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Review

Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness

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ABSTRACT

This paper reviews published papers related to neurophysiological measurements (electroencephalography: EEG, electrooculography EOG; heart rate: HR) in pilots/drivers during their driving tasks. The aim is to summarise the main neurophysiological findings related to the measurements of pilot/driver's brain activity during drive performance and how particular aspects of this brain activity could be connected with the important concepts of "mental workload", "mental fatigue" or "situational awareness". Review of the literature suggests that exists a coherent sequence of changes for EEG, EOG and HR variables during the transition from normal drive, high mental workload and eventually mental fatigue and drowsiness. In particular, increased EEG power in theta band and a decrease in alpha band occurred in high mental workload. Successively, increased EEG power in theta as well as delta and alpha bands characterise the transition between mental workload and mental fatigue. Drowsiness is also characterised by increased blink rate and decreased HR values. The detection of such mental states is actually performed "offline" with accuracy around 90% but not online. A discussion on the possible future applications of findings provided by these neurophysiological measurements in order to improve the safety of the vehicles will be also presented.

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1. Introduction

It is well-known that driving a car (and to a major extent, an aircraft) requires substantial cognitive effort and attention from the operator's brain. According to the World Health Organisation (WHO) the primary cause of death in adults from 18 to 29 years old, and the ninth cause of human death globally, is represented by car accidents (Preventing Road Traffic Injury: A Public Health Perspective For Europe, 2009). These facts might indicate that the brain's capacities of attention, memory and awareness are often overestimated when we choose to drive a car. In fact, all individuals make mistakes, even when performing common everyday tasks. It is easy to quickly adapt strategies to avoid repeating errors, and this is called a learning process. When it comes to interactions with complex environments like those constituted, for instance, by thousands of vehicles moving in a chaotic traffic day, in a great city like Beijing or Paris, it is much harder to isolate and understand the problem quickly. In these situations, a driver could be involved in a crash, even without being responsible for the error. Depending on the different conditions in which the subject acts, errors can have a significant impact on the success of the performance or even on the safety of the human subject.

Hence, variables, such as situation awareness (SA), mental workload and fatigue, are important in the assessment of safety conditions.

Aircraft pilots have to operate more complex vehicles, and therefore go through a strict training programme before getting their flying license. Modern glass cockpits look tidy from the outside and are designed to be as intuitive as possible, but a complex system is functioning behind the scenes. As a result, it becomes increasingly challenging for pilots to fully and continuously manage the display systems of the new models of modern aircrafts, such in the evolution occurred from the MD-80 to the Airbus 330 cockpit. A proper understanding of the relevant information among the many presented on the cockpit is crucial for the pilot in emergency situations in which the time available for understanding the problem could be very short. Fortunately, both situations are rarely encountered in actual flights due to the excellent reliability of aircraft and on board systems. However, when they do occur, the pilot's mental state – a construct including SA, mental workload and fatigue – plays a crucial role in solving the problems.

Unfortunately, safety statistics show that inadequate SA has contributed to a significant number of accidents. Worldwide data shows that, in the period 1993–2007, 46% of the contributing factors that led to fatal accidents were cockpit crew related (CAANL, 2008). Also, the latest data published by Boeing (2011) shows that the in-flight loss of control and controlled flight towards the terrain caused the majority of fatalities in worldwide commercial jet accidents in the period 2001–2010. Pilots are normally trained to deal with system failures and emergency cases that were foreseen in the aircraft development phase. Also, modern aircrafts provide electronic guidance for the completion of mitigating procedures. Nevertheless, situations exist that require alertness from the pilot for noticing issues as well as clear judgement for tackling them. An example is provided by the crash of the Turkish Airlines Flight TK1951 during its landing in Amsterdam Schiphol Airport, The Netherlands, on 25 February 2009 (Dutch Safety Board, 2010). In this accident, nine people in the aircraft died, including the three pilots. The aircraft, a Boeing 737-800 with a glass cockpit, was damaged beyond repair. In the investigation that followed the accident, it was found that the crash was caused primarily by an automatic reaction of the aircraft in response to a faulty radio altimeter. In a situation with a higher workload than normal, the crew did not realise that the fault caused the auto throttle to reduce to idle power during the approach. Eventually, they were unable to successfully recover the aircraft from the resultant stall.

As is evident from the quoted accident statistics and illustrated by the above case, the flight crew is still the most commonly contributing factor in fatal accidents worldwide. Also, an ineffective pilot mental state (e.g., peak workload, lack of SA, fatigue) plays a role in the sequence of events leading to many of these accidents. Therefore, the need for a continuously improved understanding of pilot behaviour and how to optimise crew performance is particularly important.

While the concept of mental workload could be investigated with a large amount of different experimental setups, the characterisation of cerebral activity directly during the driving of vehicles or aircrafts in humans is of high interest for the potential translational characteristic of the results. In fact, understanding the cognitive workload of humans during driving tasks could be extremely useful for realising a class of devices in the future that could alert the driver or the pilot about the low level of his/her internal cognitive resources during travel.

These driving tasks could have similar characteristics in terms of the visuomotor and cognitive activities required in the driver/pilot.

It may be argued if the drivers and pilots perform the same tasks in terms of attention and cognitive demands. Of course there are significant differences for all concerns the internal environment (e.g., the cockpit versus the internal seat of the car) and for all concerns the external environment. For all concerns the internal environment, the pilots are requested to have a higher attentional demands due to the complexity of the instrumentation to be mastered along the cruise. Such kind of visual attention requirement is certainly higher than in normal drivers. In fact, the level of instrumentation inside the car is moderate and easy to understand when compared with the sequence of instruments available within the cockpit. In addition, the pilots have surely a higher level of attention request also from the acoustic point of view, due to the frequent radio interaction they have with the air traffic management system on the ground during the entire travel. Except the landing and take-off phase, the visual attention for the external environment is surely reduced in pilots when compared to the normal drivers, since pilots are trained to be more confident on the instruments instructions than on their senses (even visual). From this point of view, normal drivers put more attention to the environment outside the vehicle than the pilots. However, the external environment poses additional request for the mental workload for pilots when compared to the normal drivers, since the influence of weather on

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the travel is completely different for the two categories. Thus, the level of attention required could therefore be significantly lower in the car environment when compared to the cockpit environment and the occurrence of drowsiness more frequent when compared to the aircraft environment.

There are also similarities in the modulation of the difficulty of the tasks during the travel with the two kinds of vehicles. In fact, both tasks require high cognitive demands for certain time periods (for instance during take-off or landing, as well as when in heavy city traffic) intermingled by periods of low cognitive demands (for instance during the cruise time of an aircraft or when driving a car on an empty highway). Of course, differences in the quality of the tasks demands could be appreciable, such in the case of the pure instrumental flight in which the pilots have to rely on the interpretation of the instruments information to guide properly the aircraft.

Nevertheless, distraction or drowsiness could have a remarkable impact on the quality of the manoeuvres performed, with potential catastrophic consequences for the passengers as well as for the pilot/driver of the vehicle. Roughly speaking, these two tasks could share similar visuomotor and cognitive characteristics, could provoke similar modulations of the workload profile and could result in a potentially catastrophic outcome in the case of a period of simple distraction or drowsiness. However, the absolute levels of cognitive workload and attentional resources needed for the pilots during the travel are greatly superior to those required by the normal car drivers.

Whether discussing car drivers or aircraft pilots, it is essential to know and to understand as much as possible about the pilot's behaviour during a multitude of operative circumstances.

A pilot or driver's behaviour could be measured through several human factor tools, such as the explicit measurement of drive errors performed during the task, or by using questionnaires related to the perception of the severity of the task executed and so forth (such as for instance the NASA-TLX or the SWAT questionnaires). However, it is also possible to collect neurophysiological measures that assess the activity of the central and the autonomous nervous system of the pilot/driver during the analysed driving tasks. In fact, it is possible to collect the time-varying spatial potential distribution over the scalp produced by the cortical brain activity during driving tasks with the electroencephalogram (EEG), or its magnetic counterpart (magnetoencephalography, MEG). Another indirect measurements of the activity of the central nervous system is obtained by analysing the variation of the potential distribution across the eye, that returns information about the eye blinks and the eyes movements (electrooculogram, EOG). Measurements of the activity of the autonomous nervous system are instead the gathering of the variation of the heart rate by the electrocardiogram (EKG) or the variation of the galvanic skin responses, (GSR), as well as for instance the measurement of driver's respiration rate.

Such neurophysiological measurements and their related features have been used for a long time in an attempt to characterise different mental states and estimate the activity of the central and autonomous nervous system related to the driving tasks.

This paper reviews several published papers related to neurophysiological measurements in the pilots/drivers during their driving tasks. The aim is to summarise the main neurophysiological findings related to the measurements of pilot/driver brain activity during drive performance and how particular aspects of this brain activity could be connected with important concepts, such as "mental workload", "mental fatigue" or "situational awareness". A discussion on the possible future application of findings provided by these neurophysiological measurements in order to improve the safety of vehicles will be also presented.

2. Mental workload: its definition, importance and relationship with situation awareness

The "mental workload" concept has been defined, in the contexts of interest for this review, as "the portion of an individual's limited mental capacity that is actually required by task demands" (O'Donnel and Eggemeier, 1986). The assessment of mental workload and the identification of the "functional state" of the pilot's brain could help both in optimising driving tasks (if possible) and planning work–rest rhythms in order to avoid hazardous errors during driving. In addition, such assessment could avoid the occurrence of sustained periods of mental overload during driving, which eventually may result in a drastic decrease of performance with possibly dangerous consequences (Holm, 2010). It must be noted that mental workload is not an inherent property of a pilot's brain, but rather emerges from the interaction between the requirements of a driving task, the circumstances under which it is performed, and the skills, behaviours, and perceptions of the pilot (Hart and Staveland, 1988).

The assessment of mental workload had a major impact on aircraft system design with respect to the decisions to downsize the flight deck from three to two crew members by eliminating the flight engineer's position (Sheridan and Simpson, 1979). In addition, the driver's mental workload is also considered in the design of the dashboard of modern cars, balancing the information made available to the driver from the engine and other car systems and the need to stare at the road. The idea that workload is not only "performance" has led researchers to examine ways of assessing the residual attention available for performing a task, which is an important measure that can be fully dissociated from performance.

