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Commercial Motor Vehicle Operator Fatigue Detection Technology Catalog and Review

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LIST OF ABBREVIATIONS AND SYMBOLS

ASTiD	Advisory System for Tired Drivers
CI	confidence interval
CMV	commercial motor vehicle
CNRS	Centre National de la Recherche Scientifique
DFM2	Driver Fatigue Monitor
ECG	electrocardiography
EDA	electrodermal
EEG	electroencephalography
EOG	electrooculography
GSR	galvanic skin response
HR	heart rate
HRV	heart rate variability
Hz	hertz
IR	infrared
IRR	incidence rate ratio
JDS	Johns Drowsiness Scale
KSS	Karolinska Sleepiness Scale
LED	light-emitting diode
MDF	Multi Modal Driver Distraction and Fatigue Detection/Warning System
MRI	magnetic resonance imaging
Osler	Oxford Sleep Resistance Test
PERCLOS	percentage eye closure
PVT	Psychomotor Vigilance Task
VOG	video oculography
VTTI	Virginia Tech Transportation Institute

CHAPTER 1. BACKGROUND

IMPACT OF FATIGUE ON DRIVING PERFORMANCE AND CRASH RISK IN COMMERCIAL MOTOR VEHICLE OPERATIONS

The effects of fatigue on commercial motor vehicle (CMV) drivers is a public safety issue, and it is important to understand how fatigue affects driver performance and the implications of these effects on highway safety. Driver impairment due to sleepiness and fatigue is a major contributing factor in many truck crashes. Of the approximately 4,000 fatalities due to CMV crashes that occur each year, up to 20% are estimated to involve drowsiness or fatigue (National Academies of Science, Engineering, and Medicine, 2016).

Although the terms "driver drowsiness" and "fatigue" are often used interchangeably, they are defined very differently. Fatigue is a state of reduced physical or mental alertness that impairs performance and is often the result of physical or mental exertion (Williamson et al., 1996). Drowsiness is the inclination to sleep resulting from lack of sleep, boredom, hunger, or other outside factors (Stutts et al., 1999). Both are experienced by CMV drivers to a greater degree than many other occupations due to the nature of the industry. CMV drivers experience physical and mental fatigue in their daily operations, which include long periods of driving, loading and unloading, and managing and troubleshooting stressful situations. CMV drivers also experience poor quantity and quality of sleep due to many workplace factors, including erratic scheduling and time pressures, as well as personal factors, including family obligations and health conditions (e.g., sleep disorders). In many cases, a combination of factors is responsible for causing and exacerbating driver fatigue. Despite their distinct etiologies, fatigue and sleepiness can result in impaired driving performance and increased crash risk; therefore, for the purpose of this literature review, the term "fatigue" will be used to describe both fatigue and drowsiness.

Fatigue may negatively influence behavior and can result in poor judgement and impairments in concentration, memory, cognitive function, reaction time, and alertness (Lim & Dinges, 2010; National Academies of Science, Engineering, and Medicine, 2016). Operating a CMV is a task that requires high levels of alertness and concentration. CMV drivers are often faced with scenarios that require rapid and critical decision-making.

Fatigue is very difficult to define and measure objectively. It is therefore difficult to assess and consequently regulate how to avoid driving while fatigued (National Academies of Science, Engineering, and Medicine, 2016). As fatigue is difficult to assess via post-crash reconstruction, estimates of the frequency and outcomes of fatigued driving are likely conservative. Drivers may be hesitant to disclose their level of drowsiness while driving, or the severity of the crash leaves the driver too incapacitated to report this information. Fatigued drivers are more likely to be involved in crashes and are more likely to be involved in higher severity crashes as drivers' reaction times are often delayed or drivers have not initiated crash avoidance maneuvers (National Academies of Science, Engineering, and Medicine, 2016).

FATIGUE DETECTION TECHNOLOGIES

It is very difficult for drivers to accurately assess their own level of fatigue. Subjective ratings of fatigue generally underestimate the magnitude of performance deficits due to fatigue (Banks et al., 2010; Van Dongen et al., 2003). Furthermore, the ability to self-assess fatigue becomes increasingly impaired as the level of fatigue increases; however, drivers' self-confidence in their ability to self-assess fatigue remains (Banks et al., 2010; Van Dongen et al., 2003). For these reasons, fatigue detection technologies can be an important life-saving tool for fatigue detection and crash avoidance and/or mitigation. Such technologies are becoming increasingly popular among fleet operations to assist in the detection of the onset of fatigue and interface with the driver to prevent crashes. Commercially available fatigue detection technologies use sensors to monitor and record a variety of measures, including physiological data (e.g., heart rate, oxygen saturation, electroencephalography [ECG], etc.), driver positioning and movement behaviors (e.g., gaze location and patterns, blink frequency, head position, etc.), and driver performance metrics (e.g., steering behavior, lane position, steering wheel pressure, etc.). As technologies advance, hybrid systems (i.e., combining multiple measures) result in a more-refined and robust fatigue monitoring and detection system. Fatigue detection technologies provide supplementary solutions, which, combined with education, safety culture, and safety management techniques, address the increasing problem of CMV driver fatigue.

RESEARCH OBJECTIVES

The Virginia Tech Transportation Institute (VTTI) research team conducted a comprehensive literature review to identify the types of fatigue detection technologies that are commercially available and detail their respective features for application in CMV operations. The literature review discusses technologies that (i) detect fatigue using physiological sensors from the driver; (ii) use computer vision to monitor driver behavior and positioning; (iii) record and monitor driver performance metrics, and (iv) combine multiple measures in a hybrid approach to monitoring and detection. The literature review does not discuss technologies that predict fatigue using neurobiological predictive modeling or scheduling algorithms. The literature review also does not discuss crash-mitigation technologies such as automatic braking systems, lane departure warning systems, and forward collision warning systems that are designed to cover a broad spectrum of crash types in addition to fatigue-related crashes.

Informed by the technologies discussed in the literature review, the VTTI research team developed an inventory of fatigue detection technologies that are currently commercially available for implementation in CMV operations. The inventory details their specific features, capabilities, limitations, applications, and efficacy (where available). Availability, cost, practicality for the industry, and stage of development for testing or implementation are also detailed for each technology. Finally, each technology is categorized, taking into consideration factors such as empirical validation, effectiveness, practicality, and availability. Development of this central and thorough inventory of fatigue detection technologies and their specific capabilities and applications for CMV operations is a helpful resource for the industry and may inform future research and evaluations using the most promising fatigue detection technologies.

CHAPTER 2. LITERATURE REVIEW

Physiological Sensors

Homeostatic and circadian processes are the primary neurobiological processes that impact drowsiness (Sparrow et al., 2018). As time awake increases, there is a progressive build-up of sleep pressure, which then dissipates with time asleep. The circadian process, which drives the 24-hour rhythms in the brain and body, represents peaks and lulls of wake and sleep pressures throughout the day (Borbely et al., 2016). Drowsiness results from high homeostatic pressure for sleep and low circadian pressure for wakefulness. Understandably, working populations that experience short sleep and shift work, such as CMV drivers, may experience the highest levels of drowsiness.

Drowsiness produces a variety of neurobiological changes in the brain and body that can be measured as correlates of fatigue (Sparrow et al., 2018). The reliability and accuracy of physiological signals to detect driver drowsiness is high compared to other methods; however, the intrusive nature of measuring physiological signals remains an issue in on-road and naturalistic driving studies (Sahayadas et al., 2012). Important and promising physiological indicators of fatigue are biomedical signals, such as electroencephalography (EEG), electrooculography (EOG), ECG, and electrodermal (EDA) activity. EEG is the measurement of the electrical activity of the brain. EOG, or the measurement of the electrical potential of the eye, is used to investigate movements of the eye. ECG is the measurement of the electrical activity of the heart, and electromyography (EMG) measures the electrical activity produced by skeletal muscles.

