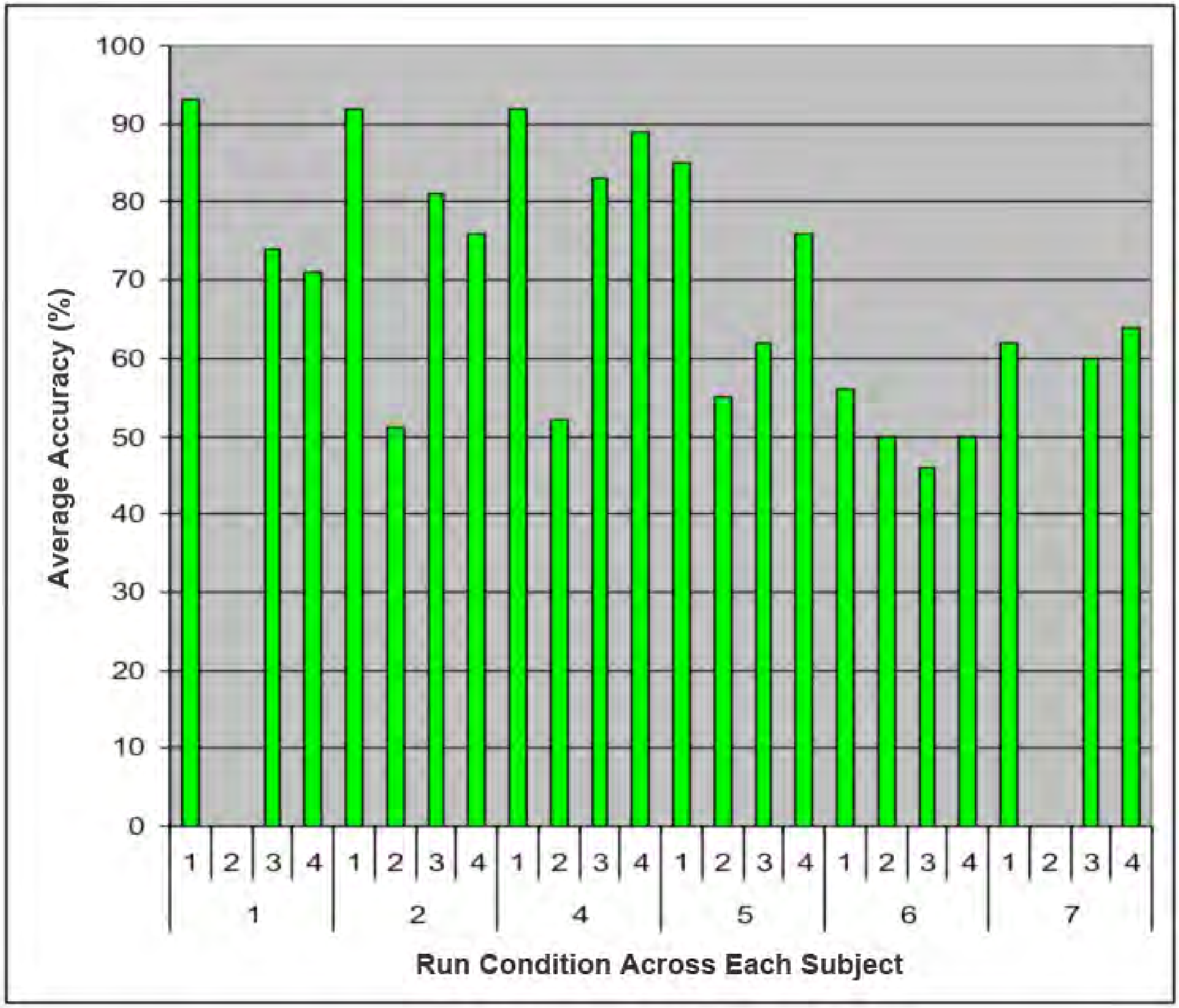


Figure 36. Average Accuracy of MV Eye Closure Sensor as a Function of Each Run Condition Across All Subjects

The following section of the report will examine the MV eye closure sensor accuracy for each subject. Because of the small sample size, observations will be made on a subject by subject basis. For each subject, a table summarizing individual demographics will be provided. To illustrate the MV eye closure sensor's responsiveness to eye opening and closings, photo examples of the MV eye closure sensor view are shown. The example was captured with the eyes fully open to illustrate the MV eye closure sensor's responsiveness to this open state. When the MV eye closure sensor has developed a face model, there should be red dots at the corners of the mouth and corners of both eyes. The eye opening magnitude sensed by the MV eye closure sensor is indicated by green bars at the outside of each eye. The length of these green bars should be approximately the same length as the height of the eye opening.

Subject 1 is a 36-year-old male with dark brown eyes and did not wear eyeglasses. Table 15 lists the MV eye closure sensor percent accuracies for Subject 1.

Table 15. Subject 1's MV Eye Closure Sensor Percent Accuracy for Each Task

Run Number	Task 2	Task 4	Task 7	Task 8	Task 10	Task 13
1	96%	81%	97%	94%	91%	96%
3	75%	61%	84%	77%	61%	83%
4	75%	56%	83%	77%	56%	81%

Key observations that can be made about the MV eye closure sensor accuracy for Subject 1:

- Under high levels of illumination (daytime levels in Run 1), the MV eye closure sensor performs well.
- Under low levels of illumination, the MV eye closure sensor did not perform as well in determining the key facial landmarks (e.g., corners of the mouth and corners of the eyes) necessary to generate the face model to locate the eyes. Throughout both nighttime runs, the facial landmark indicators (shown as red dots on the pseudo-driver's face) jumped from the corners of his mouth to his mustache and from the corners of his eyes to his eyebrows and cheeks.
- Opacity of sunglasses made eye closure estimation during Run 2 impossible.

Subject 2 is a 23-year-old female with blue eyes. Table 16 lists the MV eye closure sensor percent accuracies for Subject 2.

Table 16. Subject 2's MV Eye Closure Sensor Percent Accuracy for Each Task

Run Number	Task 2	Task 4	Task 7	Task 8	Task 10	Task 13
1	90%	95%	89%	93%	94%	88%
2	56%	65%	31%	60%	48%	43%
3	94%	61%	69%	85%	88%	86%
4	89%	75%	67%	57%	88%	80%

In summary, under low levels of ambient illumination, Subject 2's blue eyes appeared lighter and brighter than under higher ambient illumination levels. Based on the data, this does not appear to degrade the operational performance of the MV eye closure sensor.

Subject 4 is a 22-year-old male with dark brown eyes and did not wear eyeglasses. Table 17 lists the MV eye closure sensor percent accuracies for Subject 4.

Table 17. Subject 4's MV Eye Closure Sensor Percent Accuracy for Each Task

Run Number	Task 2	Task 4	Task 7	Task 8	Task 10	Task 13
1	95%	92%	92%	93%	91%	89%
2	59%	48%	73%	43%	43%	44%
3	85%	93%	76%	80%	93%	72%
4	84%	89%	89%	97%	90%	85%

In summary, except for Run 2 (daytime with sunglasses), the system performed reasonably well for Subject 4.

Subject 5 is a 31-year-old female with blue eyes and did not wear eyeglasses. Table 18 lists the MV eye closure sensor percent accuracies for Subject 5.

Table 18. Subject 5's MV Eye Closure Sensor Percent Accuracy for Each Task

Run Number	Task 2	Task 4	Task 7	Task 8	Task 10	Task 13
1	75%	96%	68%	80%	96%	92%
2	58%	56%	33%	42%	76%	62%
3	56%	72%	80%	55%	90%	18%
4	82%	92%	85%	42%	86%	67%

Key observations that can be made about the MV eye closure sensor Accuracies for Subject 5:

- As with Subject 2, Subject 5's blue eyes appeared lighter and brighter under low ambient illumination levels.
- The MV eye sensor had a difficult time locating key facial landmarks. This was more prevalent under lower ambient conditions because the illumination of the face was coming predominantly from the infrared-illuminators. With the position of the infrared-illuminators below the pseudo-driver's eyes, this subject's facial features (e.g., cheek structure) appeared to create shadows on the face. This illumination unevenness may have hindered the system in identifying facial landmarks and locating the eyes.
- The MV eye closure sensor performed better for eye closure tasks (Tasks 4 and 10) that did not involve head drooping (average accuracy = 83 percent; SD = 14 percent) than the remaining eye closures (Tasks 2, 7, 8, and 13) that had the subject droop the head (average accuracy = 62 percent; 21 percent).

Subject 6 is a 31-year-old male with brown eyes and wore eyeglasses. Table 19 lists the MV eye closure sensor percent accuracies for Subject 6.

Table 19. Subject 6's MV Eye Closure Sensor Percent Accuracy for Each Task

Run Number	Task 2	Task 4	Task 7	Task 8	Task 10	Task 13
1	74%	38%	47%	71%	64%	44%
2	40%	77%	26%	31%	85%	40%
3	42%	62%	21%	53%	59%	28%
4	74%	46%	43%	57%	50%	40%

Key observations that can be made about the MV eye closure sensor Accuracies for Subject 6:

- There was no notable difference between the normal prescription lenses (Run 1) and the photochromatic lenses (Run 2).
- Under all four conditions, there were reflections present on Subject 6's prescription eyeglasses. These reflections appear to be caused by the MV eye closure sensor's infrared-illuminators. The positions of these infrared-illuminators were near the narrow end of the manufacturer's recommended distances of 100–500 mm in an attempt to make an integral system out of the sensor and illuminators. However, this integral approach should be reconsidered. It appears that the infrared illuminators should be more widely separated in both the vertical and horizontal dimensions from the camera used.
- The MV eye closure sensor performed better for eye closure tasks (Tasks 4 and 10) that did not involve head drooping (average accuracy = 60 percent; SD = 16 percent) than the remaining eye closures (Tasks 2, 7, 8, and 13) that had the subject droop the head (average accuracy = 45 percent; 17 percent).

Subject 7 is a 27-year-old male with dark brown eyes and wore eyeglasses. Table 20 lists the MV eye closure sensor percent accuracies for Subject 7.

Table 20. Subject 7's MV Eye Closure Sensor Percent Accuracy for Each Task

Run Number	Task 2	Task 4	Task 7	Task 8	Task 10	Task 13
1	56%	54%	66%	78%	76%	40%
3	53%	95%	39%	48%	73%	50%
4	60%	87%	41%	69%	86%	41%

Key observations that can be made about the MV eye closure sensor Accuracies for Subject 7:

- Under all three run conditions, the infrared-illuminator reflections were not present on Subject 7's eyeglasses. Therefore, these reflections do not affect all participants wearing eyeglasses equally. These reflections may be more dependent on the height difference between the driver's eye and the infrared illuminator or the unique lens coatings that might exist on some eyeglasses.

- Subject 7 had a tendency to squint under higher ambient illumination levels. This relatively small eye opening may have reduced the accuracy of the estimated PERCLOS computation. Since PERCLOS is derived from the extent that the eye is open, a relatively small eye opening reduces the detection resolution for the MV eye closure sensor.
- The MV eye closure sensor performed better for eye closure tasks (Tasks 4 and 10) that did not involve head drooping (average accuracy = 79 percent; SD = 14 percent) than the remaining eye closures (Tasks 2, 7, 8, and 13) that had the subject droop the head (average accuracy = 53 percent; 13 percent).

5.4.4.3 DDMS PERCLOS Estimate Algorithm Accuracy

To determine the accuracy of the DDMS PERCLOS estimate, it was necessary to define "acceptable" accuracy. According to Wierwille et al. (2003), numerical distributions of accuracy are unnecessary, because this would result in a two-dimensional distribution of data, one axis signifying accuracy and the other axis signifying treatment condition. This previous report also states that there would likely be insufficient data in several circumstances to create two-dimensional distributions. With this understanding, the DDMS PERCLOS estimate of accuracy for eye closure tasks was assessed with the similar operational definition (Table 21) used in the Wierwille et al. (2003) study. This operational definition is believed to provide a realistic appraisal of the accuracy of the DDMS PERCLOS estimate output. The current study used a 0.08 difference as the maximum allowable error between the DDMS PERCLOS estimate data and the manually created "ground-truth" plot during eye closure tasks. Wierwille et al. (2003) stated that 8 percentage points are acceptable because the drowsiness threshold limits are typically between 12.5 and 25 percent closure. The "YES-BIASED" condition was provided as the "gray" zone between acceptable and unacceptable accuracy. Error rates between 0.08 and 0.20 for eye closure tasks are not acceptable for production-intent systems; however, this range of values for the "YES-BIASED" condition should indicate where improvement may be made in this development system. The "NO" operational condition represents the DDMS PERCLOS estimate that contains an unacceptable level of error.

Table 21. Operational Definitions Used to Assess Accuracy of DDMS PERCLOS Estimate Output During Eye Closure Tasks

Operating Condition	Definition
YES	The output of the DDMS PERCLOS estimate has a shape similar to the "ground-truth" plot manually created by the data reductionists, and there is less than or equal to a 0.08 difference throughout the interval.
YES-BIASED	The output of the DDMS PERCLOS estimate bears a resemblance to the "ground-truth" plot manually created by data reductionists, *but* there is a bias of more than 0.08 yet less than or equal to 0.20.
NO	Neither of the above conditions is met.

Following this classification procedure, shown in Table 21, the segmented task data were reduced as stated in section 5.3.4, and the mean error between the DDMS PERCLOS estimate and the ground-truth PERCLOS estimate was computed. Figure 37, Figure 38, and Figure 39 illustrate examples of the segmented task data that were evaluated as "YES," "YES-BIASED," and "NO," respectively. The abscissa units for these figures are in tenths of a second.

It is important to note the rationale for assessing the DDMS operational performance by the analysis of plots. According to Wierwille et al. (2003), the “shape” criteria listed in Table 21 could prove to be difficult to assess mathematically. The authors of that study state that shape analysis appeared to be effective in providing insight into the operational performance of the G2PM system.

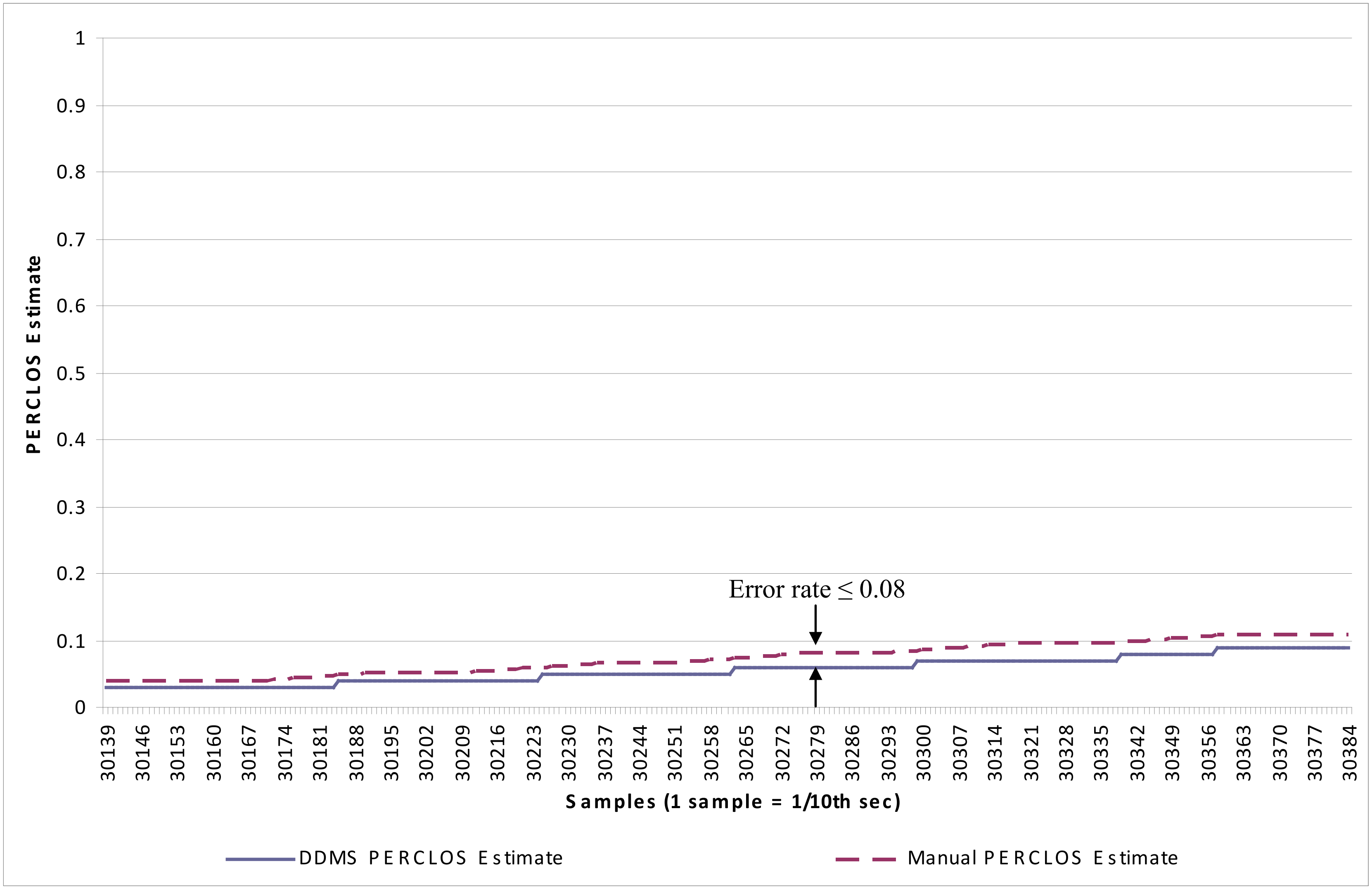


Figure 37. Example of a PERCLOS Plot Scored as a "YES" Used to Compare the DDMS Output With the Ground-Truth Track

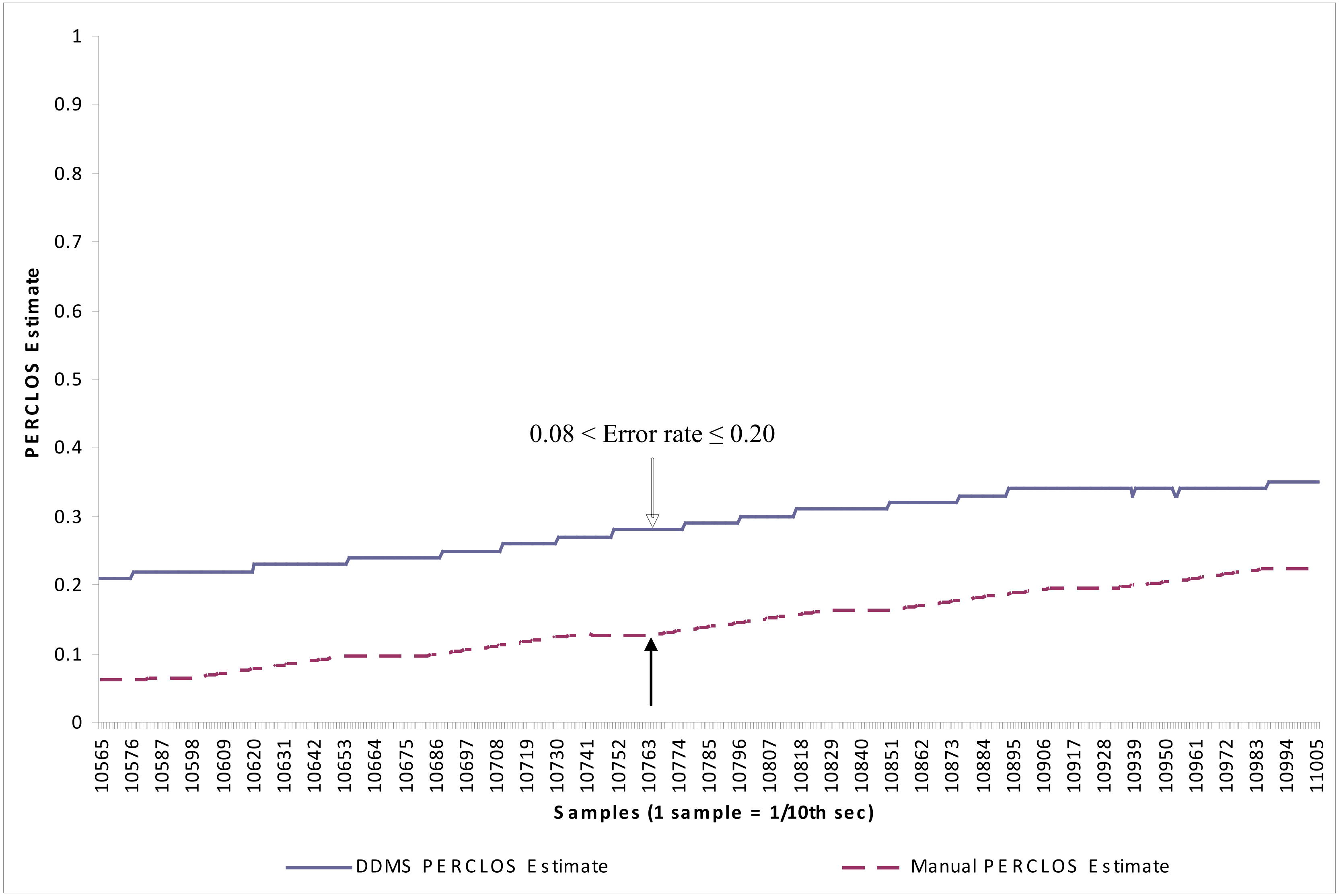


Figure 38. Example of a PERCLOS Plot Scored as a "YES-BIASED" Used to Compare the DDMS Output With the Ground-Truth Track