For example, consider two pilots (or drivers) A and B, controlling an aircraft (or a car) in a simulator through a series of predefined routes, obtaining the same score in terms of driving performances (e.g., time to complete the task). Despite the fact that they were awarded the same score, pilot (or driver) A performed the task with plenty of attention resources still available to be allocated in a secondary concurrent task, whereas pilot B used all of their attention resources. In fact, pilot B experienced a greater mental workload during task than pilot A, even though the external performance was identical (Vidulich and Wickens, 1986; Yeh and Wickens, 1988). Sometimes, a pilot's performance decrements may result more from an inadequate interface than from a depletion of mental resources. In contrast, an environment requiring the pilot to hold a large amount of information in their working memory while seeking more information or while attending to a secondary task (i.e., answering a radio call) clearly describes a potential workload problem. This could be especially true during the unexpected occurrence of new operative demands. The perception of the level of workload can also be affected by the experience, the skills or simply the individual differences between pilots. For example, novice and expert aircraft pilots will clearly experience different levels of workload when performing the same task (Borghini et al., 2011; Parasuraman and Jiang, 2012; Doppelmayr et al., 2008). In fact, skill development produces both an economy of action and automated "motor programs" that do not require conscious effort; in aviation these motor programs are called Bold-Face and they are the steps (Emergency procedure memory items) necessary to promptly and completely deal with in-flight emergencies. They are memorised by pilots to ensure a methodical, consistent approach to a hazardous situation. The same is true for the car drivers, to a less extent, as the procedures are simpler than those required for the aircraft control.

A possible definition of "situation awareness" related to pilots involves their perception of different environmental elements with respect to time and space, together with a comprehension of their meaning and the projection of their status after some variable has changed with time. The relationship between mental

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Fig. 1. The relationship between the concepts of mental workload, situation awareness and operative performance. Being a precursor for performance, mental workload is an important measure of success. However, performance might be biased and subject to variations due to circumstances beyond an individual's control. There is a causal and logical relationship connecting mental workload with situation awareness and situation awareness with performance. An increase in mental workload (a more demanding task) leads to a decrease in situation awareness, which, in turn, leads to lower performance. The results are also an empirical justification of the use of the concept situation awareness.

workload, SA and performance shows a pattern that recurs in several studies, involving different participants, which is common to real and simulated flights, in both military and civil settings. There is a causal and logical relationship connecting mental workload with SA and SA with performance (Fig. 1). An increase in mental workload (a more demanding task) could eventually lead to a decrease in SA, which, in turn, could lead to worse performances (Nählinder, 2004, 2009; Endsley and Garland, 2000). As described before with the two pilot examples, that chain of events could not produce a decrease in performance but a substantial depletion of the cognitive resources of the pilots, meaning that they may not be ready to cope with other simultaneous situations occurring during the task. Being aware of your surroundings and understanding what the information means both now and in the future, is the basis for SA. When people are required to make critical choices (Parasuraman et al., 2008; Lundberg, 1999; Endsley, 1995a,b) – sometimes at a fast pace – the majority of errors occurring is a direct result of failures in SA. In the operation of complex systems, the outcome can be catastrophic (e.g., airplane crash, poor emergency team response, critical commercial systems failure) and at a great cost in terms of lives and money. In addition, ineffective teamwork, poor judgment, and a lack of coordination can lead to inconsistent and dangerous behaviour by teams that lack a shared SA (Hameroff, 2010; Alfredson, 2007).

3. Mental fatigue and drowsiness: definition and importance

Another important concept in the description of the human behaviour during car or aircraft control is that of mental fatigue. In fact, mental fatigue is believed to be a gradual and cumulative process and is thought to be associated with a disinclination for any effort, a general sensation of weariness, feelings of inhibition and impaired mental performance, reduced efficiency and alertness (Grandjean, 1979, 1988). Such factors could account for the 40% of all vehicle accidents (Idogawa, 1991). A distinction between mental fatigue and drowsiness is that the former does not fluctuate rapidly over periods of a few seconds, while the latter does. As testified by normal experience, rest and inactivity relieves fatigue, but make drowsiness worse (Johns et al., 2008). In professional drivers, fatigue may be quite severe before routine driving performance is noticeably affected. This situation is similar to mental workload, where an increase could affect overt behaviour only in the final stage. It is important to note that, at lower levels of fatigue, decreases in physiological arousal, slowed sensorimotor functions and impaired information processing can still diminish a driver's ability to respond to unusual and emergency situations (Mascord and Heath, 1992). Therefore, to measure the impact of fatigue on driver performance, it is important to also measure the pilot's reactivity for motor and sensorimotor stimulations and tasks (Williamson et al., 1996). This fact has been addressed by researchers, during simulated driving, by using secondary tasks, i.e., behavioural tasks to be performed during continuous driving. Such secondary tasks can occur at any time during driving and can consist of, for instance, altering the radio channel or volume during the drive, or answering a routine mobile phone call. Mental fatigue and the occurrence of drowsiness during driving is a serious problem in transportation systems and is believed to be a direct or contributing cause of road-related accidents, especially in night-drivers (Philip, 2005; Campagne et al., 2004; Connor et al., 2001; Gander et al., 1993; Hakkanen and Summala, 2000; Torsvall and Åkerstedt, 1987; Mackie and Miller, 1978; Haworth et al., 1989; Kecklund and Åkerstedt, 1993). Both causes are a major factor in accidents occurring during monotonous driving conditions (Horne and Reyner, 1995; McDonald, 1984; Hamblin, 1987).

Mental fatigue and sleepiness may rise to unacceptably high levels during civil air operations as a result of relatively long duty periods that may coincide with the lowering of alertness and the disruption of the circadian rhythm due to time zone shifts (Wright et al., 2005). For all of these pilot categories, critical aspects of driving impairments associated with drowsiness include slow reaction times, reduced vigilance, and deficits in information processing, all of which lead to an abnormal driving behaviour (Dinges and Kribbs, 1991; Dinges et al., 1997).

It is important to stress that although the sequence of internal brain states can be described as a series of transitions from the "alert state" to the "fatigued" one, and from there to the "drowsy state", these transitions do not necessarily occur in this order. In addition, each internal state is characterised by a proper and peculiar variation of the neurophysiologic signals typically gathered in these conditions, such as the electroencephalogram (EEG), the electro-oculogram (EOG) and the measurement of the heart rate (HR).

4. The effects of mental workload, mental fatigue and drowsiness on the neurophysiologic measurements performed in car drivers or aircraft pilots

In this section we review the main results presented in literature related to the measure of the neurophysiological variables (namely EEG, EOG and HR) in car drivers or aircraft pilots during task performances characterised by different degrees of difficulty. By increasing the task difficulties, authors attempted to elicit different "brain states" described by an increased mental workload, and eventually a state of mental fatigue in the analysed subjects. In the following paragraph this will be reviewed as the increased task difficulties significantly changed the statistical properties of the EEG, EOG and HR signals recorded in car drivers or pilots.

A separate section will be devoted to the analysis of drowsiness. In fact, it is well-known that one of the major sources of road accidents is due to the drivers' drowsiness, with the relative cohort of lapses of attention during driving. Driver's drowsiness is estimated to cause more than 4 deaths and 100 injuries per day in the US (Laube et al., 1998; Lyznicki et al., 1998). This impressive data pushed the scientific community to investigate putative neurophysiologic indicators of the occurrence of such dangerous conditions in drivers (Boyle et al., 2008). Although drowsiness is usually a car driver's problem, it is also becoming a problem for

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aircraft pilots, due to the competitive flight conditions between companies (http://www.telegraph.co.uk/travel/travelnews/8433199/Long-haul-pilots-fell-asleep-at-controls.html). For instance, in the Indian news 2 years ago a commercial aircraft was reported having missed the target airport because both pilots were sleeping (http://articles.timesofindia.indiatimes.com/2009-12-23/india/28090514_1_air-traffic controllers-dgca-pilots).

In the following it will be described how in the literature the neurophysiological measurements (including EEG, HR and EOG) have been correlated to drivers' and pilots' drowsiness and fatigue (Brown, 1967; Chase, 2000; Dureman and Boden, 1972; Lal and Craig, 2001a; Zilberg et al., 2009).

4.1. The use of EEG for the assessment of mental workload and fatigue

The electroencephalogram (EEG) is the measurement of the electrical activity originated by the brain and recorded on the scalp surface through a net of regularly spaced electrodes. The analysis of EEG waveforms, and their decomposition in different frequency bands, has often been employed in the assessment of the variation of the "internal" state of the subjects during the execution of simple cognitive or sensory-motor tasks (Smith et al., 2001; Boucsein and Backs, 2000; Gevins et al., 1998; Hankins and Wilson, 1998; Wilson and Fisher, 1995; Sterman and Mann, 1995; Wilson, 1993). It has been already demonstrated by several studies that EEG is sensitive to fluctuations in vigilance and has been shown to predict performance degradation due to sustained mental work (Matousek and Petersen, 1983; Gevins et al., 1990). Associations between a decrease of human alertness and a reduction in vigilance as well as fatigue have been found to generate precise signs in the on-going EEG, especially in alpha and theta waves (Roth, 1961; Makeig, 1993; Makeig and Jung, 1995). In particular, it has been shown that a decrease in vigilance and deterioration in performance are associated with increased EEG power spectra in theta band and a change in EEG alpha power (Davies, 1965; Morrel, 1966; Gale et al., 1977). Moreover, Okogbaa et al. (1994) pointed out that an increase of EEG power spectra in the beta band was associated with increased alertness and arousal; alpha waves occurred during relaxed conditions at decreased attention levels, and in a drowsy, but wakeful state; and theta waves mainly occurred during the sleep state.

Most studies of EEGs gathered from car drivers or aircraft pilots focus on fluctuations in the power of EEG signals in the theta (4–8 Hz), alpha (8–12 Hz) and beta (12–18 Hz) bands (Holm et al., 2009; Dahlström and Nählinder, 2009a; Poythress et al., 2006; Berka et al., 2007; Dussault et al., 2005; Gevins and Smith, 2003; Caldwell et al., 2002; Smith et al., 2001; Klimesch, 1999; Sterman and Mann, 1995; Grandjean, 1988; Lal and Craig, 2001a; Akerstedt et al., 1991) or their combinations (Brookhuis and de Waard, 1993; Jap et al., 2009). In a recent study (Zhao et al., 2012), how the relative power of all bands, except the delta rhythm, showed statistically significant differences between the beginning and the end of a driving simulation of 90 min ($p < 0.05$) was demonstrated. The relative power of the alpha and theta rhythms significantly increased, while the relative power of the beta rhythm significantly decreased in different scalp regions (Fig. 2).

