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Detecting fatigue in car drivers and aircraft pilots by using non-invasive measures: The value of differentiation of sleepiness and mental fatigue

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ABSTRACT

Introduction: Fatigue is one of the most crucial factors that contribute to a decrease of the operating performance of aircraft pilots and car drivers and, as such, plays a dangerous role in transport safety. To reduce fatigue-related tragedies and to increase the quality of a healthy life, many studies have focused on exploring effective methods and psychophysiological indicators for detecting and monitoring fatigue. However, those fatigue indicators rose many discrepancies among simulator and field studies, due to the vague conceptualism of fatigue, per se, which hinders the development of fatigue monitoring devices. *Method:* This paper aims to give psychological insight of the existing non-invasive measures for driver and pilot fatigue by differentiating sleepiness and mental fatigue. Such a study helps to improve research results for a wide range of researchers whose interests lie in the development of in-vehicle fatigue detection devices. First, the nature of fatigue for drivers/pilots is elucidated regarding fatigue types and fatigue responses, which reshapes our understanding of the fatigue issue in the transport industry. Secondly, the widely used objective neurophysiological methods, including electroencephalography (EEG), electrooculography (EOG), and electrocardiography (ECG), physical movement-based methods, vehicle-based methods, fitness-for-duty test as well as subjective methods (self-rating scales) are introduced. On the one hand, considering the difference between mental fatigue and sleepiness effects, the links between the objective and subjective indicators and fatigue are thoroughly investigated and reviewed. On the other hand, to better determine fatigue occurrence, a new combination of measures is recommended, as a single measure is not sufficient to yield a convincing benchmark of fatigue. Finally, since video-based techniques of measuring eye metrics offer a promising and practical method for monitoring operator fatigue, the relationship between fatigue and these eye metrics, that include blink-based, pupil-based, and saccade-based features, are also discussed. To realize a pragmatic fatigue detector for operators in the future, this paper concludes with a discussion on the future directions in terms of methodology of conducting operator fatigue research and fatigue analysis by using eye-related parameters.

1. Introduction

Operators in many industries suffer from fatigue to varying degrees. In particular, in industries where safety plays an important role, such as in aviation and road transport, operator fatigue poses a potentially severe threat to human lives (Flight Ascend Consultancy, 2017; Maycock, 1996). In order to mitigate fatigue effects on on-road and in-air transport safety, one solution lies in fatigue-risk management, where employers of operators need to identify fatigue-related factors and reduce relevant risks (Phillips, Kecklund, Anund, & Sallinen, 2017). Another solution relies on the development of new technology, where fatigue detection devices play a significant role. Being able to indicate an operator's fatigue status by using non-invasive and objective indicators, especially before or close to the onset of their sustained attention decrease, could help to reduce the risk of operational errors.

Unfortunately, although researchers from distinct disciplines have made significant progress for indicating fatigue status, there are still very few findings that can be put into practice robustly. The first and one of the most significant reasons for this is the environmental complexity in which a human can be involved. In other words, too many endogenous and exogenous factors contribute to operator fatigue development. Sleep debt, circadian rhythm, and time awake are three main factors regulating sleepiness, while time-on-task and cognitive workload accumulate mental fatigue (Balkin & Wesensten, 2011). Taking all the factors into account

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requires a high degree of environmental control for the experiment when designing experiments for fatigue detection. The second reason is that the underlying mechanism of fatigue is not fully understood in the transport field. The most obvious case is that drowsiness is frequently used as the single fatigue response to represent fatigue status among some transport research (Dawson, Searle, & Paterson, 2014). However, fatigue has multiple types and responses (Matthews & Desmond, 1998, 2002; Saxby, Matthews, Hitchcock, & Warm, 2007). Being fatigued is not merely equal to being sleepy or drowsy (Matthews & Hancock, 2017). The third reason for stemming fatigue detection from practicality is that the existing non-invasive fatigue detection methods still have limitations integrating into real-world transport applications. Those methods either do not have well-developed hardware to be readily integrated with operators' tasks, such as neurophysiological measures (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014), or have poor maneuverability such as subjective self-rating scales (Di Stasi et al., 2012; Diaz-Piedra et al., 2016) and vigilance tests (Dawson et al., 2014).

Given these three limitations, it is evident that operator fatigue analysis contains diverse research questions in psychology, transportation, mechanical engineering, and many other research fields. This phenomenon indicates that realizing a reliable fatigue detection device in the future is not only about the development of a fatigue detection algorithm in computer science and hardware in mechanical engineering, but also about the understanding of the underlying mechanism of fatigue in a transport scenario from a psychological point of view.

This review comprehensively summarizes non-invasive fatigue detection methods for car drivers and aircraft pilots by differentiating drowsiness and mental fatigue. It is important to stress that although fatigue in railway and maritime also jeopardizes operator's health and safety, this review particularly concentrates on driver and pilot fatigue because they share more similarities in many aspects (as discussed in Section 3.3). This review provides a psychological insight and studies have been selected critically and consistently as to guide further fatigue research to realize a fatigue detection system in the future. It would be very useful for researchers and industry engineers to have a broader view to look at operator fatigue since studies in independent discipline do not always reference each other. Furthermore, considering the feasibility and practicality of those non-invasive fatigue measures, the present paper suggests that the future of a fatigue detection device could be based on eye metrics as fatigue indicators and eye-tracking devices. That would especially interest researchers who aim to explore the effective and robust fatigue indicators for monitoring operator status so as to ensure transport safety. It is also important to mention that results of fatigue indicators in this review is provided in qualitative way (such as the increased or decreased trend from alert to fatigue status) rather than quantitative way (such as the cut off value between fatigue and non-fatigue situation) because of the various units and parameters for indicators among different papers (e.g., the alpha spectral change of EEG were described by averaged power spectral value (Craig, Tran, Wijesuriya, & Nguyen, 2012), relative power ratio (Puspasari, Iridiastadi, Sutalaksana, & A. S. , 2017), and relative power level (Ahn, Nguyen, Jang, Kim, & Jun, 2016), although they represented the same concept in nature), different strategies for demonstrating the difference of fatigue indicators (such as simply using graph (Borghini et al., 2012; Kar, Bhagat, & Routray, 2010) and using effect size (Craig et al., 2012)). Therefore, it is more doable to review the results of fatigue indicators in qualitative way in review work (Borghini et al., 2014).

In the rest of this review, the essence of fatigue and the types of fatigue in air and on-road transport scenarios will be discussed in the third section. To give a psychological insight into the most common non-invasive fatigue detection methods, several papers including objective and subjective methods for determining fatigue occurrence will be reviewed in the fourth section. As eye metrics present a promising measure of fatigue with minimal engagement, the links between eye-related parameters and fatigue will be discussed in the fifth section. Lastly, we provide several future research interests with a discussion regarding the methodology of conducting operator fatigue research and fatigue analysis by using eye-related parameters.

2. About this review

The scientific literature in this review is retrieved by searching terms [“driver” or “pilot”] + “fatigue” + [“detection or measurement or monitoring”] + [“EEG” or “ECG” or “EOG” or “eye tracking” or “subjective scales”] into the following database from 1975 up to 2019.

- Science Direct
- Scopus
- Google Scholar

There is no doubt that the previous reviews on drivers/pilots collectively covered a wide range of fatigue indicators and measurements, but those reviews vary in scope. Comparatively, the main contributions of this review to current review literature on this subject is as below:

(1) The importance of distinguishing sleepiness and mental fatigue is discussed and highlighted, when using psychophysiological measures as fatigue indicators in driver/pilot fatigue research.
(2) Given that the big gap in the volume of review papers of fatigue detection and monitoring research between on-road (Dong, Hu, Uchimura, & Murayama, 2011; Lal & Craig, 2001; Phillips et al., 2017) and air transport (Borghini et al., 2014; Di Stasi, Catena, Canas, Macknik, & Martinez-Conde, 2013), this review simplifies current existing research into basic non-invasive fatigue detection methods, which could better guide researchers whose interests is in conducting pilot fatigue research and experiment.
(3) Regarding eye metrics as a detector of fatigue (McKinley, McIntire, Schmidt, Repperger, & Caldwell, 2011), this review adds more value to the current literature by clarifying the relationship between fatigue concepts (sleepiness, mental fatigue and workload) and pupil-based, saccade-based and blink-based features in both air- and land-transport fatigue detection.

3. Fatigue definition and forms

3.1. Passive fatigue and active fatigue: definition and mechanism for situation awareness impairment and performance decrement

It is commonly acknowledged that fatigue is a vaguely defined concept. Most of fatigue definitions appear to conceptualize fatigue with multiple characteristic descriptions such as the increased discomfort with lessened capacity for work, loss of power or capacity to respond to stimulation, and is usually accompanied by a feeling of weariness and tiredness (Rudari, Johnson, Geske, & Sperlak, 2016). The definition also varies in different discipline usage (Ream & Richardson, 1996), in which fatigue responses are very subject to the human's related tasks and activities.

