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Drowsiness measures for commercial motor vehicle operations

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ABSTRACT

Timely detection of drowsiness in Commercial Motor Vehicle (C MV) operations is necessary to reduce drowsiness-related CMV crashes. This is relevant for manual driving and, paradoxically, even more so with increasing levels of driving automation. Measures available for drowsiness detection vary in reliability, validity, usability, and effectiveness. Passively recorded physiologic measures such as electroencephalography (EEG) and a variety of ocular parameters tend to accurately identify states of considerable drowsiness, but are limited in their potential to detect lower levels of drowsiness. They also do not correlate well with measures of driver performance. Objective measures of vigilant attention performance capture drowsiness reliably, but they require active driver involvement in a performance task and are prone to confounds from distraction and (lack of) motivation. Embedded performance measures of actual driving, such as lane deviation, have been found to correlate with physiologic and vigilance performance measures, yet to what extent drowsiness levels can be derived from them reliably remains a topic of investigation. Transient effects from external circumstances and behaviors – such as task load, light exposure, physical activity, and caffeine intake – may mask a driver's underlying state of drowsiness. Also, drivers differ in the degree to which drowsiness affects their driving performance, based on trait vulnerability as well as age. This paper provides a broad overview of the current science pertinent to a range of drowsiness measures, with an emphasis on those that may be most relevant for CMV operations. There is a need for smart technologies that in a transparent manner combine different measurement modalities with mathematical representations of the neurobiological processes driving drowsiness, that account for various mediators and confounds, and that are appropriately adapted to the individual driver. The research for and development of such technologies requires a multi-disciplinary approach and significant resources, but is technically within reach.

1. Introduction

Drowsiness-related road accidents (crashes) result in substantial cost to the economy as well as loss of life (Dinges, 1995; Williamson et al., 2011; Hege et al., 2015). In Commercial Motor Vehicle (CMV) drivers, drowsiness may be responsible for as much as 20% of heavy vehicle crashes (Åkerstedt, 2000). Here, drowsiness is used as synonymous to sleepiness and fatigue, and antonymous to alertness. Depending on the context, these terms are not necessarily interchangeable (e.g., Shen et al., 2006). In operational settings, however, the temporal dynamics

(i.e., changes over time) of drowsiness are often of primary interest, and in that framework the distinction between drowsiness and related terms is largely inconsequential (Satterfield and Van Dongen, 2013). Regardless of the terminology, timely detection of drowsiness in CMV drivers is essential to help reduce drowsiness-related crashes.

A range of drowsiness detection measures has been developed to assess drowsiness. These measures vary with regard to signal modality (e.g., driver physiology, driver behavior, vehicle behavior, driver self-report) and operational implementation (e.g., roadside use, or while driving). They also vary with regard to their psychometric properties (e.g., reliability, validity, and predictive capability), their usability, and the extent to which they are susceptible to confounding factors (Dinges and Grace, 1998; Balkin et al., 2004; Abe et al., 2014; Kosmadopoulos et al., 2017; Sandström et al., 2017). Different drowsiness measures may show poor concurrent validity with each other (Leproult et al., 2003; Van Dongen et al., 2003a; Van Dongen et al., 2004; Van Dongen et al., 2011d); they are typically not simply interchangeable.

The suitability for operational use of any measure of drowsiness is determined by many or all of these issues. An understanding of the science of drowsiness detection is needed to avoid misguided use, inaccurate predictions, and erroneous conclusions, as well as to further

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the development of valid and reliable technologies for drowsiness detection. Here we provide an overview of the science pertinent to a range of drowsiness measures, with an emphasis on those that may be most relevant for CMV operations. We also briefly discuss current and future work on the integration of multiple drowsiness measures as part of drowsiness detection and warning systems, and explore the impact of new developments in semi-autonomous driving.

2. Neurobiology of drowsiness

Measures of drowsiness essentially all try to capture aspects of the neurobiology underlying the dynamics of drowsiness over time. The primary neurobiological processes that impact drowsiness are the homeostatic and circadian processes. The homeostatic process represents a progressive build-up of sleep pressure across time awake, which dissipates across time asleep; whereas the circadian process, which drives 24 h rhythms in the brain and body (circadian = around a day), represents a waxing and waning of wake pressure across time of day (Borbély et al., 2016). Drowsiness results from high homeostatic pressure for sleep and low circadian pressure for wakefulness. In other words, CMV drivers (and other shift workers) are prone to drowsiness after extended wakefulness and/or at night.

Aside from the homeostatic and circadian processes, there are many additional factors that impact drowsiness. Broadly, these can be classified as internal states and external circumstances (Gabehart and Van Dongen, 2016). Internal states include variables such as psychological states (e.g., mood, anxiety) and pharmacological substances (e.g., caffeine, prescription drugs). External circumstances include variables such as environmental conditions (e.g., ambient temperature, light level) and time constraints (e.g., task load, time pressure). Drowsiness levels are determined by the net effect of these concurrent influences in relation to the homeostatic and circadian processes; see Fig. 1.

In the context of Hours-of-Service regulations, time on duty (or time driving) is also considered to be an important modulator of drowsiness (Hanowski et al., 2003). There is no known neurobiological process underlying changes in drowsiness with time on duty, per se, but an increase in time on duty is associated with an increase in time awake and a change in time of day. Pending further research, it is reasonable to assume that drowsiness measures capture the effects of time on duty through the association with time awake and time of day. (However, see the discussion of task-induced fatigue in Section 8.2.)

The neurobiology underlying drowsiness produces a number of changes in the brain and body that can be measured as correlates of drowsiness. Specific electroencephalographic (EEG) brainwave patterns can be distinguished in response to changes in the homeostatic and circadian processes. These are measurable through electrodes attached to the scalp (Rechtschaffen and Kales, 1968; Amzica and Steriade, 1997; Bastien et al., 2002).

Likewise, changes in the homeostatic and circadian processes that produce drowsiness cause changes in measurements of the eyes, including pupil diameter, eyelid closure, and the appearance of slow eye movements (SEMs). Relative changes in these physiologic correlates of drowsiness can be measured with electrooculography (EOG) through electrodes attached near the eyes (Kinomura et al., 1996) and with camera-based systems that record eye movements, pupil diameter, and/or eyelid closure (Dinges and Grace, 1998; Hu et al., 2012; Ftouni et al., 2013a; Sigari et al., 2013).

The homeostatic and circadian processes driving drowsiness also affect cognitive functioning. As drowsiness ensues, momentary sleep intrusions into wakefulness are believed to cause lapses of attention (Doran et al., 2001). Lapses of attention progressively increase in frequency and duration as drowsiness progresses (Williams et al., 1959; Lim and Dinges, 2008). Drowsiness levels can therefore be measured through cognitive tasks that detect instability in cognitive functioning (Durmer and Dinges, 2005; Van Dongen and Dinges, 2005).

Cognitive instability associated with drowsiness is believed to affect driving performance as well. Driving performance becomes progressively worse with high homeostatic pressure for sleep and low circadian pressure for wakefulness. One frequently used measure of driving performance that seeks to capture performance variability is lane deviation, or the standard deviation of lateral lane position. This and other “embedded” performance measures in CMV drivers can be recorded from the vehicle directly or from camera views of the road analyzed with computer vision algorithms (Bittner et al., 2000; Liu et al., 2009).

Thus, there are multiple, different modalities of drowsiness detection that can be deployed in CMV operations, as illustrated in Figs. 2 and 3. The sections that follow discuss these different modalities further.

