using Technology or IMPACT, a program of research into detecting alcohol-impaired driving based primarily upon vehicle-based measures to the domain of drowsy driving (Lee et al., 2010). IMPACT has developed alcohol detection algorithms for all drivers (general algorithms) and algorithms that take into account individual driving differences (individualized algorithms). This work explores how well the previously developed algorithms that detect impairment from alcohol are able to detect drowsiness, and how to best to modify those algorithms, if necessary, to detect both. The algorithms that were previously developed to detect alcohol impairment were effective at levels comparable to the Standardized Field Sobriety Test in 8 to 25 minutes. One algorithm used logistic regression of standard speed and lane-keeping measures; a second used decision trees and a broad range of driving metrics that were grounded in cues NHTSA has suggested police officers use to identify alcohol-impaired drivers; a third used support vector machines and the standard deviation of lane-keeping. 2 To better place these algorithms in the context of existing research, four research questions must first be addressed: • Can algorithms designed to detect alcohol impairment and distraction also detect drowsiness? • Can algorithms designed to detect alcohol impairment be generalized to detect both alcohol and drowsiness? • Can algorithms distinguish between alcohol and drowsiness-related impairment? • Do real-time algorithms perform better in detecting drowsiness in advance of a drowsiness-related mishap? The following sections describe what has been learned from previous research that can help to inform this project. Terminology: While this project focuses on studying drowsy drivers as opposed to fatigued drivers, it should be noted that while reviewing the literature, the words fatigue and drowsiness were often used interchangeably. For example, the recent NHTSA Traffic Safety Facts on Drowsy Driving defined a drowsy driving crash as one “in which the driver was reported as drowsy, sleepy, asleep, or fatigued” (NHTSA, 2011). For the purpose of this research, drowsy is defined as instances where the driver wishes to sleep, and fatigued as instances where the driver wishes to cease working (driving). In reviewing the open literature, while an author may have used the term fatigued, the keywords of the publication generally included drowsiness or related physiological and cognitive indices of drowsiness, such as attentional resources, vigilance, or effort. This was also true in the reverse, as authors that used the term drowsiness had key words that included fatigue, inattention, fatigued driving, and sustained attention. Fatigue and drowsiness can co-occur. However, in the following review of literature, careful attention was paid to ensure that when articles concerning fatigue were reviewed, the fatigue symptoms and methodology were indicative of a study of drowsy driving. All studies solely of physical fatigue were excluded from the review. Exclusion of all articles that used the term fatigue, however, would have produced a review that does not yield a full understanding of the behavioral indicators of drowsy driving and the environments in which those indicators are found. For the purposes of this review discussion, fatigue can be interpreted as synonymous with drowsy driving.

**2.1 Technique for Detecting Drowsy Drivers**

Possible techniques for detecting drowsiness in drivers can be generally divided into the following categories: sensing of physiological characteristics, sensing of driver operation, sensing of vehicle response, monitoring the response of driver

**2.2 Monitoring Physiological Characteristics**

Among these methods, the techniques that are best, based on accuracy are the ones based on human physiological phenomena [9]. This technique is implemented in two ways: measuring changes in physiological signals, such as brain waves, heart rate, and eye blinking; and measuring physical changes such as sagging posture, leaning of the driver’s head and the open/closed states of the eyes [9]. The first technique, while most accurate, is not realistic, since sensing electrodes would have to be attached directly onto the driver’s body, and hence be annoying and distracting to the driver. In addition, long time driving would result in perspiration on the sensors, diminishing their ability to monitor accurately. The second technique is well suited for real world driving conditions since it can be non-intrusive by using optical sensors of video cameras to detect changes.

**2.3 Other Methods**

Driver operation and vehicle behavior can be implemented by monitoring the steering wheel movement, accelerator or brake patterns, vehicle speed, lateral acceleration, and lateral displacement. These too are non-intrusive ways of detecting drowsiness, but are limited to vehicle type and driver conditions. The final technique for detecting drowsiness is by monitoring the response of the driver. This involves periodically requesting the driver to send a response to the system to indicate alertness. The problem with this technique is that it will eventually become tiresome and annoying to the driver.