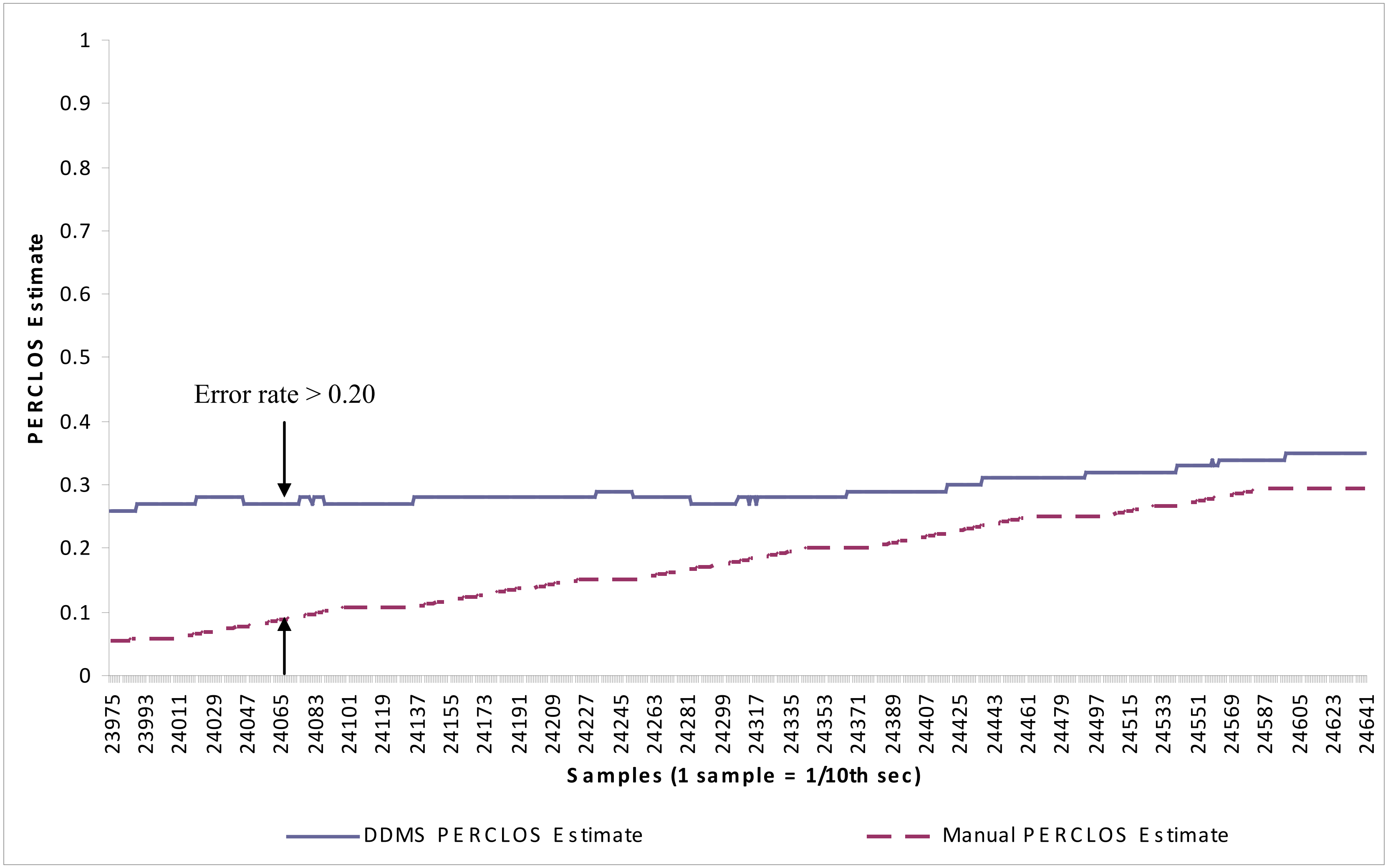


Figure 39. Example of a PERCLOS Plot Scored as a “NO” Used to Compare the DDMS Output With the Ground-Truth Track

5.4.4.4 DDMS PERCLOS Estimate Algorithm Accuracy Results

Table 22 summarizes the results from the analysis of the DDMS PERCLOS estimate operational performance as a function of run condition. The operational performance classifications for the eye closure tasks were pooled for each run condition. The numerical values in each cell are the number of occurrences. Figure 40 depicts the tallied results from Table 22 as a function of the percent of samples collected during each run.

Again, Run 1 was performed during daylight conditions, with the pseudo-drivers either wearing no eyewear or wearing the normal eyeglasses they would use for driving. Run 2 was performed under daylight conditions with the pseudo-drivers wearing sunglasses. Note that the sample size for this run condition was 24. As stated earlier, during data reduction, it was discovered that Subject 1's sunglasses were too opaque for eye closure analysis. Therefore, Subject 1's Run 2 data were removed from the analysis. The second subject who did not participate in Run 2 was Subject 7. Subject 7 did not complete Run 2 because he did not normally wear tinted eyeglasses. In a pre-study briefing, Subject 6 indicated that on occasion he wore a different pair of eyeglasses with photochromic lenses. Therefore, Subject 6 was asked to bring both his normal and photochromic eyeglasses. Subject 6 completed all run conditions except Run 2 with his normal eyeglasses. Subject 6 completed Run 2 wearing the photochromic lenses. Run 3 was completed at nighttime with artificial overhead lighting, while Run 4 was completed at night without artificial overhead lighting.

Table 22. Overall Operational Performance of the DDMS as a Function of Run Condition

	Run 1 (*n* = 36)	Run 2 (*n* = 24)	Run 3 (*n* = 36)	Run 4 (*n* = 36)
YES	17	7	11	16
YES-BIASED	13	7	15	9
NO	6	10	9	11

Figure 40. Overall Operational Performance of the DDMS Eye Closure Sensor by Run Condition

Several observations can be made from Table 27 and Figure 40 about the operational performance of the DDMS PERCLOS estimate:

- Using the shape criteria developed by Wierwille et al. (2003), 73 percent of the DDMS PERCLOS estimate algorithm's output were classified as either a "YES" (having the same shape as the manual PERCLOS estimate) or a "YES-BIASED" (having a similar shape as the manual PERCLOS with some discrepancies).
- The accuracy of the DDMS PERCLOS estimate is better during daytime illuminance levels (Run 1) than nighttime illuminance levels (Tasks 3 and 4).
- The accuracy of the DDMS PERCLOS estimate decreased when the subjects were wearing any form of eyewear. For Run 1, all instances where the accuracy was categorized as "NO" involved subjects who were wearing prescription eyeglasses. The impact of wearing sunglasses can also be seen in Run 2 with the greater number of trials labeled as "YES-BIASED" and "NO."
- When comparing Run 3 (nighttime with overhead lighting) and Run 4 (nighttime without overhead lighting), there appears to be a slight increase in accuracy under nighttime conditions without overhead artificial lighting.

5.4.5 Analysis of Eye Closure False Alarm Tasks

In accordance with Table 10, there were two eye closure false alarm tasks. Tasks 6 and 14 were visual scanning tasks that are typically performed by drivers. However, the motions of the head and eyes may have appeared to the MV eye closure sensor that the eyes were closed. For Task 6, the pseudo-driver performed a visual scan of the mirrors by starting the scan in the left-side mirror and ending the scan pattern in the right-side mirror. The second false alarm task, Task 14, had the pseudo-driver look down at the instrument panel and then return looking at the forward road scene. The task intervals were extracted from the data and will be referenced as sample numbers in the results to follow.

The DDMS PERCLOS estimate accuracy for eye closure false alarm tasks was assessed with the same definition used in the Wierwille et al. (2003) study. This operational definition (Table 23) is believed to provide a realistic appraisal of the accuracy of the DDMS PERCLOS estimate output. As with the G2PM evaluation, this study used 0.05 as the maximum allowable error between the actual PERCLOS data and the manually created ground-truth plot during false alarm tasks. As mentioned in section 5.3.4, it was not necessary to track eye closures because the pseudo-driver was alert and there were no intentional slow closures. For the DDMS PERCLOS estimate's output to be considered accurate, the estimated PERCLOS output during a false alarm task should remain the same or decrease across the task time interval.

Table 23. Operational Definitions Used to Assess Accuracy of Eye Closure Sensor Output for False Alarm Tasks

Operating Condition	Definition
YES	The change in the DDMS PERCLOS estimate's output was a decrease, no change, or an increase of less than or equal to 0.05 points from its initial task value throughout the task interval.
YES-BIASED	The increase in the DDMS PERCLOS estimate's output was more than 0.05 yet less than or equal to 0.10 from its initial task value throughout the task interval.
NO	Neither of the above conditions is met.

The classification procedure shown in Table 23 was used to classify each segment of task data that was reduced, as stated in section 5.3.4. Figure 41 illustrates an example of these segmented task data that were evaluated. Note that in this example, the DDMS PERCLOS estimate decreases slightly throughout the task, indicating that the DDMS PERCLOS algorithm did not detect the visual scan as an eye closure. The abscissa units for these figures are in tenths of a second.

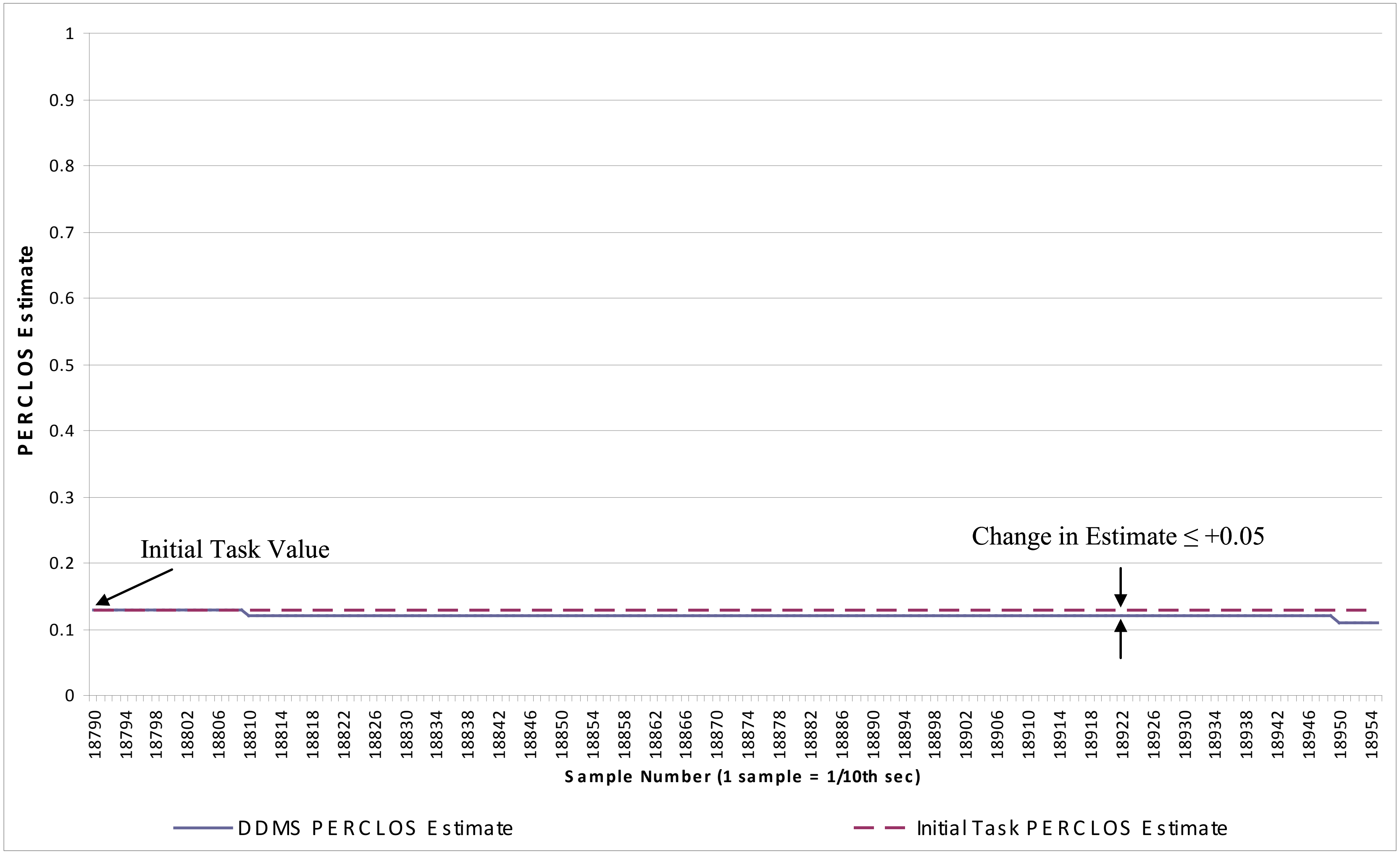


Figure 41. Example of Eye Closure False Alarm Plots Used to Determine the DDMS Algorithms' Response to a False Alarm Condition

5.4.5.1 Eye Closure False Alarm Tasks Results

Table 24 summarizes the classification results from the analysis of the DDMS PERCLOS estimate's tendency to generate false alarms. The numerical values in each cell are the number of occurrences.

Table 24. Operational Performance of the DDMS as a Function of the Eye Closure False Alarm Task

	Run 1 Mirror Check (Task 6)	Run 1 Instrument Panel Look Down (Task 14)	Run 2 Mirror Check (Task 6)	Run 2 Instrument Panel Look Down (Task 14)	Run 3 Mirror Check (Task 6)	Run 3 Instrument Panel Look Down (Task 14)	Run 4 Mirror Check (Task 6)	Run 4 Instrument Panel Look Down (Task 14)
Sample Size	*n*=6	*n*=6	*n*=4	*n*=4	*n*=6	*n*=6	*n*=6	*n*=6
YES	6	6	4	4	6	6	6	6
YES-BIASED	0	0	0	0	0	0	0	0
NO	0	0	0	0	0	0	0	0

The false alarm analysis revealed that the MV PERCLOS estimate algorithms have a low propensity to generate false alarms for visual scanning tasks typical of commercial driving (e.g., visually scanning the side mirrors, looking down at the instrument panel). When the average accuracy of the MV eye closure sensor was examined for these two false alarm tasks, the results indicated that the MV eye closure sensor performs at a higher accuracy for the mirror scan task as compared to the accuracy while the pseudo-driver looks down at a target on the dash (Figure 42). One possible explanation is the change in the eyes' position relative to the camera. As the head and eyes were rotated down, the eye opening level detected by the MV eye closure sensor appears to be reduced.

In summarizing the findings of the DDMS PERCLOS estimate false alarm tasks, the results clearly indicate that the DDMS PERCLOS algorithm was performing correctly and was able to correctly identify eye movements during visual scans and not classify these eye movements as indicators of drowsiness. However, further refinement of the MV eye closure sensor is necessary to account for changes in perceived eye opening levels as the head and eyes move to complete visual scanning tasks.

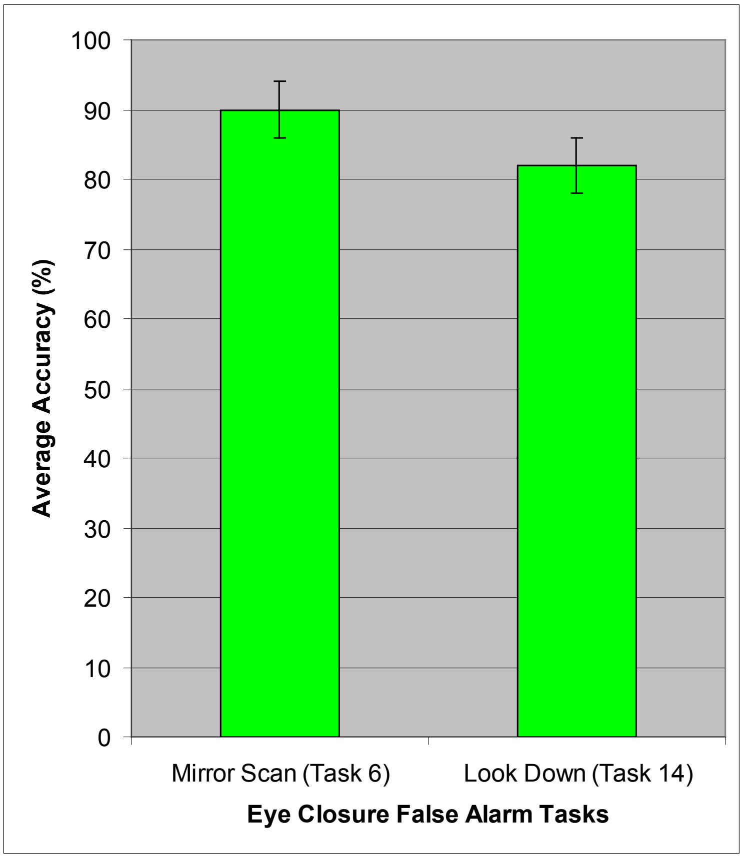


Figure 42. Average Accuracies for MV Eye Closure Sensor as a Function of False Alarm Task

5.4.6 Analysis of Lane Deviation Tasks

The analysis of lane deviation tasks was performed with data from the lane crossings completed by the driver. Again, the lane deviation tasks were completed under varying conditions for ambient illumination (i.e., daytime, nighttime with artificial overhead illumination, and nighttime without overhead illumination). These are the same conditions that were used for the PERCLOS estimation procedures.

As indicated in Table 10, there were three "Lane Deviation Only" tasks. There were tasks 3, 5, and 12, which involved 30-second, 60-second, and 10-second durations of lane deviation, respectively. Tasks 8, 10, and 13 were lane deviations performed simultaneously with eye closures. These combined tasks involved a 30-second lane deviation in Task 8, a 10-second lane deviation in Task 10, and a 60-second lane deviation in Task 13. The task intervals were extracted from the data and are referenced as sample numbers in the following results.

5.4.6.1 MV Lane Position Sensor Accuracy

Similar to the analysis of the MV eye closure sensor accuracy, the accuracy of the MV lane position sensor was assessed by comparing lane position tracks to manually derived lane position tracks. The accuracy was assessed for all lane deviation tasks across all run conditions. In addition to the accuracy values of the MV lane position sensor, the analysis provides an average confidence level for the MV lane position sensor and the percent of task interval that the MV lane position sensor was confident in whether the vehicle was in-lane or out-of-lane.

5.4.6.2 MV Lane Position Sensor Accuracy Results

The accuracy of the MV lane position sensor during the On-road Evaluation is illustrated as the solid bars in Figure 43. The level of confidence that the MV lane position sensor possessed during the task and the percentage of the task interval the sensor had this confidence are depicted as the diagonal hatched bars and the checked pattern bars, respectively. Based on these results, the MV lane position sensor performed well and worked in daytime conditions with an accuracy of 94 percent. In nighttime conditions, the accuracy was as high as 88 percent. The confidence level of the MV lane position sensor remained high across all run conditions, but the percentage of task interval in which the sensor was confident decreased during nighttime illumination levels, especially those lower illumination levels augmented by artificial overhead lighting.