In transportation field, as the fatigue responses and perception particularly change on overload and underload driving (or flying) conditions for drivers (or pilots), Desmond and Hancock (2001) proposed a theory that differentiates fatigue concept under these two situations as active fatigue and passive fatigue. Active fatigue is derived from continuous and prolonged, task-related perceptual-motor adjustment, whereas passive fatigue is in the condition that operator is required to monitor display but exert rare effort to respond.

In the high workload scenario, drivers/pilots could be induced active fatigue and related responses due to the high mental effort demand derived from all concerns of the internal and external environment. The external driving environment might involve: (1) the unpredictable road with high density of traffic; (2) the cruel weather condition such as fierce wind or rain, while the internal deployment of vehicle could require drivers/pilots to handle multiple secondary tasks such as looking for a detour in GPS map in car, managing the complex instrumentation in cockpit. Drivers and pilots tend to frequently mobilize their mental resource to meet the high demand of those tasks under prolonged driving and flying condition, which is more likely to cause active fatigue. This atmosphere aligns with the resource theory account (Warburton, 1986) that resources for divers/pilots may be defined as reservoirs of "fuel" or "energy" for processing and higher demanding tasks typically require more resources. Actively mobilizing resources to maintain attention causes vigilance decrement due to resource depletion (Helton & Russell, 2012; Smit, Eling, & Coenen, 2004). This impaired attention ability could play a very risky role to on-road and in-air safety.

On the other hand, passive fatigue is induced when the drivers/pilots almost appear to do nothing at all in a prolonged driving or flying condition. Driving scenario such as car driving in a monotonous highway or aircraft cruising requires little active mental effort from the operators in particular when the car is in cruise control or a plane in autopilot mode. Since humans can exert the corresponding effort according to the changing demand following the effort regulation theory (Hockey, 1986), in this passive fatigue condition, operators tend to exert little effort and resource to maintain their situation awareness and lower their performance standard. That can easily mean that humans cannot respond efficiently and accurately to the unexpected events (Saxby, Matthews, Warm, Hitchcock, & Neubauer, 2013), because of their deficit in the mobilization of sufficient compensatory effort under passive fatigue. However, this passive fatigue scenario would not consume much attention resource, so it would not impair their internal attentional ability if the drivers/pilots do not voluntarily fight with their drowsiness and if they are not mentally fatigued caused by time on task. In addition, the monotony characteristic in passive fatigue situation is commonly considered to uncover the overt sleepiness and drowsiness as the fatigue responses (Larue, Rakotonirainy, & Pettitt, 2010), which is even riskier than the status of insufficient situational awareness without any apparent physical sleepy symptoms (such as tiring eyes) for driver/pilot safety. It is also noteworthy that the insufficient awareness is not necessary to cause the immediate effects such as abnormal driving behaviors. However, another more hazardous aspect in the passive fatigue scenario is that it could lead to obvious performance decrement such as the deterioration in lane-keeping, which has been proven by many laboratory and empirical experiments (Verster & Roth, 2013), and some of the research has been applied in on-road by the industry (such as Greenroad (https://greenroad.com/) and the Lytx company (https://www.lytx.com/en-us/)). Therefore, both active and passive fatigue have a detrimental effect on vigilance and could lead to performance decrement under certain circumstance, which represents a significant risk in crashes, injuries, and fatalities.

Except for the harmful task-induced fatigue effects on driver/pilot's vigilance and performance, the multidimensional feature of task-induced fatigue has been exploited in drivers, which is rarely explored, but also has research significance in the aviation field. Saxby et al. (2007) have proven that fatigue is multidimensional in nature and qualitatively different tasks elicit different fatigue responses. Distress is found to be higher in an active fatigue condition, while lower task engagement and less motivation are more common in passive fatigue (Matthews & Desmond, 1998, 2002). Other fatigue responses such as the use of coping strategies could also be different in an active or passive fatigue condition. In the high workload condition, the drivers/pilots might consistently receive the deficit feedback message, which tend to elicit the emotion-focused coping strategy (e.g., worry). However, the underload condition could induce the avoidance-based coping strategy in which drivers/pilots tend to lower performance goals and withdraw effort from task. Task-focused coping strategy also could occur following individual's personality so that some operators tend to apply more effort or use their task strategy.

Although fatigue's multidimensional feature makes it difficult to design an effective fatigue detection system in a car or an aircraft, there are still many studies working toward indicating driver/pilot fatigue by measuring some aspects of fatigue responses. The most common ones are the reduced alertness and increasing feelings of drowsiness. However, the two types of mental fatigue – passive fatigue and active fatigue, which interactively with sleepiness contribute to performance decrement and vigilance impairment, should also be taken into consideration. Doing so could bring more face validity to fatigue detection and measurement.

3.2. Mental fatigue and sleepiness: definition, causal factors and importance for differentiation

Most of the research accepts the following definition of mental fatigue (Grandjean, 1979; Grandjean & Kroemer, 1997), which is believed to be a gradual and cumulative process and is thought to be associated with a general sensation of weariness, a disinclination for any effort, feelings of inhibition and impaired mental performance, and reduced efficiency and alertness (Borghini et al., 2014; Lal & Craig, 2001). However, these studies also abandoned the drowsy feeling description in those very original works and highlighted that mental fatigue and sleepiness differ from each other. A brief distinction between mental fatigue and drowsiness is that the former does not fluctuate rapidly over periods of a few seconds, while the latter does. Rest and inactivity alleviate mental fatigue but make drowsiness worse.

In the transport industry, the conventional approach to address the fatigue-related problems for drivers and pilots is largely oriented toward sleep research and the causal factors to sleep such as sleep debt, circadian rhythm, and time since awakening (Brown, 1994; Caponecchia & Williamson, 2018; Rosekind et al., 1994). Therefore, it is common that the widespread work uses fatigue (mental fatigue or general fatigue) as a synonym of sleepiness for drivers and pilots. However, there are many endogenous and exogenous factors that can influence the fatigue-related physiological states that impair diver/pilot performance and vigilance, but that are not only associated with sleep. Among many endogenous factors, time-on-task and high workload accumulate mental fatigue, while the sleep-related causal factors worsen sleepiness. The exogenous factors such as the characteristics of road geometry and roadside environment could possibly increase mental fatigue and sleepiness. For example, the monotonous driving on a highway leads to many sleepiness-related accidents (Dinges, 1995), while the rough road could accrue driver' mental fatigue.

Tragedy caused by sleepy pilots is not rare anymore. A Boeing 737-800 passenger jet crashed, resulting in 158 fatalities. The captain was reported to be asleep for 90 min of the 3-h flight; even the snoring sound was recorded (https://en.wikipedia.org/wiki/Air_India_Express_Flight_812#Investigation). Causal factors for pilot fatigue were also investigated in short-haul and long-haul flights. The number of flight sectors and duty length (time-on-task) were found to be the most influential factors to pilot fatigue in short-haul flight, and the time of day (circadian rhythm) had a weaker influence (Powell, Spencer, Holland, Broadbent, & Petrie, 2007). Bourgeois-Bougrine, Carbon, Gounelle, Mollard, and Coblentz (2003) also found that pilot fatigue in short-haul flight is caused by prolonged duty periods such as multi-segment flights over a sequence of 4–5 days (time-on-task) and successive early wake-ups (sleep-debt), while the night flights and jet lag (circadian rhythm) are the main contributors to pilot fatigue in long-haul flight. In more recent years, unmanned aerial vehicles (UAVs) have been of great interest in worldwide military departments and institutions. The pilots also shifted from in-vehicle to on-ground operation, resulting in the dramatic change of their operating tasks. However, the fatigue does not disappear with the development of vehicle automation. The mental states and cognitive process of operators under a high workload environment is a research hotspot in the UAV area. The high workload and time-on-task are widely acknowledged to induce mental fatigue, while the long-term monotonous monitoring task is unavoidable, which still makes sleepiness a frequent occurrence among UAV operators (Roy, Bovo, Gateau, Dehais, & Chanel, 2016; Senoussi et al., 2017).

Therefore, due to the complex environment of aircraft operating/manipulating and various causal factors contributing to fatigue, mental fatigue and sleepiness may rise to unacceptably high levels in civil and military air operation, which could impair their performance and situation awareness to further endanger the safety.

It is also important to stress that a distinction between sleepiness and mental fatigue is critical when it comes to the determination of the precise mechanism and nature impairing driver/pilot performance or vigilance, although in most cases they interactively influence driver/pilots' status during their continuous operation. In addition, to address fatigue-related problems, working on the regulation aspect is not enough, as most of the work tends to focus on the causal factors for driver/pilot performance decrement. A recent survey from the professionals' perception in aviation industry suggests that safety improvement lies more on the technology advances (https://www.flightglobal.com/products/airline-business/ – Article: Perception again weighs on reality March 2018).