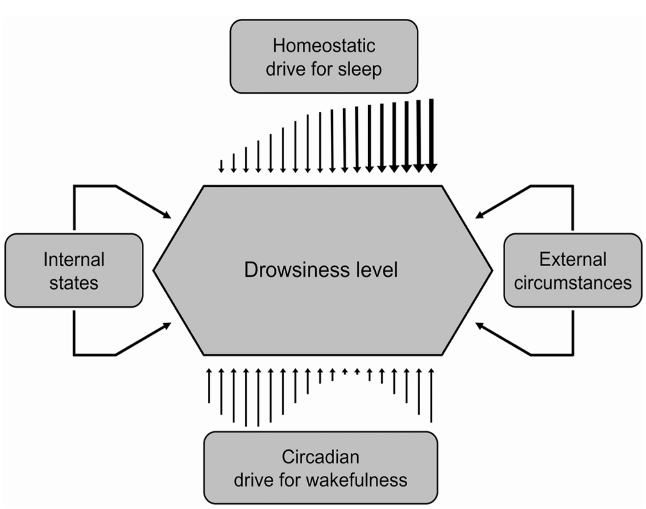

Fig. 1. Schematic representation of the interactions between the homeostatic and circadian processes and modulating internal states and external circumstances. The homeostatic process builds pressure for sleep with time awake and thereby increases drowsiness. The circadian process provides an oscillatory counter-effect by promoting pressure for wakefulness during daytime hours and withdrawing that pressure during nighttime hours. Internal states, such as stress, anxiety, and motivation, and external circumstances, such as light exposure, ambient temperature, and distractions, transiently increase or decrease drowsiness in interaction with the homeostatic and circadian processes. Adapted from Gabehart and Van Dongen (2016) with permission.

Fig. 2. Illustration of different modalities of drowsiness measures in CMV operations, including EEG-based, eye- and eyelid-based, camera-based, cognitive test performance-based, and driving performance-based measures.

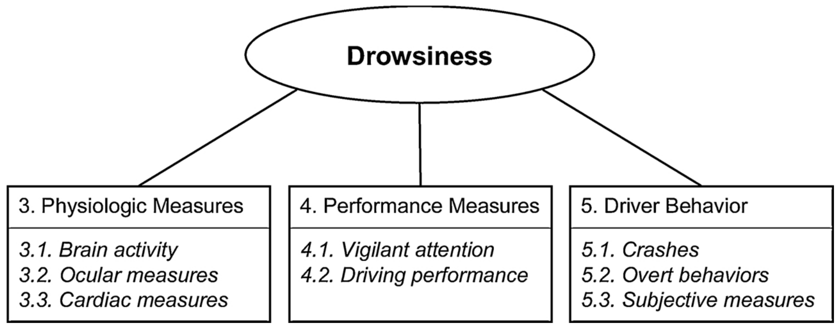

Fig. 3. Different modalities of drowsiness measures in CMV operations, grouped by the sections in which they are described. Numbers identify (sub)sections in this paper.

3. Physiologic measures of drowsiness

3.1. Brain activity

Neuronal activity in the brain reflects the state of drowsiness, and this is captured by the EEG, which can be recorded through surface electrodes attached to the scalp (Amzica and Steriade, 1997; Bastien et al., 2002). The degree of synchronization among neurons, which is a correlate of the level of drowsiness, is reflected in the dominant brain wave frequencies present in the EEG. That is, spectral power in the EEG (i.e., the strength of the EEG signal) gradually shifts from the beta band (12–30 Hz) to the alpha band (8–12 Hz) and through to the theta band (4–8 Hz) as drowsiness increases (Aeschbach et al., 1997), and ultimately to the delta band (1–4 Hz) after falling asleep (Rechtschaffen and Kales, 1968). The EEG also reveals microsleep episodes – brief periods of inattention and intrusion of sleep into wakefulness – as indicated by transient activity in the alpha and theta bands (Rechtschaffen and Kales, 1968; Moller et al., 2006). Computer algorithms can be used to detect drowsiness from the EEG automatically and in real time (e.g., Meiring and Myburgh, 2015).

The ability of the EEG to capture drowsiness was convincingly demonstrated in a naturalistic field study of overnight train drivers, in which the EEG was used to measure drowsiness. Spectral analysis was used to determine EEG frequency bands. Increases in alpha, theta, and delta power were found throughout the night journey. The highest spectral power in the alpha and theta bands occurred in drivers who reported the highest levels of subjective sleepiness and who admitted they had dozed off during the night drive (Torsvall and Åkerstedt, 1987). Changes in EEG measures of brain activity have also been associated with impairments from drowsiness during simulator driving (Lal and Craig, 2002; Åkerstedt et al., 2013; Anund et al., 2008a, 2008b; Hallvig et al., 2013) and real-road driving (Hallvig et al., 2013, 2014).

Measurement of the EEG constitutes a passive, continuous, and objective way to measure drowsiness from the homeostatic and circadian processes. It has been suggested that this is particularly useful for the homeostatic process, for which there is no other direct marker in humans (Åkerstedt and Gillberg, 1990; Cajochen et al., 1999). However, the alpha and theta bands of the waking EEG are also affected by the circadian process (Aeschbach et al., 1997; Cajochen et al., 2002).

EEG measurements are prone to artifacts from eye blinks and physical movement (Jung et al., 2000; Caldwell et al., 2003). The Karolinksa Drowsiness Test (KDT) is a measurement procedure that seeks to minimize EEG movement artifact. During the task, participants are instructed to sit still and quietly stare at a stimulus while trying to maintain wakefulness (Åkerstedt and Gillberg, 1990). Research has shown that significant increases in alpha and theta activity occur approximately 20 s before an individual has an episode of their head falling back at the onset of sleep (Åkerstedt and Gillberg, 1990). In real-world applications that do not allow for controlled measurement conditions such as the KDT, eye and movement artifacts need to be filtered out of the EEG through computational algorithms. Finding optimal procedures for such filtering is an active area of research (Hartmann et al., 2014; Upadhyay et al., 2016).

Recording of the EEG normally requires that electrodes remain attached to the scalp, and loss of electrical contact results in data loss. Recently, "dry electrode" technologies and headbands and baseball caps with embedded electrodes have been introduced (Rajaratnam, 2011; Lopez-Gordo et al., 2014). Validation tests are needed to determine whether such new technologies can be used to measure drowsiness with reasonable degrees of reliability and sensitivity (Dawson et al., 2014).

Although short-term changes in the level of drowsiness show corresponding changes in the EEG, the longer-term build-up of impairment across days of chronic sleep restriction does not appear to be captured by the EEG (Van Dongen et al., 2003b). Furthermore, across individuals, the magnitude of changes in the EEG is not a good correlate of the magnitude of cognitive impairment (Leproult et al., 2003) or real-world driving performance (O'Hanlon and Kelley, 1977). Although the EEG can be used more reliably to detect microsleeps and actual sleep attacks, such effects happen rather late on the drowsiness spectrum. These limitations make measurements of the EEG poorly suited to detect drowsiness and performance deficits in CMV drivers, unless such measurements are augmented with other technologies for drowsiness detection.

3.2. Ocular measures

The homeostatic and circadian processes underlying drowsiness cause physiologic changes in many variables describing the eyes and eyelids (Ftouni et al., 2013a; Jackson et al., 2016). As drowsiness arises facial muscle activity is reduced, causing a slowing in a number of types of ocular activity. Relative changes in blink rate, the duration of blinks, SEMs, eyelid closure, and latency of pupil constriction can be used to measure drowsiness (Stern et al., 1994; Cajochen et al., 2000; Russo et al., 2003; Rowland et al., 2005; Marzano et al., 2007; Ftouni et al., 2013a).