4.2. Impact on the EEG rhythms of an increase in task demand and in the required focused attention

Many studies investigating the changes of EEG rhythms during increased or sustained task demands reported that the most prominent event was the increase of the EEG power spectrum in the theta frequency band over the prefrontal cortex, which is often located in a midline scalp position. This "midline theta power increase" has been reported in studies that involved visual search tasks (Yamada, 1998), flight simulations (Smith et al., 2001; Dussault et al., 2005; Borghini et al., 2011), and air-traffic control simulations (Postma et al., 2005), as well as in working memory load (Berka et al., 2007; Gevins et al., 1998; Klimesch et al., 1997; Smith et al., 2002). In addition, the EEG power spectra increase in the theta band was reported to also occur in driving simulator studies, and was linked to the emergence of fatigue (Torsvall and Åkerstedt, 1987; Gillberg et al., 1996; Horváth et al., 1976; Lal and Craig, 2001b). It must be noted that a theta increase has also been reported at parietal areas in response to an increased task demand (Fairclough et al., 2005). The increase of frontal EEG theta activity also occurs in relation to an increase of the focused attention (Doppelmayr et al., 2008) during the task. An increase of EEG power occurred in the theta frequency band over the frontal and central scalp areas during a time pressure task (Slobounov et al., 2000), and was larger at the end than at the

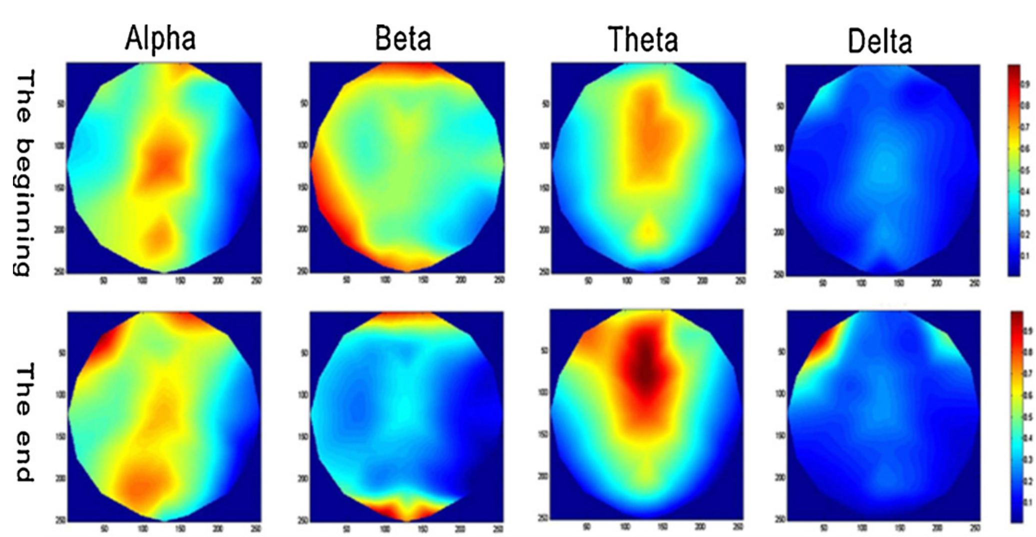

Fig. 2. Scalp topography of electroencephalogram activity. The oval topography depicts a view from above the head. The blue (red) colour indicates a reduction (increase) of the EEG power spectra in the particular frequency band analysed. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

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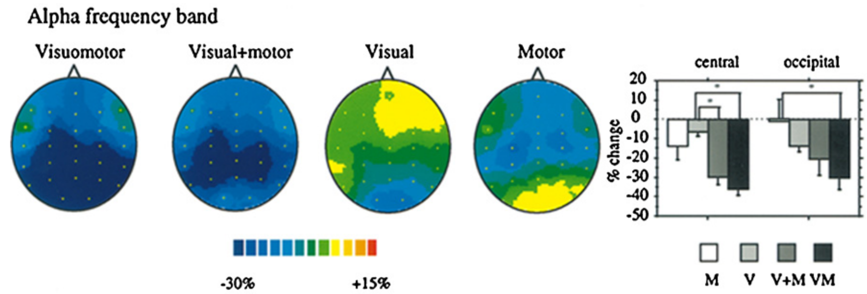

Fig. 3. Spatial pattern of task-related spectral power changes: alpha frequency band. In the alpha frequency, EEG power spectra decreases over the occipital region during the visual task and over the bilateral homologous central regions during the motor task. Tasks VM and V + M led to an extended EEG power decrease involving central, parietal, and occipital regions.

Reprinted with permission from Classen et al. (1998).

beginning of the task as a result of fatigue accumulation (Boksem et al., 2005; Smulders et al., 1997).

EEG spectral power in the alpha band has been reported to decrease during complex and cognitively demanding tasks. Such a decrement occurred over different scalp areas, such as the fronto-central and the parietal regions (Slobounov et al., 2000; Fairclough et al., 2005).

In addition to the increase of the EEG power in the theta frequencies and the related decrease in the alpha frequencies, an increase of EEG power in the delta frequency band has been observed during studies linked to the transition to a fatigued state (Lal and Craig, 2000).

4.3. Impact of sustained task demand and multi-tasking on EEG rhythms

Concurrent activities (i.e., multi-tasking) occur frequently in everyday life, as well as during driving. In fact, answering a mobile phone call or tuning a radio station while driving are usual events for everybody during a standard workday. In this section what has been done in the literature to understand the impact of these multi-tasking duties on the brain activity by investigating the changes of EEG power spectra in drivers will be described. Evidences from literature suggest an increase in the EEG power spectra in the theta band during tasks involving sustained attention and multi-tasking (Fairclough and Venables, 2006; Fairclough et al., 2005; Fournier et al., 1999). Furthermore, it was also demonstrated that such an increase in EEG power in the theta band can be used to characterise a single from a multi-task activity performed by pilots.

However, it is still not clear in the literature whether an EEG has the sufficient sensitivity to differentiate several levels of complexity in a multi-task condition. Mixed results are reported regarding this possibility, with the recent results showing more confidence that such a separation could be performed (Fairclough et al., 2005), in contrast to previous results (Fournier et al., 1999). The fact that the training of pilots does not affect the EEG spectral power in the theta band has been also reported (Fairclough et al., 2005; Fournier et al., 1999).

For all concerns regarding the variation of EEG power spectra in the alpha band during the execution of concurrent tasks, a prominent decrease of EEG in the alpha band was reported when compared to the baseline level (Fournier et al., 1999). However, the capability to differentiate levels of multi-tasking activities with the variation of EEG power in the alpha band was not clear, since some groups reported success in this discrimination (Fournier et al., 1999) and others did not (Fairclough et al., 2005). In such a case, differences in the number of subjects and other variables could explain the differences between the results obtained. Classen et al. (1998) studied patterns of changes in EEG (coherence) associated with a visuomotor force (tracking task) in different subjects. They found that cortical activation related to the purely motor or visual task led to a decrease in the spectral power of oscillatory signals from electrodes overlying either the contralateral and ipsilateral motor cortex, or the visual cortex, confirming previous findings (Pfurtscheller et al., 1994; Leocani et al., 1997). Such authors extended previous findings in that both visuomotor (VM) and visual + motor (V + M) tasks led to a more widespread relative power decrease involving both the occipital and the central regions (Fig. 3).

Interestingly, decreases in alpha and increases in theta activity have also been connected to the increase of the accuracy of the performance (Klimesch, 1999).

4.4. Impact of the mental fatigue on heart rate variability and respiration

It is well-known that variations of the heart rate can be linked to the variation of the emotional states of the humans (Aasman et al., 1987). For such reasons, the role of the Heart Rate (HR) in the evaluation of the mental state of a driver during their performance has been investigated in the literature. In fact, the use of electrodes gathering the cardiac responses for different levels of tasks can catch the reflex of brain activity. It has now largely been accepted that the increment of the task difficulty leads to an increase of the HR. The cardiovascular response can thus be used to evaluate the mental load of a task in aviation (Hanson and Bazanski, 2001). However, the variation of HR is also linked to different factors besides mental workload, including the fatigue of the subjects (in terms of muscular efforts).

Another important variable that can be linked to mental fatigue using cardiovascular responses is the Fourier transform of the HR signal, known as Heart Rate Variability (HRV). From the large amount of literature available on the use of HRV to assess the activity of the parasympathetic and sympathetic nervous systems in humans, one of the most recent papers has been selected for discussion (Togo and Takahashi, 2009). It has been suggested by a systematic review of the literature that psychosocial workload (i.e., job stressors), and working time (i.e., shift work) can have a significant association with the increase of the power at the low frequency band of the HRV (low HF power).

Several studies have shown that if the internal, external and initial conditions are kept constant, HR and HRV are measures of task demands, since such variables demonstrated a very high correlation with questionnaires and behavioural tasks (Steptoe, 1985; Aasman et al., 1987; Grossman et al., 1991; Pagani et al., 1990). However, a more robust correlation of HR with the subjective measurements often used in the aircraft industry has been shown in comparison with HRV (Roscoe, 1987, 1992; Roscoe and Ellis, 1990). In addition, it has been suggested as HR has an increased sensitivity under different flight conditions, both in real and simulated operations (Wilson and Eggemeier, 1991; Caldwell et al., 1994; Eggemeier et al., 1990; Wilson and Fullenkamp, 1991). Even if the changes in HR are lower during simulated as compared to real situations, there is a co-variation between the simulated version and the real version of a specific flight or mission (Angelborg-Thanderz, 1990).

As a result, it is possible to state that the HR variables are significantly linked with the occurrence of the mental workload, although the effects of different variables such as muscular fatigue and anxiety have to be taken into account properly in the evaluation during driving. In addition, there is a systematic influence of respiration on HR that also has to be considered, while respiration per se is not a good indicator of workload (Backs and Seljos, 1994; Ohsuga et al., 2001; Pettyjohn and McNeil, 1977).

4.5. The use of electrooculogram (EOG) for estimating mental workload in tasks with high visual attention

It is a common experience that when a particular task involves the use of visual attention, the subject becomes more concentrated and decreases the time spent with the eye closed for blinking, i.e., their blink frequency decreases. Researchers have investigated whether such phenomena could lead to valid indications about the mental workload for tasks requiring high visual attention, such as driving. As a result, eye blink data has been collected in highly realistic settings of driving. Different parameters characterising the blink, such as the Blink Rate (BR), the Blink Duration (BD), and the Blink Latency (BL) have been analysed and used as workload measures in a series of studies (Eggemeier et al., 1990; Wilson and Fisher, 1991; Kramer, 1991; Stein, 1992; Wilson, 1993).