**2.4 Scenario Characteristics**

The difficulty of different driving scenarios or situations may depend upon whether a driver is impaired, and if so, the type of impairment. Alcohol impairment is generally the most understood due to the precision of its measurement (breath or blood alcohol concentration), specific legal limit, and its consequent use as a comparison for other types of impairment research. However, different types of impairment manifest in different ways, and just because a driver may find a scenario challenging when impaired with alcohol, does not necessarily mean that a drowsy driver will find it challenging. This section describes why certain scenarios may be more challenging to drowsy drivers than others. The characteristics of such scenarios that are difficult for drowsy drivers can be categorized as ones that affect either endogenous (internal) or exogenous 3 (external) contributors to drowsiness. Circadian variation, time on task, and lack of sleep are considered endogenous whereas scenario characteristics represent exogenous factors (Thiffault & Bergeron, 2003). These authors demonstrated that unpredictable roadside scenery can disrupt the deleterious effects of an otherwise monotonous driving environment. Their findings suggest that “monotony may exacerbate the impact of late night driving, whilst overloaded roadside environments may generate arousal levels that counteract this effect” (p. 382). Similarly, straight road conditions are more challenging to drowsy drivers than curved roads (Matthews & Desmond, 2002). Overall, these studies suggest that the most challenging driving situation for a drowsy driver would be a long, low demand, predictable driving environment with little driver intervention required. A scenario with a long rural straightaway, little interaction with other traffic and no curves would be consistent with the evidence presented. Additionally, this would suggest that roads with few changes in the surrounding roadway environment such as buildings and signage would also prove more challenging to a drowsy driver. Such situations that come towards the end of a drive are likely to place a greater demand on a drowsy driver because drowsiness tends to increase as time on task increases.

**2.5 Reliable and Sensitive Based Indicators**

Although there are many measures of driver fatigue and drowsiness, those that are commonly studied are generally perceptual, biological, physiological, or performance based. Vehicle-based indicators of drowsy driving have been less prevalent among studies assessing driver drowsiness or fatigue, and their associated effects on performance. However, simple functions of driving performance such as steering wheel movements, lateral shifts, standard deviation of lane position, and frequency of line crossings and have all been used to measure the effects of drowsiness on driving performance.

A review article by Liu, Hosking, and Lenne (2009) summarizes the effects on driving performance measures of driver drowsiness or fatigue based on 17 studies published in peer-reviewed journals in which at least one objective vehicle-based measure was reported. Overall, the reviewed literature indicated an increase in lane departures with increased drowsiness. Moreover, the average standard deviation of lane position (SDLP) and mean absolute value of steering wheel angle and standard deviation of steering wheel movements were shown to increase with drowsiness. It was noted that the current body of knowledge also associates drowsiness with increases in standard deviation in speed and variation in speed from the speed limit, but not consistently. The authors also point out that the research does not present analyses of time histories as the basis of determining drowsiness, but instead focuses on overall averages across entire test periods. This research provides a foundation for focusing the review of indicators of drowsy driving.

Steering wheel movements and the resultant heading error have shown to be reliable indicators of drowsiness. A review of literature related to fatigued and drowsy driving by Barr et al. (2003) found changes in steering behavior are associated with a “driver’s state of impairment.” Platt (1963) and Safford and Rockwell (1967) found that reduced driver capabilities were associated with an increase in steering reversal rates. Matthews and Desmond (2002) categorized steering reversals into three levels; fine (<2 degrees), medium (2-10 degrees), and coarse (>10 degrees). This is similar to the categories defined by Wilson and Green smith (1983) that defined fine steering reversals as those less than 2 degrees and course steering reversals as those greater than

12 degrees. It was assumed that coarse reversals reflect reactive responses to lateral drift while fine, and even medium reversals reflect controlled activity (Matthews & Desmond 2002; Mackie & Miller, 1978). One of the most prevalent measures of drowsy driving throughout the literature is SDLP. Liu et al. (2009) point out that there are variations of this measure that index different aspects of driver performance. Precision is defined as the ability of the driver to maintain straight driving, independent of their location within the lane or with respect to the center of the lane. On the other hand, bias is defined as the driver’s ability to accurately track the center of the lane. While both of these variations are used in the literature as measures of standard deviation of lane position, it is recommended that they be reported as separate measures (Liu et al., 2009). For the purposes of this report, SDLP will be defined as the deviation from the center of the lane unless otherwise noted.