Changes in ocular parameters associated with drowsiness are typically measured one of two ways. The first is through the EOG, which is the recording of electrical activity associated with eye movements through electrodes attached near the eyes (Kinomura et al., 1996; Berry et al., 2016). Recording of the EOG is passive, continuous, and objective. Ocular changes recorded through EOG, such as SEMs, correlate with alpha and theta changes in the EEG (Torsvall and Åkerstedt, 1987; Lal and Craig, 2001; Ftouni et al., 2013a), primarily during very drowsy states (Santamaria and Chiappa, 1987; De Gennaro et al., 2000; De Gennaro et al., 2005). EOG activity has also been associated with lane drifting (Ingre et al., 2006), hitting the rumble strip marking the lane boundary (Anund et al., 2008a), and drowsiness-related crashes (Rowland et al., 2005) in driving simulators; and with drifting across the lane boundary (Åkerstedt et al., 2013) and out of lane (Hallvig et al., 2014) in real-road cars.

The EOG is susceptible to movement artifact (Marandi and Sabzpoushan, 2015) and data loss from detached electrodes. In addition, EOG-based drowsiness detection technologies typically require the use of proprietary hardware and software (Balkin et al., 2004). Moreover, EOG-based measures of drowsiness are not good predictors of cognitive performance (Dinges et al., 1998); nor is one EOG measure reliably consistent with another EOG measure, even for the same individual (Dinges and Grace, 1998). Nonetheless, the EOG has been included in in-vehicle driver monitoring systems to help manage driver drowsiness (Dinges et al., 1998).

A second common way to measure ocular parameters associated with drowsiness is through the use of cameras pointed at the face (Dinges and Grace, 1998; Hu et al., 2012; Sigari et al., 2013). The ocular parameter with the highest reliability and predictive validity documented to date is the degree of eyelid closure, commonly known as Percentage of Eyelid Closure over Time (PERCLOS; Dinges et al., 1998). Lacking the need for electrodes, PERCLOS is less cumbersome and less intrusive to the user.

The primary disadvantage of camera-based drowsiness detection involves privacy concerns from CMV drivers, especially when the camera images are recorded. As such, introduction of cameras pointed at the individual into a truck or bus cabin tends to be met with opposition. Further, failure of the camera to capture the eyes due to head turns and moving out of frame or due to the use of sunglasses, as well as bright sunlight, have been found to interfere with PERCLOS technology. Proprietary camera-based systems have been developed recently to overcome such limitations (Dawson et al., 2014).

Ocular measurement systems embedded in the frame of eyeglasses worn on the face have been developed to non-invasively measure a number of ocular parameters that can be considered simultaneously (Ftouni et al., 2013b; François et al., 2016). From a combination of ocular measurement variables (duration of blinks, relative velocity of eyelid movements during blinks, etc.), the Johns Drowsiness Scale metric has been derived (Johns et al., 2007). Although still undergoing further development, such systems have the potential to produce drowsiness estimates that correlate with EEG activity as well as objective performance measures (Abe et al., 2014; Dawson et al., 2014). However, a disadvantage of glasses-based systems is that drivers may not tolerate wearing the glasses, or may not be able to wear the glasses due to the use of prescription glasses or sunglasses. Another complication is that such systems must typically be calibrated to the individual user (Sommer and Golz, 2010).

Ocular parameters that may capture drowsiness may also be measured with the Fitness Impairment Tester (FIT), which measures changes in pupil size and eye movements in response to controlled flashes of light and moving light targets. A bulky device not suitable for real-time tracking of drowsiness, the FIT assesses fitness for duty in terms of impairment from drowsiness or other causes such as drug use (Balkin et al., 2000). Validated to be associated with objective performance measures (Morad et al., 2009), evidence for its sensitivity to drowsiness is mixed (De Gennaro et al., 2000; Van Dongen et al., 2006; Goldich et al., 2010).

In general, ocular measures are useful to detect high levels of physiologic drowsiness (Anderson et al., 2013). Technologies for the measurement of ocular indices of drowsiness are approaching a stage of development that could soon allow large-scale deployment in CMV settings, but whether or not these technologies will be accepted by the user remains to be seen. And importantly, as with the EEG, the majority of ocular metrics are not predictive of cognitive performance (Dinges and Grace, 1998) or driving impairment (Dinges et al., 1998), raising questions as to their suitability for detecting drowsiness and performance deficits in CMV drivers. Of the ocular metrics that have been experimentally validated, PERCLOS thus far remains the most accurately predictive of performance impairment.

3.3. Cardiac measures

Heart rate and heart rate variability (HRV) capture cardiac autonomic activity, which is affected by drowsiness. Passive recording of the electrocardiogram (ECG) through electrodes attached to the chest or elsewhere on the body has been explored as a way to detect drowsiness (e.g., Vicente et al., 2016). However, although the circadian process appears to modulate cardiac measures in a systematic manner (Kräuchi and Wirz-Justice, 1994; Burgess et al., 1997; Kerkhof et al., 1998), findings have been inconsistent for the homeostatic process (Kato et al., 2000; Holmes et al., 2002; Zhong et al., 2005; Vaara et al., 2009; Glos et al., 2014). Results from a laboratory study suggest that HRV measurements in a controlled laboratory environment predict performance impairment due to sleep deprivation-induced drowsiness (Chua et al., 2012). However, ECG recordings are susceptible to numerous types of artifacts and other confounding influences (Thayer et al., 2012) and are not widely pursued as a means of measuring drowsiness in operational settings.

4. Performance measures of drowsiness

4.1. Vigilant attention performance measures

The homeostatic and circadian processes that affect brain wave patterns and ocular movements also impact cognitive performance. As drowsiness progresses, lapses of attention, believed to result from sleep intrusions into wakefulness, increase in both frequency and duration (Doran et al., 2001). The most accurate and sensitive way to determine performance impairment from drowsiness appears to be through the use of vigilance performance tasks that can measure lapses of attention (Lim and Dinges, 2008). During these tasks, individuals must quickly respond to a stimulus or inhibit a response to a stimulus across a series of consecutive trials. Quick responses are indicative of alert states, while slower responses and greater variability in reaction times indicate drowsiness and/or time-on-task-related fatigue (Luce, 1991). Vigilance performance tasks provide an objective snapshot of an individual's level of cognitive performance impairment.

There is continuing research and debate regarding the extent to which different aspects of cognition are impacted by sleep loss (Lim and Dinges, 2010; Jackson et al., 2013b; Honn et al., 2018). Nonetheless, there is convincing evidence that vigilant attention is among the most reliably and consistently affected (Balkin et al., 2004; Durmer and Dinges, 2005). It has been argued that the ability to maintain vigilance is a fundamental requirement for normal cognitive functioning (Lim and Dinges, 2008), from which is may be inferred that vigilant attention deficits should translate to performance impairments across the board (although evidence to the contrary has been reported; see Tucker et al., 2010). Vigilant attention deficits have also been shown to correlate with driving performance impairment during simulator studies (Gillberg et al., 1996; Forsman et al., 2013).