Results in the literature suggested that both the blink rate and blink duration decrease with increases in task demands, and they have been found to significantly decrease during high load segments of missions (Wilson and Fisher, 1991). In addition, the blink rate has been found to be sensitive and capable of differentiating among mission types (Wilson et al., 1982), and it was found that it could also distinguish fatigue in pilots and non-flying co-pilots of military aircraft (Stern, 1993). Blink patterns can be used to provide information about the subjects' response to different stimuli and thus SA, and the latency measure has been found to increase with memory demands (Eggemeier et al., 1990).

A general conclusion that can be drawn is that the blink rate may be most related to visual information requirements and fatigue. Blink duration and blink latency could be also measures of workload (Carmody, 1994; Kramer, 1991). Wilson and Fisher (1991) have demonstrated the advantage of using both HR and eye blink data in the analyses of pilots' mental workloads. Fewer and shorter blinks have been associated with increased workload, in tasks such as city driving, reading and aircraft weapon delivery (Brookings and Wilson, 1994; Krebs et al., 1977).

4.6. Impact of task demands, age, and working memory load on the EEG rhythms

Theta activity increases in the frontal midline with increased task difficulty in younger adults, and to a lesser degree in middle-aged individuals, whereas no increase has been found in older subjects (McEvoy et al., 2001). Alpha activity, in turn, decreases with increasing task difficulty in more widespread areas in older than in younger subjects, whose alpha activity decreases only at the parietal areas. These findings are in good accordance with a previous study that showed an increase in theta activity in the young and a decrease in alpha activity in the elderly during challenging task performance (Smulders et al., 1997).

Conversely, alpha activity at the parietal sites has been reported to decrease with increases in working memory load (Fairclough and Venables, 2006; Sauseng et al., 2006; Fairclough et al., 2005; Fournier et al., 1999; Gevins et al., 1998; Ryu and Myung, 2005; Smith et al., 2001; Sterman and Mann, 1995).

4.7. EEG rhythms and mental fatigue and drowsiness

The link between brain arousal and the variation of the oscillatory brain activity recorded by the EEG is well described in literature (Makeig, 1993; Jung and Makeig, 1994; Lehmann et al., 1995). Studies on the transition from mental fatigue to drowsiness and eventually sleep have also underlined that such transitions are different with respect to the standard transition from awake state to sleep (Yeo et al., 2007; Eoh et al., 2005; Moller et al., 2006; Lin et al., 2005). In fact, in the former case, the subject attempted to resist and struggled to maintain an awaking state in a condition characterised by mental fatigue and drowsiness, when compared to the normal transition from being awake to being sleep.

As described before, a continuum between an awaking and alert state towards mental fatigue and eventually drowsiness is characterised, from an EEG point of view, by an emergence in the delta, theta and alpha activity in frontal and parietal areas with a concurrent diminution of the brain activity in the beta band (Lal and Craig, 2000,2002; Eoh et al., 2005; Papadelis et al., 2007; Papadelis, 2010). This increase of EEG power in delta, theta and alpha bands also occurs during monotonous driving tasks, but the increase of power spectrum in the alpha band, in particular in the occipital areas, is more evident than in the other frequency bands (Horváth et al., 1976; Torsvall and Åkerstedt, 1987).

However, the EEG spectral power is not the only way to get information about the drowsiness of a driver. Recently, the detection of EEG alpha spindles, defined as short bursts in the alpha band, was suggested as an objective measure for assessing the driver's fatigue during real driving conditions when compared to the normal EEG spectral analysis (Simon et al., 2011). Authors developed an offline system for the detection of EEG spindles in car drivers, and it was reported that the EEG alpha spindle parameters increase both fatigue detection sensitivity and specificity as compared to EEG alpha band power (Simon et al., 2011). There are multiple studies indicating the crucial role of alpha waves after mental fatigue of drowsiness (Hirvonen et al., 1997; Mano et al., 1995; Papadelis et al., 2006, 2007, 2009), especially in the occipital cortex. More specifically, Papadelis et al. (2007) showed the occurrence of brief paroxysmal bursts of alpha activity (around 1–2 s, in the lower band of alpha) that were accurately linked to severe driving errors. Regions involved in this phenomenon are located at central and parietal brain sites and the enhancement of alpha activity, highlighted in orange in Fig. 4, is often accompanied with longer eye blink durations. During real driving experiments (Papadelis et al., 2006), it has been shown that the alpha activity increases over the central and parietal channels. In Fig. 5, the mean values of the alpha relative band ratio (RBR) for EEG channels C3 and C4 are shown during the 5 min period of a real driving experiment with sleep deprived subjects. Comparing the mean values of RBR of the first and the last 5 min periods, Papadelis et al. (2006) observed an increase of alpha RBR for the central and parietal channels: C3 ($p < 0.03$) and C4 ($p < 0.02$).

Mano et al. (1995), in their long distance highway field driving experiments, observed a diffuse slower alpha activity when the drivers closed their eyelids as the driving time went on. These findings were severe when drivers complained of sleepiness, but they were recognised even when drivers did not complain of any sleepiness. Broughton and Hasan (1995) also observed sleepiness-onset alterations in the lower band of alpha. More recently, other authors (Kalauzi et al., 2012) explored the dynamics of the wake-to-drowsy

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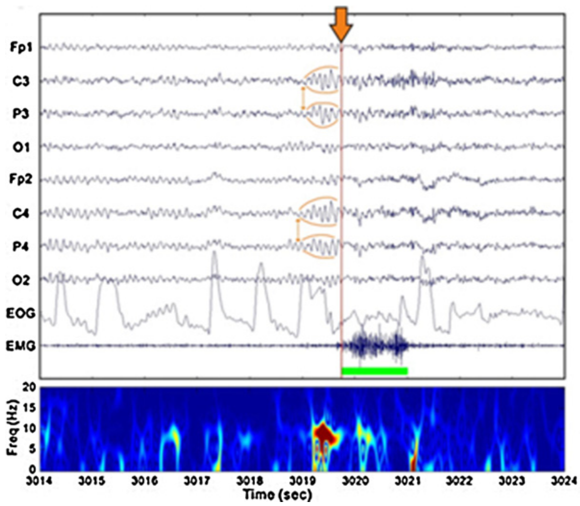

Fig. 4. Representation of the EEG activity during the occurrence of a severe driving error. Orange colour in the EEG time course box-plot highlights alpha activity bursts occurring at central and parietal cerebral regions. The time–frequency plot showing the increment of EEG activity in the alpha range is representative of the channel C3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

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transition and observed frontal and fronto-temporal cortical areas showing more extensive changes than posterior regions in the alpha carrier frequency modulation.

The EEG changes during the transition from wakefulness to drowsiness have been clearly characterised in the literature, as with Hori's sleep stage I (Hori et al., 1994). Stage I is characterised by the first appearance of EEG alpha dropouts from a previous predominance of EEG activity in beta frequency band. The increase of the EEG power in alpha and theta bands also correlate with the length of the prolonged monotonous driving and with the poor driving performance (de Waard and Brookhuis, 1991; Eoh et al., 2005; Kecklund and Åkerstedt, 1993; Horne and Reyner, 1995; Lal and Craig, 2002).

The simulation of night driving essentially returns the same information described above, except for the fact that the alpha band also differentiates young unskilled drivers when compared to skilled ones. In the unskilled condition, the power in the alpha band increases when compared to the skilled drivers. The temporal variation of the EEG power spectra also correlates with the duration of the drowsiness period, in particular in the alpha band. Such fluctuations appeared to be located in the posterior temporal and in the occipital scalp areas (Santamaria and Chiappa, 1987; Lal and Craig, 2001a).

The importance of these changes in the EEG spectral power during drowsiness onset is due to the correlation with the specific driving events. In particular, it was found that the number of "attention lapses" comprising EEG episodes of increased alpha or theta activity lasting more than 3 s correlated with several parameters related to the car position in the street as well as with the number of crashes in simulations (Risser et al., 2000).

The detection of lapses of the driver's responsiveness has been attempted recently in a series of offline studies by the laboratory of Jones and co-workers (Jones et al., 2010; Davidson et al., 2007; Peiris et al., 2011), which reached a sensitivity up to 73.5% and a selectivity up to 25.5% in the detection of such events using EEG spectral power information.

4.8. HR and EOG for the estimation of mental fatigue and drowsiness

It has already been described that the HR variable correlates to some extent with the occurrence of mental workload. In particular, it has been suggested that increased HR could be related with an increased mental workload. In the transition between mental fatigue and drowsiness, the HR variable appears instead to decrease. In fact, HR has been shown to decrease during prolonged simple driving (Lal and Craig, 2001a) as well as prolonged night driving (Riemersma et al., 1977) when compared to normal driving conditions. The HR variability index (HRV) seemed sensitive to the variation of fatigue associated with the driving (Tsuchida et al., 2009; Harris et al., 1972). However, it remains unclear how such an index could be related to the occurrence of the pilot's drowsiness.

Previously, it has been described how the different parameters of the eye blink (namely duration and frequency) gathered by the EOG are inversely correlated with the increase of the mental

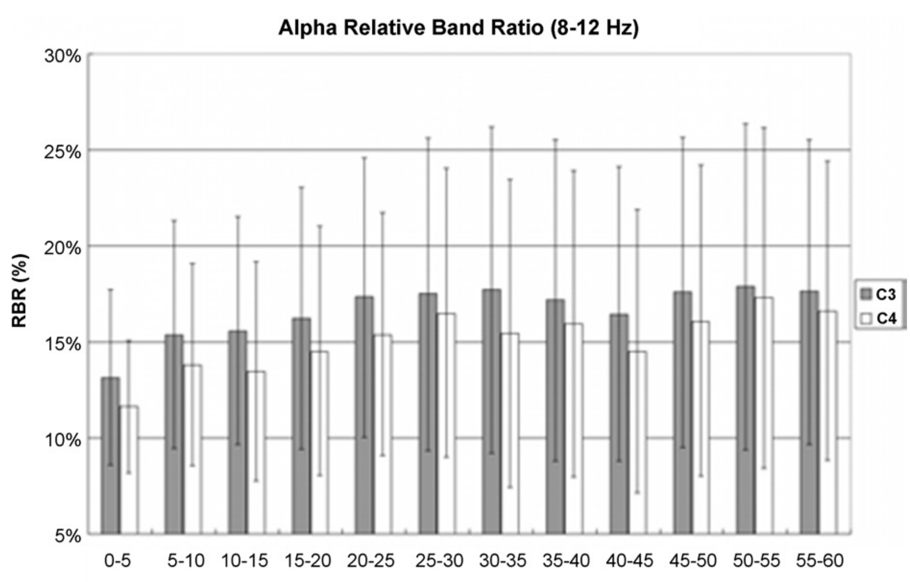

Fig. 5. The mean values of alpha relative band ratio (RBR) (in percentage) for the channels C3 and C4 per 5-min period.