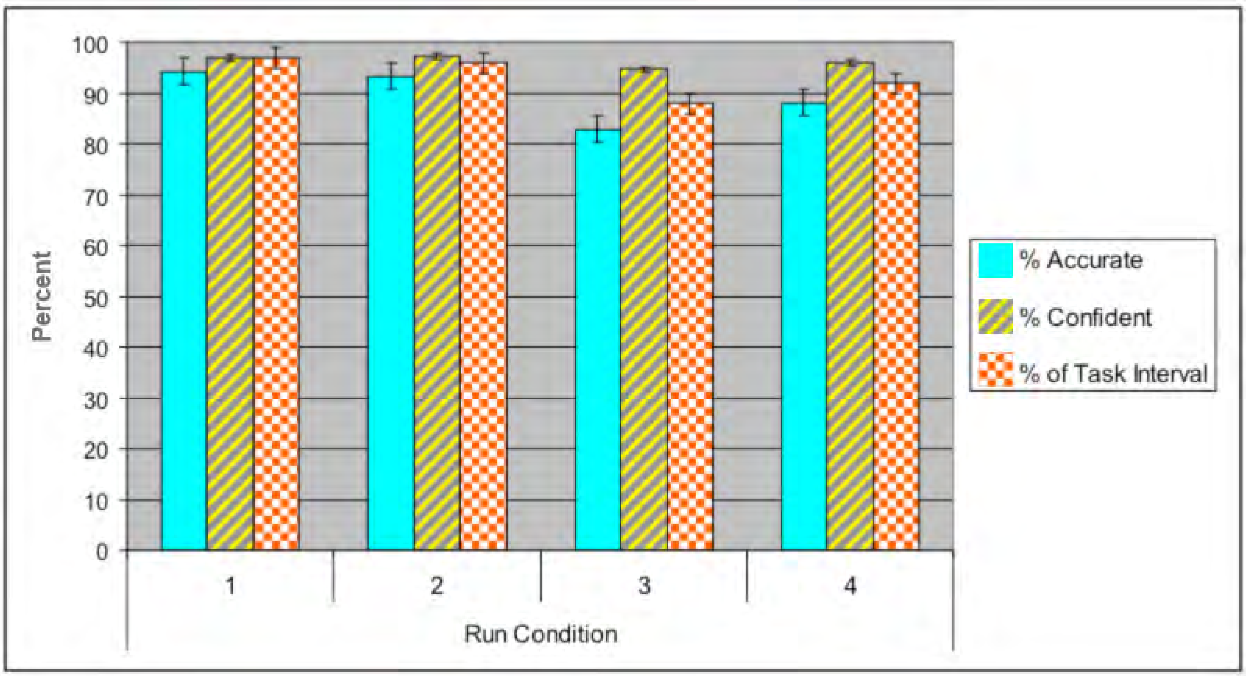


Figure 43. The MV Lane Position Sensor's Percent Accuracy, Percent Confidence, and Percent of Task Interval as a Function of Run Condition

5.4.6.3 DDMS Lane Deviation Estimate Algorithm Accuracy

The same rationale presented in the analysis of the DDMS PERCLOS estimate algorithm was considered when determining the accuracy of the DDMS lane deviation estimate. Therefore, the DDMS lane deviation estimate accuracy during lane deviation tasks was assessed in a similar manner. These operational definitions, as seen in Table 25, are believed to provide a realistic appraisal of the accuracy of the lane deviation metric. For lane deviation tasks, an error value of 0.10 points was used as the maximum allowable difference between the actual DDMS lane deviation estimate and the manually created ground-truth plot during lane deviation tasks. Since the thresholds for the DDMS lane deviation estimate were 0.33 and 0.66 of a 1-minute average (as explained in section 4.2), any differences between the actual percent out-of-lane deviation data and the "ground-truth" plot less than or equal to 0.10 points will be inconsequential to the operation of the system. As with the analysis of the eye closures, error values between 0.10 and 0.20 are not considered "acceptable," but these values in the "YES-BIASED" operational condition are provided to identify opportunities for improvement within the DDMS. The "NO" operational condition represents the DDMS lane deviation estimate that contains an unacceptable level of error.

Table 25. Operational Definitions Used to Assess Accuracy of DDMS Lane Deviation Estimate Output During Lane Deviation Tasks

Operating Condition	Definition
YES	The output of the DDMS lane deviation estimate has a shape similar to the "ground-truth" plot manually created by the data reductionists, and there is less than or equal to a 0.10 difference throughout the interval.
YES-BIASED	The output of the DDMS lane deviation estimate bears a resemblance to the "ground-truth" plot manually created by data reductionists, *but* there is a bias of more than 0.10 yet less than or equal to 0.20.
NO	Neither of the above conditions is met.

As with the eye closure analysis, the scoring procedure shown in Table 25 was used to classify each segment of task data that was reduced, as stated in section 5.3.4. Figure 44, Figure 45, and Figure 46 provide examples of segmented task data that were evaluated as "YES," "YES-BIASED," and "NO," respectively. The abscissa units for these figures are in tenths of a second.

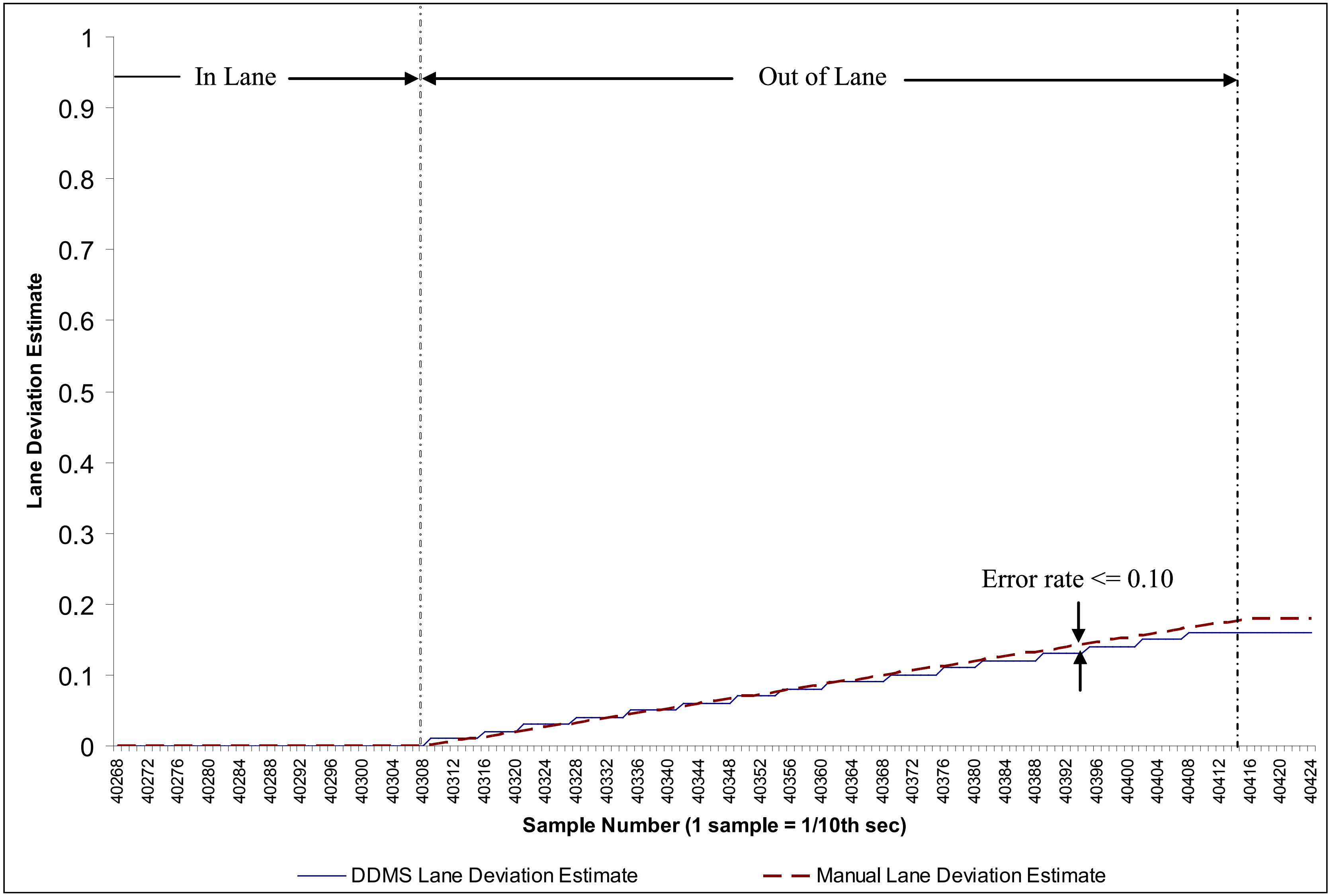


Figure 44. Example of Lane Deviation Plot Scored "YES" Used to Compare the DDMS Output With the "Ground-Truth" Track

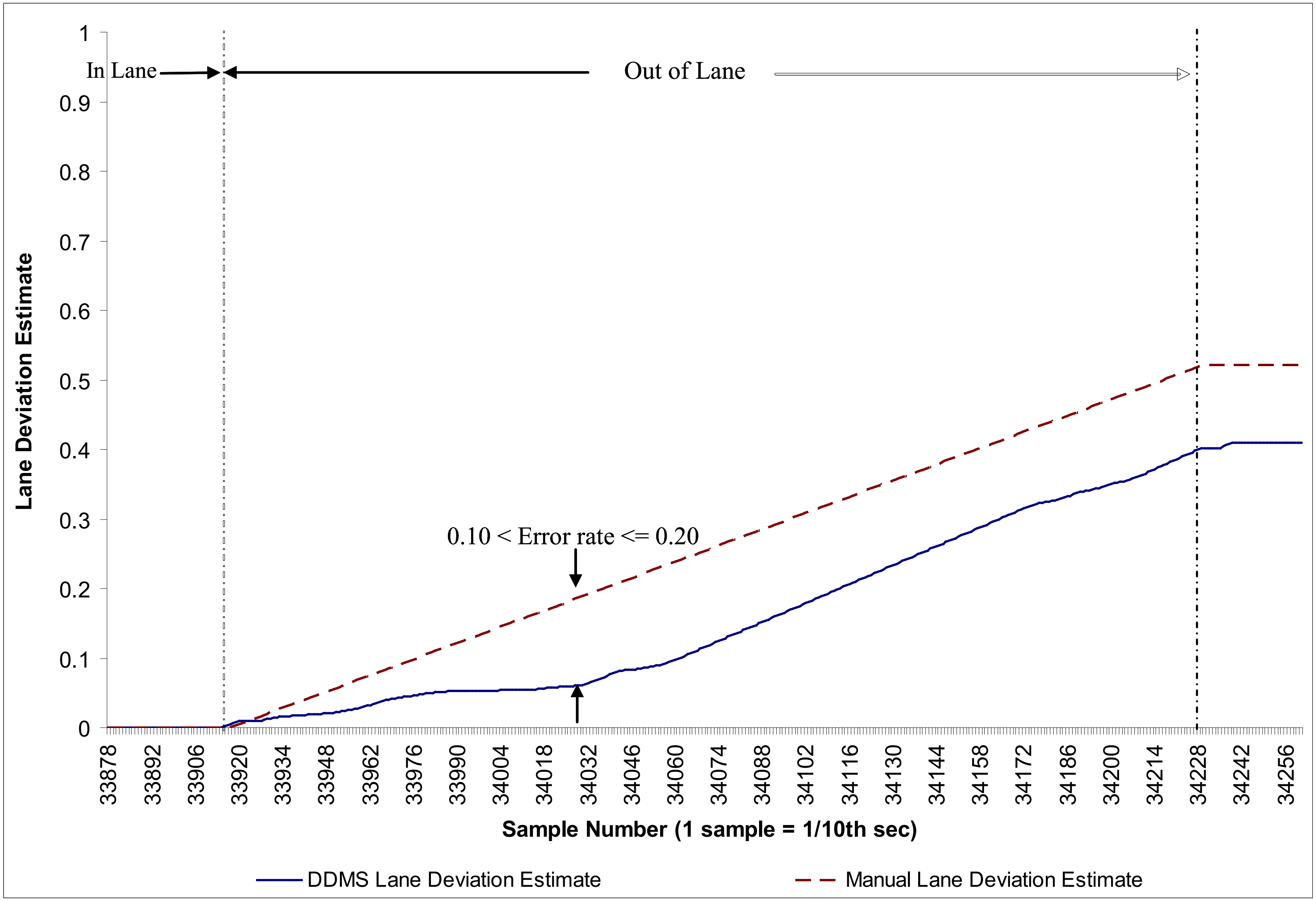


Figure 45. Example of Lane Deviation Plot Scored "YES-BIASED" Used to Compare the DDMS Output With the "Ground-Truth" Track

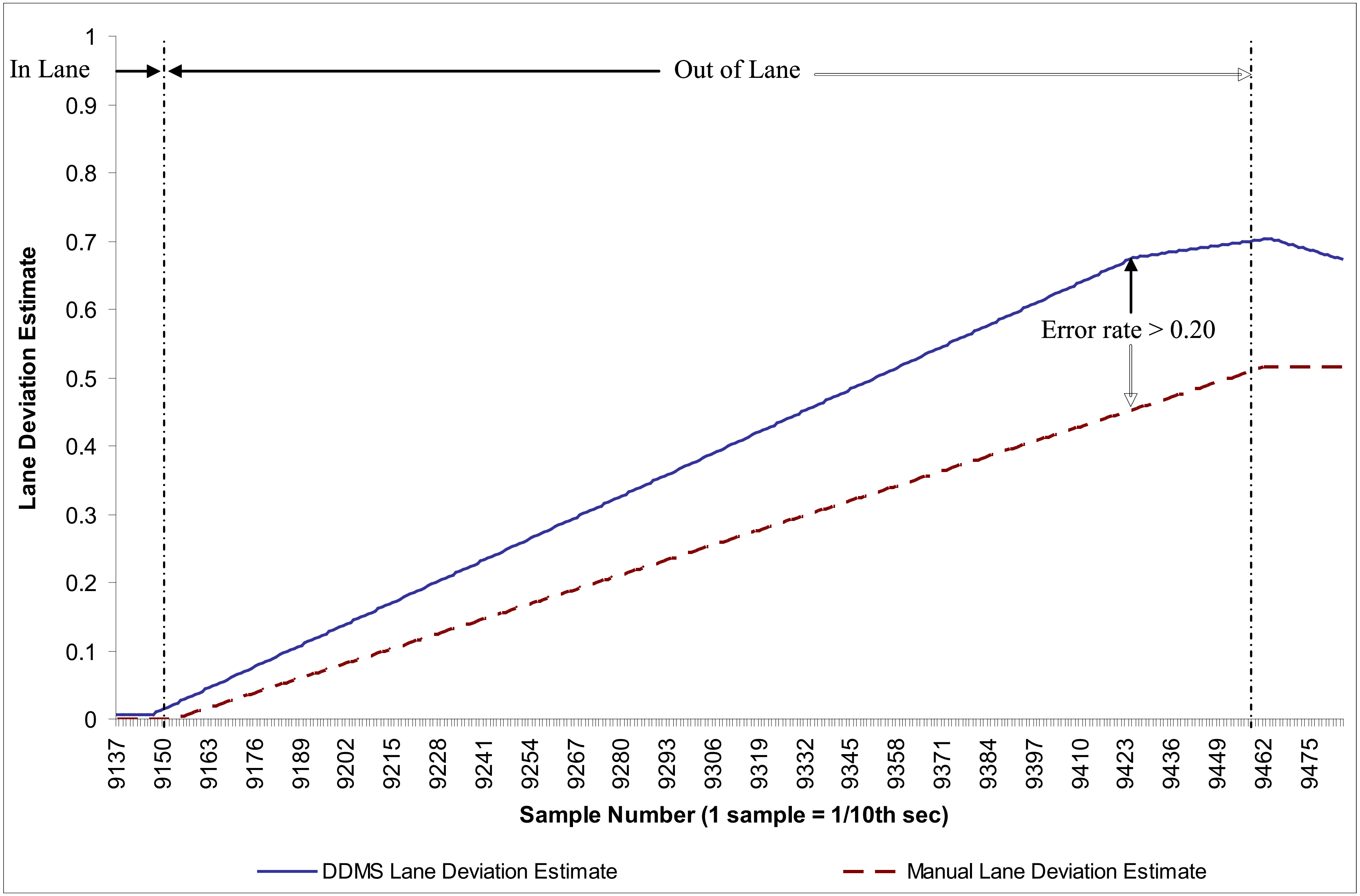


Figure 46. Example of Lane Deviation Plot Scored "NO" Used to Compare the DDMS Output With the "Ground-Truth" Track

5.4.6.4 Lane Deviation Task Results

Table 26 summarizes the results from the analysis of the DDMS lane deviation estimate operational performance as a function of run condition. The numerical values in each cell are the number of occurrences. Figure 47 depicts the tallied results from Table 26 as a function of the percent of subjects who participated in that run.

Table 26. Operational Performance of the DDMS as a Function of Lane Deviation Tasks and Run Condition

	Run 1 (n = 36)	Run 2 (n = 24)	Run 3 (n= 36)	Run 4 (n = 36)
YES	34	29	29	35
YES-BIASED	2	1	4	1
NO	0	0	3	0

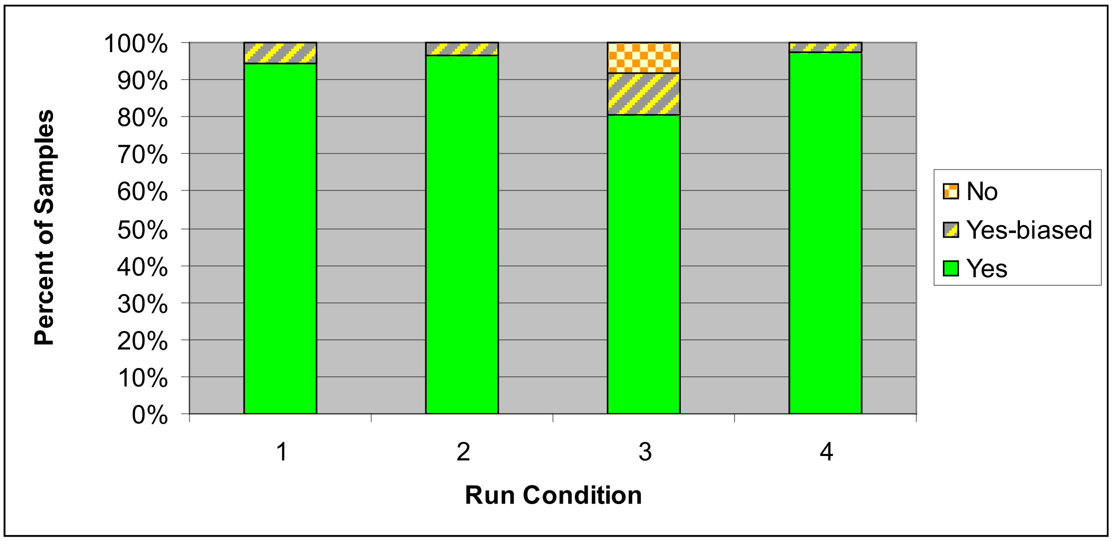


Figure 47. Overall Operational Performance of the DDMS Lane Deviation Sensor by Run Condition

Across all conditions (e.g., ambient illumination), the DDMS lane deviation estimate's correct classification ("YES" and "YES-BIASED") of lane deviations was 98 percent. The accuracy of the DDMS lane deviation estimate appears to be reduced for nighttime illumination levels with artificial overhead lighting (Run 3) when compared to daytime illumination levels (Runs 1 and 2) and nighttime illumination levels without artificial overhead lighting (Run 4).

A plausible explanation for the reduced performance of the MV lane position sensor may be due to instances when there is a low contrast ratio between the lane markings and the surrounding scene. Figure 48 illustrates causes of low contrast between lane markings and the surrounding scene. The images in Figure 48 were captured from the MV lane position sensor view taken at 10-second increments during the 60-second lane deviation task (Task 5). The images of the second column of Figure 48 were from Run 1 to illustrate the impact of daytime illumination levels on the MV lane position sensor. Note the lack of contrast between the lane markings and the concrete pavement surface in the images taken at 40 seconds and 50 seconds into the task.

The third column consists of images taken during Run 3 to illustrate the impact of nighttime with artificial overhead illumination on the performance of the MV lane position sensor. Note the “blooming” that is created by the vehicle’s headlights through the entire 60-second task. In addition, the artificial overhead lighting further reduces the contrast ratio when the vehicle is traveling on a concrete surface, as seen at 40 seconds and 50 seconds into the task.