Lapses of attention observed during vigilance performance tasks are a reflection of moment-to-moment variability in behavioral alertness associated with drowsiness (Williams et al., 1959). The greater the level of drowsiness, the greater the moment-to-moment variability in behavioral alertness (Doran et al., 2001). This variability can be seen as a hallmark symptom of drowsiness, believed to be caused by wake state instability in the brain produced by homeostatic and circadian pressures for sleep competing with effort to stay awake (Doran et al., 2001) or by local sleep-like states in neuronal pathways involved in cognitive processing (Van Dongen et al., 2011a). Lapses of attention may be associated with brief eye closures (lapses correlate with PERCLOS; Dinges and Grace, 1998) or even microsleeps (Anderson et al., 2010), but they may also occur when no overt symptoms of drowsiness are observable.

The Psychomotor Vigilance Test (PVT) is a widely used test of vigilant attention, known for its high reliability and predictive validity and lack of aptitude and learning effects (Dorrian et al., 2005; Basner et al., 2018). Individuals performing the task are instructed to press a response key as soon as they see a stimulus appear on a display. The stimulus appears after a random interval, typically varying between 2 and 10 s. In the earliest reported version of the task (Dinges and Powell, 1985), the stimulus is a millisecond counter, which stops as soon as the response key is pressed (thereby providing instant feedback on response time) and disappears 1 s later. Then the next stimulus appears after another random interval. The task continues for a fixed duration, traditionally set at 10 min. Variations of the PVT have been developed, with a bulls-eye or other picture as the stimulus and/or with a shorter task duration (e.g., Honn et al., 2015; Grant et al., 2017). A 3-minute version of the PVT, known as the PVT-B, was developed for use in field studies and other settings where little time is available for performance testing (Basner et al., 2011).

The PVT has shown to be a sensitive means of measuring drowsiness-induced performance impairment in the field (Balkin et al., 2004; Smith-Coggins et al., 2006). However, in operational settings, work demands often make 10-minute testing periods unfeasible, which may result in significant data loss (Rosekind et al., 1994). The shorter, 3-minute task duration of the PVT-B addresses this issue. A smartphone-based implementation of the PVT-B was used recently in a naturalistic field study of sleep and drowsiness in truck drivers (Sparrow et al., 2016). Across a period of approximately 2 weeks (two duty cycles), drivers completed the PVT-B three times daily: once before starting their duty day, once during an off-duty break approximately halfway through their duty day, and once after ending their duty day. The PVT-B was deployed as a roadside tool for assessing drowsiness; it was disabled when the truck was in motion to ensure performance testing would not contribute to distracted driving behavior. Although drivers were instructed to take the PVT-B at a location with minimal distractions, it was sometimes difficult for drivers to find such a place. Additional experimental controls, including asking drivers to record any distractions that occurred during testing and maintaining daily telephone contact between drivers and researchers, were needed to maintain high data quality during the field study. Under these conditions, the PVT-B proved to be a sensitive and reliable tool for objectively measuring drowsiness-induced performance impairment in the field (Sparrow et al., 2016).

Outside of the context of experimental research studies, performance testing on vigilance tasks such as the PVT-B in order to assess drowsiness may be quite challenging in the field. Drowsiness detection by means of vigilant attention performance testing requires continuing willingness and repeated, active cooperation from individuals. As such, testing of vigilant attention is subject to confounds from loss of motivation or compliance during testing, especially if there is no strong incentive to participate in the testing or when the detection of drowsiness may bring repercussions (Dorrian et al., 2005). Testing conditions, such as body posture (Caldwell et al., 2003) and light exposure (Phipps-Nelson et al., 2009), influence performance on vigilance tasks and may produce error variance. Testing of vigilant attention is also prone to confounds from distractions – a problem that is amplified by increased distractibility in drowsy individuals (Anderson and Horne, 2006). It has been suggested that roadside vigilance performance testing may be suitable for drowsiness detection in the context of law enforcement (Randun, 2009), but the many potential sources of error variance in performance testing at a single point in time (i.e., without repeated measurements) make this a questionable proposition.

4.2. Driving performance measures

Although loss of vigilant attention is arguably one of the most important risk factors associated with drowsiness as it pertains to driving performance and safety, driving involves many domains of cognition, including multiple aspects of attention, various perceptuomotor skills, rapid and/or complex decision making, and short- and long-term memory (Anstey et al., 2005; Gunzelmann et al., 2011). One way to capture the effects of drowsiness on driving, without having to be concerned with the multi-faceted impact of drowsiness on cognition, is to observe the driving performance itself. This can be done by recording so-called "embedded" performance measures, which quantify one or more aspects of driving performance based on signals drawn directly from the driving task. Usually these signals are derived from sensors integrated with the vehicle (in the factory or as post-market accessories), such as accelerometers, steering wheel sensors, cameras recording the road, forward radar, and various vehicle and engine data streams from the Controller Area Network (CAN) bus found in essentially all modern vehicles. Embedded performance measures are unobtrusive and require no additional responsibilities from the driver.

Embedded performance measures sensitive to the effects of drowsiness on driving include lateral position on the road and variability therein (lane deviation, lane departure); speed and variability therein (speeding, hard braking); steering wheel movements and variability therein (frequency of course corrections, jerky movements); following distance (late braking, near-crashes); and fuel economy (inefficient driving) (e.g., Pizza et al., 2004; Otmani et al., 2005; Hanowski et al., 2007a, 2007b; Anund et al., 2008a, 2008b; Mortazavi et al., 2009; Van Dongen et al., 2011c; Forsman et al., 2013; Mollicone et al. this issue). The most frequently reported measures of drowsy driving include lateral lane deviation and lane departures (Ingre et al., 2006; Anund et al., 2008a, 2008b; Liu et al., 2009). Out of many embedded driving performance measures proposed to detect drowsiness (Forsman et al., 2013), lane deviation appears to be among the most sensitive.

There is mounting evidence of the utility of embedded performance measures of driving for the detection of drowsiness from the homeostatic and circadian processes, in simulator experiments (Balkin et al., 2004; Anund et al., 2008a; Van Dongen et al., 2011c; Åkerstedt et al., 2010) and real-road studies (Åkerstedt et al., 2013; Van Dongen and Mollicone, 2013; Hallvig et al., 2014). For reasons that are not well understood, driving simulator studies tend to show greater effects of drowsiness than are typically observed in real-road driving (Philip et al., 2005; Sandberg et al., 2011; Hallvig et al., 2013). Regardless, vehicle-derived measures of drowsiness vary considerably in their sensitivity to drowsiness, with many of them indicating drowsiness only when safety may already be significantly compromised. In an automobile simulator study, measures of steering wheel variability were found to be more sensitive to even moderate levels of drowsiness (Forsman et al., 2013). However, due to differences in mass and length, the dynamics of steering wheel control in an automobile are not the same as those in a truck or bus; to what extent steering wheel variability may be useful in CMV operations therefore remains to be determined.

A fundamental challenge for the effective use of embedded performance measures to detect drowsiness is that these measures are also influenced by the circumstances on the road (traffic, winds, etc.). For example, hard braking may reflect a drowsiness-related, delayed reaction to slowing traffic, or it may reflect an alert reaction to another driving causing a dangerous situation on the road. Even complex signal processing algorithms based on signals from multiple sensors have difficulty differentiating these possibilities and avoiding false detections of drowsiness. Nonetheless, motor vehicle manufacturers have developed proprietary systems that purport to detect drowsiness. Independent, scientific evaluation of these systems is lacking, leaving uncertainty as to their effectiveness (Forsman et al., 2013).