Electroencephalography (EEG)

EEG uses electrodes on the scalp to measure and record electrical activity and brain waves. EEG is one of the most reliable sources to detect sleep onset while driving (Mardi et al., 2011) and may be used as a predictive tool in detecting changes in alertness and vigilance (Lal & Craig, 2001). EEG has a high time resolution and can capture the physiological changes underlying cognitive processes. Furthermore, EEG sensors are able to detect subtle electrical impulses, providing valuable information on cognitive and attentional processing in the absence of behavioral responses. Finally, EEG systems are portable, lightweight, noninvasive, and inexpensive compared to other brain monitoring systems (such as magnetic resonance imaging [MRI]), allowing for more flexible data collection in naturalistic environments. In contrast to other single-channel physiological measurement tools, EEG recordings are made with electrode arrays consisting of 10 to 500 electrodes. For ease of application in a field test research environment, such as a vehicle, EEG electrodes are mounted in elastic caps or grids. This also ensures that data are collected from identical scalp positions across sessions or respondents.

The EEG signal is a mixture of several underlying base frequencies that reflect certain cognitive states and vary slightly depending on individual factors, stimulus properties, and internal states (Schomer & Lopes da Silva, 2011). EEG frequencies are classified based on specific amplitude ranges. The delta band represents the slowest and highest amplitude brainwaves [1–4 Hz] and are only present during deep non-rapid eye movement sleep. Delta band waves are indicative of deep sleep. Theta bands represent brain oscillations in the 4–8 Hz range and correlate with increasing task difficulty. Theta band activity is associated with brain processes underlying mental workload or working memory. Alpha band EEG activity (8–12 Hz) correlates with sensory, motor, and memory functions, while beta band activity (12–25 Hz) correlates with active, busy, or anxious thinking and active concentration. The associations between gamma band frequencies (above 25 Hz) and neurological activity are unknown. Alpha and theta spectral ranges are most typically associated with fatigue or drowsiness (Craig et al., 2012). In general, activities that require more wakefulness and less probability of sleep are associated with an increase in EEG activity in the alpha and theta power waves (Brown et al., 2013).

Simulator and on-road driving studies with passenger car and CMV drivers have shown increases in EEG alpha and theta activity at night, after extended periods of wake time, and during monotonous driving (Akerstedt et al., 2013; Anund et al., 2008; Jagannath and Balasubrammian, 2014; Kecklund and Akerstedt, 1993; Lal & Craig, 2002). To further validate findings, EEG changes have also been associated with subjective and objective signs of fatigue, including physical signs of drowsiness recorded and verified by video, driving-related errors, and simulated crashes (Akerstedt et al., 2013; Lal & Craig, 2002). Studies have also shown that mental fatigue from time on task may be observed with EEG measurements, specifically alpha and theta spectra, while driving (Perrier et al., 2016).

Although the literature supports EEG as a reliable tool for detecting sleep onset while driving (Mardi et al., 2011) and as a predictive tool for detecting changes in alertness and vigilance (Lal & Craig, 2001), a limitation for operational buy-in and implementation may be the intrusiveness of the technology in day-to-day applications under real-world environments. Commercially available EEG technology often requires the driver to wear a skullcap, which is connected to a computer by wires and may be constraining and uncomfortable (Bowman et al., 2012). Wireless EEG systems are in development and becoming increasingly available, but they still require the individual to wear head-mounted electrodes or sensors.

Electrooculography

EOG is considered a standard eye-movement measurement technique due to its safe, convenient, and efficient means of recording eye position in persons of all ages. The rich sensory and motor connections between the eye and brain make eye movement an insightful tool in identifying fatigue. Eye blinks associated with the onset of sleep or microsleeps display unique properties that reflect central nervous system changes related to sleep and wakefulness (Stern & Skelly, 1984). Electrodes are positioned above and below the eye, and the EOG signal records eye blinks, identifying blink types such as the small and slow blinks that characterize fatigue. Video oculography (VOG) will likely replace EOG as the preferred method for recording eye movements as VOG is able to allow horizontal and vertical eye-movement recordings. VOG systems have a high capacity for spatial localization of point of gaze and enable freedom of head movement, which are important features for driving studies (Morgan et al., 1999).

Independent studies have assessed drowsiness-related changes in ocular measures, such as the amplitude and velocity ratio of blinks (Anderson et al., 2010), blink duration (Anund et al., 2008), blink closing and opening durations (Picot et al., 2012), and percentage eye closure (PERCLOS) (Chua et al., 2012), in relation to sleep quantification. Simulator and on-road driving studies have shown EOG changes that characterize fatigue, including increases in EOG slow eye movements, small and rhythmic blinking patterns, and variations in eyelid parameters at night and after extended periods of wake time (Akerstedt et al., 2013; Hu & Zheng, 2009; Lal & Craig, 2002; Sandberg et al., 2011). Sandberg and colleagues (2011) also determined that sleep-related EOG indicators increased with time on task during day driving, suggesting the utility of EOG for identifying mental fatigue in addition to physical drowsiness.

The reliability and accuracy of EOG for identifying driver drowsiness through eye movements is widely supported in the literature (Sahayadhas et al., 2012); however, the intrusive nature of measuring physiological signals remains an issue to be addressed. Less intrusive wireless devices are becoming increasingly popular among researchers, but often at the sacrifice of accuracy due to movement artifacts and errors due to improper electrode contact. Recent research efforts aim to validate nonintrusive systems (Sahayadhas et al., 2012); however, finding the balance between sensor accuracy and user friendliness will prove challenging for implementation into CMV operations.

Heart Rate

The association between cardiovascular function, including heart rate (HR) and heart rate variability (HRV), and states of arousal and fatigue are well documented in the literature (Hartley et al., 1994; Jagannath et al., 2014; Lal & Craig, 2000; Lal & Craig, 2001; Lal & Craig, 2002; Raggatt & Morrissey, 1997; Riemersma et al., 1977). Considered the gold standard for recording and monitoring cardiac activity, ECGs are most frequently used in laboratory and controlled environments. Novel, video-based systems to measure non-contact HR are currently being evaluated; however, research is limited on the validation of these novel technologies (Sarkar et al., 2017). HR may be used as a physiological measure of workload during driving conditions and has the potential for indicating driver fatigue (Hartley et al., 1994; Lal & Craig, 2001). HR has been shown to decrease during prolonged night driving and monotonous driving tasks in simulator and on-road studies (Jagannath et al., 2014; Lal & Craig, 2000; Lal & Craig, 2002; Riemersma et al., 1977). A study with professional CMV drivers demonstrated similar findings as passenger car studies, including reduced HR and subjective arousal ratings during the final hours of an extended driving shift (Raggatt & Morrissey, 1997).

HRV is the variation in the time interval between heartbeats and provides information about emotional response by considering physiological activity, including respiration, vasomotor activity, internal temperature changes, and central nervous activity (Rogado et al., 2009). To interpret HRV, the amplitudes of the low and high frequency in the ECG are assessed. Their ratio decreases progressively as the driver transitions from an alert to a drowsy state (Philip et al., 2005). Increases in HRV have also been associated with fatigued driving and deterioration in driving performance (Harris & Mackie, 1972). These changes in cardiovascular indicators are interpreted as signs of diminished alertness as the body's autonomic nervous system shifts to favor parasympathetic activation (i.e., the body's rest and digest response) and sympathetic relaxation (i.e., the body's fight or flight response). In a study of the autonomic nervous system activity of CMV drivers in relation to their work activities and behaviors, Sato et al. (2001) observed a dominance of drivers' parasympathetic activity in the morning, which could cause drowsiness during morning driving. Conversely, completing mentally difficult tasks and maneuvers leads to an increase in HR and a decrease in HRV as the autonomic nervous system shifts to favor sympathetic activation over parasympathetic stimulus. A recent review of the literature further supports the association between mental and physical fatigue and HRV, suggesting that psychosocial workload (job stress) and working time (shift work) can have significant implications for HRV (Togo & Takahashi, 2009).

Blood Oxygen Saturation

Normal blood oxygen saturation is maintained at over 95% measured in the atmosphere at sea level altitude and is critical for maintaining physiological and cognitive processes and functions (Sung et al., 2005). Blood oxygen saturation can be measured easily and accurately in the field with pulse oximeter devices, which are worn unobtrusively on the finger and measure the ratio of oxygenated versus deoxygenated hemoglobin in the blood and blood volume. Oxygen saturation has been shown to decrease with the onset of fatigue (Schutz, 2001) and can impact brain functions critical for driving, including attentiveness, memory, and decision making (Sung et al., 2005). However, the literature review yielded inconclusive findings regarding oxygen desaturation accompanying fatigue while driving (Jagannath et al., 2014; Sung et al., 2005).