The fourth column provides images from Run 4 (nighttime illumination without artificial overhead lighting). Note that, without the overhead illumination, the blooming is nearly constant across pavement type, except for the stretch of asphalt pavement the vehicle crosses 10 seconds into the task. This section of pavement is referred to as Open Grade Friction Course (OGFC) because it is constructed to be more porous and allow precipitation to drain quickly from its surface. There are three possible explanations for its light absorption properties. First, this section of asphalt has a much higher texture rating (mean: 1.52) than the section west of it (mean: 0.82) or the section east of it (mean: 0.92). The added texture may serve to diffuse the reflected light, thus reducing the blooming effect. The second explanation is that, because of its construction properties, this section has higher, darker asphalt content, which acts as an absorber of light. The third explanation may be the age of the pavement. The OGFC pavement section is relatively new and was installed in 2005. All of the other sections of pavement on the Smart Road were installed prior to the road opening in March 2000. Therefore, this newer stretch OGFC has not experienced the level of traffic that the remaining Smart Road pavement has. In essence, the asphalt covering the pavement’s aggregate has not been worn away by the tires of the research vehicles to the same degree as the remaining road. As the aggregate is exposed, the lighter surfaces reflect more light.

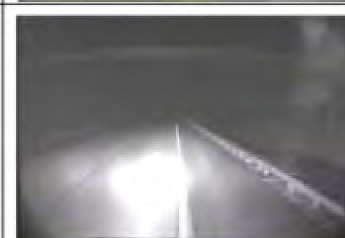
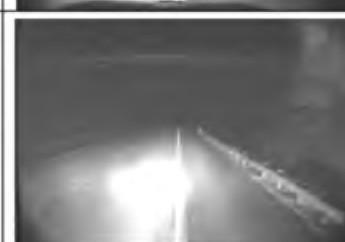
60 s Lane Deviation	Run 1	Run 3	Run 4
At the beginning of task			
At 10 s into task			
At 20 s into task			
At 30 s into task			
At 40 s into task			
At 50 s into task			

Figure 48. Images from MV Lane Position Sensor Illustrating Changes in Lane Line Contrast

5.4.7 Analysis of Lane Deviation False Alarm Task

In accordance with Table 10, there were two lane deviation false alarm tasks: maintaining vehicle's position within the lane and intentionally changing lanes using the vehicle's turn signals. The first false alarm task, maintaining the vehicle's position within the lane, was examined to understand if the DDMS lane deviation estimate would indicate the vehicle was out-of-lane when it was not. Data from the Baseline Tasks 1 and 9 were used because the vehicle did not deviate out of the lane. The other false alarm condition involved intentionally changing lanes while using the turn signals (Task 15). Because the DDMS algorithms are programmed to ignore intentional lane changes, evidenced by the use of the turn signals, this task would provide an indication as to the efficacy of the algorithms to detect whether the lane deviations were intentional. The task intervals were extracted from the data and will be referenced as sample numbers in the results to follow.

The DDMS lane deviation estimate accuracy for the lane deviation false alarm tasks was assessed with a modified definition used in the Wierwille et al. (2003) study. This operational definition (Table 27) is believed to provide a realistic appraisal of the accuracy of the lane deviation sensor output. The intent of this analysis was to determine if the MV lane deviation sensor correctly identifies lane position for tasks that have the driver maintain in-lane positioning and tasks that involve intentional lane deviations.

Table 27. Operational Definitions Used to Assess Accuracy of Lane Position Sensor Output During False Alarm Tasks

Operating Condition	Definition
YES	The change in the lane deviation sensor output was a decrease, no change, or an increase less than or equal to 0.05 points from its initial task value throughout the task interval.
YES-BIASED	The increase in the lane deviation sensor output was more than 0.05 yet less than or equal to 0.10 from its initial task value throughout the task interval.
NO	Neither of the above conditions is met.

The classification procedure shown in Table 27 was used to classify each segment of task data that was reduced as stated in section 5.3.4. Figure 49 illustrates an example of these segmented task data that were evaluated. Note that, in this example, the DDMS lane deviation estimate responded correctly by decreasing throughout the task, indicating the DDMS algorithm did not detect the intentional lane change as an unintentional lane crossing. The abscissa units for these figures are in tenths of a second.

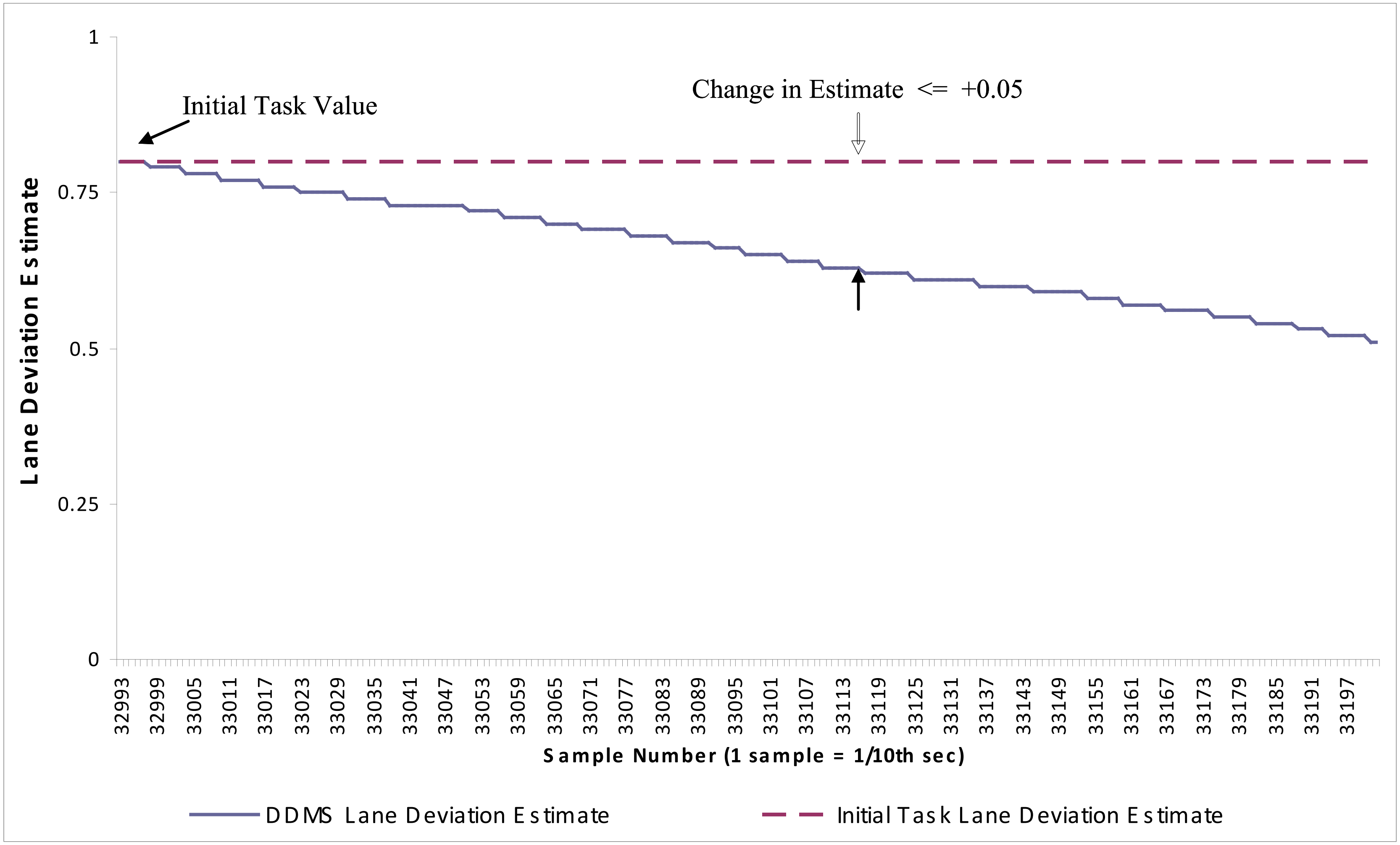


Figure 49. Example of Lane Deviation False Alarm Plots Used to Determine the DDMS Algorithms' Response to a False Alarm Condition

5.4.7.1 Lane Deviation False Alarm Task Results

Table 28 summarizes the classification results from the analysis of the DDMS lane deviation estimate's tendency to generate false alarms. The numerical values in each cell are the number of occurrences.

Table 28. Operational Performance of the DDMS for the Lane Deviation False Alarm Task as a Function of Run Condition

Run	Run 1 (*n* = 6)	Run 2 (*n* = 5)	Run 3 (*n* = 6)	Run 4 (*n* = 6)
Task	Lane Change with Turn Signal (Task 15)	Lane Change with Turn Signal (Task 15)	Lane Change with Turn Signal (Task 15)	Lane Change with Turn Signal (Task 15)
YES	6	5	6	6
YES-BIASED	0	0	0	0
NO	0	0	0	0

With the average accuracy for both false alarm tasks above 95 percent, the MV lane position sensor performed well (Figure 50).

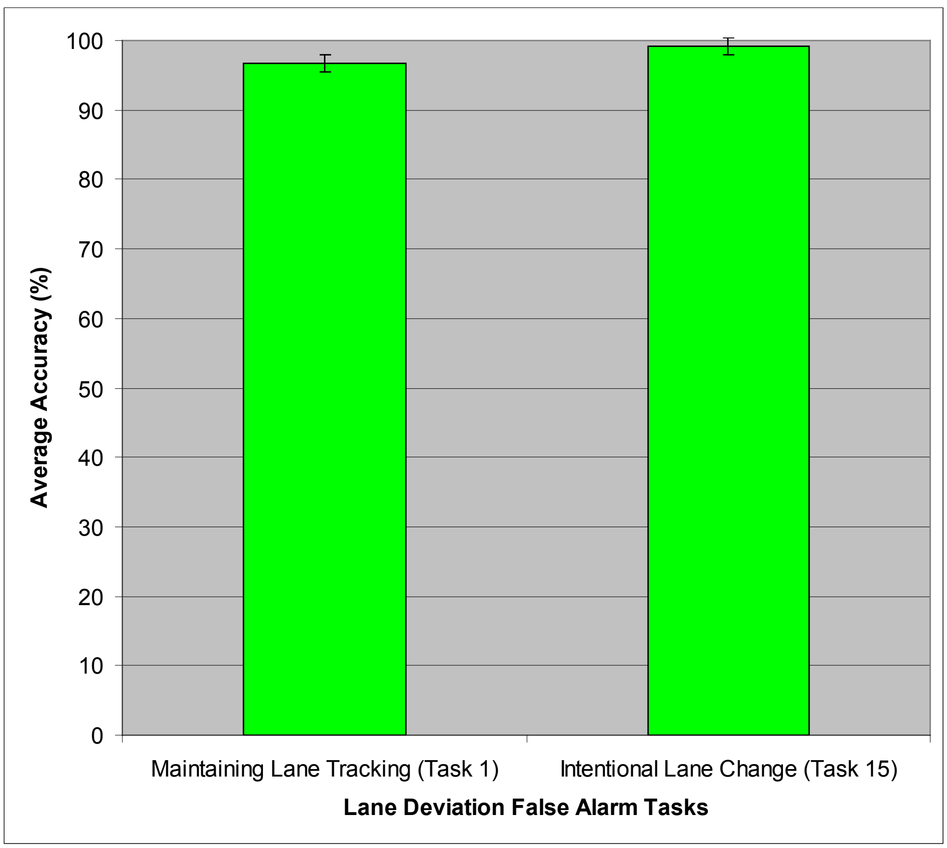


Figure 50. Average Accuracies for MV Lane Position Sensor as a Function of False Alarm Task

The lane deviation sensor performed successfully during a false alarm task designed to evaluate whether intentional lane deviations (as indicated by turn signal use prior to the lane deviation maneuver) could be differentiated from unintentional lane deviations (as indicated by no turn signal use at the time of lane deviations). The lane deviation sensor performed correctly and was able to differentiate between intentional and unintentional lane deviations.

5.4.8 Analysis of DDMS Algorithm Sensitivity

Finally, the overall sensitivity of the DDMS algorithms to changes in stimulus levels (e.g., PERCLOS and lane position) was evaluated. The purpose of this analysis was to determine if the algorithms were sufficiently responsive to the sensor inputs to generate the expected DVI indicator output. The DDMS model algorithms' output was tracked during all tasks as three separate quantities: 1) PERCLOS alone, 2) lane deviation alone, and 3) combined measure of drowsiness. The sensitivity was determined by the output's response to each. This DDMS output display depicted the system's response to the varying level of stimulus via three square indicators. A concept of these three indicators was depicted at the bottom of the illustration of the DDMS drowsiness model (Figure 22). If there were insufficient data (e.g., less than 3 minutes of data for estimating PERCLOS) to compute any of the three metrics, the indicator square for that metric was blue (Figure 51). If the output data were sufficient for algorithm computation and were below minimum thresholds, the square indicator color was green. When the output was above the minimum threshold but below the maximum threshold, the color was magenta. Note: the use of magenta was a result of a software limitation for this project. The authors recommend that future human-machine interface development for the DVI use colors (e.g., yellow) that have standardized meanings for system warnings. However, magenta was sufficient for the purposes of this project because the color only needed to indicate a change in state of the system for data reduction purposes. When the output was above the maximum threshold, the color was red. Again, this output display was for evaluation purposes only. For instance, it would be expected that the DDMS algorithms would provide a higher indication for eye closures during the "Eye Closure Only" tasks (Figure 52). Also, the DDMS algorithms should provide a higher indication for "Lane Deviation" during those tasks that are only associated with lane deviations (Figure 53).

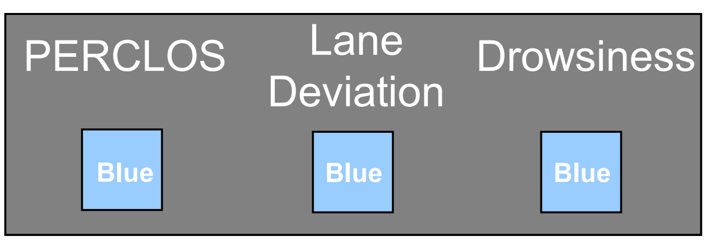


Figure 51. DVI Output Display for Insufficient Data

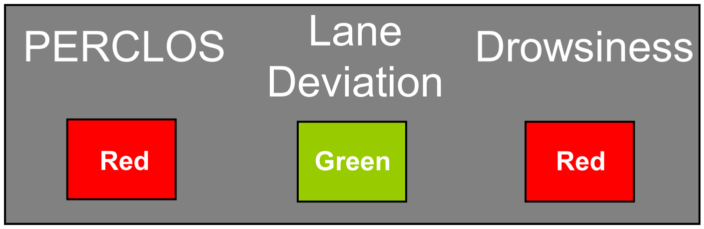


Figure 52. Expected DVI Output Display Near the End of the 10-Second "Eye Closure Only" Tasks

Figure 53. Expected DVI Output Display Near the End of the 60-Second "Lane Deviation Only" Tasks

The DDMS algorithm sensitivity (Table 29) was assessed using a similar method to that used for the sensor accuracy analysis previously described. Operational definitions (Table 30) were developed to provide a realistic appraisal of the sensitivity of the DDMS algorithms for the 10-second eye closure task, 60-second lane deviation task, and the combined 10-second eye closure task and 60-second lane deviation task. These three tasks were examined across all four runs. Because the purpose of the system is to assess trends in both driver and vehicle behavior, the state of the system at the initiation of the task must be taken into account. Therefore, the sensitivity of the DDMS algorithm was assessed by comparing a baseline of the system at the initiation of the task to the resulting display output at the end of the task.

The primary difference between the algorithm sensitivity operational definitions in Table 30 and the sensor accuracy operational definitions used for analyses in sections 5.4.4 through 5.4.7 was the metric used for assessment. The MV sensor accuracy operational definitions assessed acceptable performance using shape criterion (Table 21, Table 23, Table 25, and Table 27) as the metric. The algorithm sensitivity operational definitions used to assess the responsiveness of the DDMS algorithms employed the color of the DVI's display indicator output as the metric. For instance, the "YES" condition required the display to change two levels from either green to red or, if the DVI indicator was magenta from the beginning of the task, from magenta to red during the condition. As in the sensor accuracy operational definitions, the "YES-BIASED" condition was provided as the gray zone between acceptable sensitivity and unacceptable sensitivity. This operational definition would classify the DDMS sensitivity as "YES-BIASED" if the display only changed one level from green to magenta. The intent of the "YES-BIASED" condition was to indicate where improvement may be made within the DDMS. The "NO" operational condition represents the MV lane position sensor output that contains an unacceptable level of error.

Table 29. DDMS Integrated Drowsiness Metric Threshold Algorithm Matrix

Categories	**PERCLOS Category 1** *Low Percentage of eye closures over a 3-minute interval*	**PERCLOS Category 2** *Moderate Percentage of eye closures over a 3-minute interval*	**PERCLOS Category 3** *High Percentage of eye closures over a 3-minute interval*
Lane Deviation Category 1 *Low Percentage of lane deviation over a 1-minute interval*	Low drowsiness	Moderate drowsiness	Severe drowsiness
Lane Deviation Category 2 *Moderate Percentage of lane deviation over a 1-minute interval*	Low drowsiness	Moderate drowsiness	Severe drowsiness
Lane Deviation Category 3 *High Percentage of lane deviation over a 1-minute interval*	Moderate drowsiness	Severe drowsiness	Severe drowsiness

Table 30. Operational Definitions Used to Assess the DDMS Algorithm Sensitivity

Operating Condition	Definition
YES	The display output of the DDMS algorithms changes two levels from either: • Green to red. • Magenta to red if the DVI indicator color was magenta when the task commenced.
YES-BIASED	The display output of the DDMS algorithms changes only one level, from green to magenta.
NO	Neither of the above conditions is met.

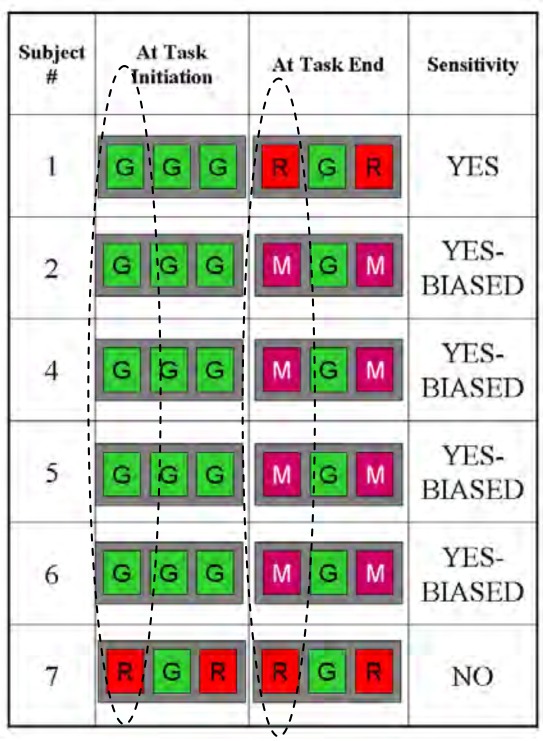
5.4.8.1 DDMS Algorithm Sensitivity Results

10-second "Eye Closure Only" Task: Table 31 summarizes the DDMS algorithm sensitivity for the 10-second eye closure task for each run condition.

Table 31. DDMS Algorithm Sensitivity Summary for 10-Second Eye Closures

	Run 1	Run 2	Run 3	Run 4
Sample Size	n=6	n=5	n=6	n=6
Yes	1	0	1	1
Yes-biased	4	0	2	5
No	1	5	3	0

The expected DVI output is shown in Figure 52. This expected display would have a red indication for PERCLOS, a green indication for Lane Deviation, and a red indication for drowsiness near the end of a 10-second eye closure task. Figure 54, Figure 55, Figure 56, and Figure 57 depict the state of the DVI display at both the initiation and the end of the 10-second eye closure task. In summary, the presence of eyewear in Run 2 severely hindered the performance of the MV eye closure sensor, as there was no reliable response from the system to the eye closures performed by any of the participants.



G = Green, M = Magenta, and R = Red

Figure 54. DDMS Algorithm Sensitivity for 10-Second Eye Closure Task During Run 1

Subject #	At Task Initiation	At Task End	Sensitivity
1	R G R	R G R	NO
2	G G G	G G G	NO
4	R G R	R G R	NO
5	R G R	R G R	NO
6	G G G	G G G	NO
7	N/A: Does Not Wear Sunglasses while Driving		

G = Green, M = Magenta, and R = Red

Figure 55. DDMS Algorithm Sensitivity for 10-Second Eye Closure Task During Run 2

Subject #	At Task Initiation	At Task End	Sensitivity
1	R G R	R G R	NO
2	G G G	M G M	YES-BIASED
4	G G G	M G M	YES-BIASED
5	G G G	R G R	Yes
6	G G G	G G G	NO
7	G G G	G G G	NO

G = Green, M = Magenta, and R = Red

Figure 56. DDMS Algorithm Sensitivity for 10-Second Eye Closure Task During Run 3

Subject #	At Task Initiation	At Task End	Sensitivity
1	R G R	R G R	NO
2	G G G	M G M	YES-BIASED
4	G G G	M G M	YES-BIASED
5	G G G	M G M	YES-BIASED
6	G G G	M G M	YES-BIASED
7	G G G	M G M	YES-BIASED

G = Green, M = Magenta, and R = Red

Figure 57. DDMS Algorithm Sensitivity for 10-Second Eye Closure Task During Run 4

60-second "Lane Deviation Only" Task: Figure 58 summarizes the DDMS algorithm sensitivity for the 60-second lane deviation task for each run condition. This graph depicts higher algorithm sensitivity during daytime illumination levels.