5. Behavioral measures of drowsiness

5.1. Crashes

The homeostatic and circadian processes that influence drowsiness are directly relevant to driver crash risk. In fact, there is strong scientific evidence that drowsiness is associated with increased crash risk (Williamson et al., 2011; Hege et al., 2015; Bioulac et al., 2017). In the U.S., it has been estimated that at least 7.0% of all road crashes and

16.5% of fatal road crashes involve drowsy driving (Tefft, 2012). For CMV drivers, it has been reported (a number of years ago) that drowsiness is responsible for 13% of all crashes (Federal Motor Carrier Safety Administration, 2006). Yet, although drowsiness is believed to be directly responsible for a substantial number of accidents on the road, demonstrating causality in the link between drowsiness and CMV crashes proves to be difficult (Morrow and Crum, 2004). Police crash reports often lack sections that help to document the presence of drowsiness. Law enforcement officers are also not trained to investigate the possible role of drowsiness in a vehicle crash. As such, drowsy driving crashes may be significantly underreported (Higgins et al., 2017).

Part of the problem in determining causality in drowsy driving crashes is more intractable, having to do with the inherent variability of drowsiness-related impairment produced by the homeostatic and circadian processes (as discussed in Section 4.1). Thus, even under conditions of extreme drowsiness, individuals maintain the ability to respond normally at least part of the time (Lee and Kleitman, 1923; Doran et al., 2001) and may continue to perform effectively enough to avoid crashing (Van Dongen et al., 2016). Accidents are typically characterized by multiple contributing factors. According to Reason's "Swiss cheese" model of accident causation (Reason, 2000), an accident occurs when safeguards fail while risk factors align in space and time – i.e., when the "holes" in the "Swiss cheese" line up so that error can propagate to evolve into an accident; see Fig. 4. Because of the performance variability associated with drowsiness, there is considerable randomness in when this occurs, and actual accidents resulting from drowsiness are therefore rather unpredictable. This also implies that, despite the relatively high number of drowsy driving crashes (Tefft, 2012), they may actually be less common than could be expected based on the prevalence of drowsiness per se (cf. Morrow and Crum, 2004).

5.2. Safety-critical events and overt driver behaviors

Obviously, drowsiness detection is no longer helpful once a crash has occurred, but it could still be useful when crash antecedents occur.

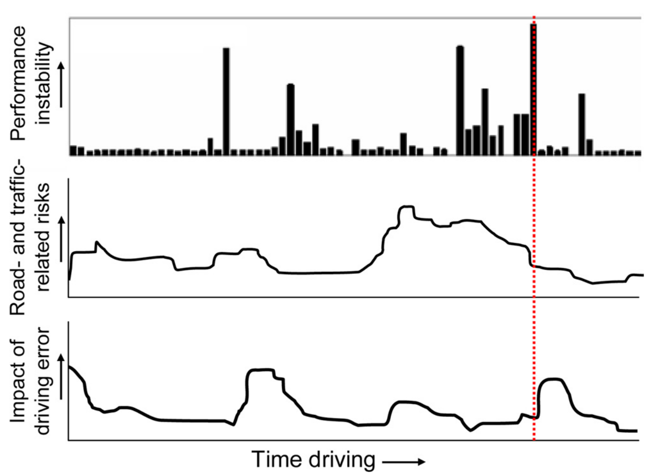

Fig. 4. Schematic illustrating drowsy driving crash causation in the context of the Swiss cheese model of accident causation. The top panel represents drowsiness-induced instability over time in driver performance (longer bars indicate longer reaction times; see Doran et al., 2001). The middle panel represents changes in the demands on the driver associated with the driving circumstances (e.g., road and traffic conditions). The bottom panel represents the potential impact of error in driving performance (e.g., failure to brake). The risks associated with each of the three panels fluctuate over time. According to Reason's Swiss cheese model, an accident occurs when these risks occur simultaneously (Reason, 2000). In the hypothetical scenario illustrated here, this does not occur, but there could have been a close call (dotted line) – a minor difference in the timing of events would have resulted in a crash. Figure adapted from Van Dongen et al. (2016) with permission.

On-board monitoring systems (OBMS) have been installed in commercial motor vehicles to record safety-critical events (SCEs) – such as hard-braking events, sudden swerves, and near-crashes – and incidents less severe than an accident (Hanowski et al., 2009). Typically requiring post-hoc assessment by a human evaluator (e.g., through review of camera images of the road and the driver), SCEs have been used in naturalistic field studies based on the assumption that they can serve as proxy measures of crash risk (Guo et al., 2010; Tarko, 2012; Jonasson and Rootzén, 2014). The validity of this assumption for CMV operations has not been unequivocally shown (Morrow and Crum, 2004), and is complicated by the lack of a standard of proof regarding the validity of proxy measures as indicators of crash risk (Motor Carrier Safety Research Analysis Committee, 2017). SCEs during driving may happen for all kinds of reasons, and establishing the involvement of drowsiness is subject to the same challenge associated with the inherent variability of drowsiness-related impairment that pertains to accident causation (see Fig. 4).

OBMS often include video and audio recordings of the driver, and this allows for the observation of overt driver behaviors indicative of drowsiness. These include fidgeting and moving about, yawning, stretching, and talkativeness (Weinberg and Brumback, 1990; Watling et al., 2015), facial expressions (Sigari et al., 2013), and changes in speech and voice parameters (Greeley et al., 2007; Krajewski et al., 2009; Baykaner et al., 2015; Dhala and Samant, 2016). They also include application of (perceived) drowsiness countermeasures, such as consumption of coffee (Horne and Reyner, 1996) or energy drinks (Reyner and Horne, 2002) and turning up the radio volume or circulating cold air (Reyner and Horne, 1998a). Although automated systems for the detection of drowsiness-related driver behaviors observed through video and audio recordings are being developed (e.g., Fitzharris et al., 2017), currently the assessment of such behaviors requires time-consuming, post-hoc classification by a human evaluator. Nonetheless, driver behavior data have been found to be insightful in the investigation of crash risk factors in naturalistic field studies (Dingus et al., 2016). That said, large-scale utilization of driver behavior recordings is unlikely, as the recorded data may be subject to subpoena in the event of a crash. Many CMV drivers therefore consider such recordings a legal liability and oppose their implementation.

Driving simulator studies would allow for more feasible and controlled studies of the relationships between drowsiness, overt driver behaviors, SCEs, incidents and accidents (e.g., Anund et al., 2008a). However, in-depth, simulator-based research studies in this area have yet to be documented.

Outside the vehicle or driving simulator, by the roadside, drowsiness may be detected by observing reduced postural control (e.g., Cuthbertson et al., 2015) using a balance or force platform (Forsman et al., 2014). This approach may be useful for law enforcement in jurisdictions that prohibit drowsy driving. To what extent it can be implemented practically remains to be determined.

5.3. Subjective drowsiness

Drowsiness-related driver actions and behaviors – in particular the application of countermeasures such as caffeine intake – are at least partially dependent on drivers' awareness of their own level of drowsiness. There has long been interest in the question of whether drivers are self-aware of drowsiness. Published evidence shows that when drivers are prompted to evaluate their level of drowsiness, they provide responses that correlate relatively well with objective indices of drowsiness (Reyner and Horne, 1998b; Horne and Baulk, 2004; Åkerstedt et al., 2013; Williamson et al., 2014; Watling et al., 2016b; Kosmadopoulos et al., 2017), although they may not fully appreciate the attendant risks (Watling et al., 2016a). However, it remains unclear to what extent drivers are self-aware of being in a state of drowsiness when not externally prompted to introspect. Furthermore, the relatively high prevalence of drowsiness-related crashes suggests that regardless of whether drivers recognize that they are drowsy, they do not adequately mitigate the risks. As the effectiveness of roadside signs and other strategies for alerting drivers to the dangers of drowsiness depends on their impact on drivers' behavior, it is important to conduct further research to elucidate these issues.