Therefore, such distinction is considerably useful for researchers who concentrate more on the pilot/driver's physiological states on duty or near duty, since the mental fatigue and sleepiness lead to the difference in psychological and physical responses, and the discrepancy of the psychophysiological fatigue indicators for driver and pilot is a norm. For instance, Wilson, Caldwell, and Russell (2007) collected the pupil diameter change during performance of three aviation-related tasks of increasing complexity under sleep deprivation condition. They expected that the pupil diameter should have decreased after sleep loss, which aligns with most of the previous studies (Caldwell et al., 2004; Stern & Ranney, 1999). However, they argued that the pupil diameter showed an increase because the high workload of tasks overcame the sleepiness effects, as the pupil diameter has been found to rise with the increasing difficulty of tasks (Sirevaag & Stern, 2000). This study shows very obvious evidence that drowsiness and mental fatigue could lead to different physical responses. In addition, the different psychological responses caused by sleepiness and mental fatigue have been widely proved by Matthew's driving studies (Matthews, 2016). Developing new technology by recognizing the difference between mental fatigue and sleepiness could improve the effectiveness and accuracy of the current fatigue detection devices in vehicles, since most on-vehicle human sleepiness detection or general fatigue detection devices on the market receive pessimistic attitudes from users because of their poor practicality and inaccuracy (Haworth & Vulcan, 1991). Therefore, in our work, we suggest that distinguishing between mental fatigue and sleepiness for designing a fatigue detection device is necessary and could improve the detection accuracy. Such a fatigue detection device would improve on-road and in-air transport safety in the future.

3.3. The similarity and difference between driver fatigue and pilot fatigue

It is common that fatigue research has a general focus on pilots, drivers, or even shift workers. However, is pilot fatigue exactly the same as driver fatigue? The first review paper (Borghini et al., 2014) systematically integrated the previous research of the neurophysiological measures of fatigue and drowsiness for car drivers and aircraft pilots. In this work, they acknowledged that there are differences of operators' attention and cognitive demands between drivers and pilots due to the difference of their external and internal environment. Car drivers tend to focus more on the external environment such as monitoring the outside geometry or traffic situation, while aircraft pilots need to allocate more attention and cognitive resources to the internal environment such as managing the complex cockpit instrumentation. However, the similarity seems to be more outstanding. A constant monitoring task under low workload occurs both in drivers and pilots (for instance when operators are driving in highway or cruising during flight), while they also both experience high workload periods (for instance during the taking-off or landing for commercial pilots, fighting situation for military pilots, as well as the heavy traffic or severe weather for car or truck drivers). In addition, they share many similar endogenous and exogenous factors favoring their fatigue and drowsiness. Time-on-task and workload still plays a role in accumulating mental fatigue, while circadian rhythm, sleep debt, and awaking time aggravate their sleepiness. Even for the UAV operators, different workload and time-on-task are considered as the main factors for causing mental fatigue and widely used to manipulate fatigue effects (Roy et al., 2016; Schmidt, Wilson, Funke, Davis, & Caldwell, 2008; Wilson et al., 2007).

Another interesting aspect is that the non-invasive measures of fatigue among pilots and drivers are very similar, although the volume of the work in driver fatigue is much larger than the one in pilot fatigue. Neurophysiological measures such as EEG, ECG, and EOG have been used to examine drivers/pilots experience sleepiness and mental fatigue. Performance measures based on human or vehicle has turned mature, and many of the research results have been converted to real technology, which is widely applied by road safety companies. Subjective scales such as sleepiness scale are used interchangeably in these two fields.

It is common that a research group's research project originated from the study of driver fatigue topic and further extended their research in pilot fatigue. Di Stasi et al. (2012) examined the influence of mental fatigue on the dynamics of saccadic eye movements for drivers. Furthermore, the examined saccade-based eye metrics were applied in aviators (Di Stasi et al., 2016). The two studies showed that mental fatigue has a very similar impact on the saccade-based metrics for both drivers and pilots. It might also be very beneficial to drawing on relevant research from pilots to drivers. For example, Lohani et al. (2019) suggests that the power ratio of different EEG band in different brain region could be used for workload analysis in driving research, as a ratio of frontal theta and parietal alpha power spectral density has been proved to be a reliable mental workload measure for pilots (Borghini et al., 2015).

Similar to on-road transportation, fatigue is also multidimensional in the aviation industry that therefore causes similar safety issues. The studies into different patterns of fatigue responses in aviation, however, remain scarce. Although there is some research on pilot fatigue in drowsiness and tiredness aspects, task-induced fatigue has not been discussed. Therefore, when it comes to research non-invasive measures to detect pilot fatigue, it would be very beneficial to draw on research results from ground transportation field since both areas share a lot of similarities in terms of the operator's visuomotor and cognitive activities.

4. Non-invasive determination of fatigue

Extensive work has reviewed and summarized different non-invasive measures to analyze fatigue for drivers and pilots, and classified those non-invasive measures into subjective, behavioral, and physiological measures (Lohani et al., 2019). The advantages and disadvantages of those non-invasive measures have been summarized for lab-setting and real driving use (Lohani et al., 2019). However, the research results need to be interpreted with caution as was already mentioned by Lal and Craig (2001), since the definition of fatigue is usually very vague and multidimensional. Given the intent of this work, mental fatigue and drowsiness are the main focus of the fatigue construct. A wide range of studies of non-invasive measures to assess and detect mental fatigue and drowsiness in simulator and reality settings for drivers and pilots will be reviewed in this section.

4.1. Using electrophysiological signals (EEG, ECG, EOG) as fatigue indicators

Psychophysiological measures for assessing driver/pilot fatigue have been progressively reviewed over the last two decades (Borghini et al., 2014; Lal & Craig, 2001; Lohani et al., 2019). Lal and Craig (2001) first summarized psychophysiological indicators (EEG, ECG, EOG) associated with driver fatigue with a discussion of the concepts of fatigue, and they suggested that EEG was the most promising measure for indicating driver fatigue. After a decade of research, Borghini et al. (2014) provided more clear and convincing evidence of the relationships between fatigue and neurophysiological signals (EEG, ECG, EOG) by introducing and clarifying concepts such as mental workload, mental fatigue, and drowsiness for drivers and pilots. A most recent review provided by Lohani et al. (2019) added more psychophysiological measures such as pupillometry and compared the strengths and limitations of those measures for the application in the real driving world. From those reviews, it is clear that EEG still receives the most attention from researchers among neurophysiological signals to analyze drivers/pilots' cognitive states and fatigue. Other psychophysiological measures also have their advantages to be transited from lab-setting research to application in real-world driving so as to advance the development of an effective in-vehicle fatigue detection system.

EEG has been widely acknowledged as the "gold standard" to assess driver and pilot fatigue. Its signals originate from the inhibitory and excitatory postsynaptic potentials of cortical nerve cells, measured through a set of electrodes distributed on the scalp surface. Conventionally, the recorded waveforms with different frequency power bands (such as delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz)) in EEG from different cortical regions are extensively of researchers' interests to infer the brain status including fatigue, emotional state, cognitive process, and vigilance decrement.

It has been demonstrated by many studies that the spectral power in alpha and theta band increases as a person feel fatigued. This phenomenon has been confirmed by Craig et al. (2012) conducting a 2-h monotonous simulated driving experiment. The averaged spectral power values in alpha, theta, and beta band showed an obvious increase over all brain regions (see Fig. 1), as they used obvious sleepiness symptoms such as extended eye

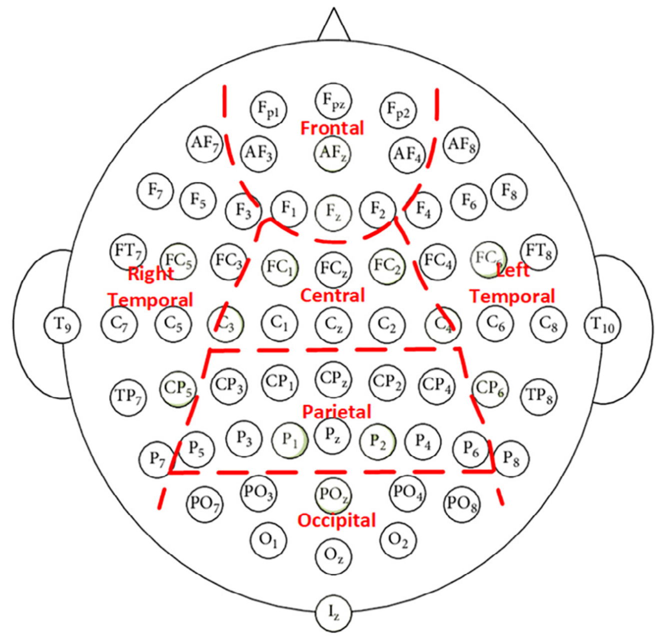


Fig. 1. The distribution of EEG electrodes and brain regions.