Galvanic Skin Response

Galvanic skin response (GSR) is a measurement of electrical conductance between two points on the skin and is used in research to measure emotional arousal and stress level (Bundele and Banerjee, 2009). GSR devices typically consist of two electrodes placed on the skin, an amplifier, and a digitizer; some devices allow arbitrary sensor placement, while others have electrodes rigidly mounted in wristbands or elastic straps. Wireless GSR devices are available that contain Bluetooth data transmission modules for communication with the recording computer. GSR has been demonstrated to increase with fatigue; however, because skin conductance also varies in response to other influences, including stress and sweat, the validity of GSR to accurately identify changes that are specific to work-related fatigue is unclear (Dawson et al., 2014; Miro et al., 2002;). Dorrian and colleagues (2008) investigated the sensitivity of a GSR monitoring device to detect experimentally induced sleepiness and fatigue during a driving simulator study. The authors found that GSR levels did not change significantly during a 28-hour period of sustained wakefulness, despite changes in subjective sleepiness, driving simulator performance, and Psychomotor Vigilance Task (PVT) performance. Several studies reported positive results for using GSR in combination with other physiological sensors, including EEG and ECG, for identifying fatigue; however, the literature lacks support for GSR as a stand-alone sensor associated with fatigue (Baek et al., 2009; Boon-Leng et al., 2015; Lim et. al., 2006).

DRIVER BEHAVIOR MONITORING/COMPUTER VISION

Drowsiness is displayed in several facial movements that can be monitored with computerized video technologies (Lew et al., 2007; Xiao et al., 2009). Visual-cue-based methods have attracted attention because they are noninvasive and can be used to predict drowsiness before an adverse driving event occurs (Darshana et al., 2014). Rapid eye movements and constant blinking, slow eyelid closure, nodding or swinging head, frequent yawning, facial tone, and eye rubbing are all behaviors characteristic of drowsiness (Lal and Craig, 2001; Xiao et al., 2009). Advancements in computer hardware and software have enabled affordable driver fatigue monitoring systems based on computer vision (Huang et al., 2007).

A limitation in using a video-based approach to detect fatigue is the amount of light. Standard cameras do not perform well at night, so researchers use active illumination with an infrared light-emitting diode (LED) to overcome this limitation (Bergasa et al., 2006). However, the daytime results with LEDs are less robust. After capturing the video, techniques are applied to detect the face, eyes, or mouth, and localize the specific region of interest within the image. Next, features of interest, such as PERCLOS (defined in next section), yawning frequency, and head angle are extracted. The behavior is analyzed and drowsiness is rated using a variety of classification methods (Sahayadhas et al., 2012). It is important to consider that the high success rate of many fatigue detection methods and tools is because they are validated during highly controlled conditions, such as simulator environments with controlled lighting and views of the driver without obstructions (i.e., not wearing glasses or hats that cover the eyes). The positive detection rate decreases significantly when carried out in a real-world operational environment (Philip et al., 2005). Another limitation in using behavioral measures to detect fatigue was highlighted by Golz and colleagues (2010), who concluded that behavioral measures alone were not powerful enough to correlate the state of driver fatigue to driving performance. Published research on behavioral approaches in determining drowsiness largely focuses on blinking and eye tracking (Bergasa et al., 2006; D'Orazio et al., 2007). Research on other behavioral measures, such as yawning, and head and body positions, is less validated for real-world applications (Murphy-Chutorian & Trivedi, 2010; Smith et al., 2003).

Blinking, Eye Closure, and Tracking

Ocular measures, such as eye-blinking and eyelid closure, are validated ways to monitor alertness (Ji and Yang, 2002). Technologies have been available for several decades that recognize whether a driver's eyes are open or closed and the degree of openness (Boverie et al., 1998; Grace, 2001; Ueno et al., 1994). PERCLOS is defined as the percentage of time during which the pupils are covered by the eyelid by more than 80% of their area (Wierwille et al., 1994). PERCLOS is more reflective of slow eyelid closures rather than blinks where the eyelids droop and close slowly. PERCLOS is a validated tool for predicting drowsiness and detecting fatigue and is significantly correlated with lane departure and attention lapses (Dinges & Grace, 1998; Knipling, 1998; McKinley et al., 2011; Sahayadhas et al., 2012). PERCLOS is measured most frequently using videography and processing techniques, though devices that directly measure PERCLOS in real time and provide immediate alerts and feedback have been developed and are being evaluated (Darshana et al. 2014; George & Routray, 2012).

Eye locating and tracking can be difficult, but are crucial tasks of real-time driver fatigue monitoring from computer vision. Microsleeps, or short sleep periods lasting several seconds, are good indicators of fatigue and are best detected by continuously monitoring the eyes of the driver (Singh et al., 2011). Variable lighting and illumination conditions, changing backgrounds, vibrations, and presence of eye or sunglasses can present unique challenges in a real-world operational environment. Researchers are continuing to refine precise algorithms to address and overcome these challenges in order to accurately monitor the driver during these conditions (Huang et al., 2007). Most eye tracking systems begin with an image of a driver in which the face and then eyes are detected (Singh et al., 2011). The next step is recognition of whether the eyes are open or closed, then a calculation of criteria for judging the drowsiness and fatigue level of the driver. Systems with a warning component provide an auditory, tactile, and/or visual warning if a driver is identified as being drowsy. Most eye tracking algorithms are faster than the standard PERCLOS, with processing times less than a half second, allowing fast and timely warnings to the driver (Singh et al., 2011).

PERCLOS and eye tracking systems have been used in commercial products designed specifically to detect fatigued driving (Abulkhair et al., 2015; Grace et al., 1998; Seeingmachines, 2018). These technologies are well documented and validated in simulator and naturalistic driving studies with passenger-car and CMV driver populations (Dasgupta et al., 2013; Garcia et al., 2010; He et al., 2013; Li et al., 2014; Wiegand et al., 2009).

Head Movement and Yawning

Techniques for monitoring head movement are limited and are not acceptable as a stand-alone technology detecting driver fatigue (Cheng et al., 2012). However, head position is a robust indicator of the driver's field of view and focus of attention. When used with other subjective, behavioral, physiological, and vehicular techniques, head dynamics have been found to be precise in detecting driver drowsiness and the gaze zone (Mittal et al., 2016; Tawari et al., 2014; Tawari & Trivedi, 2014). A multiperspective framework to continuously monitor a driver's head dynamics uses a multi-camera setup to monitor driver head movements (Martin et al., 2013). Selecting the optimal perspective to observe head dynamics is completed by identifying the ideal camera selection and setup. Fu et al. (2013) proposed an automatic calibration method supported by an algorithm to track head movements with a single camera, which operates all of the mirrors and instrument board. Complex systems that detect the driver's head and face, estimate head position, and constantly track the head's position and orientation in six degrees of freedom in daylight and nighttime lighting conditions are also available (Murphy-Chutorian et al., 2007; Murphy-Chutorian & Trivedi, 2010).

Yawning, a symptom of fatigue, can be monitored and detected with a single camera-based system with applications and programs that measure the geometric features of the mouth size and shape and texture of the mouth corners (Fan et al., 2007; Kuamr & Barwar, 2014). The yawn is modeled with a large vertical mouth opening, distinguished from speaking by mouth width. When yawning, the mouth opens wide and the geometric features of the mouth change (Ji et al., 2004; Rongben et al., 2004). Using face and mouth tracking, yawns may be detected based on an opening rate of the mouth and the changes in mouth size and shape.

The majority of research that supports yawning as a fatigue detection tool takes place in the laboratory by applying specific software and complex algorithms to existing video frames (Fan et al., 2007; Ojo et al., 2017; Saradadevi & Bajaj, 2008). Newer methodologies are being evaluated that provide real-time detection of driver fatigue by monitoring yawning behavior; however, these methodologies have not been evaluated in simulator or naturalistic driving environments (Kuamr & Barwar, 2014; Li et al., 2009).

Driver Performance

Driving requires cognitive effort, including sustained vigilance, selective attention, complex decision-making, and perceptual-motor control skills (Lal & Craig, 2001). Performance over time, like that required during driving, requires greater cognitive effort than physical effort (Brown, 1994). Long hours of continuous driving, a monotonous driving environment, and driving during early morning hours or at night often lead to degradation in driver performance (Miller & Mackie, 1980). Circadian rhythms further impact driving performance as levels of arousal change (Adkins, 1964). Driving during periods of the day when physiological activity is increasing improves driver performance, while driving during times of the day when physiological activity is diminishing acts synergistically and reduces performance.