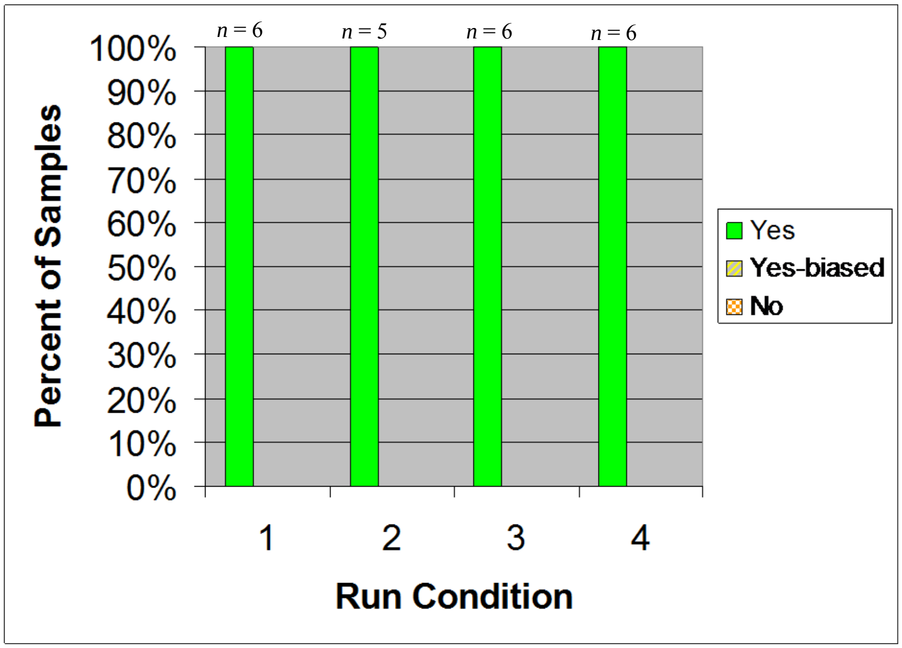


Figure 58. DDMS Algorithm Sensitivity Summary for 60-Second Lane Deviations

The expected DVI output is shown in Figure 53. This expected display would have a green indication for PERCLOS, a red indication for Lane Deviation, and a magenta indication for drowsiness near the end of a 10-second eye closure task. Figure 59, Figure 60, Figure 61, and Figure 62 depict the state of the DVI display at both the initiation and the end of the 10-second eye closure task. In summary, the DDMS lane deviation algorithms were sensitive for the 60-second lane deviation task across all runs.

Subject #	At Task Initiation	At Task End	Sensitivity
1	M G M	G R M	YES
2	G G G	M R R	YES
4	G G G	M R R	YES
5	G G G	M R R	YES
6	R G R	R R R	YES
7	R G R	R R R	YES

G = Green, M = Magenta, and R = Red

Figure 59. DDMS Algorithm Sensitivity for 60-Second Lane Deviation Task during Run 1

Subject #	At Task Initiation	At Task End	Sensitivity
1	R G R	R R R	YES
2	G G G	G R M	YES
4	M G M	M R R	YES
5	G G G	G R M	YES
6	G G G	G R M	YES
7	N/A: Does Not Wear Sunglasses while Driving		

G = Green, M = Magenta, and R = Red

Figure 60. DDMS Algorithm Sensitivity for 60-Second Lane Deviation Task During Run 2

Subject #	At Task Initiation	At Task End	Sensitivity
1	R G R	R R R	YES
2	G G G	G R M	YES
4	G G G	G R M	YES
5	M G M	G R M	YES
6	G G G	G R M	YES
7	G G G	G R M	YES

G = Green, M = Magenta, and R = Red

Figure 61. DDMS Algorithm Sensitivity for 60-Second Lane Deviation Task During Run 3

Subject #	At Task Initiation	At Task End	Sensitivity
1	R G R	R R R	YES
2	G G G	G R M	YES
4	M G M	M R R	YES
5	G G G	G R M	YES
6	G G G	G R M	YES
7	M G M	M R R	YES

G = Green, M = Magenta, and R = Red

Figure 62. DDMS Algorithm Sensitivity for 60-Second Lane Deviation Task During Run 4

5.4.9 Summary of Results

The on-road evaluation provided a relatively straightforward approach to assess the operational performance of the prototype DDMS. This assessment was made under varying conditions, as outlined in the functional specifications section of this report (section 2.2). While all of the functional specifications guided system development decisions, the results analysis focused solely on several key functional specifications. The results of this assessment are summarized as they pertain to these key functional specifications:

5.4.9.1 Environmental Conditions

- Overall, MV eye closure sensor performance was in-line with expectations.
  - The MV eye closure sensor worked most effectively (accuracy of 90 percent) during daytime operations without the presence of eyewear.
  - Under daytime illumination levels (with and without prescription eyeglasses), the MV eye closure sensor's accuracy was 80 percent, the highest of the four run conditions.
  - Under daytime illumination levels (with sunglasses), the MV eye closure sensor's accuracy was 52 percent, the lowest of the four run conditions.
  - Under nighttime illumination levels (with artificial overhead lighting), the MV eye closure sensor's accuracy was 67 percent.
  - Under nighttime illumination levels (without artificial overhead lighting), the MV eye closure sensor's accuracy was 71 percent.
- The MV eye closure sensor accuracies were consistent with the results of the static MV eye closure sensor Selection study conducted earlier in this project.
- The assessment of the DDMS PERCLOS estimate algorithm's accuracy revealed that it will require future refinement. Across all conditions (e.g., ambient illumination, eyewear, and skin complexion), 73 percent of the DDMS PERCLOS estimate algorithm's output were classified as either a "YES" (having the same shape as the manual PERCLOS estimate) or a "YES-BIASED" (having a similar shape as the manual PERCLOS with some discrepancies). Roughly 28 percent were classified as a "NO." It is apparent that the varying conditions of this on-road evaluation impacted the operational performance of the system.
  - An explanation for the lower than expected performance of the DDMS PERCLOS estimate algorithm could be the introduction of head motion for this study. The effect of head motion can be seen in the performance reduction between those eye closure tasks that do not require head nodding and those that do. Two tasks did not require head nodding (Tasks 4 and 10) and four tasks did (Tasks 2, 7, 8, and 13). The average correct classification for those non-head-nodding tasks (Tasks 4 and 10) across all tasks was 59 percent while the average correct classification for those head-nodding tasks (Tasks 2, 7, 8, and 13) across all tasks was 28 percent. Since this evaluation was dynamic, the pseudo-driver's head would have been in near-constant motion throughout the evaluation. While small, slow head motions are tolerated by the system, the dynamic nature of the study meant the pseudo-driver was frequently jostled, causing the system to lose track of the eyes. Once the tracking of the eyes was

lost, the system had to redefine the key facial landmarks and then relocate the eyes, creating a pause in the data stream and DDMS algorithms.

- The MV eye closure sensor performed better under daytime illumination levels (i.e., above 1,680 lx of ambient illumination as measured inside the cab near the pseudo-driver's eye with the light sensor aimed forward). Under daytime illumination, the correct classification of eye closures for the entire group (no eyeglasses and eyeglasses) occurred 47 percent of the time. When the data from participants wearing eyeglasses were removed, the correct classification of eye closures climbed to 67 percent for daytime illumination.
  - The remaining incorrect classifications may be attributed to head motion resulting from the dynamic nature of the study.
- The performance of the MV eye closure sensor degraded under nighttime illumination levels (below 3.64 lx of ambient illumination as measured outside the driver's window with the light sensor aimed upward).
  - One explanation for the lower performance of the MV eye closure sensor during lower levels of ambient illumination may be the lack of uniform illumination on the pseudo-driver's face.
  - Again, another explanation may the head motion previously discussed.
- The false alarm analysis revealed that the DDMS PERCLOS estimate algorithms have a low propensity to generate false alarms for visual scanning tasks typical of commercial driving (e.g., visually scanning the side mirrors, looking down at the instrument panel).
- The DDMS PERCLOS estimate algorithms were not equally sensitive across the eye closure tasks.
  - As was the case in many areas of the prototype DDMS operational performance, eyewear severely hindered the sensitivity of the prototype DDMS PERCLOS algorithms.
- Overall, the MV lane position sensor performed well.
  - Under daytime illumination levels, the MV lane position sensor's accuracy was 94 percent, the highest of the four run conditions.
  - Under nighttime illumination levels (with artificial overhead lighting), the MV lane position sensor's accuracy was 83 percent, the lowest of the four run conditions.
  - Under nighttime illumination levels (without artificial overhead lighting), the MV lane position sensor's accuracy was 88 percent.
- Across all conditions (e.g., ambient illumination), the DDMS lane deviation estimate's correct classification ("YES") of lane deviations was 92 percent. Six percent of the lane deviation classifications were marginal ("YES-BIASED"), and roughly 2 percent were completed out of tolerance ("NO").
- The DDMS lane deviation estimate performed worse under nighttime levels of illumination (with artificial overhead lighting). Under daytime illumination and nighttime illumination (without artificial overhead lighting), the correct classification of lane

crossing for all lane deviation tasks occurred 95 and 97 percent of the time, respectively. Under nighttime illumination (without artificial overhead lighting), the correct classification of eye closures for all lane deviation tasks occurred 81 percent of the time.

  – The low contrast ratio between the lane markings and the surrounding scene may explain these results. During nighttime illumination levels (with artificial overhead lighting), the contrast ratio between the lane markings and the surrounding scene is reduced by the overhead lighting and the "blooming" effect from the vehicle's headlights. Figure 48 provides examples of this effect. This "blooming" in the image is caused by the reflection of the vehicle's headlights on the pavement surface. This blooming eliminates the color contrast because all of the pixels in the image's affected area are assigned the value of 255 on a scale of 0–255 (0 = black, 255 = white); thus, the algorithm cannot distinguish any contrast between objects in that affected area.

- Based on the results of the false alarm analysis, MV lane deviation algorithms have a low propensity to generate false alarms when the driver maintains the vehicle's position within the lane or performs an intentional lane change.
  – The sensitivity of the prototype DDMS lane deviation algorithms was sensitive under all levels of ambient illumination

5.4.9.2 Operator Physical Characteristics

- The primary limitation of the MV eye closure sensor was the presence of eyewear. The MV eye closure sensor performed better (approximately 10 percent improvement) when the participant was not wearing any form of eyewear.
  – During daytime illumination levels, the MV eye closure sensor's accuracy was 90 percent for those participants who did not wear eyewear.
  – During nighttime illumination levels with artificial overhead lighting, the MV eye closure sensor's accuracy was 75 percent.
  – During nighttime illumination levels without artificial overhead lighting, the MV eye closure sensor's accuracy was 80 percent.
- For the entire group (eyeglasses and no eyeglasses), the DDMS PERCLOS estimate's correct classification of eye closures occurred 47 percent of the time. When the participants wearing eyeglasses were removed, the correct classification of eye closures climbed to 67 percent. These results might be explained by factors that affect the eye closure sensor's ability to see through the lenses of the glasses (i.e., reflections, refraction, infrared-suppressive lens coatings). Other factors that may influence the performance of the MV eye closure sensor are the color and size of the frames (i.e., do larger dark frames confuse the MV eye closure sensor?).
- The presence of sunglasses also degraded the performance of the MV eye closure sensor.
- The MV eye closure sensor's accuracy was 52 percent when the participants wore sunglasses (Run 2).

- For the daytime illumination condition without eyewear (Run 1 without Subject wearing eyeglasses), the DDMS PERCLOS estimate's correct classification of eye closures was 67 percent. For the daytime illumination condition with those individuals wearing sunglasses, the correct classification of eye closures dropped to 28 percent. The degree of the sunglasses' opacity may explain the difficulties the MV eye closure sensor had discerning the location and closures of the eyes.
- There were no notable effects from skin complexion or eye color.

5.4.10 Conclusions and Recommendations

The key finding of this On-road Evaluation is that a multiple sensors integrated approach may provide a more robust approach to assess driver drowsiness. Table 32 summarizes the operational performance of the DDMS against the functional specifications outlined in this report's section 2.2. For each functional specification attribute, an indicator is provided to show that the performance for that DDMS component is: at an acceptable level of accuracy (+), at a marginal level of accuracy (±), or at an unacceptable level of accuracy (-). For the instances of marginal and unacceptable performance, the recommendation number from the report is listed. The final column in Table 32 provides an indication of whether the integrated prototype DDMS performed to a higher level than the two independent sensors alone. For nearly all of the functional specifications assessed, the strength of one sensor was able to overcome weaknesses of the other sensor. There were only two instances when both sensors' performance was marginal and, therefore, the performance of the integrated prototype DDMS needs improvement. It is believe that with further system improvements, an integrated DDMS would be effective across all necessary functional specifications. Therefore, this report provides seven recommendations for improving the performance of the DDMS.

Recommendation 1

The main recommendation of this evaluation is to continue the development of the DDMS, beginning with an isolated examination of each technology limitation discovered in this evaluation.

Table 32. Summary of DDMS Operational Performance for Functional Specifications

Report Section	Functional Specifications	Description	DDMS PERCLOS Estimate	Recommendation #	DDMS Lane Deviation Estimate	Recommendation #	Integrated DDMS Performance
2.2.2	Accounts for common driving behaviors						
		Visual Scanning	+ -	4	+		**Successful**
		Shifting gears	+ -	4	+		**Successful**
		Adjusting posture	-	4	+		**Successful**
		Reaching for Items	-	4	+		**Successful**
		Common driving postures	+ -	4	+		**Successful**
2.2.4	Environmental Conditions						
	Daytime Illumination	≥ 753.2 lx	+		+		**Successful**
	Nighttime Illumination	≤ 0.5 lx	+ -	2	+ -	5, 6, & 7	**Improvement Area**
	Nighttime Illumination with Artificial Overhead Lighting	≥ 0.6 lx and < 753.2 lx	+ -	2	+ -	5, 6, & 7	**Improvement Area**
2.2.5	Accounts for Various Driver Physical Characteristics						
		No Eyewear	+		+		**Successful**
		Prescription Eyeglasses	-	3	+		**Successful**
		Sunglasses	-	3	+		**Successful**
		Light Skin Complexion	+		+		**Successful**
		Dark Skin Complexion	+		+		**Successful**
2.2.6	Accounts for Multiple Drivers		+		+		**Successful**

Report Section	Functional Specifications	Description	DDMS PERCLOS Estimate	Recommendation #	DDMS Lane Deviation Estimate	Recommendation #	Integrated DDMS Performance
2.2.7	Human Interface Needs	Warning must be noticed, heard, understood, and accepted	Not Assessed in this phase		Not Assessed in this phase		Not Assessed in this phase
2.2.8	Non-encumbering Design						
		Not obstruct operator's field of view	+		+		**Successful**
		Access to necessary controls	Not Assessed in this phase		Not Assessed in this phase		Not Assessed in this phase
2.2.9	Minimal Calibration	Minimum On-going Calibration	+		+		**Successful**
2.2.10	Real-time data gathering	Acceptable short delays in updating status and issuing warnings.	+		+		**Successful**
2.2.11	Cost-Effectiveness		Not Assessed in this phase		Not Assessed in this phase		Not Assessed in this phase

Based on the results of this dynamic evaluation, the authors believe that the sensor technologies selected provide a promising approach to the development of a DDMS, but this study's realistic driving conditions revealed several weaknesses for each of the technologies, which the authors recommend be examined and remedied before an effective integration of these technologies can occur. The next sections will outline the key areas of focus for the next development phases.

5.4.10.1 MV Eye Closure Sensor

The primary factors that impacted the performance of the MV eye closure sensor were:

- Ambient illumination.
- Eyewear.
- Dynamic motions of the head generated by the ride of the vehicle.
- A development plan for each of these will be presented below.

5.4.10.2 Ambient Illumination

The results of this evaluation indicated the MV eye closure sensor performed better under higher levels of ambient illumination as compared to lower levels of ambient illumination. As stated, the possible explanation may be associated with the evenness of illumination on the face. The source of illumination is more widespread during higher levels of illumination (daytime), coming from many points of entry through the windows of the cab. At night, the illumination is produced by only infrared-illuminators spaced symmetrically on either side of the camera and typically below the driver's eye height. The authors recommend future development work design an illumination system that provides an even illumination of the driver's face in *both* the lateral and vertical dimensions. It is apparent that the infrared illuminators will not be integral to mounting the eye closure camera. Instead, multiple infrared illuminators will need to be positioned away from the sensor in both the lateral and vertical dimensions to create an array of illumination. By having more sources of illumination, the intensity of the individual illuminators can be reduced to create a balanced illumination across the face. It appears that the illumination system will require as many as four or more infrared illuminators positioned symmetrically on either side of the camera, above and below the driver's horizontal eye height. Infrared illuminators above the driver's eye height will reduce the shadows created by the driver's cheek structure.

Recommendation 2

Provide an even illumination of the driver's face. It is recommended that future development work include a small study to determine the optimum positioning of these infrared illuminators. This can be accomplished by systematically increasing the angular offset in both the vertical and horizontal planes by 5-degree increments and measuring the effective facial illumination with an optical measurement device that creates a plot of the pixel values of the image of the driver's face at each increment. The objective would be to find the infrared illuminator position that provides the most uniform pixel values.

5.4.10.3 Eyewear

Based on the results of this on-road evaluation, as well as on the MV eye closure sensor selection testing, the presence of any form of eyewear reduces the performance of the MV eye closure sensor. This may be the most challenging limitation for the MV eye closure sensor. Wierwille et al. (2003) found that more than one-third of commercial drivers wore glasses at night; therefore, eyewear is prevalent in commercial driving operations and needs to be accounted for in the development of eye closure sensors.

Recommendation 3

Improve the MV eye closure sensor's ability to discern eye closures through eyewear lenses. It is recommended that future development work include several small investigations into the eyewear factors that limit the operational performance of the MV eye closure sensor. These may include, but are not limited to:

- Reflections on the lenses.
- Lens coatings that reduce transmission of the infrared part of the spectrum.
- Opacity of sunglasses.
- Eyewear frame materials (e.g., metal versus plastic frames, dark versus light frames, thin versus thick).

The identification of the multiple sources of reflection on the lenses of eyewear needs to be determined along with possible solutions. One solution could be a larger array of infrared pods.

Study of the effect of various eyewear characteristics on the operational performance of the MV eye closure sensor could examine various lens coatings by sampling a large assortment of eyeglasses to determine the levels of infrared suppression. This can be accomplished by building an apparatus that has an infrared source with a known output on one side and an infrared measurement device on the other. The eyeglasses are then placed between the infrared source and infrared measurement device with the path of infrared energy passing through the lens of the eyeglasses. The reduction of infrared energy reaching the infrared measurement device with the lens present will be the infrared suppression factor created by the coatings of that eyewear. These results can be analyzed, and recommendations on the types of eyewear coatings can be generated. Similar work can be performed to determine the optimal opacity of sunglasses. These recommendations can guide future commercial users in selection of eyewear when using the DDMS. This study could also explore the influence that eyewear frames may have on the performance of the MV eye closure sensor. A sample of varying eyewear frames could be worn by subjects to determine the impact to the MV eye closure sensor's accuracy during both stationary eye closures and eye closures that involve head droop.

5.4.10.4 Dynamic Head Motions

It is important to discuss briefly the impact of ride in commercial vehicles as compared to passenger vehicles. In passenger vehicles, the energy from the interface between the tires and the road is primarily absorbed in the vehicle's suspension; therefore, the driver and the vehicle body are more stable in relation to one another. However, because the function of commercial vehicles is to transport heavy cargo, commercial vehicle suspensions are designed to be stiffer than passenger vehicles to support such loads. The stiffer suspensions transmit more energy generated at the interface between the tires and the road surface, creating more jostling in commercial trucks. Through the years, manufacturers have introduced air-ride seats and, most recently, air-ride cabs to isolate some of this energy. With these energy-isolating features, the drivers of the vehicle are continuously subjected to motion as energy is absorbed within the cab and seat. Thus, the cab and the driver are in essence moving in different directions. Since the MV eye closure is affixed to the cab, its motion is related to the cab and not necessarily to the driver.