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workload of the drivers. Therefore, an interesting question is whether such eye blink parameters could be related to the occurrence of the drowsiness in drivers. In a study on an accurate car simulator, Lal and Craig (2001a) observed that the transition from normal driving to drowsiness was characterised by an increase of blink rate and the cessation of vertical or horizontal eye movements. This observation (among the others existing in literature) appears to be consistent with the existence of a continuum of the increased frequency of the eye blinks, from a very low blink rate related to a performance involving high visual attention to a high frequency blink rate during time periods before drowsiness. A more recent study suggested that the change in drowsiness of drivers can be associated with significant variations in the eyelid parameters extracted from the EOG (Hu and Zheng, 2009).

4.9. Putative cerebral sources underlying the occurrence of mental workload

In the previous section it has been underlined how the execution of demanding behavioural tasks in humans caused remarkable changes of the EEG power spectra. These changes are often related to the increase or decrease of particular EEG power in different frequency bands, but mainly in the theta and alpha frequency bands. It could, therefore, be of interest to understand which kind of cerebral structures are involved during the occurrence of mental workload, as derived from the literature.

Mental workload has been investigated often during the execution of mental computations or working memory operations. In these experimental conditions, the activity of several cortical areas, including the pre-supplementary motor areas (pre-SMA), thalamus and dorsolateral prefrontal cortex (DLPFC), has been assessed. In particular, the activation of the pre-SMA has been observed during tasks involved in mental calculations (Menon et al., 2000), while the involvement of the thalamus was noted during mental arithmetic (Cowell et al., 2000; Kong et al., 2005). A verbal representation of a comparison between precise and approximate calculations induced a significant brain activity in the inferior parietal lobule (Dehaene et al., 1999), as well as in the left angular gyrus (Dehaene et al., 2004).

While these observations have often involved the use of haemodynamic brain imaging, investigations performed using neuroelectromagnetic recordings suggested marked variations of the EEG in the theta band, roughly located on the frontal midline (Gevins et al., 1997). The medial prefrontal cerebral regions and anterior cingulate cortex were also suggested as the main cerebral structures involved in the phenomena of the EEG or MEG power spectra increase in the theta band during difficult tasks (Ishii et al., 1999). Such variation of the EEG or MEG power in the theta band have been also found in relation with the self-monitoring activity during the task performance in the posterior cingulate gyrus (Luu et al., 2004).

Simultaneous EEG and fMRI recordings during difficult behavioural tasks revealed the existence of a diffuse network of cerebral structures sub-serving the increase of EEG theta power spectra as well as the reduction of the alpha power spectra (Sammer et al., 2007). Such cerebral structures are associated with temporal and hippocampal haemodynamic activation, general cingulate activation, and frontal superior and cerebellar activation. These results suggest the emergence of a wide distribution of cortical and subcortical networks, involving the hippocampus, thalamus and DLPFC, which sub-serves mental activity during the execution of difficult tasks. Such a network would be responsible for the changes of power spectra of the surface EEG in the theta and alpha frequency bands (Klimesch, 1999; Astolfi et al., 2007).

4.10. Discussion

Table 1 provides a summary of the main results discussed so far. The general idea from viewing Table 1 is that there appears to be a continuum between the changes of the neurophysiological variables considered (EEG, EOG and HR) and the "internal brain states" experienced by the subjects during the execution of the tasks.

In particular, it appears that a relaxing state is characterised by a high alpha EEG power spectra when compared to the resting state. Here, the resting state is the condition in which the driver/pilot is in front of the operative environment but no action or attention is required by him/her while the relaxing state is the eye close condition. By increasing the general alertness, the alpha rhythm returns to the baseline level and the appearance of an increased EEG power spectrum in the beta band appears. An increase in focused attention or an increase of the time pressure of the proposed task promotes an increase of the EEG power spectra in the theta band over the prefrontal and central scalp areas. This phenomenon is reinforced during the increase of the task demands that, in turn, changes the appearance of several EEG rhythms promoting an increase of the EEG power spectra in the theta band over the prefrontal areas, as well as a decrement of the EEG power spectra in the alpha band over mainly parietal areas. Interestingly, prefrontal areas are the target of the main cortical and subcortical structures that monitor conflicts and decision-making, while the parietal areas are related to the space relations between the subjects and the external world (Hare et al., 2009). These spatial relations should be considered during the driving conditions. It is worth noticing that the decrement of the EEG power spectra in alpha bands means an increase of the cortical activity, and vice versa. Important variations of the blink rate and of the blink duration also emerged during the increased task demands. In particular, subjects started to have less blinks with lower durations when compared to the rest state. In addition, the heart rate increased, always with respect to the rest state. This framework seemed peculiar to this increased mental workload condition. During the transition from increased mental workload to mental fatigue, an increase of EEG power spectra in the delta and alpha frequency bands and a decrease of EEG power in beta bands were observed, with the other variables remaining identical to the previous conditions (Zhao et al., 2012; Torsvall and Åkerstedt, 1987; Gillberg et al., 1996; Horváth et al., 1976; Lal and Craig, 2001a; Fairclough et al., 2005). Transition from mental fatigue to drowsiness is signalled only by an increase of the blink rate and duration, and a decrease of HR. In this last case, the autonomic information coming from EOG and HR seems important for qualifying such a transition between these mental states (Lal and Craig, 2000). However, in cases in which the transition is from the awake state directly to the drowsy state (without passing to mental fatigue) then the variation of the EEG power spectra are characterised by an increase of the EEG power spectra in the alpha band (Mano et al., 1995; Kalauzi et al., 2012; Lal and Craig, 2000). In addition, an increase of the blink rate and duration and a decrease of the HR was also observed when compared to the rest conditions (Lal and Craig, 2000).

5. The link between neurophysiologic measurements and external drive performances

5.1. Introduction

It has been previously described that the neurophysiological variables obtained from different techniques, such as EEG, HR and EOG, could correlate with different "mental states", including levels of workload and/or the occurrence of drowsiness during driving a

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Table 1
Variation of the main neurophysiologic variables during drive tasks. The table provides a summary of the main results from the literature. In the first row, table presents the main EEG frequency bands considered namely delta, theta, alpha and beta. In addition, it also presents the main autonomic variables employed, such as the EOG for the blink duration and for the blink rate, and the heart rate. In each cell of the table the arrows indicate the variation of the variable considered in the proper column when compared to the resting conditions. For instance, an arrow pointing up in the column of the theta band means that for the particular task condition considered (a particular row of the table) the increase of the EEG spectra in the theta band was statistically significant when compared to the resting state. The names near to the arrow represent, in each cell of the column, the authors that published the particular results presented in that cell. The rows of the table are related to the description of the different factors considered in this review. The variations of EEG power spectra during drive tasks are reported in the table for different scalp areas. The following abbreviations are used: F stands for frontal scalp areas, Fm for midline frontal scalp areas, P for parietal areas, C for central scalp areas and O for occipital scalp areas.

	Delta	Theta	Alpha	Beta	EOG (blink rate)	EOG (blink duration)	HR
↓Vigilance		↑(Davies, 1965; Morrel, 1966; Gale et al., 1977; Makeig and Jung, 1995)	↑(Davies, 1965; Morrel, 1966; Gale et al., 1977; Makeig and Jung, 1995)				
↑Alertness				↑(Okogbaa et al., 1994)			
↑Arousal							
↑Relax			↑(Okogbaa et al., 1994)				
↑Drowsy			↑(Okogbaa et al., 1994)				
↑Task demands		↑Fm,P (Yamada, 1998; Smith et al., 2001, 2002; Dussault et al., 2005; Borghini et al., 2011; Postma et al., 2005; Berka et al., 2007; Gevins et al., 1998; Klimesch et al., 1997; Fairclough et al., 2005)	↓F,C,P (Slobounov et al., 2000; Fairclough et al., 2005; Fairclough and Venables, 2006; Sauseng et al., 2006; Fournier et al., 1999; Gevins et al., 1998; Ryu and Myung, 2005; Smith et al., 2001; Sterman and Mann, 1995)	Faircloug	↓(Eggemeier et al., 1990; Wilson and Fisher, 1991; Kramer, 1991; Stein, 1992; Wilson, 1993; Wilson et al., 1982; Wilson and Fisher, 1991; Stern, 1993)	↓(Eggemeier et al., 1990; Wilson and Fisher, 1991; Kramer, 1991; Stein, 1992; Wilson, 1993; Wilson et al., 1982; Wilson and Fisher, 1991; Stern, 1993)	↑(Hanson and Bazanski, 2001; Steptoe, 1985; Aasman et al., 1987; Grossman et al., 1991; Pagani et al., 1990; Wilson and Eggemeier, 1991; Caldwell et al., 1994; Eggemeier et al., 1990; Wilson and Fullenkamp, 1991; Angelborg-Thanderz, 1990)
↑Fatigue	↑(Lal and Craig, 2000)	↑Fm,P (Zhao et al., 2012; Torsvall and Åkerstedt, 1987; Gillberg et al., 1996; Horváth et al., 1976; Lal and Craig, 2000; Fairclough et al., 2005)	↑F,O (Zhao et al., 2012)	↓P (Zhao et al., 2012)	↓(Eggemeier et al., 1990; Wilson and Fisher, 1991; Kramer, 1991; Stein, 1992; Wilson, 1993; Wilson et al., 1982; Stern, 1993; Brookings and Wilson, 1994; Krebs et al., 1977)	↓(Eggemeier et al., 1990; Wilson and Fisher, 1991; Kramer, 1991; Stein, 1992; Wilson, 1993; Wilson et al., 1982; Stern, 1993; Brookings and Wilson, 1994; Krebs et al., 1977)	↑
↑Focused attention		↑Fm (Doppelmayr et al., 2008)					
↑Time pressure		↑Fm,C (Slobounov et al., 2000; Fairclough et al., 2005)					
↑Sustained attention and multi-tasking		↑(Fairclough and Venables, 2006; Fairclough et al., 2005; Fournier et al., 1999)	↓(Fournier et al., 1999)				
↑Accuracy of the performance		↑(Klimesch, 1999)	↓(Klimesch, 1999)				
↓Accuracy of the drive performance		↑(de Waard and Brookhuis, 1991; Eoh et al., 2005; Kecklund and Åkerstedt, 1993; Horne and Reyner, 1995; Lal and Craig, 2002; Davies, 1965; Morrel, 1966; Gale et al., 1977; Makeig and Jung, 1995)	↑(de Waard and Brookhuis, 1991; Eoh et al., 2005; Kecklund and Åkerstedt, 1993; Horne and Reyner, 1995; Lal and Craig, 2002)				