In order to measure the impact of fatigue on driver performance, direct indices of driving must be assessed, including steering control and behavior and speed maintenance. However, it is also important to measure perceptual, motor, and cognitive skills associated with driving performance, as decrements in these skills may be observed with lesser levels of fatigue (Williamson et al., 1996).

Driving simulators can be used to measure driver performance metrics; however, the behavioral validity of these performance measures, compared to those collected in real-world driving situations, has been challenged (Mullen et al., 2011). Naturalistic driving research provides a unique way to unobtrusively evaluate driving performance using cameras and sensors that record continuous data in real time (Dingus et al., 2001). Sensors placed on the vehicle monitor performance metrics, such as steering, lateral and longitudinal acceleration, lane deviation, time-to-collision, and side collision. A recent analysis from a large-scale naturalistic driving study concluded that errors in driver performance increase the overall risk of a crash more than 18 times compared with model driving (Dingus et al., 2016).

Technological countermeasures based on objective driving performance data and vehicle dynamics have been designed to detect driver drowsiness so that a driver can be warned before a crash. Researchers are developing complex predictive algorithms from real-time measures of vehicle-based driver performance metrics in order to detect fatigue early and thus prevent or mitigate crashes (McDonald et al., 2012). Vehicle-based driver performance measures typically involve lateral control, such as steering behavior and steering-wheel angle (Eskandarian & Mortazavi, 2007; Krajewski et al., 2009; Krajewski et al., 2010; Sayed & Eskandarian, 2001), and lane position deviation (Hanowski et al., 2008).

Steering Behavior and Lane Position

Commonly used driver performance measures for detecting drowsiness are steering wheel movement and lane position (Stork et al., 2015). Steering wheel movement is measured using steering angle sensors mounted on the steering column. When the driver is drowsy, the number of micro-corrections to the steering wheel (which are common in normal driving) are reduced (Nopsuwanchai et al., 2008; Wiskott et al., 1999). Steering behavior monitoring is one of the most promising methods in fatigue detection, as these systems continuously measure driver steering responses, are inexpensive, nonintrusive, and robust under demanding environmental conditions such as high background noise, temperature, or humidity (Oussama et al. 2013; Tsunai et al., 2008). Patterns of slow drifting and fast corrective counter steering are observed as fatigue sets in and influences steering behavior. Lane position, measured by the standard deviation of lateral position, is an index of weaving and a stable measure of driving performance with high reliability (Verster & Roth, 2011). Lane position is a continuous driver performance measure that is sensitive to sleepiness; however, it is also dependent on external factors that are not always specific to the driver's drowsiness (Stork et al., 2015). To measure lane position, a vehicle-mounted camera measures the vehicle's lateral position relative to the lane and roadway markings (Verster & Roth, 2011).

Steering behavior and lane position are influenced by characteristics of the driving task (speed or roadway variables), traits of the drivers (age and experience), and driver state (distraction or fatigue) (Krajewski et al., 2009). Drivers are constantly assessing the roadway ahead and applying small movements and adjustments in response to surrounding conditions. Fatigue can impair steering behavior, which is measured in several behaviors, such as pronounced and rough steering adjustments, zigzags and slow oscillations, larger erratic steering movements and corrections, and lateral drift outside the driver's comfort zone (Paul et al., 2006; van der Hulst et al., 2001). Steering behavior and steering wheel movement have been shown to be powerful predictors of drowsiness and are favorable indicators for detecting fatigue (Eskandarian & Mortazavi, 2007; Krajewski et al., 2009; Krajewski et al., 2010; Sayed & Eskandarian, 2001). However, studies have determined that vehicle-based measures by themselves are poor predictors of drowsiness as these metrics are not specific to drowsiness and can also be caused by impaired and distracted driving (Sahayadhas et al., 2012).

HYBRID SYSTEMS

Driver fatigue is a complex phenomenon that can be measured indirectly from a variety of visual (driver behavior and driving performance) and nonvisual (physiological variables) metrics, each of which have strengths and weaknesses. Visual-cue-based methods are appealing because they are noninvasive and can be used to predict drowsiness before an adverse event occurs (Darshana et al., 2014); however, environmental conditions, such as variable lighting and illumination, changing backgrounds, vibrations, and the presence of eyeglasses or sunglasses, can present unique challenges in a real-world operational environment (Huang et al., 2007). The reliability and accuracy of physiological signals to detect driver drowsiness is high compared to other methods; however, the intrusive nature of measuring physiological signals remains an issue in road and naturalistic driving studies (Sahayadas et al., 2012). Using hybrid systems that combine multiple metrics to detect fatigue can result in a more refined, robust, and intelligent fatigue monitoring system.

The advantages of physiological measures and the increasing availability of nonintrusive measurement equipment make it beneficial to combine physiological sensors with driver behavioral and vehicle-based measures (Sahayadhas et al., 2012). Analyzing biological and environmental variables has shown promising results for detecting loss of alertness prior to the driver falling asleep (Rogado et al., 2009). Cheng and colleagues (2012) combined behavioral measures and vehicle-based measures, concluding that the reliability and accuracy of the hybrid method was significantly higher than methods using single sensors. A combination of subjective, behavioral (PERCLOS), and physiological measures (ECG and EEG) was used to detect driver drowsiness, and the authors concluded that this combination resulted in a significantly higher success rate than any individual metric (Yang et al., 2010). Rogado et al. (2009) developed algorithms that use HRV, steering-wheel grip pressure, and temperature difference between the inside and outside of the vehicle to estimate driver fatigue level.

To address the limitations of PERCLOS as a single-measure device (i.e., loss of data based on eye-closure metrics), Bowman and colleagues (2008) developed and investigated an integrated

PERCLOS + model that combined two drowsiness measures, PERCLOS and lane position. Key findings from the study were that combining a machine-vision-based eye-monitoring technology with analysis of operator and vehicle performance parameters would provide a robust metric to reliably assess driver drowsiness and would be superior to a single-measure approach. As the authors hypothesized, the strength of one sensor was able to overcome the weaknesses of the other sensor for nearly all of the functional specifications that were assessed. Razzaq and colleagues (2017) furthered the work of Bowman et al. (2008) and introduced a hybrid approach to quantify a driver's fatigue level by combining PERCLOS, yawn factor, and lane departure. Their Fatigue Quantifying System integrates a video-based fatigue detection system along with lane departure technology, combining both visual and road features to detect driver drowsiness. The authors claim this system will achieve more precision than stand-alone systems and reduce the rate of false alarms, with preliminary results showing high accuracy, decreased false alarm rates, and low cost. The Fatigue Quantifying System also demonstrates accuracy for real-world application in suboptimal environments or situations, such as low light and when the driver's face or eyes are obstructed.

Several fatigue technologies and drowsiness warning systems that use a hybrid approach for detecting fatigue are in development, undergoing beta testing, or are recently commercially available. This market will continue to expand as the advantages of hybrid systems are increasingly recognized and validated. Currently, however, the majority of these technologies lack independent and scientific evaluations.

CHAPTER 3. METHODS

Numerous fatigue detection technologies are commercially available, and a thorough inventory of these technologies and their capabilities and limitations will be a helpful resource for the CMV industry. To address this need, the VTTI research team conducted a comprehensive inventory of existing fatigue detection technologies that details the key features, functions, and applications of systems used by or that have application for the CMV industry. Technologies that are currently available or that are in development or beta testing and nearly available for commercial distribution were included. Fatigue technologies include physiological sensors and wearable systems, driver behavior monitoring and computer vision systems, driver performance systems, and hybrid systems that monitor a combination of metrics to detect fatigue.

To guide the structure and process of the comprehensive catalog and review, the following tasks were completed:

1. All available technologies were identified from a review of the literature and peer-reviewed journals, Web searches, interviews with fatigue and CMV industry experts, and technical and white papers.