The MV eye closure sensor performs well for tracking slow head motions, as evidenced by the MV eye closure sensor selection static study. However, under realistic driving conditions, the sudden jostling of the drivers and the quick head turns associated with visual scanning cause the system to lose tracking of facial features. These facial features include the corners of the mouth and corners of both eyes.

Recommendation 4

Improve the MV eye closure sensor's ability to handle head motions. The authors recommend that MV eye closure sensor manufacturers improve software algorithms to handle head motions induced by vehicle ride, visual scanning patterns, or head nodding. Once these software improvements are developed, they may be evaluated under conditions similar to those used in this report. Another possibility would be to move toward another type of sensor that uses more robust facial landmarks to create a face model for locating the eyes.

5.4.10.5 MV Lane Position Sensor

While the MV lane position sensor performed well in many cases, the results of this evaluation indicate several limitations that need to be addressed. The primary limitation of this system is a low contrast ratio between the lane markings and the surrounding scene. The possible causes of the low contrast between lane markings and the surrounding scene include artificial overhead lighting and headlight "blooming."

Recommendation 5

Update MV lane position sensor with advanced camera technology that incorporates "back-light compensation." The MV lane position sensor consists of a low-quality camera with few features to compensate for the headlight blooming. One camera that was recently tested had a feature which created uniform image contrast across each frame (Figure 63). The result was that blooming could be minimized. It is believed that blooming resulting from pavement reflections was a major cause of reduced lane-line detections.

Figure 63.Sensata ACM 100 Automotive Camera Module

Source: Sensata Technologies (2007)

Recommendation 6

Update MV lane position algorithms to account for headlight "blooming." The MV lane position algorithms can be updated to include functions that identify areas of the image where white-out low-contrast conditions are likely occurring. In a monochrome image, each pixel is assigned a number representing the brightness level at each segment of the image, ranging from 0 for black to 255 for white. These white-out low-contrast conditions will be associated with the clustering of these maximum pixel values of 255. These areas of high pixel values can then be segregated from the remaining image and can either be ignored by the algorithm or further analyzed by the algorithm.

Recommendation 7

Provide guidance regarding the pavement types that enhance the performance of optically-based lane position sensors. Based on the findings of this evaluation, pavement type has a potential effect on the operational performance of lane trackers. The authors recommend that further testing explore the effects on these types of optical trackers and determine which pavement types facilitate or hinder the performance of these sensors.

5.4.10.6 Concluding Remarks

All sensors will have operational limitations, and the test conditions implemented in this study were on a real road (not a simulator). However, even if the limitations of these systems are mitigated, new limitations may be encountered under operational conditions. Therefore, it is still important to balance the strengths and weaknesses of multiple sensors through integration of their capabilities. This is especially important for the development of a DDMS.

As with any equipment assessment, this evaluation was made on equipment that is constantly being developed and improved, so these results represent a snapshot in time. The authors are aware of current development efforts for both the MV eye closure sensor and the MV lane position sensor to address many of the issues found in this assessment. Therefore, this evaluation's conclusions may not apply to these more recent technology developments.

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6. FUTURE RESEARCH NEEDS

6.1 OVERVIEW

As stated, the authors recommend that future research efforts focus on improving the fundamental operational performance of the MV eye closure sensor and MV lane position sensor. This future development work will expand the operational domain of these sensors greatly and allow for more actual operations research to be conducted with confidence. Once this preliminary development, as outlined in the section 5.4.10, is completed, there are three primary areas of future research needs. These include:

- Drowsy Driver Threshold Determination.
- Refinement of DDMS Design Including the DVI.
- The Driver Inattention Monitor.

These research areas are intended to improve the application of the DDMS and to expand its capabilities to be an all-inclusive driver awareness monitor.

6.1.1 Drowsy Driver Threshold Determination

As mentioned earlier, the focus of this project was to exercise a prototype integrated driver drowsiness monitoring system. While these threshold criteria are founded on previous research (i.e., Wierwille et al., 2003) and expert judgment, they were preliminary. There is a need to collect real-world commercial driving data to determine the appropriate thresholds to be used in future systems. This need became evident in the database analysis of two recent naturalistic commercial driving studies. While the first study, DDWS FOT, had the specific purpose of evaluating a current driver drowsiness monitor technology, the methods of the study may have influenced the natural onset of the participant's drowsiness (e.g., participants were aware of the purpose of the study, participants may have established fatigue countermeasures such as getting more sleep for study, etc.). The second study, "Naturalistic Data Collection," had the specific purpose of collecting general driving parameters; therefore, it lacked an eye closure monitor in its data acquisition system. Without this eye closure monitor, the data set cannot provide insight into the levels of estimated PERCLOS that are associated with the onset of CMV driver drowsiness.

6.1.2 Refinement of DDMS Design Including the Driver/Vehicle Interface (DVI)

The DVI utilized for the current project used a very basic design to provide system status and a warning when system thresholds were breeched. The intent of this DVI was for simple evaluation purposes only. Based on results of the focus group that was conducted in support of this project (see section 4.3), the development of a drowsy driver DVI is a complex challenge. Drivers have expressed preferences regarding system location and alerts, as well as the need for the DVI feedback to overcome motivations to continue driving. Therefore, a more comprehensive approach must be taken for the development of production DVI. While Wierwille et al. (2003) provides an excellent source for initial design information, more work is needed to ensure driver acceptance of an integrated monitoring system. For instance, the participants of this project’s focus group shared their concern over the demonstrated potential placement of the DDMS with DVI. The focus group feedback indicated that the integrated unit should not be mounted directly in front of the driver, since this position could be distracting or irritating or could possibly hamper visibility. From a design standpoint, mounting the unit directly in front of the driver may cause the sensor view to be obscured by the steering wheel, especially with the newer extended tilt/telescoping steering columns being offered by commercial truck original equipment manufacturers. However, the current eye closure technology requires the unit to be mounted directly in front of the driver to provide the best view of the driver’s eyes. This technology limitation will need to be explored to determine if system enhancements can be made to overcome this mounting requirement. Other areas of exploration include the types of alerts/warnings. This is an important aspect of any DDMS. Since the onset of drowsiness can last for more than an hour (Grace, 2001), many drivers can sense drowsiness onset and have adopted countermeasures (e.g., consuming drinks, rolling the window down, talking) to resist the oncoming effects of drowsiness. The problem occurs when these countermeasures become less effective due to drivers pushing further down the road, pressured by external and internal motivators (e.g., demanding work schedules, pay by the mile). Further work needs to be completed with focus groups to understand what feedback will be effective throughout the entire onset of the drowsiness cycle.

6.1.3 Driver Inattention Monitor

Once the DDMS has been optimized for detecting bouts of drowsiness, the system can be further expanded into other areas of driver monitoring. Although the literature does not adequately address drowsiness and inattention, one could speculate that the driver’s ability to attend to the tasks of driving diminishes with the onset of drowsiness. Therefore, the measures of drowsiness may translate to detecting inattention and, with some refinement, driver distraction. Driver distraction has been found to occur when inattention leads to a delay in recognition of the information necessary to accomplish the driving task. Crash database analyses have estimated that driver distraction is a primary factor in 25–30 percent of crashes (Wang, Knipling, and Goodman, 1996), while recent data from naturalistic driving studies indicate the percentage of crashes related to driver inattention to be much higher at 80 percent (Dingus et al., 2006). Though these statistics are dominated by light vehicle drivers, driver inattention also occurs in commercial vehicle operations. A study by Hanowski, Perez, and Dingus (2005) investigated driver distraction in commercial vehicle operations by studying distraction-related “critical events” with instrumented vehicles on normal revenue-producing runs (i.e., a naturalistic approach). Hanowski et al., analyzed 178 distraction-related critical events and found 34 unique distraction types. Therefore, it can be said that driver inattention is an important issue in both light and heavy vehicle operations and that countermeasures are needed.

The expansion of the capabilities of the DDMS as a countermeasure directed at driver inattention is a logical choice. The first step would be to expand the unit’s ability to track the gaze direction of the driver. Then, the algorithms could be modified to allow the unit to give indications when the driver’s current gaze direction is away from the forward road scene for longer than a prescribed amount of time. In addition, the unit’s algorithms could be tailored to provide indication to the driver when he or she is failing to adequately scan the mirrors and surrounding roadway. The appropriate thresholds and scanning patterns can be determined through the data collection effort mentioned in the above section, “Drowsy Driver Threshold Determination.”

APPENDIX A—FATIGUE MONITORING DEVICE MARKET ANALYSIS

Table 33 provides a summary table describing a number of commercially available or research-tested fatigue monitoring devices. Most systems discussed in this list provide either an in-vehicle based approach or a vehicle-based approach to monitoring fatigue. Only one system, AWAKE (Williamson and Chamberlain, 2005; Bekiaris, Nikolaos, and Mousadakou, 2004; Polychronopoulos, Amiditis, and Bekiaris, 2004) provides a combined approach of using both in-vehicle and vehicle-based approaches via parameters of eyelid changes, steering grip changes, lane tracking, use of accelerator, and brake and steering position. This system is in exploratory stages and is not ready for the commercial market.

Table 33. Survey of Commercially-Available Drowsy Driver Monitoring Systems

Monitoring System	Reference	Technique
Attention Technology, *DD850 Driver Fatigue Monitor (DFM)*	Barr et al., 2005	Real-time, on-board, video-based drowsiness monitor that measures slow eyelid closure to estimate PERCLOS. Uses a structured infrared illumination approach to identify the driver's eyes and track eye movements. Monitor mounts on vehicle dashboard with a camera module mounted on a rotating base to allow the driver to adjust the camera angle. Device emits an audible warning when driver reaches a present drowsiness threshold. Real-time, immediate feedback is available to the driver via six Light Emitting Diodes (LEDs), each representing drowsiness levels. Studies have found that the success of the monitor depends on brightness and size of the driver's pupils, which can be affected by a number of variables (e.g., sunlight, sunglasses, and eyeglasses). Thus, the device is ideal for use in commercial operations involving nighttime driving.
Delphi Electronics and Safety, *Driver State Monitor (DSM)*	Barr et al., 2005	Automotive-grade, real-time, vision-based driver-state monitoring system. Does not require driver training. Uses a single camera mounted on the dashboard directly in front of the driver and two illumination sources. Device detects and tracks driver's facial features and analyzes eye closures and head pose to infer fatigue/distraction. System provides feedback regarding the driver's distraction and drowsiness levels as well as an audible warning alert (eye closure warning for closures longer than 2.5 s). Fatigue detection algorithm predicts AVECLOS, similar and comparable measure to PERCLOS. Has been shown to be a reliable predictor of drowsiness under all illumination conditions and for drivers wearing eyeglasses and most types of sunglasses.
Generation 2 PERCLOS Monitor (G2PM) Development Project	Wierwille et al., 2003	The CoPilot showed a high degree of validity as an on-line measure of PERCLOS. Two main variables that affected the G2PM performance were in-cab ambient illumination level and whether or not the driver is wearing glasses.

Monitoring System	Reference	Technique
Seeing Machines, *faceLAB*	Barr et al., 2005; Williamson & Chamberlain, 2005	Provides real-time head and face tracking, as well as eye, eyelid, and gaze tracking using a noncontact, video-based sensor. Enables analysis of naturalistic behavior, including head pose, gaze direction, and eyelid closure. Drowsiness is determined using blink analysis and PERCLOS assessment by measuring eyelid position. Information is obtained using a pair of cameras to estimate head pose and fast tracking recovery to cope with temporary loss of the face. Data gathering is completely PC-based. Operates and maintains tracking integrity in a range of lighting and movement conditions; not sensitive to sudden movement. Studies indicate that the device works in bright sunlight or at night and with subjects at different proximities from the device. Reliable when contact lenses or most eyeglasses are present.
Smart Eye AB, Smart *Eye Pro 3.0*	Barr et al., 2005	Computerized, vision-based software that enables detection of human face/head movement, eye movement, and gaze direction. Remote and unobtrusive sensor measures face and eye movement using a three-dimensional head model that is generic and adapted to each user. If tracking is lost, a face detection procedure allows system to quickly reacquire subject's face and resume tracking. Device has flexible camera mounting positions and can accommodate up to four high-speed cameras, which allows for the tracking of large-head movements or tracking when one camera is fully occluded. Does not develop an algorithm for measuring driver drowsiness, but PERCLOS can be provided with camera system. Able to provide accurate detection in all illumination conditions. Reliable in drivers with contact lenses, eyeglasses, and most sunglasses.
SensoMotoric Instruments GmbH (SMI), *InSight*	Barr et al., 2005	Advanced, non-invasive, computer-vision monitoring systems that measures head position and orientation, gaze direction, eyelid opening, and pupil position and diameter. Calculates PERCLOS and employs automatic tracking algorithms that allow accurate driver state monitoring under all lighting conditions. Uses one high-speed, dashboard-mounted camera and three sources of low-intensity infrared illumination. Provides large tracking range because it uses a small tracking area on the face. Suitable for 24-hour data collection. Eye closure measurement accuracy is 1 mm.
Applied Science Laboratories (ASL), *ETS-PC II*	Barr et al., 2005	Remote eye tracking system suited for real-time monitoring of driver alertness. PC-based system of eye trackers; utilizes pupil/corneal reflection technique to measure eye movements. Suitable for outdoor/in-vehicle tracking operations. Camera is mounted on an adjustable headband. Can accommodate subjects wearing sunglasses and is suitable in all driving conditions. Computer must be present in the vehicle to process data. Does not include algorithm for detecting and alerting the driver. System can integrate eye gaze data with a time stamp to other data signals from the vehicle (e.g., steering position, vehicle speed).

Monitoring System	Reference	Technique
LC Technologies, Inc., *Eyegaze Analysis System*	Barr et al., 2005	Hands-off, unobtrusive, remote human-computer interface that can be used to track a user's gaze point or to allow an operator to interact with the environment using only his/her eyes. Objective is to monitor driver's eye point-of-regard, saccadic and fixation activity, and percentage eyelid closure reliability in real-time and under all driving conditions. Subject's gaze point is tracked on screen in real-time, and gaze direction is determined using the Pupil Center Corneal Reflection (PCCR) method; a low-power LED illuminates the eye and provides a direct reflection off the cornea of the eye. Remote video camera can be mounted in the vehicle cab. System will alert drivers when they are becoming drowsy and losing alertness. Camera must have a clear, unobstructed view of the driver's eye to accurately monitor gaze. Usually works with eyeglasses and contact lenses. Has not been validated against measures of driver drowsiness or eye gaze behavior.
Johns Hopkins University Applied Physics Laboratory (APL), *Drowsy Driver Detection System (DDDS)*	Barr et al., 2005	Small sensor system to alert drivers when they are in danger of being impaired by fatigue. Contains a transceiver that detects drowsiness prior to driver falling asleep. Issues warnings that can begin as driver becomes sleepy and intensify as system detects increasing drowsiness. Noninvasive and collects data under all conditions through the use of a Doppler radar system. Can monitor and measure speed, frequency, and duration of eyelid closure, rate of heartbeat and respiration, and pulse rate by analyzing Doppler components. Small enough to fit above the windshield and cost-effective. Testing has shown good correlation between measurements with the DDDS and PERCLOS methodology; however, the device is still in the basic research phase of development.
Rensselaer Polytechnic Institute (RPI), driver vigilance monitoring system	Barr et al., 2005; Ji, Zhu & Lan, 2004	Driver vigilance system composed of a remotely located charge coupled device (CCD) video camera, a specially designed hardware system for real-time image acquisition and controlling the illuminator and alarm systems, and various computer vision algorithms for real-time monitoring of visual behaviors. Systematically combines a variety of visual cues that represent a driver's level of alertness. Visual cues include eyelid and gaze movement, pupil movement, head movement, and facial expression. A Bayesian Networks model is applied to form an index that can accurately and consistently characterize a driver's alert level. Eye tracking is achieved through near-infrared illumination to ensure high-quality image under varying real-world conditions. Two miniature CCD cameras are embedded on the vehicle dashboard to measure additional visual cues. Ocular measures to characterize eyelid movement include blink frequency, eye closure duration, eye closure speed, and PERCLOS.
Optalert	Johns, Tucker, & Chapman, 2005	Preliminary results with Optalert™ in volunteer drivers, including commercial truck drivers, have demonstrated that dangerous levels of drowsiness can arise while driving that are not recognized at the time.

Monitoring System	Reference	Technique
George Washington University (GWU), *Artificial Neural Network (ANN)*	Barr et al., 2005	Observes steering angle patterns and classifies them into drowsy and non-drowsy driving intervals. Analyzes vehicle performance output data only; not dependent on environmental conditions, so it is practical for in-vehicle 24-hour fatigue/drowsiness monitoring. The use of neural networks allows for extracting patterns and detecting complex trends in data. Based on premise that there is a relationship between driver state of alertness and steering wheel position (i.e., in alert state, drivers make small amplitude movements, whereas movements become less precise and larger in amplitude during a drowsy state).
Precision Control Design, Inc., *SleepWatch*	Dinges et al., 2005	Actigraphically-based, wrist-worn device combined with an internal algorithm ("Sleep Management Model") to detect rest-activity patterns. Feedback includes estimated sleep need and an alert to take more alertness-promoting countermeasures. The watch displays a "performance fuel gauge" with a displayed percentage corresponding to the subject's sleep debt. The "Sleep Management Model" can be used to collect objective data on sleep time.
Attention Technologies, *CoPilot*	Dinges et al., 2005; Grace, 2001	Uses infrared-based retinal reflectance monitoring to measure PERCLOS. A structured illumination approach is used to identify the driver's eyes. Device must be operated at low ambient light levels. CoPilot can be mounted on dashboards, typically just to the right of the steering wheel. Feedback from the system is displayed on a separate digital display box and consists of an algorithm score of eyelid closure.
Applied Perception and AssistWare Technology, Inc., *SafeTRAC*	Dinges et al., 2005	Provides feedback on lane tracking by detecting lane departures, erratic movements, and other possible errors. Consists of a feedback monitor mounted on the dashboard and a video camera mounted on the windshield. The camera feeds information to a computer that continuously analyzes the image of the road, lane markings, and other roadway features. An auditory warning signal is available if the driver makes an abrupt deviation from the lane without signaling.
Hellenic Institute of Transport, *AWAKE*	Williamson & Chamberlain, 2005; Bekiaris, 2004; Polychronopoulos et al., 2004	Introduces a hybrid system of centralized communication between separate monitoring systems to reduce the frequency of false alarms. Measures real-time hypovigilance and drowsiness in drivers. Parameters measured include eyelid changes, steering grip changes, lane tracking, use of accelerator, and brake and steering position. Data are combined with information from digital navigation maps, anticollision radar, odometer readings, and driver gaze direction sensors to determine the presence of driver risk. If risk is detected, a driver warning system is activated.
Driver Assisting System (DAISY)	Williamson & Chamberlain, 2005	Neural network approach is used to warn drivers of high risk events. Device has not yet been used in a road test.

Monitoring System	Reference	Technique
DriveCam	Williamson & Chamberlain, 2005	Uses video camera and high G-force levels to trigger the recording of 10 seconds before and after unexpected events. The recording consists of information drivers see and hear surrounding the event. Device is currently used by commercial fleets to improve driver safety. Incentives also exist to reduce insurance premiums for good driving. Data recorded by the device can be downloaded for further review and analysis.

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APPENDIX B—STATIC MV EYE CLOSURE MONITOR SELECTION TECHNOLOGY SELECTION MATRIX

Technology Description: Drowsiness Monitoring System (sample, not filled in)

Parameter Description		***MV System A***			***MV System B***	
Musts:	YES	NO	Comments	YES	NO	Comments
Accurate track of eye closures						
A "failure to track eye closure" indication						
Adequate viewing angle to accommodate driver positions & ride motions						
Satisfactory performance under both day and night operation						
Does not present unacceptable risks to drivers						
Works with No Corrective Eye Wear						
Works with a sample of externally-worn eyewear with no glare present						
Operating temperature range 0–120^{o} F						
System durability withstands normal truck vibration						
Wants:						
Power Requirements (12 volts)						
Work with Glasses with glare present						
Works with Contacts						
Works with Sunglasses						
Standard parametric data interface						
Standard video data interface						
Capable of following/tracking head						
Allowable head rotation/translation						
Capable of maintaining eye track under normal driver ride motions						
Calculation of PERCLOS (or acceptable surrogate)						
Capable of handing shadows on face (hats)						
Sensitivity to gradual light changes						
Sensitivity to rapid light changes						

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APPENDIX C—STATIC MV EYE CLOSURE MONITOR SELECTION SUBJECT INSTRUCTIONS

Greet Participant

Explain Purpose of Study: **The purpose of this study is to exercise a device that monitors drowsiness in drivers. The device works by monitoring your eye closures. You will be asked to perform several tasks that simulate both becoming drowsy and driving. We will be measuring how well the system is able to pick-up and evaluate your eye closures while you perform these tasks.**

Obtain participant's **age**; Need for **corrective eyewear**; if they do not wear eyeglasses, ask if they brought their **sunglasses**; and note **skin tone**.