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From awake to mental fatigue to drowsiness	↑(Lal and Craig, 2000, 2002; Eoh et al., 2005; Papadelis et al., 2007; Papadelis, 2010)	↑Fm,P (Yeo et al., 2007; Eoh et al., 2005; Moller et al., 2006; Lin et al., 2005; Lal and Craig, 2000,2002; Papadelis et al., 2007; Papadelis, 2010)	↑F,O,T (Mano et al., 1995; Kalauzi et al., 2012; Yeo et al., 2007; Eoh et al., 2005; Moller et al., 2006; Lin et al., 2005; Santamaria and Chiappa, 1987; Lal and Craig, 2001a,b, 2002) P,C (Papadelis et al., 2007; Papadelis, 2010)	↓P (Yeo et al., 2007; Eoh et al., 2005; Moller et al., 2006; Lin et al., 2005; Lal and Craig, 2000, 2002; Papadelis et al., 2007; Papadelis, 2010)	↑(Lal and Craig, 2000)	↑(Lal and Craig, 2000)	↓(Lal and Craig, 2000)

vehicle. A successive step would be to consider how to link these variables' information to the external performances in driving, in order to derive a suitable set of neurophysiological parameters that could account (or even "predict") for the outcome of driving performances. The difficulty in this task lies in the fact that, as seen previously, different mental workload levels can correspond to the same driving behaviour. This might result in a confounding factor when assigning a "prediction" function to neurophysiological parameters (i.e., linking signals to overt task performance).

5.2. EEG parameters and their correlation with car driving performance and driver's drowsiness

Over the years, several attempts have been made to correlate the car driver's performance with the variation of EEG rhythms, and several of these rhythms appeared to be significantly correlated with the occurrence of driving errors. In simulated driving tasks, a significant correlation was found between the EEG power in the alpha + theta bands with the deviations from the correct lane (Horne and Baulk, 2004) as well as with the drive duration (Otmani et al., 2005; Lin et al., 2005). A correlation between lower EEG power spectrum (delta band) and the number of errors was also found in the study of Campagne et al. (2004). In a simulated car accident study, a significant correlation between the ratios of EEG slow and high frequency bands (i.e., [alpha + theta]/beta) was observed in the seconds following the simulated car accident as compared to the previous 10 s (Eoh et al., 2005).

Taken together, all of these evidences suggested that particular EEG rhythms might be indicators of mental activity related to overt driving performances and/or to the occurrence of errors. A definitive conclusion however, cannot be drawn on the specificity of EEG rhythm variations and the car accident relationship, due to the disparity of the experimental setups adopted in the different studies to monitor/measure driving performance expressed as number of occurred errors.

The detection of signs of drowsiness by means of neurophysiological variables was rather more homogeneous for the employed methodology with respect to the previously described studies. In fact, all of the studies focusing on drowsiness were performed under controlled conditions (car simulators) and studied the correlation between different EEG parameters and the occurrence of late stages of mental fatigue, as well as the successive insurgence of drowsiness, both in normal or professional drivers.

Gevins et al. (1995) generated a sleepiness "detector" based on the ratio between delta and alpha EEG power spectra estimated during different baseline and drowsiness periods in normal volunteers. The authors reported an 89% of offline correct classification of EEG samples associated to drowsiness states. The EEG power spectra in alpha band frequency were considered to implement a detector of sleepy state (Ninomija et al., 1993). Such a detector accounted for a drowsiness state classification with an error rate of about 25–35%. This latter score was successively improved by integrating the driver HR variable in the algorithm. Another offline classification approach was proposed by Lal et al. (2003). The authors developed an algorithm that was able to detect several progressive stages of "mental" fatigue as validated by an independent examination of driver's videos. The reported findings suggested that the 10 truck drivers examined were in a fatigue state for at least 60% of the total time they spent in the driving simulator. A remarkable percentage of offline detection of alertness state, up to 91%, was achieved by Lin et al. (2006) by employing EEG spectral power combined with the use of independent component analysis (ICA).

The application of more sophisticated offline signal processing methodologies yielded a high level of discriminability between a different driver's mental state and reliability well above 90%. An artificial neural network (ANN) was applied as a classifier to generate decisions between drowsy and alert periods based on EEG rhythm variations (Wilson and Bracewell, 2000; Vuckovic et al., 2002). Baldwin and Penaranda (2012) investigated the capability of such ANNs to classify the EEG features in different working memory tasks (reading span, visuospatial n-back, Sternberg task) and difficulty levels for novel participants. Hence, the authors estimated both within- and cross-task workload classification accuracy, and obtained good results in the first case (ranging from 85.3% to 87.1%) which were not replicated in the second (44.8%). The poor result may be due to the difference in working memory tasks process. In fact, authors reported that higher cross-task classification accuracy could be achieved by employing tasks relying on different forms of attentive processing (i.e., sustained and focused). High within-task classification accuracy rates are similar to those observed in previous ANN classification investigations (Wilson and Russell, 2003a) with highly trained participants in a simulated air traffic control task. Authors reported achieving, on average, 85.8% classification accuracy for ANNs trained on within-difficulty manipulation types. In a following experiment, Wilson and Russell (2003b) used ANNs to classify operator state on a multi-task combination contained in the Multi-Attribute Task Battery (MATB; Comstock and Arnegard, 1992). Heart rate, respiration and eye movement measures were used in addition to EEG, as ANN inputs resulting in classification accuracies that were 98.5% on average across participants and achieving online classification accuracies ranging from 82%, in the low workload condition, to 86% in the high workload condition. They demonstrated that adaptive aiding based on physiological measures could be conducted in real-time. They also reported that workload classification by ANNs trained on individual participants improved performance, instead of using grouped classifiers. Later, Wilson and Russell (2007) implemented an ANN-based classification algorithm to drive adaptive aiding in an unmanned aerial vehicle (UAV) task. However, all of the existing workload classifiers discussed above are subject-specific, meaning a new classifier has to be trained for each subject and session. In fact, these tools do not achieve good performances when classifying a group of subjects with the same training dataset and also the same subject in different sessions (Wilson et al., 2010). In this context, Wang et al. (2012) showed that it is possible to build an EEG-based workload classifier based on the hierarchical Bayes model which is able to handle multiple subjects achieving classification accuracies comparable to a specific-subject ANN. Moreover, they also proved that such a performance is stable across three levels of workload, in comparison with ANNs which have been demonstrated to accurately separate no more than two levels of workload.

Accordingly, with the use of high-resolution EEG (Urbano et al., 1997; Babiloni et al., 2002, 2003, 2004) and probabilistic principal components, this group was able to extract EEG features that were capable of distinguishing a series of classifications between awake, drowsy and sleep states in drivers with an accuracy score of 97% (Fu et al., 2008). Such recognition accuracy decreased to 89%, however, when, instead of a binary, a three class classification was attempted. Increasing the complexity of the classification algorithms, by using support vector machine (SVM) methodologies, allowed a decrease in the number of required electrodes from the 64 (Fu et al., 2008) to only 19 (plus an EOG channel) while still maintaining a high classification accuracy (99%). Sophisticated SVM methodology was also employed to classify more than three states (classes) associated with mental fatigue by Shen et al. (2008). By applying a multi-class SVM detector on EEG data obtained during a drive test performed by 10 subjects after a sleepless night, they found offline classification accuracy up to 91.2% with a data set originating from three slasting EEG recordings. Although all of these findings were obtained from offline studies, this latter methodology appears promising because of the short recording time needed. Finally, a recent study showed that the combination of EEG, ECG and EOG signals made it possible to achieve 95–97% of correct detections of drowsiness also in conjunction with the use of wavelet transform and a particular feature extraction method (Khushaba et al., 2011).

The main limitation of these studies resides in the fact that they were conducted offline with a limited sample size population. Another possible confounding factor might be the use of predetermined frequency bands (i.e., theta band from 4 to 7 Hz, alpha band from 8 to 12 Hz, etc.). With this in mind, the determination of the frequency band range in agreement to each individual alpha frequency should be considered (IAF; Klimesch, 1999). In fact, the IAF allows the individual appropriate alpha, theta and beta bands to be set by referring to each individual alpha frequency value. This could explain some statements found in the literature that reported that group statistics could not be used to accurately predict changes in alertness and performance for many drivers (Jung et al., 1997). The use of full spectra to define the mental state of drivers could be better suited since removing the confounding effect of the *a priori* band definition (Jap et al., 2009).

The correlation between EEG power variation and overt drive behaviour in the vehicle has been also obtained in the case of aircraft pilots, during simulation and real flight studies. The ongoing EEG measurements based on EEG power spectra and synchronicity estimation in theta, alpha and beta frequency bands were used to estimate performance level during cognitive task in pilots (Besserve et al., 2008).

By applying a particular SVM classifier, it was possible to significantly correlate the above-mentioned spectral EEG parameters with the occurrence of "high" or "low" reactivity period of pilots during driving. In another study on a large sample of aircraft pilots, a particular neurophysiologic index, which was built on theta and alpha frequency increase/decrease ratios with respect to a baseline condition, was demonstrated to correlate with the pilot's reports on the difficulty of the task performance (Borghini et al., 2011). The estimation of such an index was supported by a detailed analysis of brain activity based on advanced high-resolution EEG techniques (Gevins et al., 1999, 1989; He and Lian, 2002) applied on a set of data acquired during both simulated as well as real aircraft operations (Borghini et al., 2011). One example is given in Fig. 6, which illustrates the topography of the estimated brain activity recorded during a demanding flight manoeuvre performed by expert and novice aircraft pilots. It can be seen that the cortical prefrontal areas engagement within the theta frequency band results from the contrast between the two groups of subjects estimated activity indicating that pilots who were naïve to the task relied on the engagement of this area to accomplish it (expert and naïve subjects; blue colour in Fig. 6). Moreover, such differences in the estimated cortical activity were correlated to the different mental efforts required by the operational task (Borghini et al., 2011).

5.3. *Open issues in the detection of mental states using neurophysiological variables*

From the review of the current literature, it appears that the accuracy of the detection of the mental states in driver/pilot using neurophysiologic signals such as EEG, EOG and HR is close to 90%.

This happens although the fundamental mechanisms for the generation of brain signals are not yet fully understood (Tsai et al., 2007; Wilson et al., 2010). Different methods are often used in literature for the detection of mental states from neurophysiologic signals and no consensus has been reached in the literature related to the best algorithms and features to be used for such detection (Kohlmorgen et al., 2007; Cinaz et al., 2010).