2. The most promising technologies were identified by considering the availability and costs of systems, efficacy and practicality for the industry, and current stage of development. Information was gathered on the most promising technologies identified from technology vendor materials, reports, and correspondences (interviews, emails, etc.), correspondence with fleet representatives who have experience with these technologies, and peer-reviewed publications, when available. The VTTI research team used a similar approach to that detailed in Hickman et al. (under Agency review) to identify and rate fatigue technologies. Technologies were grouped according to the following criteria:

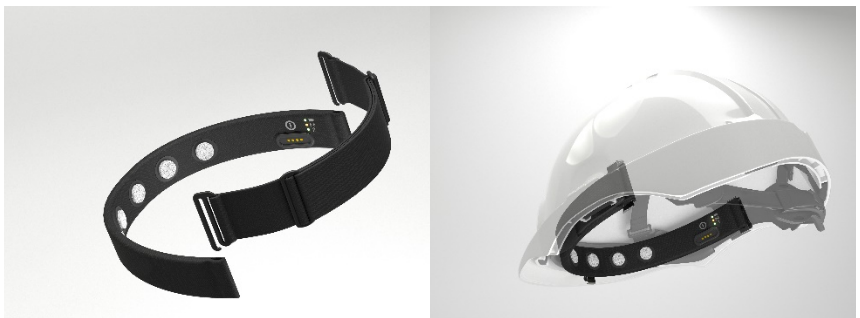
    - **Validated**: Empirically studied and effective technologies using sound experimental and statistical techniques.
    - **Promising but insufficient data**: Likely to be effective technologies, but minimal published research exists.
    - **Unvalidated:** Technologies that have not been empirically researched.
    - **Ineffective**: Fatigue technologies that were found to be ineffective at improving safety.
    - **Unlikely to be used in the future**: Fatigue technologies that are outdated (e.g., no longer needed or another fatigue technology incorporates the same features).

CHAPTER 4. INVENTORY OF FATIGUE DETECTION TECHNOLOGIES

This comprehensive inventory of existing fatigue detection technologies details key features, functions, and applications of systems used by or that have applications for the CMV industry.

VALIDATED TECHNOLOGIES

Table 1. SmartCap.

Name of Technology: Life by SmartCap  **Figure 1. Photo. Equipment for Lifeband by SmartCap.**
URL: http://www.smartcaptech.com
Key Features: Life by SmartCap is a band of sensors that can be worn in a hat or by itself around the head. The Lifeband measures the ability to resist sleep by monitoring brainwaves. The Life system provides real-time feedback to the wearer and audibly and visually alerts the wearer before microsleeps occur through a display or an app on a smartphone or tablet. Though this technology relies on self-monitoring, it can alert management and/or family of fatigue levels.
Functions: Physiological Sensor (EEG, wearable device)
Effectiveness: Evaluation of the SmartCap was conducted by Monash University. Researchers used the Osler (Oxford Sleep Resistance Test) task to evaluate the SmartCap. The Osler is a behavioral measure of sleep latency in which four consecutive misses are indicative of having brief periods of EEG-defined sleep. Researchers found that an average score of 4 with the SmartCap (very drowsy) provided a high sensitivity (94.75%), correctly identifying most of the 1-minute periods when severe sleepiness was present. An average score of 4 with the SmartCap had a specificity of 81.9% to 82.1%. Thus, it has a small to moderate false positive rate (Rajaratnam, S., & Howard, M., personal communication, June, 2011). In addition, the University of Chile determined that the SmartCap utilizes signals that reliably represent EEG and reflect expected circadian patterns (University of Chile, 2015).
Availability: Currently on the market
Cost: Must inquire for exact pricing. Costs include a one-time purchase of the required hardware and the potential purchase of a LifeDisplay; however, transport customers can integrate Life into their

telematics system, so there may be no need for an additional screen. The charge for all software licensing, maintenance, and support is on a per user per month basis.
Practicality for CMV Industry: Life works in most operational environments. There are no known environmental limitations, such as day versus night or rainy versus dry weather. However, drivers must wear the cap (or at a minimum the band) at all times while driving and keep the battery charged in order for it to work. The Life battery needs to be charged while the driver sleeps. Alerts are given directly to the driver; however, fleet managers have the option of being made aware of the fatigue levels of their drivers. If fleet managers choose to be alerted to a fatigued driver, they must filter through and monitor all the fatigue alerts they receive and get in touch with fatigued drivers to address concerns. Drivers must feel comfortable wearing the device in order to remain compliant. Drivers must also clean the hat/band approximately every three months for optimal performance.
Rating: Validated

Table 2. Eagle Industrial and Eagle Portable.

Name of Technology:
Eagle Industrial and Eagle Portable

Figure 2. Photo. Optalert glasses and depiction of portable display.

URL:
http://www.optalert.com/

Key Features:
The Eagle Industrial and Eagle Portable are glasses that monitor eye and eyelid movements. The system calculates multiple variables from the neuromuscular function of muscles in the eyelids during their reflex-controlled movements with each blink. The glasses have infrared (IR) reflectance oculography that provides a continuous measurement of drowsiness using the validated Johns Drowsiness Scale (JDS). The JDS is reported to the wearer continuously in real time every minute as a value between 0.0 and 9.9. The constant feedback to the driver allows the driver to self-manage fatigue. Drivers are warned 15 to 20 minutes before they actually have microsleeps. An auditory alert sounds when a high level of fatigue is detected. Managers are able to access the drowsiness levels of all their drivers in real time, as well as opt to receive an email or text alert when a driver receives a "High Risk" warning. Data collected by the system can be analyzed and used to help fleets mitigate fatigue. There are two versions available, a portable system and an industrial system. The portable system is a plug-and-play version that uses a smartphone as the display for the JDS and wireless glasses. Both systems use over-the-air software updates.

Functions:
Driver Behavior Monitoring (wearable device, eyelid movement, changes in blinking)

Effectiveness:
Validation of the JDS scores was conducted by assessing homeostatic and circadian change (Anderson, Chang, Ronda, & Czeisler, 2010). Fourteen participants completed 30 hours of wakefulness while wearing the Eagle glasses and completing bi-hourly neurobehavioral tests, including the Karolinska Sleepiness Scale (KSS) and PVT. Researchers concluded that the average JDS scores above the cautionary level were associated with delayed response times and subjective sleepiness when compared to average JDS scores below the cautionary level.

Stephan et al. (2006) investigated lane deviations of alert and sleep-deprived drivers up to 30 minutes after a driver scored a cautionary and critical JDS. Their study showed a significant increase in the proportion of time a vehicle left its lane during the 30 minutes following a cautionary JDS level (4.5; $p <. 002$) or a critical level (5; $p < .01$) than for periods that cautionary or critical JDS levels had not been reached. In addition, under sleep-deprived conditions, the study showed a sensitivity range of 70.6 to 75.0 for 5 to 30 minutes following a cautionary JDS and 45.8 to 56.3 for 5 to 30 minutes following a critical JDS value. The study showed a specificity range of 65.4 to 71.4 for 5 to 30 minutes following a cautionary JDS and 56.3 to 70.0 for 5 to 30 minutes following a critical JDS.

Availability: Currently on the market worldwide
Cost: $1,000 per unit if 100 or more units are ordered and one's own Android tablet is used as a display. There is also a monthly subscription fee of $20 to $50 depending on the level of service requested.
Practicality for CMV Industry: The glasses have three different interchangeable shades of lenses so data collection can continue in all light conditions (bright sunlight, dim light, and complete darkness). The lenses can be adapted for prescriptions as well. However, if the light changes during a driving shift, drivers may try to change lenses while driving, wear the incorrect shade lenses for the environment, or take off the glasses altogether in order to see properly. Fleet managers have the option to receive alerts regarding drivers if they receive a "high risk" warning. The drivers must wear the glasses in order for the system to operate, and some individuals might find the glasses uncomfortable or feel they obstruct their view of the road. The glasses come with or without a wire for portability. Software updates are automatically downloaded and installed. The Eagle Portable version is plug-and-play, so there is no downtime for fleets during installation.
Rating: Validated

Table 3. Guardian.