closure to recognize fatigue status. Another independent research group conducted a similar 1.5-h simulator-based driving experiment in the same year (Zhao, Zhao, Liu, & Zheng, 2012). They observed that averaged power spectral values in alpha (over central, parietal and occipital regions), theta band (over frontal, central and occipital regions) increase, while values in beta band (over frontal, central and temporal regions) decrease, as the drivers were mentally fatigued after driving. The decreased spectral power in beta band is also observed after tiring cognitive tasks (Tanaka et al., 2012), which is consistent with a recent study (Ahn et al., 2016), as the beta waves decrease significantly in the fronto-central region with increasing driving times. In this work, we inferred that mental fatigue and sleepiness in driving studies compound their effects on alpha, theta, and beta band. Sleepiness and mental fatigue could have the same impact on some spectral band's power change, while have the opposite influence on other bands. For example, sleepiness (with obvious sleepiness symptoms) increases alpha spectral power and beta spectral power, while mental fatigue increases alpha spectral power, but decreases beta spectral power. That also potentially explained why the summarized studies by Craig et al. (2012) shows consistently increased alpha spectral power, but there is no significant change in beta band across many studies (Simon et al., 2011). In order to augment the difference of EEG indicators between alert and fatigue status, many studies explored power spectral ratio among spectral bands. Compared to other combination, the increased ratio such as (theta + alpha)/beta and (theta + alpha)/delta has been extensively proven to be one of the most effective indicators for driver's general fatigue (Jap, Lal, Fischer, & Bekiaris, 2009; Kar et al., 2010; Simon et al., 2011). Ratio (theta + alpha)/beta has also been proven to be a good sleepiness and fatigue indicator for pilots, as Sauvet et al. (2014) conducted a 10-h long-haul EEG-based experiment during real flights.

However, in the field of aviation, it appears a more complex change of EEG spectral power across all bands for analyzing pilot fatigue. Caldwell, Hall, and Erickson (2002) examined the EEG spectral power change in alpha, theta, beta, and delta bands in flight and laboratory environment overnight from 8:45 p.m. to 9:00 a.m. the next day. Two flights were operated, and three test sessions in laboratory were conducted before and after each flight. They suggested that EEG theta and beta activity increase in both settings for indicating sleep-deprived mental fatigue, but the change of alpha activity shows inconsistence in lab and flight settings. For the decrease of alpha spectral power it was explained that a laboratory environment is more likely to cause sleep status, while the increase of alpha power in-flight environment is due to the high arousal. Zhang, Li, Meng, and Li (2013) also conducted a simulated flight training study and claimed that alpha, beta, theta (most obvious), and gamma waves tended to increase with the increased mental fatigue during the flight. Di Stasi et al. (2015) conducted a study that tracked the changes of EEG activity during a 60-min real flight. According to their research, spectral power in alpha and beta band decreases during the two consecutive cruising phases.

As the research results demonstrated above, rather than the sleepiness focus of driver fatigue, pilot fatigue research put more focus on pilot's mental fatigue status caused by high workload (such as training), sleep deprivation, and time on task. In addition, the change of EEG spectral power is very different from the findings in driver fatigue research. Sleepiness in driver research is related to increased alpha activity, while it shows opposite effect in pilot sleepiness research. Mental fatigue shows consistence in both areas, with increased alpha activity. That gives more proof that mental fatigue needs to be distinguished from sleepiness in fatigue research, as the emergence of mental fatigue disturb the EEG signal activities.

In addition to EEG spectral power, EEG alpha spindle measures can also be used as driver fatigue indicators, as the alpha spindle rate (over frontal, central and parietal-occipital sites) showed a higher detection sensitivity and specificity than EEG alpha-band power in a 4-h real road study (Simon et al., 2011). That is consistent with other independents studies (Borghini et al., 2012; Papadelis et al., 2007), in which alpha bursts (the same concept as alpha spindles) over the centro-parietal sites occurred frequently just before drivers drove off the road during a monotonous driving task, as a signal of drowsiness and reduced vigilance. In the study by Borghini et al. (2012), EEG features were also explored to characterize mental fatigue. This work claimed that increased power spectral density in theta band is a sign of the insurgence of mental fatigue. However, there is no research regarding the relationship between EEG spindle measures and pilot fatigue.

In more recent years, as wavelet entropy measure has been considered as a better method for capturing the non-stationary nature of EEG signal, compared to the traditional power spectral analysis, various entropy-based features have been compared and explored for generating the most effective driver fatigue indicators. Kar et al. (2010) compared 5 types of entropies and suggested that Shannon's entropy, Renyi entropy of order 2 and 3 along with the traditional spectral power-based indicators – alpha relative spectral power and (theta + alpha)/delta relative power ratio can be used together to estimate driver fatigue. To increase EEG equipment wear-ability, minimizing the electrodes without sacrificing fatigue detection accuracy could facilitate the practicality of EEG technology in real road driving (Fu, Wang, & Wang, 2017; Li, He, Fan, & Fei, 2012). Hu (2017) compared another four types of entropy feature based on one single EEG channel and suggested that fuzzy entropy can help to achieve better accuracy of driver fatigue detection. However, the entropy analysis method of EEG signal for assessing pilot fatigue has not been explored in aviation industry yet. It is obvious that there is no consensus in terms of the best indicators for driver/pilot fatigue and discrepancies emerged across a wide range of driver/pilot fatigue work. However, the most effective fatigue indictors have been compared and explored in a wide range of driving scenarios (summarized in Table 1). Alpha spectral power and alpha spindles are widely considered as good indicators for driver sleepiness, while the change of theta and beta spectral power are usually associated with the emergence of mental fatigue. Power spectral ratio (theta + alpha)/beta has been proven as a good indicator for low vigilance for both driver and pilot fatigue. In addition, entropy-based EEG features combined with channel and classifier selection become a hotspot for achieving high fatigue detection accuracy, along with reducing EEG electrodes.

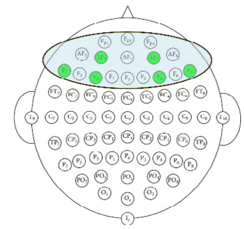
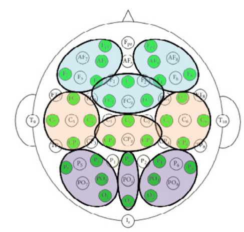
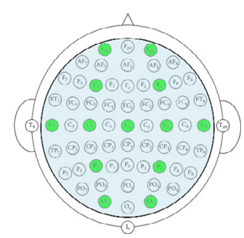
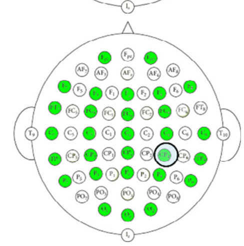
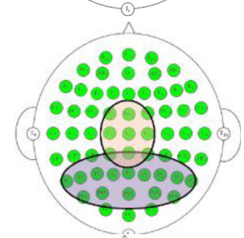
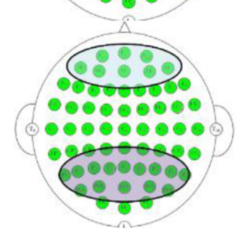
Another extensively used measure to detect fatigue and drowsiness is using EOG, which is an eye movement-dependent voltage recorded between electrodes placed near the eye at the inner and outer canthus (Frishman, 2013). In many studies, blink, pupil, and saccade measures, as well as their interactions, have been proven to be associated with brain information processing including decision-making and memory tasks and fatigue (Hosseini et al., 2017), so EOG has been widely used to track driver and pilot's eye movement so as to assess their sleepiness and mental fatigue. Concerning driver fatigue, Schleicher, Galley, Briest, and Galley (2008) recorded EOG data during a 2-h simulated driving task and drew the conclusion that blink characteristics (blink duration, delay of lid reopening, blink interval, and standardized lid closure speed) and saccadic features are associated with rising sleepiness. Among many EOG studies, the increased occurrence of slow eye movement and slow blinks have been widely recognized signs to determine the onset of fatigue and drowsiness for drivers (Lal & Craig, 2002). In a more recent study, a portable blink-based system based on EOG principles has been designed for detecting driver fatigue (Hsieh & Tai, 2013). Compared to car drivers, aircraft pilots seem to have more visual tracking tasks and need to consume cognitive resource and engagement during the flight because they have to take charge of more complicated instrument panels with multiple indicators such as altitude, airspeed, direction, and orientation, which noticeably increases their visual workload and mental fatigue. Morris and Miller (1996) assessed the blink and saccade parameters during a simulated flight by using EOG, and they found that blink amplitude appears to be a good predictor of increased error in both flight manoeuver tasks and a straight and level flying task with increased drowsiness and fatigue. However, EOG measure technology seems to be gradually replaced by camera-based eye-tracking system in recent years for the driver/pilot fatigue research purpose, as the latter equipment is more convenient to operate and less interferential to operator's primary task. The relationship between eye-movement parameters (blink-based, saccade-based, and pupil-based eye metrics) and sleepiness and mental fatigue of drivers/pilots are provided in Section 5. Regardless of the non-invasive measure is using EOG technology or eye-tracking system, in essence, these two types of technology are utilized to capture the eye movement.