Notwithstanding the complexities of the relationship between driver drowsiness awareness and behavioral outcomes, self-report measures of subjective sleepiness have been used effectively in many laboratory and field studies of driver drowsiness. The most extensively characterized instrument for measuring subjective sleepiness is a 9-point Likert scale called the Karolinska Sleepiness Scale (KSS; Åkerstedt and Gillberg, 1990). Predictive validity of the KSS has been confirmed based a range of physiologic and performance-based measures of drowsiness, and the KSS has been shown to correlate with crash risk in simulator studies and on the road (Åkerstedt et al., 2014). Correspondence between KSS ratings and performance impairment is particularly good at high levels of drowsiness, with KSS scores in the upper third of the scale predicting unintentional lane departures during simulated driving (Anund et al., 2008a; Hallvig et al., 2013; Hallvig et al., 2014). That said, whereas the KSS and other instruments measuring subjective sleepiness tend to correlate relatively well with physiologic and performance measures of drowsiness at the group level, laboratory and field experiments have found much poorer correspondence at the level of individuals (Leproult et al., 2003; Van Dongen et al., 2004, 2011c; Sparrow et al., 2016).

In contrast with the KSS, which assesses momentaneous (state-based) subjective sleepiness, the Epworth Sleepiness Scale (ESS; Johns, 1991) assesses enduring (trait-based) subjective sleepiness or drowsiness. Consisting of eight scenarios that are to be rated for the likelihood of falling asleep (e.g., while sitting and reading; while watching TV), the scale is (moderately) indicative of the presence of pathological drowsiness from sleep disorders such as sleep apnea and other drowsiness-promoting medical conditions (Fong et al., 2005; Kendzerska et al., 2014). CMV drivers who demonstrate high scores on the ESS or other self-report instruments measuring excessive sleepiness have a heightened probability of having sleep apnea (Burns, 2014; Kales and Straubel, 2014) and, if so diagnosed, would not be fit for duty until successfully treated. CMV drivers with medically based, pathological drowsiness are outside the scope of this paper.

Despite the scientific utility of self-report measures of (state or trait) drowsiness and their ease of implementation, caution is warranted for their use in operational settings. Subjective sleepiness scales are prone to report bias from demand characteristics and social desirability, as well as purposeful falsification (Carskadon and Dement, 1979; Shahid et al., 2010; Soubelet and Salthouse, 2011; Gabehart and Van Dongen, 2016).

6. Trait and State moderators of drowsiness outcomes

6.1. Inter-individual differences in vulnerability to drowsiness

There is substantial variability among individuals in the effects of drowsiness from sleep loss, displaced sleep, and shift work; i.e., from the homeostatic and circadian processes (Van Dongen et al., 2006). Such differential vulnerability to drowsiness affects driving performance (Ingre et al., 2006; Anund et al., 2008a, 2008b; Åkerstedt et al., 2010) and has been shown to be a trait (Van Dongen et al., 2004). However, differential vulnerability to drowsiness is not expressed in the same manner across different physiologic, performance-based, and subjective measures of drowsiness (Leproult et al., 2003; Van Dongen et al., 2011d). Thus, inter-individual differences in the effects of drowsiness observed on one measure do not necessarily correspond to those observed on another measure (Oonk et al., 2008).

Inter-individual differences in vulnerability to drowsiness may be due to multiple person-specific factors (Grant and Van Dongen, 2013), including age differences (Forsman and Van Dongen, 2017), differences in prior sleep history (Rupp et al., 2009) and genetic make-up (King et al., 2009). Several genes potentially involved in differential vulnerability to drowsiness have been identified (e.g., Viola et al., 2007; Bodenmann et al., 2012; Satterfield et al., 2015). The impact of these genes across various distinct measures of drowsiness has yet to be fully elucidated, but is likely to be relatively small (Satterfield et al., 2015).

Recent laboratory studies have revealed that ensembles of biological substances measurable in biological samples (blood, saliva, urine, hair follicles) may serve as indicators of the states of the circadian and homeostatic processes (e.g., Möller-Levet et al., 2013; Davies et al., 2014; Laing et al., 2017; Uyhelji et al., 2017). While still under development (Mullington et al., 2016), these "biomarker panels" show promise as a novel approach to passive detection of drowsiness. However, the issue that inter-individual differences in the effects of drowsiness observed on one measure do not necessarily correspond to those observed on another measure also complicates the further development and application of biomarker panels.

The substantial variability among individuals in the effects of drowsiness has important implications for psychometric standards to which drowsiness measures must be held in order to be reliable in research and practice. That is, as long as a drowsiness measure is only used to assess change within individuals over time, then it can be used as a relative measure and differential vulnerability is not a confounding factor. However, when a drowsiness measure is used to compare against a set threshold (a debatable practice; Van Dongen and Belenky, 2012) or between different individuals, then it must be used as an absolute measure and must therefore be properly calibrated. Most physiologic measures and many performance measures (e.g., those that show aptitude differences) do not meet this criterion, nor do subjective measures of drowsiness.

Inter-individual differences in the effects of the homeostatic and circadian processes underlying drowsiness also affect the way in which individuals would prefer to organize their sleep, wake and work activities across the 24 h of the day (Roenneberg et al., 2007). For example, systematic differences among people in the timing of the biological clock that drives the circadian process (Kerkhof and Van Dongen, 1996) give rise to morningness/eveningness – the phenomenon that some people prefer to place their waking activities in the early morning hours and some prefer to place them much later in the day (Kerkhof, 1985). These and other systematic differences among individuals – such as in the amplitude of circadian rhythm (Baehr et al., 2000), the preferred timing of sleep relative to the timing of circadian rhythm (Mongrain et al., 2004), the dynamics of the homeostatic process (Mongrain et al., 2006), and the effects of aging on the effects of displaced sleep (e.g., Härmä et al., 1994; Blok and de Looze, 2011) – codetermine not only the *magnitude*, but also the *timing* of driver impairment due to drowsiness.

6.2. Transient states

As illustrated in Fig. 2, a multitude of internal and external state moderators influence drowsiness in interaction with the homeostatic and circadian processes (Gabehart and Van Dongen, 2016). Internal states include stress and motivation (Oken et al., 2006) and physical activity and body posture (Caldwell et al., 2003), and also encompass pharmacological agents such as sedatives and stimulants (Wesensten, 2012), including caffeine (Snel and Lorist, 2011). External circumstances relevant to CMV operations include weather conditions, visibility, changes in traffic density (Hanowski et al., 2009), the amount of environmental light (Cajochen, 2007), etc. Most of these factors have effects on drowsiness that dissipate rapidly (on the order of minutes). This has been shown, for example, for commonly applied countermeasures to drowsiness, such as turning up the radio volume or opening a window to get cold air (Reyner and Horne, 1998a). Other such factors have somewhat longer effect durations, including caffeine – although caffeine's effects on drowsiness vary widely among individuals (e.g., Attwood et al., 2007; Landolt, 2008). What all these factors have in common is that their impact on drowsiness is transient. This is a challenging issue in the context of drowsiness detection; it is not *a priori* clear whether these transient factors should be accounted for in drowsiness measurements or whether they should be seen as confounds and ignored. And from a technical perspective, it may not even be possible to make this distinction.