Name of Technology:
Guardian

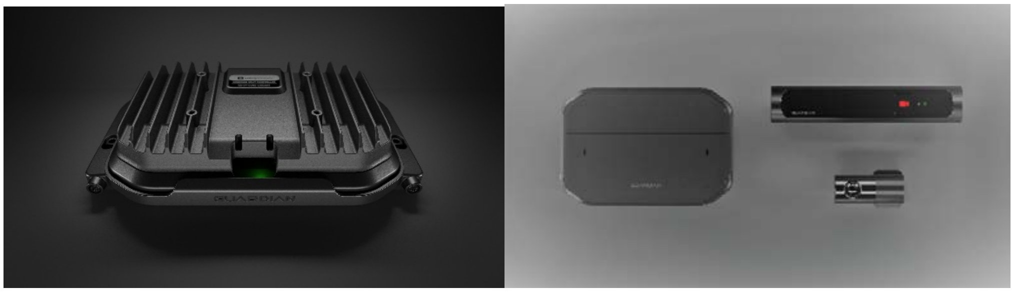


Figure 3. Photo. Guardian controller and system layout.

URL:
www.seeingmachines.com/guardian

Key Features:
This system is composed of two cameras. One camera captures the forward roadway and the other captures the driver. The forward-facing camera uses a wide-angle lens to capture footage in the event of an incident. The in-vehicle system uses infrared sensors to detect fatigue and distraction through proprietary face- and eye-tracking algorithms that measure eyelid closure, blink rate, and the head position of the driver. When these sensors detect microsleeps or driver inattention, the system alerts the driver with an audio tone and vibrating seat. The 24/7 SafeGuard Center provides around-the-clock fleet protection through live data analysis and human intervention. In case of a verified fatigue event, managers will be notified within two minutes.

Functions:
Driver Monitoring (PERCLOS, blink rate, head position)

Effectiveness:
A study of three long-haul trucking companies in South Africa showed a 93.2% reduction in fatigue events per hour in the intervention period (incidence rate ratio [IRR]: 0.068, 95% confidence interval [CI]: 0.059–0.078, $p \leq 0.001$) versus the baseline period during which the trucks were installed with Guardian but no feedback was given to the driver. When fatigue-related events were compared on a per distance travelled basis, there was a 90.9% reduction in fatigue related events (IRR: 0.091, 95% CI: 0.080–0.105, $p \leq 0.001$) (Lenne & Fitzharris, 2016).

Availability:
Currently on the market globally

Cost:
Must inquire for pricing.

Practicality for CMV Industry:
Guardian operates and maintains tracking integrity through a range of lighting from bright sunlight to nighttime. It also functions with most glasses, even sunglasses, as the system will then use head pose to determine fatigue level. Managers are notified and can take action should a driver receive a fatigue alert. They can also use data from the system to analyze the entire fleet and find ways to mitigate fatigue. Moreover, should an event occur, the video from the forward-facing camera offers the company additional protection. Drivers may like the privacy feature that the camera only records if it senses a fatigue or distraction event.

Rating:
Validated

PROMISING TECHNOLOGIES

Table 4. LUCI.

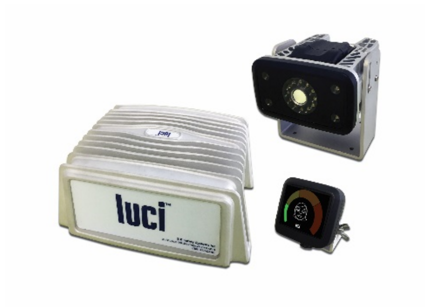
Name of Technology: LUCI  **Figure 4. Photo. LUCI driver monitoring system.**
URL: http://www.sixsafetysystems.com/
Key Features: LUCI is a dash-mounted driver monitoring system that uses near-infrared sensors to detect and measure the operator's eye movements. The readings are analyzed to determine real-time levels of fatigue and distraction. Through an interface, LUCI offers feedback to operators on their current state of alertness and sends both visual and audible alerts to the operator when it detects unacceptable levels of alertness or distraction. If a risk threshold is reached (frequent alerts from the same operator), alerts will also be sent to supervisors, managers, or other responsible parties to inform them of operator fatigue and distraction.
Functions: Driver Monitoring (eye movements)
Effectiveness: Six Safety Systems claims that the system is validated by Simon Fraser University; however, the authors of this catalog were unable to obtain the report.
Availability: Currently on the market. Currently available for installation in North America, South America, and Africa.
Cost: Must call company for an estimate.
Practicality for CMV Industry: LUCI is an unobtrusive system that detects the operator's eye movements regardless of operating environment. Eyewear, including prescription glasses, contact lenses, sunglasses (including polarized), and safety glasses, does not hinder detection. The fatigue alerts are first given only to the driver unless a certain threshold (which can be determined individually by the fleet) has been reached. This threshold-setting feature cuts down on supervisors having to sift through alerts. It also may make drivers feel more comfortable with the system if they know not every incident is reported to their supervisor. Fatigue data are available through an online portal for managers. The fatigue data can help organizations better understand operational risk. Drivers do not need to wear any special equipment in order for the system to function, making compliance easy. In addition, there are no stored video recordings, which may put drivers more at ease with using the system.
Rating: Promising

Table 5. Smart Eye Antisleep.

Name of Technology: Smart Eye – AntiSleep
URL: http://smarteye.se
Key Features: Smart Eye's AntiSleep technology uses one camera to track multiple fatigue factors, focusing on gaze direction, eyelid closure, and head position and orientation. AntiSleep uses 3-D mapping and an algorithm to derive real-time data output. The system uses a single standard VGA camera together with IR flash illuminators tuned to frequencies that receive minimum interference from outdoor light, making the system robust to all natural illumination conditions in automotive applications (Ahlstrom & Dukic, 2010). It is currently an extensible system; although it does not give any specific alarms or feedback to the driver following the detection of fatigue, such features can be integrated by manufacturers as they wish. One-camera systems, such as the Smart Eye AntiSleep, are cheaper, easier to operate, and easier to install in a vehicle compared to multi-camera systems, which are more accurate and widely available. A one-camera system is most suitable for in-vehicle applications, such as systems that warn drivers of drowsiness or internal distractions (Ahlstrom & Dukic, 2010).
Functions: Driver Behavior Monitoring (head tracking, eye position, eye gaze, pupil diameter, blinks, eyelid opening).
Effectiveness: N/A
Availability: Currently on the market to be integrated with vehicle manufacturing
Cost: Unknown
Practicality for CMV Industry: The AntiSleep creates its own light and thus is functional in all natural lighting conditions and with almost all types of eyeglasses. Over time, the system learns each face it analyzes and builds a detailed profile of it. Eventually, only a few features are needed to determine head pose, even if the face is partially obscured. The system currently is developed for integration within a vehicle and is not available after-market.
Rating: Promising

Table 6. Drover Fatigue Alarm StopSleep.

Name of Technology: Drover Fatigue Alarm StopSleep
URL: http://www.stopsleep.biz/driver-fatigue-alarm
Key Features: StopSleep is worn on two adjacent fingers and senses drowsiness through EDA. The processing algorithm of the signal is used to detect two different states of alertness. When the StopSleep senses a strong EDA decrease, it recognizes that as an indication of falling asleep and warns the driver through tactile (i.e., vibration) and auditory alerts.
Functions: Physiological Sensors (wearable, EDA)
Effectiveness: The National Scientific Research Centre (CNRS) in France completed a study on StopSleep's effectiveness. Their results support the effectiveness of StopSleep in alerting at two levels: initial signs of drowsiness (progressive decline in concentration and awareness) and sleepiness (significant drop in concentration and awareness).
Availability: Currently on the market
Cost: The StopSleep device costs approximately $199. For the StopSleep device with additional chargers (car, wall, and extra USB), the cost is approximately $234. The cost is approximately $293 for the StopSleep device, additional chargers, and a one-year warranty.
Practicality for CMV Industry: StopSleep has a battery life of 15 hours. The device must be worn and be charged (takes approximately one hour to charge) in order to function. The StopSleep does not have back-office support and thus relies on the driver taking action when alerted. However, a log file, which can be manually downloaded via a USB cable to a computer, provides a record of when the device emitted a warning or attention signal, or an alarm,. A driver must wear the device for 3 to 5 minutes while alert to calibrate it. If a driver is already fatigued during calibration, the device will not provide alerts to the driver. StopSleep does not work if left in a cold environment. Therefore, an individual must wait until the device warms up to a functional temperature before calibration, which can take up to 10 minutes. This delay in cold temperatures may reduce use due to scheduling pressures.
Rating: Promising

Table 7. BioHarness.