ECG is one of the most important sources for fatigue indicators. In particular, it has been described that heart rate (HR) and heart rate variability (HRV) are related to fatigue and workload in the psychophysiology field. Michail, Kokonozi, Chouvarda, and Maglaveras (2008) suggested that slower low frequency (LF) of HRV corresponds to lower wakefulness characteristics, while faster high frequency (HF) of HRV indicates sleepy characteristics. The discoveries of the relation between ECG parameters and fatigue and drowsiness gave rise to the development of a fatigue detection system for drivers. Similar studies in the aircraft industry have shown that HR is related to different levels of task difficulty during a simulated flight, whereas HRV is sensitive to mental workload (Wilson, 2002).

4.2. Using human physical movement

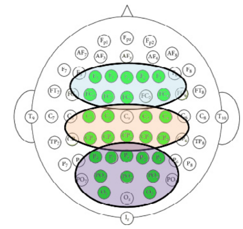
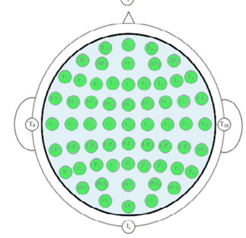
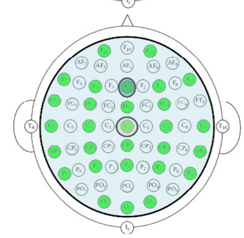
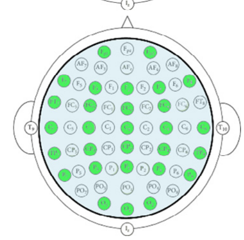
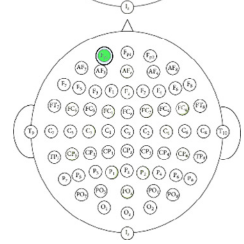
Since a great deal of drowsiness evidence is easily recognizable in video footage, including yawning, tearing eyes, eye closure, and head inclination, many studies have used video techniques such as high-speed cameras to detect fatigue symptoms so as to determine the onset and occurrence of fatigue. It has been described (Saradadevi & Bajaj, 2008) that locating and tracking mouth movements by using various classifiers (Support Vector Machine (SVM), Artificial Neural Network (ANN)) is a feasible means to detect fatigue and alert states. Also, a wide variety of eye movements has

Table 1
Comparison of the most effective fatigue indicators for drivers and pilots by using EEG system.

Reference	EEG system	Measured indicators	Most effective indicators	Driving task	Drowsiness/mental fatigue/general fatigue	Measured brain region	Tested channels
Puspasari et al. (2017)	EMOTIV EPOC+	Relative Power Ratio (RPR) in band α, θ, β, δ, θ/β, $\theta/(\alpha+\beta)$, $(\theta+\alpha)/\beta$, $(\theta+\alpha)/(\alpha+\beta)$	α, θ, $\theta/\alpha+\beta$ (Combination)	3-h drive on simulated motorway – no other car	Sleepiness (KSS)		6 out of 14
Correa et al. (2014)							
Craig et al. (2012)	BioSemi Active-Two	Averaged power spectral values in band $\alpha1$, $\alpha2$, θ, β, δ	$\alpha1$, $\alpha2$, θ, β (all regions)	2-h drive on simulated motorway – no other car	During driving: Sleepiness (video check the fatigue-related behaviour such as extended eye closure, increased eyeblinks, head nodding, and yawning) Before and after driving: General fatigue (Chalder Fatigue Scale)		32
Kar et al. (2010)	Not Provided	5 types of entropies (Shannon's entropy, Renyi entropy of order 2 and 3, Tsallis wavelet entropy and Generalized Escort-Tsallis entropy), α band relative energy and $(\theta+\alpha)/\delta_1$ relative energy ratio	Shannon's entropy, Renyi entropy of order 2 and 3,α band relative energy, $(\theta+\alpha)/\delta_1$ relative energy ratio	1-h drive on simulated motorway with heavy traffic; A battery of simulated driving, auditory and visual tasks (to generate mental fatigue) with sleep deprivation (36 h); 10-h real road drive	Sleepiness and mental fatigue (Stanford Sleepiness Scale, Piper Fatigue Scale, Epworth Sleepiness Scale)		13 out of 32
Hu (2017)	Neuroscan	4 types of entropies (sample entropy, fuzzy entropy, approximate entropy and spectral entropy)	Fuzzy entropy	About 1–2 h of simulator-based drive on motorway – no other car	Sleepiness and mental fatigue (Lee's subjective fatigue and Borg's CR-10 scale)		32
	Brain Products GmbH, Germany	Averaged power spectral values in band α, θ, β, δ	α bursts over central and posterior regions (sleepiness), Power spectral density of θ over prefrontal region and α over parietal region (mental fatigue)	Simulator-based drive with 5 different workload tasks	Mental fatigue (NASA-TLX) and drowsiness	 	61

(continued on next page)

Table 1 (*continued*)

Reference	EEG system	Measured indicators	Most effective indicators	Driving task	Drowsiness/mental fatigue/general fatigue	Measured brain region	Tested channels
Simon et al. (2011)	BrainAmp recording hardware (Brain Products GmnH, Germany)	Spindle rate, mean spindle amplitude, duration and frequency in band α, mean α, θ, β, δ-band power, (θ + α)/δ band power ratio	α spindle rate	4-h real road drive	Sleepiness (KSS)		43 out of 62
Ahn et al. (2016)	BioSemi Active-Two	Relative Power Level in α, θ, β, δ, γ	Relative Power Level in α, β	30-min simulator-based drive on motorway – no other car (well-rest Vs sleep deprivation)	Sleepiness		64
Zhao et al. (2012)	Neuroscan	Averaged power spectral values in band α, θ, β, δ, the amplitude of P300 wave of event-related potential	Averaged power spectral values in band α, β (over all regions), the amplitude of P300 wave of event-related potential (over frontal and central regions)	1.5-h simulator-based drive on motorway – no other car	Sleepiness and mental fatigue		32
Jap et al. (2009)	Neuroscan	Averaged power spectral ratio θ/β, α/β, (θ + α)/(α + β), (θ + α)/β	Averaged power spectral ratio (θ + α)/β	2-h simulator-based drive on motorway – no other car	General fatigue (physical signs of fatigue)		32
Morales et al. (2017)	ThinkGear AM (TGAM), NeuroSky	Averaged power spectral values in band α, θ, β, δ	Averaged power spectral values in band β, δ	2-h simulator-based drive on motorway – no other car	Sleepiness and mental fatigue (SSS, BORG and NASA-TLX)		1 out of 21

been analyzed as fatigue indicators for both car drivers and aircraft pilots, which will be described in Section 5. Regarding more comprehensive visual cues of driver fatigue, Ji, Zhu, and Lan (2004) proposed a real-time prototype, integrating eyelid movement, gaze movement, head movement, and facial expression to monitor driver fatigue, which demonstrated better performance than using any single visual feature alone.

4.3. Using vehicle-based behavior

It is a common experience that performance degradation is concurrent with human fatigue when operating vehicles. It gives researchers an idea that fatigue and drowsiness can be detected by analyzing a vehicle's behavior. Regarding car driver fatigue, Liu, Hosking, and Lenné (2009) summarized a number of vehicle-based measures for identifying increased drowsiness and fatigue, and they have reviewed that basic statistics (such as mean value and standard deviation) of lateral lane position of the vehicle, steering wheel movements, and deviation from speed limit are strongly related to driver drowsiness and fatigue. In addition, the variance of position and forces of throttle and brake pedals is also used to reflect driving performance such as inattentive driving and distraction. Other vehicle-based measures such as car-following distance and energy analysis of the steering-wheel angle dynamics have been summarized by Dong et al. (2011). Those parameters of vehicle performance were applied in real-life situation. For instance, Greenroad (https://greenroad.com/) and Lytx company (https://www.lytx.com/en-us/) detect unusual vehicle behaviors such as sharp acceleration, sharp braking, and lane departure and send alerts to drivers so as to enhance on-road safety.

In the aviation field, Morris and Miller (1996) scored variability (mean and standard deviation) of airspeed, heading, altitude, and vertical velocity of the airplane to obtain an error score, and they suggested that the error score roughly increased with pilot fatigue during eight legs of a simulated flight.