One of the possible causes of this lack of consensus is the non-homogeneous tasks studied by the different authors. In fact, it

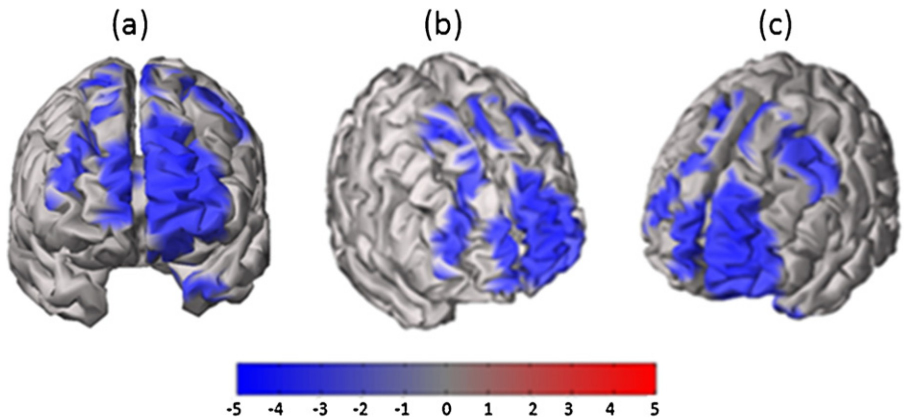

Fig. 6. The changes of EEG power spectra during difficult operations in-flight missions. EEG data were gathered from 12 experts and 12 novice military pilots during difficult flight manoeuvres in simulated flights. Cortical activity was estimated by using realistic head models and advanced high-resolution EEG techniques. Blue represents the cortical areas where the EEG power spectra in the theta band are statistically higher in novice pilots than in the expert ones. Red indicates the opposite. Three visions of the brain are presented: (a) frontal view, (b) right lateral view and (c) left lateral view. The increase of the frontal theta occurring in novice pilots when compared to the average activity of the expert pilots can be appreciated, which is signalled by the large blue areas on the cortex. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Reproduced with permission from Borghini et al. (2011).

has been noted that "the risk of circular analysis in complex pattern recognition problems (Kriegeskorte et al., 2009) also demands reliable and agreed-upon evaluation procedures for measuring estimation performance" (Kothe and Makeig, 2011). Challenges for reaching an accuracy of the detection of mental states related to the workload close to 99% includes the capability for the classifiers to deal with the problems provided by the different head geometry, incorrect electrodes scalp placements, and time-varying stationarity of the EEG signals.

As demonstrated in the case of Brain Computer Interface development, there is a need to generate a good and carefully controlled EEG dataset related to the occurrence of different mental workloads that could be made freely available on the WEB. Such a dataset can be then used by scientists to test the different pattern recognition methodologies developed in the field of the recognition of mental states. The BCI field has received a great increase in interest by launching the BCI competitions in the last years, while, for cognitive states, such a procedure has just been begun in the USA for a restricted group of scientists. There is no doubt that opening EEG datasets related to CSA to all scientists could increase the capability to develop efficient algorithms to promote further the recognition of mental states during operative conditions characterised by several levels of mental workload in the future.

6. Future directions of the research in the field

This review illustrated how some neurophysiological information can be correlated to mental workload, fatigue and drowsiness in car drivers and airplane pilots. To date, research has focused on the neurophysiological description of the correlated brain activity during driving, with the aim to characterise first, and later automatically detect, such states. The reviewed state of the art data suggests that it is possible to quantify the occurrence of mental workload or drowsiness with a remarkable precision by an offline analysis, especially when the recognition of two or three states is attempted. However, no device or convincing algorithm has been published or practically applied for a robust online recognition of such mental states to date. The implementation of online systems for assessing and detecting different drivers' and pilots' mental states is a line of research that will be further promoted by many of the researchers in the field in the next years.

In perspective, the online detection of neurophysiological indices related to fatigue or drowsiness will make the use of mobile vehicles safer for humans. The problem will be then to make the required neurophysiologic measurements miniaturised and comfortable, probably through the use of subtle tiny (and capacitive) sensors, which are able to gather such information with minimal contact on the skin of the subject. These "dry" electrodes will play surely an important role in the future in this research field, since they will allow to perform measurements of cerebral activity without generating a particular discomfort for the final users.

Other future applications linked to the online recognition of the mental states of car drivers and pilots by computerised systems are related to (i) the possibility to assess the degree of cooperation between crew members during flights, or even (ii) the possibility to command the electronic devices on board only by voluntarily modulating one's mental activity. Although these possibilities appear to belong rather to science-fiction than to science itself, in the next pages some attempts in such directions will be illustrated, promoted in recent years by researchers and industries.

6.1. Assessing the degree of cooperation of a crew using high-resolution EEG

The estimation of the degree of cooperation between pilots in a crew can be assessed by simultaneously measuring their brain activity along a flight mission in a real aircraft or in a simulator. In fact, such brain activity has been used to generate indices of the crew's joint mental workload to be correlated with the perception of the difficulties of the flight mission by the pilots, as assessed through post flight interviews (Borghini et al., 2011). Fig. 7 presents the recording of simultaneous brain activity in professional civil pilots of Alitalia during a flight mission in an MD-80 simulator. Six pairs of pilots were involved in these experiments. During the simulated flights, programmed electrical failures to the aircraft (unknown to the pilots) forced a high degree of cooperation between the crew members to appropriately control the passenger aircraft. The estimated joint mental workload of the pilots was highly correlated with the sequence of the perceived difficulties of the flight, as revealed by the post flight interviews with the pilots (Borghini et al., 2011). Brain activity recorded simultaneously from crew members can be used to assess the degree of cooperation between them and, in the future, it could generate systems that continuously check the "average" degree of mental workload of pilots during a flight mission.

Fig. 7. The collection of brain activity in a professional crew during simulated flight missions. This figure shows the simultaneous collection of brain activities of a couple of Alitalia pilots during a simulated flight mission at the Alitalia training centre in Rome. The EEG of the pilots were monitored and analysed across the different phases of the flight, which presented several simulated electrical failures to the aircraft commands in order to differentiate periods of intense work from periods of relatively quiet cruising.

Fig. 8. Guiding a car using the modulation of brain activity. The figure shows the experience reported by the researchers of Frei University of Berlin when driving a car using mental activity to rotate the steering wheel. In particular, the electrode montage on the head is presented in order to collect EEG activity during the drive. See the related video of the experience.

Figure taken from the website of the Frei University of Berlin (http://autonomos.inf.fu-berlin.de/media/brain-driver-february-2011).

The ability of the system to "understand" in real-time the degree of cooperation between crew members, as well as the degree of mental workload of pilots, could close the loop between pilots and devices, allowing future vehicles to adapt the information to be displayed to the pilots according to their estimated "situation awareness". A network of EU researchers is already involved in the research on the new concepts of the interaction between pilots and vehicles. This is clearly a fascinating direction for research, in which the human–machine interaction could become bidirectional, rather than unidirectional, as it is today.

6.2. Interactions between pilots and ground or aerial vehicles

So far, the interaction between humans and vehicles goes through the physical interaction of human's limbs with the driving commands of the vehicles. However, this situation may change in the future, when the real-time decoding of the brain activity could be used to give the car driver, or the aircraft pilot, a line of command related to the modulation of their mental activity. This area of science is known as Brain Computer Interfaces (BCI) and is a very active field in neuroscience (Lebedev and Nicolelis, 2011). In the BCI field, the capability of the user to voluntarily modulate their alpha rhythms over the sensorimotor areas using motor imagination gives them the capability to control simple electronic devices (Lebedev and Nicolelis, 2011). The application of BCI techniques to car driving or even to aircraft control has been reported in the literature. In particular, a German group from the Frei University of Berlin presented the proof-of-concept that a car could be driven using the voluntary modulation of brain activity to control the steering wheel. Fig. 8 presents a researcher of that group who is ready to command the steering wheel of the car using the modulation of his brain activity. The presentation of this experiment has been reported by the research group on their WEB page, http://autonomos.inf.fu-berlin.de/media/brain-driver-february-2011, and by several international press agencies. A video of the experiment is presented at the following link http://www.youtube.com/watch?v=iDV_62QoHjY&fmt=37.

A demonstration of the capability for using BCI technologies to command simple electronic devices during simulated flights by professional Alitalia pilots has been also shown in recent experiments. The video accompanying this paper (supplementary material) shows a pilot controlling the movement of a cursor on a screen during the flight just by using his neurophysiologic activity. The video shows the proof-of-concept that it is possible to use BCI technology (Cincotti et al., 2008; Millán et al., 2002) to generate an additional command line for the pilots during the control of a vehicle with respect to the use of their limbs. It is clear that a proper experimental design is required to evaluate precisely the additional burden for the pilots in terms of cognitive resources required for the use of BCI technology on board. In this respect, the evaluation of the global performance as well as the brain activity of the pilots during BCI-on and the BCI-off conditions will return useful information related to the increase of cognitive workload introduced by this form of interaction. In such experiment the trade-off between the increased mental workload occurring during the BCI operation (BCI-on condition) and the relative increased performance could be critically evaluated when compared to the BCI-off condition, to shed light on the possible advantages in the adoption of such technologies on board of vehicles. The use of neurophysiologic measurements related to such mental workload such as EEG, EOG and HR will be critical in the description of mental workload and attentive resources.

6.3. Open issues for future research

This review illustrated the state of the art data related to the correlation of different neurophysiologic variables to the mental states of car drivers or airplane pilots during their control of the vehicles. Currently, only a few mental states, related mainly to high workload and drowsiness, can be easily estimated from drivers and pilots. Such mental states can be reliably recognised by offline classifiers. The development of the knowledge related to the estimation of cortical connectivity from EEG measurements could lead to the opportunity to also explore signal features for the classification of mental states (Astolfi et al., 2004, 2005, 2006, 2007; Babiloni et al., 2000, 2002, 2003).

The future research will address issues such as the online detection of the drivers' and pilots' drowsiness and their mental fatigue during driving activities. The online detection of such mental states is expected to be reached in the next 2–5 years, taking into account the evolution of the scientific literature in this respect. Other aspects of interest for research in the next decade will be the possibility to assess the "global" state of the crew in an aircraft as estimated using the multiple collection of brain activity and the human–machine interaction based on the use of mental activity. A new concept of bidirectional and personalised interaction between humans and machines could thus lead to a safer and more comfortable use of vehicles.