In contrast with the state moderators influencing drowsiness transiently, the homeostatic and circadian processes affect drowsiness continually. It is thus possible to consider a “nominal” level of drowsiness; that is, the level of drowsiness that would be present in the absence of transient factors, determined solely by the homeostatic and circadian processes. This nominal level of drowsiness would be useful to know, as it determines the expected level of drowsiness (and the associated risks) after transient state moderators wear off. Biomathematical models have been developed to predict the nominal level of drowsiness based on equations describing the temporal changes in the homeostatic and circadian processes (Hursh et al., 2016). One way to deal with transient factors that confound momentaneous measurements of drowsiness would be to use biomathematical modeling to track the homeostatic and circadian processes and apply this information to help interpret the measurements. Statistical techniques have been developed that enable real-time cross-referencing of measurements with biomathematical model predictions to improve drowsiness detection technologies (Van Dongen et al., 2007; Kogan et al., 2016). This approach is also helpful in situations where drowsiness measurements are missing intermittently (e.g., due to equipment failure); the biomathematical model predictions can then serve as a reasonably well-estimated, nominal drowsiness-level substitute.

7. Current and future drowsiness detection system development

7.1. Composite drowsiness detection systems

The reliability of drowsiness detection systems may be improved through integration of multiple drowsiness measures (Balkin et al., 2011). Most multi-measure, composite drowsiness detection systems developed to date focus on in-vehicle monitoring for signs of drowsiness while driving (see Fig. 2). Data are typically collected continuously and processed in real time using either fixed algorithms or adaptive algorithms that adjust based on data received. For example, artificial neural networks have been applied to both car and truck driving to learn the steering inputs of individual drivers associated with various levels of drowsiness (Eskandarian et al., 2012).

Some of the common features of currently available, composite drowsiness detection systems have been described (Chacon-Murguia and Prieto-Resendiz, 2015). The operational details are often proprietary and remain undisclosed, however, as developing multi-measure drowsiness detection systems is challenging and costly. Driving experiments and naturalistic studies of driver drowsiness can generate extensive amounts of vehicle-based, behavioral, and physiological data. Data reduction may involve creating hybrid drowsiness measures that are developed by extracting characteristics from each measure and then combining these characteristics using sophisticated classification algorithms (Sahayadhas et al., 2012).

Composite drowsiness detection methods are only as good as the data available for analysis during development. This puts a premium on the selection of complementary drowsiness measures based on scientific information about their psychometric and statistical properties and their operational strengths and weaknesses. Unfortunately, data reduction methods provide little guidance as to what is required of the data, leaving most feasibility and validation checks to late stages of development when significant investments have already been made. Statistical methodology to help address this issue in advance has been developed (e.g., Kogan et al., 2016), but awaits widespread implementation.

7.2. Development of drowsiness detection and warning systems

Most composite drowsiness detection systems in use today produce some sort of warning signal once drowsiness has been detected, and some provide alerting cues such as seat belt vibration or playing music in an attempt to temporarily reduce driver drowsiness (Chacon-Murguia and Prieto-Resendiz, 2015). Adaptive systems that dynamically adjust multiple components of the in-vehicle environment based on the level of detected drowsiness have been evaluated for military use (Kerick et al., 2013). However, these systems remain limited in their ability to adapt to the wide range of conditions usually encountered in real-world driving.

There are several knowledge gaps that slow down the further development of drowsiness detection and warning systems. (a) Optimal multi-measure drowsiness detection models remain unidentified (see Section 7.1). (b) Inter-individual differences in the effects of drowsiness that may not be congruent across different measures (see Section 6.1) continue to be a challenge. (c) Integration of data from smart, connected vehicles, which may offer information that could increase the effectiveness of drowsiness detection systems, has not been systematically explored. (d) The impact of progressive levels of vehicle automation on requirements for drowsiness detection systems (see Section 8.3) is understudied. (e) Design criteria for user acceptance of drowsiness detection and warning systems are largely unknown. (f) Consequences of over-reliance on drowsiness warning systems have scarcely been investigated.

While research is ongoing to fill these knowledge gaps, much work remains to be done. It is important to note that drowsiness detection is one safety component among a suite of safety management systems on board most modern vehicles. Drowsiness detection and warning systems should be developed in concert with the other components of these safety management systems.

8. Vehicle automation and drowsiness

8.1. Levels of automation

At some point in the future, fully automated vehicles may eliminate the need for drowsiness detection during road transportation. Cargo may be moved without human involvement, and passengers may be transported safely, regardless of their level of drowsiness, without having to engage in the driving process. Yet, vehicle automation experts believe that the arrival of fully automated driving environments is decades away (Kyriakidis et al., 2018). However, while driving may not be fully automated for the foreseeable future, major developments in semi-autonomous driving are rapid and wide-spread. Importantly, semi-automated driving can still be impacted adversely by drowsiness – perhaps even more so than manual driving, as semi-automated driving shifts the emphasis of human involvement from active engagement in the driving process to continuous passive monitoring and infrequent emergency intervention. A prerequisite for the safety and success of semi-automated vehicles will be the reliable, automated assessment of drowsiness and distraction levels of the driver prior to any critical events, as this will determine whether the driver can be relied upon to take control of the vehicle and intervene (Hoeger et al., 2011, Trimble et al., 2014).

Semi-autonomous driving may be categorized with six levels of vehicle automation (Levels 0–5), which determine the degree of human involvement (National Highway Traffic Safety Administration, 2013; SAE International, 2014, 2016). Level 0 (Manual – No Automation) requires full-time driver performance even in the presence of warning or intervention systems. Level 1 (Driver Assistance) involves driver assistance systems that automate steering, control acceleration/deceleration (throttle and brake), or provide parking assistance with automated steering, while the driver performs all remaining driving tasks. Level 2 (Partial Automation) allows driver assistance systems to use driving environment information to control acceleration, steering, and braking, while the driver assumes all other aspects of dynamic driving and must be prepared to intervene if needed. Level 3 (Conditional Automation) means that the automated driving system performs all aspects of the dynamic driving task including emergency braking, but the system may request the human driver to intervene. Level 4 (High Automation) allows the automated driving system to perform the dynamic driving task without driver input even if the driver fails to respond to a request for intervention, although the system may abort the trip or park the car if the driver fails to respond. Level 5 (Full Automation) involves full-time driving by an automated driving system without human intervention.

Automation research for CMV operations has focused on Level 1 cooperative adaptive cruise control (CACC), where acceleration/deceleration control is automated while the driver remains responsible for steering, roadway and traffic monitoring, and intervening in critical situations; and Level 2 (or higher) “platooning,” which involves a lead vehicle and several close following vehicles that are each coordinated in distance, acceleration/deceleration, and direction with the vehicle ahead (Nowakowski et al., 2016). Although CACC and platooning capabilities were first demonstrated using non-commercial vehicles (Thorpe et al., 1998), these types of automations have particular advantages for CMV operations, including fuel and traffic efficiency (Nowakowski et al., 2016). Drowsiness detection is particularly important for platooning, to make sure that the driver is capable of reassuming driving responsibilities in order to leave the platoon; and for next-generation, adaptive systems that are being designed to continuously monitor driver, vehicle, and environmental states and adjust automation control levels accordingly (Rauch et al., 2009; Hoeger et al., 2011).