Ensure participant is **seated comfortably** with the ability to depress the clutch; reach steering wheel and instrument panel; and adequately see the ground.

Practice eye closures:

- Relax, as if preparing to sleep. In particular, allow your face muscles to relax. Appropriate feeling is that your cheeks and forehead are sagging.
- While doing this, allow your eyelids to close slowly and naturally, also sagging. As I instruct you, allow your eyelids to close completely for the amount of time.
- There will be three eye closures, each for a different amount of time; roughly, 2 seconds, 5 seconds, and 10 seconds. The 10-second closure will be made up two back-to-back 5 second closures. Between the closures, you will need to open your eyes long enough to focus.
- For each eye closure, I will instruct you to close your eyes slowly, count the appropriate amount of time, and instruct you to open your eyes slowly. Let's practice:
- Close eyes slowly…zero…one…open eyes slowly.
- For the 5 second eye closure will also drop your head to your chest as if you are nodding off. Drop your head slowly and close your eyes slowly…zero…one…two…three…four…open eye slowly and lift your head.
- Finally, the ten second eye closure will consist of two back-to-back 5 second eye closures, except you will not raise your head in the middle.

    Drop your head slowly and close your eyes slowly…zero…one…two… three…four…open eye slowly; close your eyes slowly…zero…one…two… three…four…open eye slowly and lift your head.

- Any questions?

There will also be seven non-closure tasks:

- Looking straightforward for 10 seconds.
- While looking straightforward, for 10 seconds; bounce up and down in the seat (simulate speed bumps).
- Look down to the instrument panel and gaze at your speedometer.
- Look up to the sun visor while I count to two.
- Visually scan by first looking into left mirror, scanning across the horizon through the windshield, and end looking into the right mirror.
- Do a horizontal scan of the environment, looking through the windshield from Right to Left (not including the mirrors).
- Rotate head through the entire range of neck motion both up and down and side to side with eyes remaining open. As you rotate your head, pick eye gaze points throughout the orthogonal arcs within the hemisphere of motion.
- Any questions?

Start Recording

With artificial lights on:
No Glasses

1. Look straightforward, for 10 seconds.
2. While looking straightforward, for 10 seconds; bounce up and down in the seat (simulate speed bumps).
3. Look straightforward, for 10 seconds.

Five-second eye closure:

- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.

1. Look straightforward, for 10 seconds.
2. Look down to the instrument panel and gaze at your speedometer.
3. Look straightforward, for 10 seconds.

Two-second eye closure:

- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.

4. Look straightforward, for 10 seconds.
5. Look up to the sun visor while I count to two.
6. Look straightforward, for 10 seconds.
7. Visually scan by first looking into left mirror, scanning across the horizon through the windshield, and end looking into the right mirror.
8. Look straightforward, for 10 seconds.
9. Do a horizontal scan of the environment, looking through the windshield from Right to Left (not including the mirrors).
10. Look straightforward, for 10 seconds.

Ten-second eye closure:

- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.

11. Look straightforward, for 10 seconds.
12. Rotate head through the entire range of neck motion with eyes open.
13. Look straightforward, for 10 seconds.

Eye Glasses (if the person is required to wear eyeglasses) or Sunglasses (if not)

14. Look straightforward, for 10 seconds.
15. While looking straightforward, for 10 seconds; bounce up and down in the seat (simulate speed bumps).
16. Look straightforward, for 10 seconds.

Five-second eye closure:

- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.

17. Look straightforward, for 10 seconds.
18. Look down to the instrument panel and gaze at your speedometer.
19. Look straightforward, for 10 seconds.

Two-second eye closure:

- Close eyes slowly…Zero…One…open eyes slowly;
- Close eyes slowly…Zero…One…open eyes slowly;
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.

20. Look straightforward, for 10 seconds.
21. Look up to the sun visor while I count to two.
22. Look straightforward, for 10 seconds.
23. Visually scan by first looking into left mirror, scanning across the horizon through the windshield, and end looking into the right mirror.
24. Look straightforward, for 10 seconds.

25. Do a horizontal scan of the environment, looking through the windshield from Right to Left (not including the mirrors).
26. Look straightforward, for 10 seconds.

Ten-second eye closure:

- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.

27. Look straightforward, for 10 seconds.
28. Rotate head through the entire range of neck motion with eyes open.
29. Look straightforward, for 10 seconds.

With artificial lights off:
No Glasses

1. Look straightforward, for 10 seconds.
2. While looking straightforward, for 10 seconds; bounce up and down in the seat (simulate speed bumps).
3. Look straightforward, for 10 seconds.

Five-second eye closure:

- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.

- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.

30. Look straightforward, for 10 seconds.
31. Look down to the instrument panel and gaze at your speedometer.
32. Look straightforward, for 10 seconds.

Two-second eye closure:

- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.

33. Look straightforward, for 10 seconds.
34. Look up to the sun visor while I count to two.
35. Look straightforward, for 10 seconds.
36. Visually scan by first looking into left mirror, scanning across the horizon through the windshield, and end looking into the right mirror.
37. Look straightforward, for 10 seconds.
38. Do a horizontal scan of the environment, looking through the windshield from Right to Left (not including the mirrors).
39. Look straightforward, for 10 seconds.

Ten-second eye closure:

- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.

- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.

40. Look straightforward, for 10 seconds.
41. Rotate head through the entire range of neck motion with eyes open.
42. Look straightforward, for 10 seconds.

Eyeglasses (if the person is required to wear eyeglasses) if not STOP test.

43. Look straightforward, for 10 seconds.
44. While looking straightforward, for 10 seconds; bounce up and down in the seat (simulate speed bumps).
45. Look straightforward, for 10 seconds.

Five-second eye closure:

- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.
- Slowly drop your head, close eyes slowly…Zero…One…Two…Three…Four… open eyes slowly, lift your head slowly.

46. Look straightforward, for 10 seconds.
47. Look down to the instrument panel and gaze at your speedometer.
48. Look straightforward, for 10 seconds.

Two-second eye closure:

- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.
- Close eyes slowly…Zero…One…open eyes slowly.

- Close eyes slowly…Zero…One…open eyes slowly.

49. Look straightforward, for 10 seconds.
50. Look up to the sun visor while I count to two.
51. Look straightforward, for 10 seconds.
52. Visually scan by first looking into left mirror, scanning across the horizon through the windshield, and end looking into the right mirror.
53. Look straightforward, for 10 seconds.
54. Do a horizontal scan of the environment, looking through the windshield from Right to Left (not including the mirrors).
55. Look straightforward, for 10 seconds.

Ten-second eye closure:

- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.
- Slowly drop your head, close eyes slowly …Zero…One…Two…Three…Four… open eyes slowly; Close eyes slowly…Zero…One…Two…Three…Four…open eyes slowly; lift your head slowly.

56. Look straightforward, for 10 seconds.
57. Rotate head through the entire range of neck motion with eyes open.
58. Look straightforward, for 10 seconds.

APPENDIX D—STATIC MV EYE CLOSURE MONITOR SELECTION TECHNOLOGY SELECTION MATRIX COMPLETED

Technology Description: Drowsiness Monitoring System Date: 4/12/07

Parameter Description		***MV System A***			***MV System B***		
Musts:		YES	NO	Comments	YES	NO	Comments
Accurate track of eye closures		X	–	79% (day) 76% (night)	X	–	89% (Day) 91% (Night)
A "failure to track eye closure" indication		X	–	Obvious indication	X	–	Less obvious
Adequate viewing angle to accommodate driver positions & ride motions		X	–	Marginal	X	–	Satisfactory
Satisfactory performance under both day and night operation		X	–	Satisfactory	X	–	Exceptionally well
Does not present unacceptable risks to drivers		X	–	–	X	–	
Works with No Corrective Eyewear		X	–	Good Performance	X	–	Exceptionally well
Works with a sample of externally-worn eyewear with no glare present		X	–	Satisfactory	X	–	Satisfactory
Operating temperature range 0–120^{o} F		X	–	No Problems	X	–	No Problems
System durability withstands normal truck vibration		X	–	No Problems	X	–	No Problems

Wants:	Weight (1–10)	Score (1–10)	Total (weight * score)	Comments	Score (1-10)	Total (weight * score)	Comments
Power Requirements (12 volts)	5	10	50	–	10	50	–
Work with Glasses with glare present	7	3	21	–	6	35	–
Works with Contacts	8	10	80	–	10	80	–
Works with Sunglasses	6	5	42	–	4	28	–
Standard parametric data interface	8	10	80	–	10	80	–
Standard video data interface	5	10	50	–	10	50	–
Capable of following/tracking head	9	5	45	–	7	63	–
Allowable head rotation/translation	6	4	24	–	5	30	–
Capable of maintaining eye track under normal driver ride motions	7	4	28	–	6	42	–
Calculation of PERCLOS (or acceptable surrogate)	8	5	40	–	7	56	–

Wants:	Weight (1–10)	Score (1–10)	Total (weight * score)	Comments	Score (1-10)	Total (weight * score)	Comments
Capable of handing shadows on face (hats)	8	10	80	–	10	80	–
Sensitivity to gradual light changes	8	8	64	–	8	64	–
Sensitivity to rapid light changes	7	8	56	–	8	56	–
Sensitivity to oncoming vehicle headlights	5	9	45	–	9	45	–
Works with varying skin complexions	8	7	56	–	8	64	–
Works well for all age groups (within typical commercial driving pop.)	6	10	60	–	10	60	–
Has the ability to determine eye point of regard	3	1	3	–	8	24	–
Purchase Costs	6	–	–	Data not available	*	–	Data not available
Maintenance Costs	5	–	–	Data not available	*	–	Data not available
Software Maintenance Costs	4	–	–	Data not available	*	–	Data not available
Equipment Upgrade Costs	3	–	–	Data not available	*	–	Data not available
Totals:	–		817	–	–	914	–

APPENDIX E—THE VIRGINIA SMART ROAD

The Virginia Smart Road is a controlled test bed designed for Intelligent Transportation Systems (ITS), human factors, and safety research. The research support infrastructure of the facility makes it an ideal location for safety and human factors evaluation. The road is built to Virginia Department of Transportation and Federal Highway Administration standards. The Smart Road has a large number of features and capabilities and is highly adaptable.

WEATHER-MAKING CAPABILITY

The facility is capable of producing snow, fog-like mist, or rain over a 0.5-mile stretch of roadway under suitable temperature and wind conditions. At maximum output, the system can produce 10 cm (4 in) of snow per hour for 1 hour (Figure 64). A 1,900 kiloliter (500,000-gallon) water tank feeds 76 weather towers and allows for multiple research events. The all-weather testing towers' output is automatically controlled from Virginia Tech Transportation Institute's (VTTI) control room and can produce snow, rain, fog, or mist at varying intensities. Recently, VTTI has configured portable all-weather testing towers to further enhance the facility's flexibility for research customization. In addition, water can be sprayed by the towers onto freezing pavement to create icy conditions.

Figure 64. Fog, Rain, and Snow Equipment Installed on the Smart Road

VARIABLE LIGHTING TEST BED

A highway lighting test bed is also incorporated within the Smart Road. The system consists of 36 overhead light poles that span a 1.1-mile section of the road. The pole spacing pattern is: 40-20-20-40-40-20-20-40-40-20-20 m. This spacing, combined with the wiring of the poles on three separate circuits, allows for evaluation of lighting systems with spacings of 40, 60, 80, or 120 m. The poles incorporate a modified design to allow for easy height adjustment of the bracket arm. In addition to evaluating spacing and bracket height, various luminaires are also available, including metal halide and high-pressure sodium. Additional poles are mounted on portable bases that allow the simulation of other environments as needed (e.g., crosswalks).

The combination of weather-making capabilities and the variable lighting test bed can simulate more than 90 percent of the highway lighting in the United States and allows for a variety of different visibility conditions to be created for testing purposes (Figure 65).

Figure 65. All-Weather Testing Equipment with Experimental Lighting Test Bed Installed on the Smart Road

PAVEMENT MARKING

The road includes an additional visibility testing section. This section has been used with a variety of pavement markings for visibility testing. Periodically, as specific studies require it, the markers are reconfigured. Markers on the road may also be reconfigured or repainted as needed. Past research on pavement markings has included UV-reflective markings, prototype reflective mixtures for markings, three-dimensional markings, and installation quality effects on marking visibility.

ONSITE DATA ACQUISITION AND ROAD WEATHER INFORMATION SYSTEMS

The roadway has an underground conduit network with an access port (bunker) every 60 m. This network houses a fiber-optic data network and interfaces with several onsite DASs and road feature controls. The facility has a complement of road weather information system sensors connected to the data network. In addition, the road is outfitted in its entirety with a wireless network that ties into the research building's data network. This network may be used for data transfer between the vehicle, the research building, and infrastructure within the road (Figure 66).

Figure 66. Bunker With DAS and Weather Station Installed on the Smart Road

DIFFERENTIAL GPS SYSTEM

Differential global positioning system (GPS) corrections are broadcast from the research building to the road. Experimental vehicles are equipped with portable GPS units that, combined with the differential GPS corrections, allow for extremely accurate (on the order of ±1.5 cm) on-road vehicle positioning. VTTI has a number of portable differential GPS units available and thus is able to quickly outfit any vehicle for GPS positioning to enhance studies.

ROAD ACCESS AND SURVEILLANCE

The Smart Road is closed to live traffic, which allows for a variety of different scenarios to be created for testing purposes in relative safety. During past research, for example, experimenters have placed objects of differing size, contrast, and reflectivity on the road to determine the driver's ability to detect them under a wide range of conditions. The lack of live traffic, however, does not prevent the simulation of crash scenarios. Some research projects have used vehicle mockups and appropriately timed distractions to generate surprise conditions. Other projects have employed trained experimenters that act as a pretend maintenance crew. This last method creates the illusion of possible traffic conflicts for participants without any decrease in their safety.

In order to keep the road free of live traffic, vehicle access to the road is restricted with a gate that is controlled from the research building (Figure 67). In addition, the road is outfitted with a video surveillance system that is monitored from the research building 24 hours a day, 7 days a week. This video surveillance system also allows for visual confirmation of vehicle and personnel locations on the road during ongoing studies.

Figure 67. Gate That Restricts Access to the Smart Road

RESEARCH BUILDING AT THE SMART ROAD

The main offices and laboratories of the Virginia Tech Transportation Institute are within two research buildings located adjacent to the Smart Road. The first research building has three floors encompassing more than 2,700 square meters (29,000 square feet) of office, garage, and specialized laboratory space. In addition to the control room and the garage, discussed in the following paragraphs, this research building contains office space for research and administrative staff, conference facilities, multiple laboratories, and work areas for students. The second building is a recently constructed 2,100 square meter (23,000-square-foot) building that is accompanied by a warehouse with four additional garage bays.

CONTROL ROOM

The Control Room serves as the core control and monitoring center for the Smart Road (Figure 68). Vehicular access to the Smart Road is managed at all times by a dispatcher who has visual contact with all sections of the road through direct line of sight and through a set of surveillance cameras. This dispatcher also activates, as required, controls for lighting and weather. All research efforts using the Smart Road are coordinated and monitored through the control room with a primary focus on safety and security. To aid the dispatcher in monitoring all Smart Road operations, the control room houses a 3 m (10 ft) by 2.3 m (7.5 ft) video wall, a projection screen, and up to 12 monitors.

Figure 68. Smart Road Control Room and Dispatcher Monitoring Research

GARAGES

Two garage bays are present in the main building along with machine and electronics shops. The warehouse contains four additional garage bays. All bays have oversized outside doors tall enough to accommodate a semi-tractor. In addition, all of the garages can be isolated in case they need to be used for confidential research, as contractor-dedicated facilities, or as separate tool and work rooms. These six garages also lack windows to ensure privacy when it is needed by the sponsor.

LABORATORIES

The building has space allocated for multiple laboratories, including driver interface development, eyeglance data reduction, lighting research, accident analysis, accident database analysis, pavement research, and traffic simulation. Rooms are also available to host focus groups.

VEHICLE FLEET

VTTI has a variety of vehicles—cars, SUVs, vans, and commercial trucks—that are used for vehicle research (Figure 69). These vehicles are outfitted with basic instrumentation packages that can be quickly tailored to the specifications of a particular project. The vehicles are capable of recording a variety of data in real time from a suite of sensors and cameras that are inconspicuously mounted.

All of these vehicles have been used in a number of safety and human factors experiments. Experimental areas that have been studied with them include in-vehicle displays, driver distraction, collision warning and avoidance, fatigue assessment, navigation systems, and use of in-vehicle devices. In addition to these vehicles, VTTI owns a small number of experimental support vehicles, such as pickup trucks and passenger vans.

Figure 69. VTTI's Vehicle Fleet on the Smart Road Bridge

VEHICLE INSTRUMENTATION

Over the past 15 years and most recently as part of its efforts during the 100-Car Naturalistic Driving study, VTTI has designed and developed a self-contained vehicle DAS. The system contains a combination of commercial off-the-shelf and in-house components.

The core of the DAS is a Pentium-based PC104 computer. The computer runs custom data acquisition software and communicates with a distributed data acquisition network. Each node on the network contains an independently programmable microcontroller capable of controlling or measuring a moderate number of signals. This system configuration maximizes flexibility while minimizing the physical size of the system. The system is capable of managing up to 120 nodes, but only 10 are used in the current configuration.

APPENDIX F—ON-ROAD TEST INFORMED CONSENT

Note: The name of the device was changed during the project from Operator Drowsiness Monitoring System (ODMS) to DDMS.

INFORMED CONSENT VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY

INFORMED CONSENT FOR PARTICIPANTSIN RESEARCH PROJECTS INVOLVING HUMAN SUBJECTS

Title of Project: Development and Assessment of a Driver Fatigue Monitoring System.

Investigator(s): Richard J. Hanowski and Darrell Bowman

I. Purpose of this Research Project

The purpose of this project is to test the effectiveness of a device that monitors drowsiness in drivers. This device is called the Occupant Drowsiness Monitor System (ODMS). The device works by monitoring the vehicle's lane position and the operator's eye closure. Your role in this study is to help us test the ODMS on the Smart Road. It is anticipated that there will be a total of seven individuals who will participate in this study. There will be one individual, the driver, who will be performing all the driving for all test sessions. There will six other participants, the pseudo-drivers, who will perform all of the eye closure tasks. There will be a different pseudo-driver for each test session. The pseudo-driver will be seated in the passenger seat. It is important to stress that this research is not testing the participants, per se, but is directed at testing the ODMS. Therefore, it is important that you drive and/or perform as you normally would while following the instructions of the experimenter.

II. Procedures

Your participation in this research will involve your driving/riding in a tractor/trailer unit on the Smart Road. During this drive, a researcher will be sitting in the sleeper berth behind you. From time to time, the researcher will ask you to perform different tasks during the test. For example, you will be asked to gaze down to a target on the dash. In addition, the pseudo-driver will periodically be asked to pretend like he/she is drowsy. The purpose of this is to test how well the ODMS is able to pick-up and evaluate this individual's eye closures. Each of the tasks that the researcher asks you to perform will be used to test the ODMS. As part of this testing, we want to determine under which conditions the device does and does not work.

If you are the driver, you will drive the tractor up and down the Smart Road for approximately 1 hour per test session while performing these various tasks. However, before driving on the Smart Road, you will be given training on how to perform the tasks, including how to conduct the swerving maneuvers. Your total participation in this study will be 18 separate occasions and the total expected project participation is approximately 27 hours.

If you are the pseudo-driver, you will ride-along in the tractor for approximately 1 hour per test session while performing these various tasks. However, before riding on the Smart Road, you will be given training on how to perform the “pretend drowsiness" episodes.

To explain more fully, the steps for the driver’s and pseudo-driver’s participation will be as follows:

1. You will carefully read this informed consent form and ask any questions you wish. You may take whatever time you deem necessary. If you decide to participate, you will sign and date the form. A copy will be given to you.
2. You will be taken to the research vehicle, where you will be trained on the instructed tasks while the vehicle is standing.