Name of Technology: BioHarness
URL: https://www.biopac.com/product/bioharness-telemetry-logging-systems/
Key Features: BioHarness is a wearable harness made of elasticized webbing that monitors, analyzes, and records a variety of physiological parameters, including ECG, respiration, posture, and HR using the Acq*Knowledge* software. This technology does not provide alerts to the wearer.
Functions: Physiological Sensors (ECG, HR, respiration, wearable device)
Effectiveness: "Good to excellent quality evidence from ten studies suggested that the Zephyr BioHarness device can provide reliable and valid measurements of heart rate across multiple contexts, and that it displayed good agreements vs. gold standard comparators – supporting criterion validity." (Nazari et al., 2018)
Availability: Currently on the market
Cost: Unknown
Practicality for CMV Industry: There are no known environmental conditions in which the BioHarness does not function. BioHarness is currently designed to monitor and record biometric data, but does not provide any alerts. Thus, the system, in its current form, would not be useful as a fatigue monitoring device unless it could be integrated into another system that did provide alerts. Drivers would have to wear the BioHarness at all times while driving and keep it charged. The harness is made in different sizes to fit different body frames. Battery life is 12 to 28 hours.
Rating: Promising

UNVALIDATED TECHNOLOGIES

Table 8. DriveFit.

Name of Technology:
DriveFit

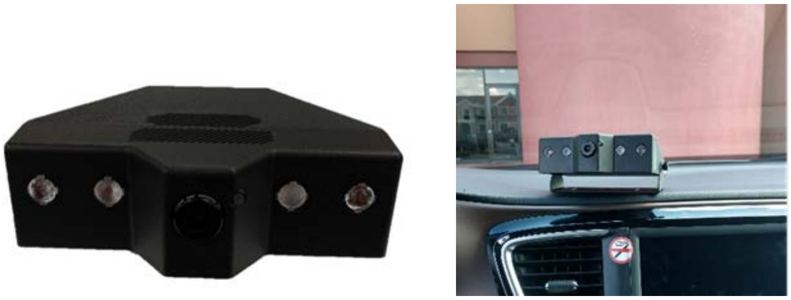


Figure 5. Photo. Front view and mounted view of DriveFit prototype.

URL:
https://www.guardvant.com/

Key Features:
DriveFit is an all-in-one camera unit measuring 4 ×4 × 1 inches that mounts on the vehicle dash. DriveFit monitors driver fatigue by measuring PERCLOS, pupils, and head and facial movements. DriveFit monitors these features in real time, and when fatigue is detected, an audible alert sounds and the driver's seat can vibrate. DriveFit uses Wi-Fi and cellular service to upload data to a server for future analysis.

Functions:
Driver Monitoring (PERCLOS, pupils, head and facial movements)

Effectiveness:
N/A

Availability:
Not yet released, but scheduled for late 2019

Cost:
Currently unknown

Practicality for CMV Industry:
DriveFit works in most operational environments from −20° to 70° Celsius. There are no environmental limitations such as day versus night or rainy versus dry weather. Currently, a similar system is used in the mining industry. The camera signals an audible alert and/or seat vibration to a driver in real time based on algorithms. All alerts are customizable. Videos of the event are synched to a server and can be sent to dispatch or a Guardvant call center, which then filters false positives and sends videos to the appropriate safety manager or supervisor. System maintenance is completed remotely through software updates by Guardvant. The cameras used for DriveFit are infrared so they are operational through various lighting environments. However, sun glare and eyeglasses with infrared filtering or mirrors can have an effect on functionality as the camera is no longer able to capture eye movements. Drivers will have to accept that they are being video recorded. Drivers can tamper with the system by covering the camera or disconnecting wires; however, tamper notifications are sent to responsible parties when any tampering of the system occurs.

Rating:
Unvalidated

Table 9. Multi Modal Driver Distraction and Fatigue Detection/Warning System.

Name of Technology: Multi Modal Driver Distraction and Fatigue Detection/Warning System (MDF)
URL: https://www.i-a-i.com/
Key Features: The MDF is still in development and has various modalities to determine whether a driver is fatigued, including cameras to monitor head position and eyes, driving metrics to monitor driving behavior such as brake usage and steering, and possibly physiological measures that are yet to be determined through a wearable device. If one of the modalities is not able to function well due to conditions, the other modalities will provide enough information to determine driver fatigue. How the feedback is provided to the driver is still being considered. This system will also assess distraction.
Functions: Driver Behavior Monitoring (head pose, PERCLOS), Driver Performance (steering entropy, lane deviation), Possible Wearable (undecided)
Effectiveness: N/A
Availability: In development phase
Cost: N/A
Practicality for CMV Industry: Using the concept of multiple modalities to gather fatigue information on a driver ensures reliability across various conditions (lighting, road conditions, etc.). However, drivers will have to accept being constantly monitored via multiple methods. If this system includes a wearable device, the drivers may find it uncomfortable, or forget to wear it or keep it charged.
Rating: Unvalidated

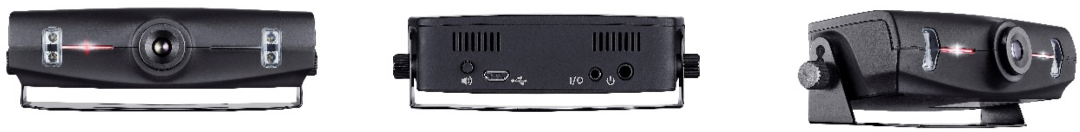
Table 10. Co-Pilot and Co-Pilot SE.

Name of Technology: Co-Pilot & Co-Pilot SE
URL: https://mavenmachines.com/
Key Features: The Co-Pilot (headset) and Co-Pilot SE (Bluetooth earpiece) are wearable devices with sensors that gather real-time data. The Co-Pilot monitors head movements and adherence to the Federal Motor Carrier Safety Administration's best practices of checking mirrors every 5 to 8 seconds. Co-Pilot detects any decay or inactivity over one minute and gives the wearer verbal updates of fatigue as it takes into account mirror check head movements and the head bob. The Co-Pilot can also provide mirror checks in real time to fleets when desired.
Functions: Driver Monitoring (wearable device, mirror checks, head bob)
Effectiveness: N/A
Availability: Currently on the market
Cost: The headset hardware starts at $99 depending on the model, and service costs $30 per month with some flexibility depending on fleet size.
Practicality for CMV Industry: No known environmental factors will influence the functionality of the Co-Pilot system since it does not rely on any imaging. Drivers and fleets get an immediate alert of early fatigue. Fleet managers can monitor drivers by receiving real-time alerts and having them mapped. Additional information such as routing, weather, messages, braking, and hours of service can also be sent to the driver through the Co-Pilot. Since all messages are auditory, drivers do not need to take their eyes off the road in order to receive them. In addition, the wearer can provide feedback to the system with head nods. No professional installation is required as all systems are "plug in" systems and can be installed within five minutes. Drivers will have to wear the headset and earpiece and feel comfortable doing so in order for the system to work.
Rating: Unvalidated

Table 11. SmartTrans.

Name of Technology: SmartTrans
URL: http://www.smarttrans.us/
Key Features: SmartTrans is a dash-mounted camera and sensory system to help monitor an individual's face and HR, as well as environmental conditions, such as light, air quality, noise, and other factors not yet disclosed. When conditions are not optimal for alertness (e.g., too warm), or a driver is nodding off and/or not looking at the road, SmartTrans provides an auditory alert of the potential sign of fatigue. An associated app claims to help manage fatigue based on fatigue-related information entered manually.
Functions: Driver Monitoring (gaze location, head position, environmental factors)
Effectiveness: N/A
Availability: Still in development
Cost: N/A
Practicality for CMV Industry: There is not any information as to how the camera works under varying light or environmental conditions. If there are signs of fatigue (head nods, etc.), the system can alert third parties. The system may be easier for a driver to accept as no video is recorded and no data leave the vehicle.
Rating: Unvalidated

Table 12. TS Driver Fatigue Monitor.