It is noteworthy that both on-road vehicles and aircrafts have been developed towards autonomous or semi-autonomous operation. Commercial aircraft manufacturers such as Boeing and Airbus have adapted an autonomous control system called autopilot, which constrains pilot fatigue detection by analyzing vehicle behaviors. Meanwhile, plenty of emerging autonomous technologies are being developed to make the on-road vehicle more intelligent. The autonomous progress of vehicles gives us a clue that fatigue detection in vehicle-based behaviors may not be the main focus of transport fatigue research in the future.

4.4. Subjective self-rating scales

Subjective self-rating scales and questionnaires have been one of the most important sources for assessing pilot and driver sleepiness and fatigue. For drowsiness, the Karolinska Sleepiness Scale (KSS) and Stanford Sleepiness Scale (SSS) are commonly used for collecting sleepiness data for drivers (Di Stasi et al., 2012; Wang & Xu, 2016). However, since fatigue has many responses, the scales related to sleep cannot quantify all fatigue responses. To evaluate the driver's overall subjective fatigue, Di Stasi et al. (2012) combined four distinct questionnaires and rating scales (the Groningen Sleep Quality Scale (GSQS), the SSS, the Chalder Fatigue Scale (CFS), and the Mental Workload Test (MWT)). The results showed that mental workload indicated by the MWT remained almost stable across the whole experimental procedure, whereas fatigue and sleepiness estimated by the SSS and the CFS increased with time-on-task and decreased after a break. These results indicate that multidimensional subjective rating scales are more comprehensive and reliable than are unidimensional scales. Although the combination of a range of disparate subjective scales and questionnaires can obtain a relatively complete fatigue status, it may result in increased complexity of the experimental protocol and difficulty in operating experiments, as well as the potential loss of data to poor timeliness. To avoid this problem, especially in complicated scenarios such as aviation, LeDuc, Greig, and Dumond (2005) developed their own subjective scales integrating multidimensional questionnaires including alertness, mental fatigue, visual fatigue, and physical fatigue by using the Visual Analog Scale (VAS). Other comprehensive subjective scales such as the NASA-TLX (task load index), the Dundee Stress State Questionnaire (DSSQ), which assess multiple states such as stress, workload, and fatigue are also widely used for analysis of driver fatigue (Matthews, 2016). In recent aviation research, Diaz-Piedra et al. (2016) only used a modified version of the Borg rating of perceived exertion scale (BORG) (Borg, 1998) to compare pilots' mental fatigue on pre-flight and post-flight.

Therefore, for the effective use of subjective scales and questionnaires to measure fatigue, it is necessary first to understand the particular fatigue response elicited by the scenario. Researchers can then use traditional subjective methods to develop an adapted version for their specific application.

4.5. Using fitness-for-duty tests

It is common that neuro-behavioral performance differs in an alert and fatigue status. Thus, many fitness-for-duty tests have been designed to determine whether operators are safe to commence work, or whether they show fatigue status. Generally, those tests aim to assess the executive functions: (1) vigilance; (2) oculomotor responses; and (3) limb-eye coordination.

Vigilance decrement is one of the most common fatigue responses. Many psychomotor vigilance tasks (PVTs) can be conducted by a palmtop or handheld devices such as PalmPVT. In essence, PVTs require the participants to attend a display task and to give a button-press response to visual stimuli on a computer over a 5- or 10-min period. Then, reaction times and 'lapses' are measured (Dawson et al., 2014). Most of those PVTs in literature are sensory vigilance tasks. However, to understand the cognitive process and mental abilities of a person, a working memory vigilance task (cognitive vigilance task) is proposed as a good method to measure human mental fatigue (Matthews et al., 2010). In addition, Heitmann, Guttkuhn, Aguirre, Trutschel, and Moore-Ede (2001) summarized two fitness-for-duty systems, SafetyScope™ (Eye Dynamics, Inc.) and the Mayo Pupillometry System, which measures pupillogram and eye movement parameters, as to be designed for alcohol and drug testing and clinical use. However, these two systems have not been validated as fatigue testing. Besides that, Software such as SkyTest is designed to assess if pilots are fit enough to operate an aircraft. It covers a wide variety of fitness-for-duty tasks including test pilots' attention, memory, orientation, and psycho-motoris etc. (https://www.skytest.com/), which provides a more comprehensive method to ensure pilots' fitness. Although some of those fitness-for-duty tests are not originally designed to detect fatigue, they still contain potential to be applied to determine fatigue occurrence or distinguish between the alert and the fatigue status.

4.6. Why psychophysiological measures are chosen to develop a fatigue detector?

In this review, five types of non-invasive methods to capture fatigue responses and determine fatigue occurrence of drivers/pilots have been reviewed. The most widely used measures and indicators in each of the non-invasive measures for driver and pilot's sleepiness and mental fatigue were also summarized according to our investigation (see Table 2). However, when it comes to applying those methods to real-time tasks for monitoring driver/pilot fatigue status, psychophysiological measures using electrophysiological signals and human physical movement have been argued to be the most promising and effective approach compared to subjective and vehicle-based behavior measures (Lohani et al., 2019). Subjective measures are limited because of their disruption to the primary driving task and inaccuracy caused by human misjudgement. Vehicle-based behavior is extensively favored by on-road safety companies, as measuring lane-keeping deviation can indicate driver performance decrement. However, vehicle automation development may restrict this method's application in the future. In addition, as we know, fatigue effects might not lead to obvious performance decrement, because drivers still can maintain their performance with mobilizing their resources or lowering their performance standard.

When it comes to fatigue detection, the priority is to detect the "potential risk" for performance deterioration, because a small mistake/decision may cause fatal disaster to the passengers. It would have a practical meaning for enhancing safety if driver's impaired situational awareness could be detected before the actual performance decrement happens. Besides, if the pilot/driver does not have enough situation awareness or ability to attend to a task in a satisfactory manner and provide good quality service, it will not only cause a potential safety risk but also reduce the passengers' loyalty and choice to their services, which may cause customer loss for many airlines and bus companies. The traditional way to capture situation awareness is to develop an additional task (e.g., to response to stimulus on the screen or by voice instruction) to test driver's vigilance, which never naturally exists in normal driving task, but is frequently being utilized in a laboratory-setting. When it comes to the real-world driving context, psychophysiological measures would perform better than those vigilance tasks, as they can be naturally integrated into driving tasks

Table 2
The most widely used measures and indicators in each of the non-invasive measures for driver and pilot's sleepiness and mental fatigue.

Non-invasive measures	The most widely used measure	The most widely used indicator for sleepiness	The most widely used indicator for mental fatigue	Potential to distinguish mental fatigue and sleepiness
Psychophysiological measures	EEG-based measure	Alpha-based spectral power-related parameters	Theta and beta-based spectral power-related parameters	High
Human physiological movement	Eye movement-based measure	Blink-based parameters such as PERCLOS	Pupil-based and saccade-based parameters such as the change of pupil diameter and saccade velocity	High
Vehicle-based behaviour	Vehicle's lane keeping-rated parameters	The basic statistics for lateral lane position of the vehicle such as mean value and standard deviation		Low
Subjective self-rating scales	Sleepiness, mental workload and fatigue-related scales	KSS and SSS	BORG and VAS	Medium
Fitness-for-duty tests	Vigilance test	PVTs		Low

after the mature technology developed (which will be discussed in Section 5.4).

Therefore, when doing the fatigue detection research and conducting experiments, it is more promising and meaningful to focus on those fatigue effects on situation awareness from the operator status rather than the vehicle performance decrement in which the hazard effects have already formed. Since the psychophysiological measures are sensitive to the variation in situation awareness compared to the others, using psychophysiological measures and technology to build a reliable system would enable the prediction of levels of vigilance and subtle mental states such as mental fatigue and drowsiness.

However, it does not mean that the other non-invasive measures are useless. They still play a very important role in determining fatigue occurrence and validate fatigue detection technology in a lab-setting. Because fatigue responses are hard to capture and different non-invasive measures have their own shortcomings, conducting fatigue detection research requires a high standard of experimental environment and protocols. Carefully selecting and combining those non-invasive measures is important for avoiding experiment failure.

It is acknowledged that no single measure alone can determine fatigue occurrence (Heitmann et al., 2001). Combining multiple sources of non-invasive fatigue methods to form a standardized benchmark of fatigue is required to have good reliability, since this review has found that many studies ignored this importance (Di Stasi et al., 2016). Dawson et al. (2014) have formed three guidelines to assess if fatigue detection technology is suitable to be appropriately implemented. One of the most important guidelines is that the technology should be based on scientific evidence in terms of the validity of the detected indicators (e.g., eye metrics, features of vehicle behavior) in comparison with standardized benchmarks of fatigue (e.g., neurophysiological measures, psychometric testing, and subjective self-reported scales).

A recent study by Morales et al. (2017) is a good example of conducting this principle. They combined the saccadic velocity of eye-movement, subjective scales (sleepiness and fatigue scales), and driving performance to form a standardized benchmark to validate the driver's fatigue status. Along with this 2-h driving experiment, the observed change of power spectra of the delta EEG band from prefrontal brain region suggests that their single-channel EEG device is able to detect mental change related to fatigue.