For the driver only:

1. If you are the driver, you will start the vehicle and drive it onto the Smart Road. (The ride-along experimenter will direct you.)
2. You will drive a half of a loop of the Smart Road for familiarization.
3. You will drive additional loops of the Smart Road while performing instructed tasks. These tasks include maintain lane tracking, looking down at a target on the dash, visually scanning from the left mirror to the right mirror, and three separate right edge line crossing maneuvers (10 seconds, 30 seconds, & 60 seconds). (There will be about 6 data gathering loops per test session and three separate test sessions.)
4. Once all test sessions are completed, you will exit the Smart Road, park the vehicle at the research buildings, be thanked, and be dismissed.
5. Your total participation in this study will 18 separate occasions, each occasion lasting approximately 1.5 hours, and the total expected project participation is approximately 27 hours.

For the Pseudo-driver only:

1. You will ride-along while performing the instructed tasks. These tasks include looking straight forward, looking down at a target on the dash, visually scanning from the left mirror to the right mirror, and three separate eye closure tasks (2-s, 5-s, & 10-s). (There will be about 6 data gathering loops per test session and three separate test sessions.)
2. At the end of each test session, you will be thanked, and be dismissed.
3. Your total participation in this study will be 3 separate occasions, each occasion lasting approximately 1.5 hours, and the total expected project participation is approximately 4.5 hours.

III. Risks and Discomforts

It is important that you are aware of the risks that you will be exposed to while participating in this research. These risks are:

- The slight risk of an accident associated with driving/riding in a commercial tractor.
- The slight additional risk of an accident that might possibly occur while swerving the vehicle and/or pretending that you are drowsy. This risk is offset by the fact that there will be no other traffic on the roadway, so you will not have to contend with interactions due to other vehicles.

There is not expected to be any additional risk in having the ODMS in the vehicle. The fatigue monitoring system involves infrared emitters to provide uniform illumination of the face. These emitters are integrated with the camera and will in no way be in contact with any part of your body. The illumination source for the fatigue monitor camera consists of 32 infrared emitting diodes (IRED) in two square configurations that measure 1 in × 1 in each. Seeing Machines is the manufacturer of the infrared emitters used in the ODMS. According to Seeing Machines compliance documentation, the IRED pods have been tested to be compliant with the International Electrotechnical Commission (IEC) standard 60825-1: *Safety of Laser Products* maximum permissible exposure limits for eyes (emission levels have a safety factor of 11) and skin (emission levels have a safety factor of 175). Therefore, these tests indicate that the infrared emitters do not pose any undue risk to the vehicle occupants.

The following precautions will be taken to ensure that the risk to you, as a research participant, is minimized:

- Speed during the testing will be limited to less than 30 mi/h. (Instructed speed is 25 mi/h.)
- There will be no other traffic on the road.
- A ride-along experimenter will be present at all times and will remain vigilant. You will only be prompted to swerve the vehicle or pretend you are drowsy on a section of the Smart Road that is straight and has wide shoulders. The prompts will not be given on bridges. When you are in the act of swerving or pretending that you are drowsy, the researcher will carefully monitor the path of the vehicle. If the path appears to be deviating to any hazardous extent, the researcher will warn you. If you are warned of this, you are to immediately end the task and restore the vehicle to a safe path.
- Both you and the experimenter will wear your seat restraints whenever the vehicle is in motion.

Because of the low travel speed, the absence of other vehicles and pedestrians on the road, and the fact that the driver will not be performing eye closures, it is believed that these procedures can be accomplished without difficulty. Nonetheless, you need to be made aware that there are slight risks inherent in participating.

In the unlikely event that an accident does occur, the experimenter will be in radio contact with the Smart Road control room. Personnel there will call the rescue squad if there is any injury or possibility of injury.

There are no known discomforts involved in your participation.

IV. Benefits

No promise or guarantee of benefits is being made to encourage you to participate.

Research, such as that being conducted here, is important in that it improves safety and helps reduce crashes. Drivers' participation is necessary to assess the efficacy of a drowsiness monitor aimed at reducing fatigue-related crashes.

You may find the experiment interesting.

V. Extent of Anonymity and Confidentially

The data gathered in this experiment will be treated with confidentiality. Shortly after participating, your name will be separated from the data and replaced with a number. That is, your data will not be attached to your name, but rather to a number.

As part of testing the system, you will be videotaped while behind the wheel of the truck or seated in the passenger seat. This video will be stored in a secured area at VTTI. Access to the tapes will be under the supervision of the Principal Investigator and Co-Principal Investigator. Only those researchers and data analysts associated with this project will have access to the data. The data will not be released to unauthorized individuals, or individuals not working on the project, without your written consent.

VI. Compensation

Your participation in this research will be completed as a part of your normal work schedule.

VII. Medical Treatment and Insurance

If you should become injured in an accident, the medical treatment available to you would be that provided to any driver or passenger by emergency medical services in the vicinity where the accident occurs. The vehicle you will be driving is insured for automobile liability and collision/comprehensive through Virginia Tech and the Commonwealth of Virginia There is medical coverage for you under this policy. The total policy amount per occurrence is $2,000,000. This coverage would apply in case of an accident, except as noted below.

Under certain circumstances, you may be deemed to be driving in the course of your employment, and your employer's worker's compensation provisions may apply in lieu of the Virginia Tech and Commonwealth of Virginia insurance provisions, in case of an accident. The particular circumstances under which worker's compensation would apply are specified in Virginia law. If worker's compensation provisions do not apply in a particular situation, the Virginia Tech and Commonwealth of Virginia insurance provisions will provide coverage. Briefly, worker's compensation would apply if your driving for this research can be considered as part of the duties you perform in your regular job. If it is not considered as part of your regular job, then the insurance policy would apply.

VIII. Freedom to Withdraw

As a participant in this research, you are free to withdraw at any time, or to choose not to participate in the first place, without any repercussions. If you choose to withdraw, you will be allowed to return to your normal work activities. Also, you are free not to answer any questions or respond to experimental situations that you choose without penalty. If, in the discretion of the researcher working with you, it is determined that you should not continue as a participant, you will be released to return to your normal work activities.

IX. Approval of Research

This research project has been approved, as required, by the Institutional Review Board for Research Involving Human Subjects at Virginia Polytechnic Institute and State University.

June 7, 2007	June 6, 2008
IRB Approval Date	Approval Expiration Date

X. Subject's Responsibilities

I voluntarily agree to participate in this study. I have the following responsibilities:

1. To be physically free from any illegal substances (i.e., drugs) or alcohol while driving or performing tasks.
2. To be reasonably well rested prior to participation.
3. To follow the experimental procedures to the best of my abilities.
4. To wear the seat restraint whenever the vehicle is in motion.
5. To inform the researchers if I encounter difficulties of any type.

XI. Subject's Permission

I have read and understand the Informed Consent and conditions of this project and I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent:

Date

Subject signature

Should I have any questions about this research or its conduct, I may contact:

Rich Hanowski Investigator(s)	231-1513 / hanowski@vtti.vt.edu *Telephone / e-mail*
Darrell Bowman Investigator(s)	231-1068 / dbowman@vtti.vt.edu *Telephone / e-mail*
David M. Moore Chair, IRB Office of Research Compliance Research & Graduate Studies	231-4991 / moored@vt.edu *Telephone / e-mail*

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APPENDIX G—ON-ROAD TEST EXPERIMENTER PROTOCOL

Truck Preparation:

1. Turning on the Truck Battery:
    - Flip-up battery box cover
    - Turn battery cut-off switch to ON position
2. Starting Truck:
    - Open driver's door
    - While seated in driver's seat, push clutch to the floor and hold
    - Turn ignition key to START position
    - Set cruise control to 1000 RPM
3. Starting OFMS:
    - Turn on two inverters behind driver's seat
    - Turn on the VGA converter (red LED on the top of cover should come on)
    - Turn on the DAS by flipping up the right toggle and let it completely boot up (be sure that the left toggle remains in its center position)
    - Turn *MV System B* switch to the ON position
    - Let the *MV System B* completely boot
    - "Touch" the Logging Tab
    - "Touch" the STOP TRACKING function
    - Enter the new network address: "192.168.0.100"
    - "Touch" the START TRACKING function
    - VERIFY, in SOL, that the *MV System B* module is receiving messages
    - Change DCS monitor to Video 1 and make sure all quadrants are showing good video

Participant Orientation:

4. Plan to meet both Driver and Pseudo-driver in Subject Briefing Room 30 minutes prior to Smart Road time.
5. Greet the Driver and Pseudo-driver:
    - Give brief explanation of the experiment and tell them they will be instructed on how to perform the tasks once they are in the truck:
        i. *The purpose of this project is to test the effectiveness of a device that monitors the drowsiness in drivers. The device is called the Operator Fatigue Monitoring System. This devices works by monitoring both the vehicle's lane position and the pseudo-driver's eye closures. It is important to stress that we are not testing you as driver or occupant, instead we are testing the drowsiness monitor; and therefore, you are more similar to a "research assistant", than a "research subject". Your participation is this research will involve you, the driver, driving a commercial tractor on the Smart Road; and you, the pseudo-driver, riding in the passenger seat. I will be sitting in the sleeper berth on a jump seat. Periodically, I will ask each of you to perform separate tasks, some at the same time, while we drive on the Smart Road course. The purpose of this*

is to test how well the drowsiness monitor is able to pick-up and evaluate your lane deviations and eye closures.

ii. *When we finish with the paperwork, we will go out to the truck and I will instruct you on how to perform the tasks.*

- Read over the important points in the informed consent that need to be stressed:
  i. Priorities (*for the driver*):
     1. *Your first priority is to drive the truck safely.*
     2. *Your second priority is to maintain a speed of 25 MPH and 15 MPH on the turnarounds.*
     3. *Your third priority is to perform the tasks to the best of your ability.*

  ii. Priorities (*for the pseudo-driver*):
     1. *Your first priority is to perform the tasks to the best of your ability.*

  iii. Risks
     1. *There is a slight risk of an accident associated with driving a tractor.*
     2. *There is a slight additional risk of an accident that might possibly occur while pretending to be drowsy and swerving the vehicle.*

  iv. Precautions taken to ensure that the risks to you are minimized:
     1. *Speed will be limited to 25 MPH.*
     2. *There will be no other traffic on the road.*
     3. *The experimenter will be in the vehicle at all times.*
     4. *Both the driver and the pseudo-driver will only be prompted to pretend you are drowsy on a section of the Smart Road that is straight and has wide shoulders. The prompts will not be given on bridges. The driver will not close his eyes while pretending to be drowsy, and he will discontinue the task if he feels the vehicle's path appears to be deviating to any hazardous extent and restore the vehicle to a safe path.*
     5. *All three occupants (the driver, the pseudo-driver, and the experimenter) will be wearing seat belts.*

  v. Freedom to Withdraw
     1. *As a participant in this research, both the driver and pseudo-driver are free to withdraw at any time without penalty. If you choose to withdraw, please make the experimenter aware of this wish and the experiment will be terminated immediately.*

- Have both participants read and sign the informed consent form and provide them with a copy to take home.
- Make sure that the participants are not wearing a hat.

6. While still in the Subject Briefing Room, instruct the pseudo-driver how to make slow eye closures:
   - *Relax, as if preparing to sleep. In particular, allow your face muscles to relax. Appropriate feeling is that your cheeks and forehead are sagging.*
   - *While doing this, allow your eyelids to close slowly and naturally, also sagging. As I instruct you, allow your eyelids to close completely for the amount of time.*

- *There will be three eye closures, each for a different amount of time; roughly, 2 seconds, 5 seconds, and 10 seconds.*
- *For each eye closure, I will instruct you to close your eyes slowly, count the appropriate amount of time, and instruct you to open your eyes slowly. Let's practice:*
- *Close eyes slowly…zero…one…open eyes slowly.*
  We will repeat the 2-second eye closure five times.
- *For the 5 second eye closure will drop your head to your chest as if you are nodding off.*
  Drop your head slowly and close your eyes slowly…zero…one…two…three…four…open eye slowly and lift your head.
  We will repeat the 5-second eye closure five times.
- *Finally, the ten second eye closure will also drop your head to your chest as if you are nodding off.*
  Drop your head slowly and close your eyes slowly…zero…one…two…three…four…five…six…seven…eight…nine…open eye slowly and lift your head.
  We will complete five 10-second eye closures.
- *Any questions?*

7. While also in the Subject Briefing Room, instruct the driver on how to make the swerving maneuvers:
    - *You will be asked to make three right edge line crossing maneuvers. There will be a short duration right edge line crossing in which you will cross the right-side edge line for a 10 s duration and return to the lane. There will be a medium duration right edge line crossing in which you will cross the right-side edge line for a 30 s duration. Finally, there is a long duration right edge line crossing in which you will cross the right-side edge line for a 60 s duration and return to within the lane.*

In-Vehicle Preparation:

8. Take both the driver and pseudo-driver to the tractor, have them get in and adjust their seats to a comfort position.
9. Make sure that the pseudo-driver's head position is within *MV System B*'s field of view on the SOL monitor.
10. Show the driver where the engine brake is located
11. Instruct the driver and pseudo-driver on the non-eye closure tasks:
    - *There will also be four tasks that do not involve eye closures.*
    - *First, you will be asked to look in the forward direction for 10 seconds.*
    - *Second, you both will be asked to look down to the dash at the target placed in front each of you.*
    - *Finally, each of you will be asked to perform a mirror check by first starting in the left mirror and scanning across the windshield, and end in the right mirror.*
12. Start data collection:
    - System should be already running from starting the system in task 3.
    - DAS will prompt you to enter some information:

i. Enter pseudo-driver's subject number (1–6)
ii. Enter run number (always use the same number "00")
iii. Enter pseudo-driver's age
iv. Enter pseudo-driver's gender
v. At the end of each group of tasks, when the driver and pseudo-driver are not performing any tasks, enter "0" for the task number.

13. Proceed to the Smart Road
14. Instruct the driver to stay at 25 MPH, 15 MPH on turnarounds (5^{th} gear, 1,800 RPM)
15. Make sure to note the time tractor enters the Smart Road and exact weather conditions. If the weather changes, (starts raining, gets cloudy, etc) note change and time.
16. Enter the Smart Road and have the driver drive the tractor to the road's lower turnaround to get used to driving the tractor and to practice the right edge line crossing maneuvers.
17. If, after the half loop, the driver indicates that he is comfortable with the handling of the tractor, the study may begin; if not, drive one additional practice loop.
18. Press "s" to begin the data collection
19. Begin the first loop of data collection

After the Experiment is Finished:

20. Stop the system by pressing "q".
21. Exit the Smart Road and note the time.
22. Have the driver return the tractor to the garage area.
23. Thank the driver and pseudo-driver for their participation and allow them to leave.
24. Retrieving the data from the Tractor:
    - Shut down the *MV System B* system
    - Turn off the VGA converter
    - Power down the DAS by flipping down the right toggle switch and returning it the center position (be sure that the left toggle remains in its center position)
    - Remove the hard drive from the DAS by turn the key and press the eject button.
    - Turn off the inverter
    - Turn off the tractor.
    - Exit the tractor and lock the doors
    - Turn off the tractor battery by flipping up the battery box cover and turning the cutoff switch to the OFF position.
    - Close battery box cover.

APPENDIX H—ON-ROAD TEST PARTICIPANT INSTRUCTIONS

DOWN THE ROAD (LOOP 1)

Section 1:

To the Driver:

- Make your way around the upper turnaround and drive to the lower turn around. Along the way, become familiar with the features of the Volvo Tractor and practice the right edge line crossings when instructed. Once at the lower turn around, you will be instructed to stop the vehicle. Remember to maintain 15 MPH on turnarounds and 25 MPH on the rest of the road.

UP THE ROAD (LOOP 1)

Section 2:

Task 1

ENTER "1" for Task Number

To the Driver:

- Maintain lane tracking

To the pseudo-driver:

- Look straight forward

Task 2

ENTER "2" for Task Number

To the Driver:

- Maintain lane tracking for the entire length of this task.

To the pseudo-driver:

- We will be completing a 5-second eye closure. Ready?
  - *Drop your head slowly and close your eyes slowly …zero…one…two…three…four…open eye slowly and lift your head.*

- *Drop your head slowly and close your eyes slowly …zero…one…two…three…four…open eye slowly and lift your head.*
- *Drop your head slowly and close your eyes slowly …zero…one…two…three…four…open eye slowly and lift your head.*
- *Drop your head slowly and close your eyes slowly …zero…one…two…three…four…open eye slowly and lift your head.*
- *Drop your head slowly and close your eyes slowly …zero…one…two…three…four…open eye slowly and lift your head.*

Task 3

ENTER "3" FOR TASK NUMBER

To the Driver:

- On my command, please complete a 30 s right edge line crossing maneuver.

To the pseudo-driver:

- Look straight forward

  ENTER "0" for Task Number

DOWN THE ROAD (LOOP 2)

SECTION 1:

Task 4

ENTER "4" for Task Number

To the Driver:

- Maintain lane tracking for the entire length of this task.

To the pseudo-driver:

- We will be completing a 2-second eye closure. Ready?
  - *Close eyes slowly…zero…one…open eyes slowly.*
  - *Close eyes slowly…zero…one…open eyes slowly.*
  - *Close eyes slowly…zero…one…open eyes slowly.*
  - *Close eyes slowly…zero…one…open eyes slowly.*

– *Close eyes slowly…zero…one…open eyes slowly.*

Task 5

ENTER "5" for Task Number

To the Driver:

- On my command, please perform a 60 s right edge line crossing maneuver. To the pseudo-driver:
  - Look straight forward

  ENTER "0" for Task Number

UP THE ROAD (LOOP 2)

SECTION 2:

Task 6

ENTER "6" for Task Number

To the Driver:

- Maintain lane tracking and when I say "begin" visually scan by first looking into left mirror, scanning across the horizon through the windshield, and end looking into the right mirror.

To the pseudo-driver:

- When I say "begin" visually scan by first looking into left mirror, scanning across the horizon through the windshield, and end looking into the right mirror.

Task 7

ENTER "7" for Task Number

To the Driver:

- Maintain lane tracking for the entire length of this task.

To the pseudo-driver:

- We will be completing a 10-second eye closure. Ready?

- *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*
- *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*
- *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*
- *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*
- *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*

ENTER "0" for Task Number

DOWN THE ROAD (LOOP 3)

SECTION 1:

Task 8

ENTER "8" for Task Number

To the Driver:

- On my command, please complete a 30 s right edge line crossing maneuver.

To the pseudo-driver:

- We will be completing a 5-second eye closure. Ready?
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three…four…open eye slowly and lift your head.*
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three…four…open eye slowly and lift your head.*
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three…four…open eye slowly and lift your head.*
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three…four…open eye slowly and lift your head.*
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three…four…open eye slowly and lift your head.*

Task 9

ENTER “9” for Task Number

To the Driver:

- Maintain lane tracking

To the pseudo-driver:

  - Look straight forward

Task 10

ENTER “10” for Task Number

To the Driver:

- On my command, please complete a 10 s right edge line crossing maneuver.

To the pseudo-driver:

- We will be completing a 2-second eye closure. Ready?
  - *Close eyes slowly…zero…one…open eyes slowly.*
  - *Close eyes slowly…zero…one…open eyes slowly.*
  - *Close eyes slowly…zero…one…open eyes slowly.*
  - *Close eyes slowly…zero…one…open eyes slowly.*
  - *Close eyes slowly…zero…one…open eyes slowly.*

Task 11

ENTER “11” for Task Number

To the Driver:

- Maintain lane tracking

To the pseudo-driver:

- Look straight forward

ENTER “0” for Task Number

UP THE ROAD (LOOP 3)

SECTION 2:

Task 12

ENTER “12” for Task Number

To the Driver:

- On my command, please complete a 10 s right edge line crossing maneuver.

To the pseudo-driver:

- Look straight forward

Task 13

ENTER “13” for Task Number

To the Driver:

- On my command, please perform a 60 s right edge line crossing maneuver.

To the pseudo-driver:

- We will be completing a 10-second eye closure. Ready?
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*
  - *Drop your head slowly and close your eyes slowly…zero…one…two…three …four…five…six…seven…eight…nine…open eye slowly and lift your head.*

Task 14

ENTER “14” for Task Number

To the Driver:

- Maintain lane tracking and when I say "begin" look down at the target on the dash. I will give a two count and then you can return looking forward.

To the pseudo-driver:

- When I say "begin" look down at the target on the dash. I will give a two count and then you can return looking forward.

Task 15

ENTER "15" for Task Number

To the Driver:

- Please merge into the left lane using your turn signal. Please merge back into the right lane using your turn signal.

To the pseudo-driver:

- Look straight forward

  ENTER "0" for Task Number

1 SET OF DATA FINISHED

- Start at the beginning and repeat once more.
- Move to the right and exit the Smart Road.

This procedure will be completed for Daylight, Nighttime, and Nighttime with artificial lighting conditions.

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