8.2. Automation-related drowsiness

The shift from active engagement in the driving task during manual driving to continuous passive monitoring and infrequent emergency intervention during semi-autonomous driving presents new challenges for drowsy drivers. First, it may amplify the vigilant attention deficits associated with drowsiness, because sustaining attention becomes a primary, continuous task. Second, it may expose drowsiness-induced problems with situational awareness and attentional control when human intervention is needed, as recent laboratory studies in drowsy individuals have shown profound difficulties in the ability to flexibly shift attention in the face of unexpected circumstances (Whitney et al., 2015, 2017; Honn et al., 2018; Satterfield et al., 2018; Slama et al., 2018). The consequences of drowsiness may be most serious at automation Levels 2 and 3, where a passive driver is expected to quickly retake control of the vehicle in a critical situation, despite the difficulty of monitoring situations and shifting attention as needed while drowsy. A simulated truck driving study found that partial automation in a CACC driving scenario resulted in lower drowsiness levels than driving during full automation; however, both automation levels produced more drowsiness than manual driving with standard cruise control (Hjälmdahl et al., 2017).

Drowsiness experienced during semi-autonomous driving may be the result of not only the homeostatic and circadian processes and various external factors as described earlier (Fig. 1), but also – probably much more so than during manual driving – fatigue induced by the semi-automated driving task itself. In this perspective, driver drowsiness may be seen as comprised of sleep- and circadian-related drowsiness as well as passive and active task-related fatigue (May and Baldwin, 2009). Passive fatigue would be due to underload conditions such as monotonous and extended driving and continuously monitoring automated systems, and active fatigue would be caused by increased task load and high-demand driving conditions. In this context, one of the main objectives of vehicle automation is to reduce active fatigue, which has the unwanted consequence of increasing passive fatigue (Jarosch et al., 2017). Passive fatigue during periods of semi-automated driving has been associated with reduced alertness, slowed braking and steering reactions to a critical event, and increased probability of a crash (Saxby et al., 2013). Sleep/circadian-related drowsiness and task-related fatigue interact and worsen each other (Doran et al., 2001; Wesensten et al., 2004; Van Dongen et al., 2011b). Therefore, until full Level 5 automation is achieved, progressive developments in automation may increase the need for reliable drowsiness detection.

Of course, being a passive occupant of a semi-autonomous vehicle does not necessarily lead to drowsiness under all circumstances. Passive drivers have the ability to engage in secondary tasks, which may help to maintain or even increase alertness during periods of autonomous driving (Schömig et al., 2015). However, secondary tasks may also distract from the primary task of system and situation monitoring and, when needed, intervening (Neubauer et al., 2014); and the adverse safety implications of distracted driving are well documented (e.g., Strayer and Fisher, 2016). Moreover, the effects of drowsiness and distraction appear to amplify each other (Anderson and Horne, 2006). To what extent secondary tasks may be useful as a countermeasure to drowsiness and fatigue during semi-automated driving has yet to be determined.

8.3. Measuring drowsiness during semi-autonomous driving

The development of drowsiness detection methods suitable for semi-autonomous driving presents some unique challenges. Drowsiness detection systems will need to adapt to dynamically changing levels of semi-automation during driving. Drowsiness measures derived from data collected during manual driving may not be available during automated phases of driving. Adaptive systems may therefore need to gather and analyze different data depending on the level of automation.

Several drowsiness measures currently in use are derived from involvement of the driver with the vehicle, which lessens with increased automation (Hoeger et al., 2011; Trimble et al., 2014). Furthermore, drowsiness measures validated for use in manual driving may produce different results during semi-automated driving. At various levels of automated driving in a simulator, reliable detection of drowsiness was reported for eye blink and pupil diameter measures of drowsiness (Körber et al., 2015; Jarosch et al., 2017). PERCLOS was found to capture drowsiness at automation Level 3 (Jarosch et al., 2017), but not at Level 2 where constant monitoring of the automation was required (Körber et al., 2015). Depending on the degree of automation, passive drivers may not show the same gaze direction, eye blinks, and other measurable behaviors as active drivers (Schmidt et al., 2018), and therefore certain eye- and face-based drowsiness measures used during manual driving may not be appropriate for semi-autonomous driving.

Monitoring systems that measure drowsiness during platooning have already been implemented in real-world CMV operations. These systems typically involve cameras to track head pose or blink rate, algorithms to detect erratic vehicle movements and monitor driver inputs related to steering, braking, and acceleration, computational estimates of driver alertness based on time of day, and audible or haptic warning systems to alert the driver if impairment is detected (Gaudet, 2014). The effectiveness of such systems has not yet been systematically assessed.

9. Conclusions

Measures of drowsiness used in CMV operations try to capture aspects of the neurobiology underlying the dynamics of drowsiness over time (see Fig. 1). In this paper, we categorized drowsiness measures by their modality: physiologic, performance-based, or behavior-based (see Fig. 2). Physiologic measures, such as the EEG and various ocular parameters, tend to accurately identify states of considerable drowsiness, but are limited in their potential to detect lower levels of drowsiness. Vigilant attention performance and other performance-based measures capture drowsiness reliably, but they require active driver involvement in a performance task and are prone to confounds from distraction and (lack of) motivation. Embedded performance measures of driving, as well as crashes and safety-critical events, have high face validity for CMV operations; yet to what extent drowsiness levels can be derived from them reliably remains a topic of investigation. Subjective estimates of drowsiness are easy to obtain, but congruence with objective drowsiness measures is questionable. The correlation among these different modalities of drowsiness measurement tends to be high when considering change over time, as they all track the homeostatic and circadian processes underlying the drowsiness state. However, the correlation across different individuals tends to be much lower, suggesting that the different modalities of drowsiness measurement may be capturing fundamentally distinct components of the functional consequences of drowsiness (Forsman et al., 2013; Jackson et al., 2013a).

Another way to categorize drowsiness measures is by whether they involve active measurement or passive real-time monitoring. Active measurement includes self-report assessment of subjective drowsiness, performance testing (e.g., on the PVT-B; Basner et al., 2011), and some observations of ocular parameters (e.g., FIT; Morad et al., 2009) or driver behavior (e.g., force platform; Forsman et al., 2014). Suitable primarily for road-side assessments, these measures have applications in research studies, fitness-for-duty testing, and law enforcement. Passive real-time monitoring measures of drowsiness include commonly recorded physiologic measures, automated observations of driver behaviors, and embedded driving performance measures. They are suitable (in principle) as input signals into drowsiness detection and warning systems (Dinges et al., 2005a, 2005b; Mallis and James, 2012; Aidman et al., 2015), which seek to not only detect drowsiness but also warn the driver (or dispatcher) regarding increased risk due to drowsiness. Such systems require high standards for sensitivity (i.e., reliably producing warnings for drowsiness when it is there) and specificity (i.e., reliably not producing warnings for drowsiness when it is not present). Most currently available drowsiness detection and warning systems are based on composite measures integrated through proprietary technology, and much publically accessible research remains to be done to assess their sensitivity and specificity.

With the increase in driving automation over the next few decades, the development of automation-appropriate drowsiness detection measures becomes ever more important. There is a need for non-proprietary, smart technologies that in a transparent manner combine different drowsiness measurement modalities and, informed in part by biomathematical models representing the homeostatic and circadian processes, predict CMV driver impairment and safety risks (cf. Vadeby et al., 2010; Mollicone et al. this issue). The development of such technologies needs to be accompanied by education and training on their proper use, and embedded within the broader context of hours of service regulations and fatigue risk management strategies in road transportation (e.g., Balkin et al., 2011; Anund et al., 2015; Higgins et al., 2017; Phillips et al., 2017). This will require a multi-disciplinary approach and significant resources, but is technically within reach.

Conflicts of interest

None.

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