Therefore, when attempting to build a fatigue detector, it is viable to use psychophysiological measures to explore subtle fatigue responses such as drowsiness and mental fatigue. In the meantime, the combination of selective non-invasive measures based on the existing scientific evidence to validate the fatigue status should act as a guideline when conducting relevant experiments, since no single measure alone can determine fatigue occurrence (Heitmann et al., 2001) and many studies ignored this importance (Di Stasi et al., 2016).

5. The link between eye metrics and fatigue

5.1. Pupil-based metrics associated with sleep-related fatigue, mental fatigue and workload

Pupillography has been found to be an objective indicator of sleep-related fatigue (Morad, Lemberg, Yofe, & Dagan, 2000). In his experiment, the average pupillary diameter was found to be correlated with the degree of subjective sleepiness, and all analyzed eye parameters showed significant changes with varying alertness and fatigue. From a medical point of view, as arousal/alertness levels decrease, sympathetic control of the dilator muscles could wane while parasympathetic control of the sphincter muscle would increase (LeDuc et al., 2005). Therefore, a decrease of pupil size should be seen with the decrease of alertness. This view has also been potentially confirmed by Hopstaken's (2015) research that increasing mental fatigue coincided with diminished stimulus-evoked pupil diameter. In this research, it is noteworthy that its visual paradigm proved that pupil size could show a robust effect to task engagement and mental fatigue, although the pupil is widely acknowledged to be very sensitive to ambient light. However, when testing the pupil diameter as a valid and objective indicator for overall fatigue in field studies, it does not always demonstrate as good of a performance as the researchers expected. Specifically, in the aviation industry, results in the literature suggest that the pupil size slightly increases with increased mental fatigue, visual fatigue, physical fatigue, and the decline of alertness (LeDuc et al., 2005). By contrast, Wu, Wanyan, and Zhuang (2015) observed that pupil diameter decreased with great fatigue when pilots operated a long-term dual-task in a Boeing 737-800 flight simulator. Regarding driver drowsiness detection, Wang and Xu (2016) analyzed 23 non-intrusive indicators for drowsiness detection and suggested that average pupil diameter is the second most significant indicator contributing the appropriate indicators group for drowsiness detection. Whether the reason for the paradoxical outcomes is caused by the task type, fatigue manipulation, and subjective state response remains unclear. Nevertheless, there is strong evidence that suggests that changes in pupil diameter are connected to workload in land and air transportation. For example, Hosseini et al. (2017) used a driving task with easy, medium, and difficult road conditions to indicate that changes in pupil diameter have a significant relationship with varying cognitive demands. In flying scenario, the same change was proven by Wilson et al. (2007), as the pupil diameter increases from cruise to low difficulty and also significantly enlarges from the low to high difficulty conditions. The high workload characteristics in active fatigue scenario is one of the most important internal factors to accumulate mental fatigue, and the workload from moderate to high levels in prolonged tasks have been proven to generate mental fatigue following resource depletion theory (Grech, Neal, Yeo, Humphreys, & Smith, 2009). Therefore, pupil diameter change as an indicator for different workload could also be very meaningful for understanding driver's mental fatigue, as well as sleepiness, because the underload situation is firmly related to sleepiness occurrence, while overload scenario is associated with mental fatigue generation.

5.2. The relationship between eye closure-based metrics and sleepiness, mental fatigue and workload

It is a common experience that some ocular physiological response occurs when people feel sleepy and drowsy, such as bleary eyes, slow eyelid closure, and more frequent eye blinks. This triggered many studies investigating sleep-related fatigue, focusing on extracting features of eyelid movements to detect and prevent fatigue. This research interest particularly stands out in automotive driving and aircraft piloting. The percentage of eyelid closure (PERCLOS) (Dinges & Grace, 1998) has been found to be the most reliable and valid indicator of driver fatigue. It has been globally found by a number of studies that the PERCLOS increases with the extension of wakefulness and with the decrement of driving performance and response to stimulus (Ji et al., 2004), therefore PERCLOS has been widely applied to commercial devices for driver drowsiness detection. Also, blink rate is ubiquitously mentioned in the literature to indicate drowsiness of drivers and mental fatigue and high workload of pilots. When pilots are in alert status, their blink rate decreases with the high visual workload and increased task demand, because they become more focused on their tasks (Wilson & Fisher, 1991). On the contrary, when close to drowsiness, a significant increase of blink frequency appears in drivers (Lal & Craig, 2001). That is why the empirical studies of fatigue always face challenges in the sense that fatigue response is multidimensional so as to cause different effects on psychophysiological responses. Fatigue responses can be related to underload and can lead to sleepiness, and they can also be associated with overload and cause mental fatigue and distress. Simply using blink rate as driver/pilot fatigue indicator might not show sufficient face validity. Lal and Craig (2002) further statistically analyzed and described different eye-closure movements occurring in alert/awake, fatigue/drowsiness, and arousal from drowsiness status during driving phase. It was concluded that the fast eye movements and the conventional blinks during the awake, alert phase were replaced by slow or no eye movements and small fast rhythmic blinks during drowsiness, while the single vertical eye movements showed up and conventional blinks reappeared on arousal from the fatigue state. Therefore, a better way to indicate driver/pilot fatigue might lie on the exploration and combination of multiple eye metrics to discover the difference between those subtle changes of eye movement corresponding to mental fatigue and drowsiness. In addition, it has been suggested that duration, speed, and amplitude of eye closures are sensitive variables for sleep-related fatigue for drivers (Åkerstedt et al., 2010). A recent study shows that blink bursts, which are defined as more than two blinks that occur in as short a period (from 0.5 to 2.0 s), significantly rise when fatigue caused by mental workload accumulates (Horiuchi, Ogasawara, & Miki, 2017).

5.3. The relationship between saccade-based metrics and sleepiness, mental fatigue and workload

Back in 1975, the term "main sequence" was proposed to describe the relationships between duration, peak velocity, and magnitude of human saccades, which have been confirmed as a useful tool for analyzing eye movements and their neurophysiological control (Bahill, Clark, & Stark, 1975). Furthermore, Henn, Baloh, and Hepp (1984) used experiments to show that the omnipause neurons significantly decrease firing rate from alertness to light sleep. That study indicates that sleep-related fatigue can be indicated by saccade-based metrics.

Based on the above neuroscience findings, researchers from the transportation field started to apply them to indicate fatigue status of drivers and pilots. In the work by Galley's research group, they examined the variation of saccade-based eye metrics in driving scenario. Various secondary tasks (Galley, 1993) and different external driving environment (monotonous driving vs. city driving) (Galley & Andres, 1996) were used to increase task difficulty for drivers. They found that saccadic velocity increased with the increased task difficulty, but decreased with the increased mental fatigue caused by time-on-task.

In recent years, many empirical studies from Di Stasi's research group (Di Stasi et al., 2016; Di Stasi et al., 2012; Diaz-Piedra et al., 2016) have shown that saccade-based metrics emerged as a promising means for indicating mental fatigue in on-road and in-air industry, however they claimed an opposite change of saccadic velocity with the increased task difficulty. Di Stasi et al. (2010) claimed that the increased task difficulty during short driving periods lowers saccadic peak velocity. Regarding the time-on-task effects, Di Stasi et al. (2012) designed a 2-h of driving task to generate mental fatigue (caused by time on task) and analyzed the saccade-based metrics, particularly peak saccadic velocity, before and after the driving task, as well as after a 15-min rest. They demonstrated that peak velocity shows a considerable decline before and after the driving task and no moderate changes after break. Concerning the saccadic variation for sleepiness research, only saccadic duration has been found to vary with driver's sleepiness by (Schleicher et al., 2008).

In the aviation field, Di Stasi et al. (2016) investigated the saccade-based metrics before and after a short-simulated flight and a long-simulated flight, drawing a conclusion that saccadic velocity can serve as a good biomarker for pilot fatigue. Furthermore, to validate the saccadic velocity as a fatigue index in field studies, Diaz-Piedra et al. (2016) conducted a study outside of a laboratory setting in which they analyzed the saccadic velocity before and after a real flight of more than 2 h and also concluded that the saccadic velocity significantly decreased.

From the research results mentioned above, mental fatigue caused by time-on-task lowered mean and peak saccadic velocity, which has reached consensus in Galley and Di Stasi's research group. The discrepancy of the variation in saccadic metrics only exists in terms of the relationship between task difficulty and saccadic velocity. This discrepancy may be explained by concluding that task difficulty in different driving studies could generate low to medium workload or medium to high workload, which could either increase arousal (without generating mental fatigue) or decrease arousal (with generating mental fatigue). For example, in Galley's driving study (Galley & Andres, 1996), compared to monotonous driving, the city environment is more interesting, which can be perceived as low to medium workload and generate more arousal without mental fatigue. On the contrary, since the task was performed in a military helicopter during official tactical training flights in the work by Diaz-Piedra et al. (2016) (which is under high workload condition), mental fatigue was very likely to occur and lower operator's vigilance.