Many researchers have shown that SDLP increases with increased drowsiness. Arnedt et al. (2001) showed that hours of wakefulness are predictive of changes in SDLP. Their research found that 19 and 22 hours of wakefulness resulted in SDLPs that were consistent with impaired performance at .05 grams per deciliter and .08 g/dL blood alcohol concentration (BAC), respectively. Using a time on task approach and partial sleep deprivation, Otmani et al. (2005) found that SDLP was greater with partial sleep deprivation than with normal sleep, and that it increased over the course of a 90-minute drive. The partial sleep deprivation condition that used moderate sleep restriction during the night prior to the driving session consisted of approximately 12 hours of wakefulness in the 16-hour period before driving. Subjects were allowed to sleep only from 3 to 7 a.m. with driving occurring during the “post-lunch dip period between 2 and 4 p.m.” Another type of study examining the effects of caffeine by De Valck and Cluydts (2001) showed that SDLP was sensitive to both the effects of hours of sleep and caffeine: increased SDLP with less sleep, and decreased SDLP after using caffeine. It should be noted, however, that SDLP is also affected by substances such as alcohol and distraction as documented in the IMPACT program (Lee et al., 2011a), and the Distraction Detection and Mitigation Through Driver Feedback (Lee et al., 2011b) final reports. While this metric may facilitate multiple impairment detection, it may not be very useful for distinguishing among them.

Inappropriate line crossings (lane departures) also increase with drowsy driving. Philip et al. (2005) found that the number of inappropriate line crossings, defined as crossing one of the lateral highway lane markers, increased for sleep-deprived drivers as opposed to well-rested drivers. Speed control is another measure where research has shown differences. This measure has not been reported as often as have lateral control measures; however, a number of researchers have found it to be sensitive to the effects of drowsiness. Arndt (2001) also found that speed variability increased with hours of wakefulness. Specifically, he found greater variability after 20 hours of wakefulness than after 16 hours; however, when comparing the effect of alcohol, the effect of hours of wakefulness is less than the effect of alcohol at the .08 g/dL BAC. De Valck and Cluydts (2001) showed that deviation from the speed limit increased with less sleep, but decreased when using caffeine under these conditions. Overall, it appears that there are potentially several diagnostic vehicle-based indicators of drowsiness with lateral control measures the most promising. Across the studies reviewed by Liu et al., the most sensitive and reliable indicator appears to be lateral vehicle control, specifically SDLP.

Real-time face and iris detection on video sequences is important in diverse applications such as, study of the eye function, drowsiness detection, virtual keyboard interfaces, face recognition, and multimedia retrieval. In this paper, a real-time robust method is developed to detect irises on faces with coronal axis rotation within the normal range of *−*40*◦* to 40*◦*. The method allows head

movements with no restrictions to the background. The method is based on anthropometric templates applied to detect the face and eyes. The templates use key features of the face such as the elliptical shape, and location of the eyebrows, nose, and lips. For iris detection, a template following the iris–sclera boundary shape is used. The method was compared to Maio–Maltoni’s and Rowley’s methods for face detection on five video sequences (TEST 1). The method was also assessed in an additional set of five video sequences for iris detection (TEST 2). Results of correct face detection in TEST 1 were above 99% in three of the five video sequences. The fourth video sequence reached 97.6% and the third 90.6%. In TEST 2, the iris detection was above 96% in all five video sequences with two above 99.7% and two at 100%. Face size estimation is also above 99.9%. The average processing time of our method was 0.02 s per frame. Thus, the proposed method can process frames at a rate near to 50 frames/s, and therefore, is applicable in real time in a standard personal computer.