Name of Technology: TS Driver Fatigue Monitor DFM2  **Figure 6. Photo. Front, back, and side views of the Driver Fatigue Monitor (DFM2).**
URL: http://www.transportsupport.co.uk/product/ts-driver-fatigue-monitor-dfm2/
Key Features: The DFM2 system is a dash-mounted camera system that detects driver fatigue based on PERCLOS and distraction based on glances away from the forward roadway. Once the system detects that the driver is fatigued, it immediately sounds an audible beep. The warning goes off when a driver's eyes are closed for a preset sensitivity time (about 1 second) or the driver looks more than 30 degrees in any direction away from the forward roadway. Another alert warns the driver when the drowsiness continues for 1 second after the first warning until the driver opens his/her eyes. If a driver shows distraction (determined by glance deviation from looking forward), a different alert will sound. The alert increases in volume and frequency when dangerous levels of fatigue are found. The system also features an output port that can be used to trigger external warning devices and telematics systems so that alerts can be monitored by fleet personnel.
Functions: Driver Monitoring (PERCLOS)
Effectiveness: N/A
Availability: Currently on the market
Cost: One kit costs approximately $323.
Practicality for CMV Industry: This system works in vehicle cabs from −20º Celsius to +70º Celsius. Infrared LEDs illuminate the driver at night and in tunnels. The detection of eyes is possible even when an individual is wearing glasses or sunglasses, with the exception of mirror-coated glasses. The system works with any skin or eye color. However, the system may not be able to recognize individuals with white or no eyebrows, rough scars, deep wrinkles near the eyes, or only one eye. If the driver's hair in any way blocks the eye, the system may not recognize eye movements. The recognition rate may be reduced before and after sunrise/sunset or be affected by sideways light or external light. The system takes up to five seconds to recognize a face and a few more seconds to lock in on the eyes to calibrate. The system indicates that it is able to identify and read the face by illuminating a green light. This system works with 12-volt and 24-volt vehicles, has a cradle mount for easy installations, and updates are available through a USB connector. The sensitivity of the system is adjustable to three different levels (high, medium, and low), as is the volume. The warnings will only sound once every 10

seconds in order to allow time for the driver to react and change behavior. The warning may go off when the system perceives that a driver's eyes may be closed, such as when the driver looks down or narrows his or her eyes. The system supports USB accessories, such as LED warning lights and vibration pads, and works with external devices, such as car navigators, dash cameras, Global Positioning Systems, telematics systems, etc. The system also features an output port that can be used to trigger external warning devices and telematics systems so that driver fatigue and alerts can be remotely monitored.
Rating: Unvalidated

Table 13. NoNap.

Name of Technology: NoNap
URL: http://www.thenonap.com/
Key Features: The NoNap is worn over the left ear with an electronic position sensor. When the wearer's head nods forward, the device provides tactile and auditory alerts to warn the driver as well as any passengers.
Functions: Driver Behavior Monitoring (wearable, head position)
Effectiveness: N/A
Availability: Currently on the market
Cost: $20 per unit
Practicality for CMV Industry: As the NoNap does not rely on cameras to detect fatigue, it works in all lighting and environmental conditions. The device does not provide back-office support, and thus relies on the driver to respond to alerts. The head tilt needed to alert the driver can be adjusted to between 15 and 20 degrees. Drivers with hearing limitations in the left ear would not be able to use this device. Drivers can wear the unit with eyeglasses and sunglasses.
Rating: Unvalidated

Table 14. Advisory System for Tired Drivers (ASTiD).

Name of Technology: Advisory System for Tired Drivers (ASTiD)
URL: https://fmiltd.co.uk/
Key Features: The ASTiD combines two systems to monitor driver sleepiness: a knowledge-based system and a steering sensory system. The knowledge-based system takes into account the time of day, circadian rhythm, and the length and type of driving. The driver can also input information on sleep quality to increase or decrease the sensitivity of the system. The steering sensory system detects monotonous driving and steering characteristics that are typical of fatigued driving, such as over-corrected steering adjustments. An early warning alert (type of alert was not noted) is given to a driver when the system detects signs of drowsiness.
Functions: Driver Performance (steering maneuvers, circadian rhythm, self sleep evaluation)
Effectiveness: N/A
Availability: Unknown
Cost: Unknown
Practicality for CMV Industry: There was no information on the ASTiD's ability to function in various environments. This system visually displays the driver's fatigue level, which is calculated every minute. It is unclear how much information is recorded and available for managers. The Fatigue Management International Company offers other products that can be integrated with ASTiD, such as fatigue self-assessment tools and e-learning and training tools to assist individuals and fleets in fatigue management. There are no video recording devices that drivers may find intrusive.
Rating: Unvalidated

Table 15. Bosch Driver Drowsiness Detection.

Name of Technology: Bosch driver drowsiness detection
URL: https://www.bosch-mobility-solutions.com/en/products-and-services/passenger-cars-and-light-commercial-vehicles/driver-assistance-systems/driver-drowsiness-detection/
Key Features: The Bosch driver drowsiness detection system uses a steering angle sensor to monitor steering movements to alert the driver of drowsiness. The system begins recording the driver's steering behavior at the start of each trip. It recognizes steering changes, such as limited steering inputs and slight, quick, and abrupt steering movements. The system calculates the driver's level of fatigue based on the frequency of these movements, length of a trip, use of turn signals, and time of day. If the fatigue level exceeds a certain value, an icon (such as a flashing coffee cup) on the instrument panel warns the driver to take a break.
Functions: Driver Performance (steering behavior)
Effectiveness: N/A
Availability: Currently available for automotive market
Cost: Unknown
Practicality for CMV Industry: There are no environmental restrictions on the Bosch driver drowsiness detection system. However, there is no back-office support; thus, the system relies on the driver to respond to alerts. The device is not available for after-market purchase.
Rating: Unvalidated

Table 16. OMsignal SmartWear.

Name of Technology: OMsignal SmartWear
URL: https://omsignal.com/
Key Features: OMsignal SmartWear is a clothing line that captures biometric data through embedded sensors. The clothing has a detachable Bluetooth-enabled hardware module clipped onto the apparel that sends data in real time to the wearer’s smartphone. The smartphone app stores the data to the cloud, where it is analyzed.
Functions: Physiological Sensors (ECG, respiration, physical activity sensors)
Effectiveness: N/A
Availability: Currently on the market
Cost: Unknown
Practicality for CMV Industry: There are no known environmental conditions in which the SmartWear does not function. SmartWear is currently designed to monitor and display biometric data from the wearer. OMsignal SmartWear is extensible; thus, developers can create parameters specific to the variable of interest. If this were to be used in the CMV industry, drivers would need to wear SmartWear while driving and keep it charged. Battery life is over 50 hours, and the clothing is machine washable and splash and water resistant.
Rating: Unvalidated

INEFFECTIVE TECHNOLOGIES

No technologies were rated as ineffective.

TECHNOLOGIES UNLIKELY TO BE USED IN THE FUTURE

Table 17. Nap Zapper.

Name of Technology: Nap Zapper (Elite and Basic models)
URL: http://www.napzapper.com/
Key Features: The Nap Zapper is worn over the right ear with an electronic position sensor. This device measures forward head tilt. When the wearer's head nods forward, the device sounds an alarm to alert the driver as well as any passengers.
Functions: Driver Behavior Monitoring (wearable, head-tilt)
Effectiveness: N/A
Availability: Currently on the market
Cost: $9.49 per Elite unit and $4.99 per Basic unit
Practicality for CMV Industry: Since the device does not rely on any cameras, functionality is maintained in all lighting and environmental conditions. The device does not record or transmit data to fleet personnel; thus, a driver must respond to the warning in order for the device to make an impact. The degree of head tilt needed to sound the alarm can be adjusted. Drivers with hearing limitations in the right ear would not be able to use this device. Drivers can wear the unit with eyeglasses or sunglasses.
Rating: Unlikely to be used in future

Table 18. Stay Awake.

Name of Technology: Stay Awake
URL: http://stayawakedevice.com/
Key Features: The Stay Awake device is a wearable "over the ear" device that measures forward head tilt. The device is worn over the right ear and when the wearer's head falls out of the "alert" position (falls forward), the device emits a high-pitched sound to alert the wearer.
Functions: Driver Behavior Monitoring (wearable, head position)
Effectiveness: N/A
Availability: Currently on the market
Cost: $21.99 per unit with bulk order pricing available
Practicality for CMV Industry: Since the Stay Awake does not rely on any cameras, it works in all lighting and environmental conditions. The device does not provide any back-office support; thus, it relies solely on the driver taking action to any alerts. Drivers with hearing limitations in the right ear would not be able to use this device. The device can be worn with eyeglasses and sunglasses.
Rating: Unlikely to be used in future

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