Therefore, it seems more persuasive that mental fatigue caused by high workload and time-on-task lead to the decreased saccadic velocity. In addition, it is also noteworthy that the workload generated by driving or flying task per se can be perceived differently by individuals.

5.4. Why are eye-related metrics promising to realize a fatigue detection system?

In this review, five types of non-invasive methods to capture fatigue responses (such as mental fatigue and sleepiness) and determine fatigue occurrence have been reviewed. When it comes to applying those methods to real transport scenario for monitoring fatigue status, however, those methods face obstacles. Although neurophysiological measurements, such as EEG, EOG, and ECG, are reliable objective signals to determine fatigue occurrence, the ''neurophysiological procedure'' for fatigue detection is still too theoretical to be applied to daily life. Some existing ''PVTs'' for testing sustained attention require much engagement and are not readily integrated with other tasks, so they cannot be easily accepted by the public for their standard of quality life. The progress of vehicle automation could restrain the technology of using vehicle movement to capture fatigue status. Regarding the subjective fatigue scales, it is not ideal for letting the operator report their status all the time. However, in a laboratory setting, those non-invasive fatigue detection methods still play an important role in determining fatigue occurrence.

As far as using human physical movement is concerned, many pieces of evidence regarding the relationship between pupil-based, saccade-based, and blink-based eye metrics and fatigue in road and air transport have been demonstrated in our review. Although there is some discrepancy among the research regarding how fatigue correlates of eye metrics, the strong connections between oculomotor activities and fatigue, drowsiness and mental workload manifest in various independent, peer-reviewed, lab-setting and field transport fatigue studies, which support that an eye metrics-based non-invasive fatigue detection method could help to realize a more reliable and practical device in the transportation field.

More precisely, multiple fatigue responses can be represented by changes of eye metrics. Blink-based eye metrics have been confirmed to be related to drowsiness and cognitive process. Saccade-based eye metrics has been found to be indicators to drowsiness and vigilance for drivers and general fatigue and vigilance of pilots. Pupil-based parameters are sensitive to emotion, and pupil changes are associated with motivation, distress, and drowsiness. Thus, eye-related metrics are beneficial to present multiple fatigue responses in a multidimensional fatigue world.

From a hardware point of view, given the particular transport operation scenario, the fatigue detection system should be designed to avoid interfering with normal vehicle operation and to require negligible engagement. With the development of video techniques and Micro-electromechanical systems (MEMS), the camera-based eye-tracking system has been making progress to meet this purpose reliably. In our work, we summarize several eye-tracking systems mentioned for research purpose in different references. Pupil Lab may be the most suitable equipment for the beginners and people who need to do secondary development because it has a relatively low price and up-to-date open source software. For its specifics, it has a blink classifier based on joint drops in pupil detection confidence, and Truschzinski (2017) has confirmed that a general model can be created for workload and pupil dilatation by using Pupil Lab. Since Pupil Lab has not been used for saccadic monitoring, EyeLink Ⅱ would be a good option for this purpose, which has the fastest head-mounted sampling rate of 500 Hz. Di Stasi et al. (2016) showed the saccadic velocity is a useful biomarker for pilot fatigue by using EyeLink Ⅱ. However, when considering the wear-ability, researchers may choose a non-glasses eye-tracking system such as Smart Eye, which can consist of multiple cameras set up in front of the subject. According to the research results from He, Liang, Pan, Wang, and Cui (2017), it has only a 70% quality assurance rate for pupil diameter detection, which may not be sufficient for researchers who need high accuracy. The Eye-tracking System SeeingMachines facelab 4.6 (Palinko, Kun, Shyrokov, & Heeman, 2010) can monitor pupil size up to $1 * 10^{-10}$ m, which can be used for very accurate detection of pupil changes (FOVIO system is updated by SeeingMachines company). Besides, there are two well-rounded brands for the eye-tracking system. One is the SensoMotoric Instruments (SMI). SMI ETG 2.0 is glass-based and has been used to analyze the change in pupil diameter so as to examine the neural systems linked to pupil dilation under varying cognitive demands (Hosseini et al., 2017). The other brand is Tobbi, which has both glass-based and non-glass-based equipment. The Tobii Eyetracker 2150 has been used to analyze task disengagement and mental fatigue covariance with pupil dynamics (Hopstaken, van der Linden, Bakker, & Kompier, 2015).

6. Conclusion and discussion

Three fatigue types and multiple fatigue responses in transportation have been identified to help researchers in the non-psychological field to better understand the underlying mechanism of operator fatigue. This review suggests that before conducting transport fatigue research, clarifying the fatigue responses and understanding fatigue nature in the targeted task environment is required to capture human status, which directly affects operator performance and transport safety. Then, five widely used non-invasive measures for determining fatigue occurrence for car drivers and aircraft pilots have been reviewed. This work confirms the idea (Heitmann et al., 2001) that a single method is not able to determine fatigue occurrence, and indicates that combining multiple sources of non-invasive fatigue methods to form a standardized benchmark of fatigue occurrence would provide good reliability. In addition, the formation of this benchmark needs to be consistent with the analysis of fatigue nature in the targeted task scenario. After investigating the relationship between fatigue and pupil-based, blink-based, and saccade-based metrics, and the available hardware support in the market, our review suggests that a camera-based eye-tracking system, integrated with the combination of multiple eye metrics could provide a promising solution to realize a fatigue detection system with little perception to operators in transport in the future. Most importantly, the main finding through this review is that recognizing the difference between drowsiness and other fatigue responses such as mental fatigue could improve the accuracy of fatigue detection for car drivers and aircraft pilots, as the physiological indicators could be different due to the different fatigue responses.

6.1. Future research

There are several directions for future research. First, to find reliable fatigue indicators for pilots, the nature of fatigue in the aviation industry needs to be further clarified. Research exploring these various fatigue responses is scarce in the aviation industry, but pilots suffer significantly from sleep deprivation and mental workload, which make sleepiness and mental fatigue occur frequently. Since DSSQ has been widely used as a basic subjective method to manifest fatigue responses in different applications (Matthews, 2016), an adapted DSSQ combined with NASA-TLX could be an efficient method to help aviation human factor practitioners and researchers to understand the fatigue responses and essence in aviation field.

Secondly, from this review, it became clear that many studies do not demonstrate a clear experimental protocol, and there is no standard methodology for the determination of fatigue occurrence in the transport field. Some of the research does not even form a standardized and convincing benchmark of fatigue status. Therefore, it is meaningful to investigate fatigue in a laboratory setting and to assess whether a combination of those fatigue analysis methods leads to a feasible and reliable benchmark of fatigue status. Since most empirical fatigue analyses did not do so, obtaining enough fatigue responses from different fatigue sources could help to generate comprehensive fatigue determination methodology. Furthermore, the effective fatigue indicators from lab setting research should be converted and tested in real driving or flying scenario. The combination of multiple non-invasive measures could also be used to validate the fatigue indicators, since the simulator environment is still different from the real world scenario.

Thirdly, aligned with different fatigue types in different scenarios, the most reliable fatigue-related features of eye movements need to be explored in transport, especially in the aviation industry. Even though many pupil, saccade, and blink-based parameters have been widely confirmed to be considerably related to operator's alertness and vigilance, other factors such as motivation and rewarding still have an adverse impact on those eye-related features. Since multiple fatigue contributing factors vary with different scenarios, it is necessary to explore either the difference or the similarity of eye-related features for different task-induced fatigue in aviation and ground transportation. For instance, fatigue generally involves reduced alertness and increasing feelings of sleepiness or drowsiness, which corresponds to the decrease of pupil size. However, compared to passive fatigue, an operator in active fatigue tend to apply more effort to a task, with the increase of motivation, which leads to the increase of pupil size. Therefore, exploring the most useful and effective eye-related metrics of task-induced fatigue could help us to better understand why there is a discrepancy in psychophysiological responses in operator fatigue and facilitate the development of fatigue detection technology in applied research.

Finally, a more effective fatigue detection algorithm based on eye movements needs to be well developed accounting for physical differences in human operators. In the current field-based studies, it has been shown that the individuality has a great impact on the specificity and sensitivity of fatigue detection system. Such a well-developed eye-metric based fatigue detection algorithm and system could help to assess the weakness of automation systems for operator manipulation, as well as screening the more eligible operators adapted to the specific industrial environment such as military flight with high workload.

Ideally, a reliable fatigue detection device in the future would be able to successfully identify the presence of fatigue in a transport operator, which could then be used to prompt the operator to take a rest or even inform a third party that intervention is necessary. This could considerably enhance transport safety and reduce accidents caused by fatigue and human error.

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