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Appendix A. Supplementary data

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References

Aasman, J., Mulder, G., Mulder, L.J.M., 1987. Operator effort and the measurement of heart-rate variability. Human Factors 29, 161–170.
Akerstedt, T., Kecklund, G., Knutsson, A., 1991. Manifest sleepiness and the spectral content of the EEG during shift work. Sleep 14 (3), 221–225.
Alfredson, J., 2007. Differences in Situational Awareness and How to Manage Them in Development of Complex Systems. (Dissertation). Linköping University, Linköping, Sweden.
Angelborg-Thanderz, M., 1990. Military Flight Training at a Reasonable Price and Risk. (Dissertation). Economics Research Institute, Stockholm School of Economics, Stockholm, Sweden.
Astolfi, L., Cincotti, F., Mattia, D., Salinari, S., Babiloni, C., Basilisco, A., Rossini, P.M., Ding, L., Ni, Y., He, B., Marciani, M.G., Babiloni, F., 2004. Estimation of the effective and functional human cortical connectivity with structural equation modeling and directed transfer function applied on high resolution EEG. Magnetic Resonance Imaging 22 (10), 1457–1470.
Astolfi, L., Cincotti, F., Babiloni, C., Carducci, F., Basilisco, A., Rossini, P.M., Salinari, S., Mattia, D., Cerutti, S., Ben Dayan, D., Ding, L., Ni, Y., He, B., Babiloni, F., 2005. Estimation of the cortical connectivity by high resolution EEG and structural equation modeling: simulations and application to finger tapping data. IEEE Transactions on Biomedical Engineering 2 (5), 757–768.
Astolfi, L., Cincotti, F., Mattia, D., Marciani, M.G., Baccalà, L., de Vico Fallani, F., Salinari, S., Ursino, M., Zavaglia, M., Babiloni, F., 2006. Assessing cortical functional connectivity by partial directed coherence: simulations and application to real data. IEEE Transactions on Biomedical Engineering 53 (9), 1802–1812.
Astolfi, L., De Vico Fallani, F., Cincotti, F., Mattia, D., Marciani, M.G., Bufalari, S., Salinari, S., Colosimo, A., Ding, L., Edgar, J.C., Heller, W., Miller, G.A., He, B., Babiloni, F., 2007. Imaging functional brain connectivity patterns from high-resolution EEG and fMRI via graph theory. Psychophysology 44 (6), 880–893.
Babiloni, C., Babiloni, F., Carducci, F., Cincotti, F., Rosciarelli, F., Arendt-Nielsen, L., Chen, A.C.N., Rossini, P.M., 2002. Human brain oscillatory activity phase-locked to painful electrical stimulations: a multi-channel EEG study. Human Brain Mapping 15 (2), 112–123.
Babiloni, F., Carducci, F., Cincotti, F., Del Gratta, C., Roberti, G.M., Romani, G.L., Rossini, P.M., Babiloni, C., 2000. Integration of high resolution EEG functional magnetic resonance in the study of human movement-related potentials. Methods of Information in Medicine 39 (2), 179–182.
Babiloni, C., Brancucci, A., Babiloni, F., Capotosto, P., Carducci, F., Cincotti, F., Arendt-Nielsen, L., Chen, A.C., Rossini, P.M., 2003. Anticipatory cortical responses during the expectancy of a predictable painful stimulation. A high-resolution electroencephalography study. European Journal of Neuroscience 18 (6), 1692–1700.
Babiloni, C., Babiloni, F., Carducci, F., Cincotti, F., Vecchio, F., Cola, F., Rossi, B.S., Miniussi, C., Rossini, P.M., 2004. Functional frontoparietal connectivity during short-term memory as revealed by high-resolution EEG coherence analysis. Behavioral Neuroscience 118 (4), 687–697.
Backs, R.W., Seljos, K.A., 1994. Metabolic and cardiorespiratory measures of mental effort – the effects of level of difficulty in a working-memory task. International Journal of Psychophysiology 16 (1), 57–68.
Baldwin, C.L., Penaranda, B.N., 2012. Adaptive training using an artificial neural network and EEG metrics for within- and cross-task workload classification. NeuroImage 59 (1), 48–56.
Berka, C., Levendowsky, D.J., Lumicao, M.N., Yau, A., Davis, G., Zivkovic, V.T., Olmstead, R.E., Tremoulet, P.D., Craven, P.L., 2007. EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. Aviation, Space, and Environmental Medicine 78 (5), B231–B244.
Besserve, M., Philippe, M., Florence, G., Laurent, F., Garnero, L., Martinerie, J., 2008. Prediction of performance level during a cognitive task from ongoing EEG oscillatory activities. Clinical Neurophysiology 119, 897–908.
Boeing, 2011. Statistical Summary of Commercial Jet Airplane Accidents Worldwide Operations 1959–2010. Boeing, June 2011.
Boksem, M.A., Meijman, T.F., Lorist, M., 2005. Effects of mental fatigue onattention: an ERP study. Cognitive Brain Research 25 (1), 107–116.
Borghini, G., Isabella, R., Vecchiato, G., Toppi, J., Astolfi, L., Caltagirone, C., Babiloni, F., 2011. Brainshield HREEG study of perceived pilot mental workload. Italian Journal of Aerospace Medicine 5, 34–47.
Boucsein, W., Backs, R.W., 2000. Engineering psychophysiology as a discipline: historicaland theoretical aspects. In: Backs, R.W., Boucsein, W. (Eds.), Engineering Psychophysiology. Issues and Applications. Lawrence Erlbaum Associates, Mahwah, NJ, USA, pp. 111–138.
Boyle, L.N., Tippin, J., Paul, A., Rizzo, M., 2008. Driver performance in the moments surrounding a microsleep. Transportation Research Part F: Traffic Psychology and Behaviour 11 (2), 126–136.
Brookhuis, K.A., de Waard, D., 1993. The use of psychophysiology to assessdriverstatus: psychophysiologicalmeasures in transportoperations. Ergonomics 36 (9), 1099–1110 (special issue).
Brookings, J.B., Wilson, G.F., 1994. Physiological and workload changes during a simulated air traffic control task. In: Proceedings of the Human Factors and Ergonomic Society, 38th Annual Meeting.
Broughton, R., Hasan, J., 1995. Quantitative topographic electroencephalographic mapping during drowsiness and sleep onset. Journal of Clinical Neurophysiology 12, 372–386.
Brown, I.D., 1967. Car driving and fatigue. Journal of Emergency Medical Services 8, 131–277.
CAANL, 2008. Civil aviation safety data, 1993-2007. Civil Aviation Authority of the Transport and Water Management Inspectorate Netherlands (CAANL).
Caldwell, J.A., Wilson, G.F., Cetinguc, M., Gallard, A.W.K., Gundel, A., Lagarde, D., Makeig, S., Myhre, G., Wright, N.A., 1994. Psychophysiological Assessment Methods, AGARD-AR-324. NATO, Neuilly Sur Seine, France.
Caldwell, J.A., Hall, K., Erickson, B.S., 2002. EEG data collected from helicopter pilots in flight are sufficiently sensitive to detect increased fatigue from sleep deprivation. International Journal of Aviation Psychology 12 (1), 19–32.
Campagne, A., Pebayle, T., Muzet, A., 2004. Correlation between driving errors and vigilance level: influence of the driver's age. Physiology & Behavior 80 (4), 515–524.
Carmody, M.A., 1994. Current Issues in the Measurement of Military Aircrew Performance: A Consideration of the Relationship Between Available Metrics and Operational Concerns. Air Vehicle and Crew Systems Technology Department, Naval Air Warfare Center: Aircraft Division, Warminster, PA.
Chase, M.H., 2000. Brain electrical activity and sensory processing during waking and sleep states. In: Kryger, M.H., Roth, T.H., Dement, W.C. (Eds.), Principles and Practice of Sleep Medicine. Saunders, New York, pp. 93–111.
Cinaz, B., La Marca, R., Arnrich, B., Tröster, G., 2010. Towards Continuous Monitoring of Mental Workload Computing. Springer, pp. 14–25.
Cincotti, F., Mattia, D., Aloise, F., Bufalari, S., Schalk, G., Oriolo, G., Cherubini, A., Marciani, M.G., Babiloni, F., 2008. Non invasive brain-computer interface system: towards its application as assistive technology. Brain Research Bulletin 75 (6), 796–803.
Classen, J., Gerloff, C., Honda, M., Hallett, M., 1998. Integrative visuomotor behavior is associated with interregionally coherent oscillations in the human brain. Journal of Neurophysiology 79 (3), 1567–1573.
Comstock, J.R., Arnegard, R.J., 1992. The Multi-attribute Task Battery for Human Operator Workload and Strategic Behavior Research. NASA. Langley Research Center, Hampton, VA.
Connor, J., Whitlock, G., Norton, R., Jackson, R., 2001. The role of driver sleepiness in car crashes: a systematic review of epidemiological studies. Accident Analysis & Prevention 33, 31–41.
Cowell, S.F., Egan, G.F., Code, C., Harasty, J., Watson, J.D., 2000. The functional neuroanatomy of simple calculation and number repetition: a parametric PET activation study. NeuroImage 12, 565–573.
Dahlström, N., Nählinder, S., 2009a. Mental workload in simulator and aircraft during basic civil aviation training. International Journal of Aviation Psychology 19 (4), 309–325.
Davidson, P.R., Jones, R.D., Peiris, M.T., 2007. EEG-based lapse detection with high temporal resolution. IEEE Transactions on Biomedical Engineering 54 (5), 832–839.
Davies, D.R., 1965. Skin conductance, alpha activity and vigilance. American Journal of Psychology 78 (2), 304–306.
de Waard, D., Brookhuis, K.A., 1991. Assessingdriverstatus: a demonstrationexperiment on the road. Accident Analysis & Prevention 23 (4), 297–307.
Dehaene, S., Spelke, E., Pinel, P., Stanescu, R., Tsivkin, S., 1999. Sources of mathematical thinking: behavioral and brain-imaging evidence. Science 970, 284.
Dehaene, S., Molko, N., Cohen, L., Wilson, A.J., 2004. Arithmetic and the brain. Current Opinion in Neurobiology 14, 218–224.
Dinges, D.F., Kribbs, N., 1991. In: Mank, T. (Ed.), Performing While Sleepy: Effects of Experimentally-Induced Sleepiness, in Sleep, Sleepiness and Performance. Wile, New York, pp. 98–128.
Dinges, D.F., Pack, F., Williams, K., Gillen, K.A., Powell, J.W., Ott, G.E., 1997. Cumulative sleepiness mood disturbance and psychomotor vigilance performance decrements during a week of sleep restricted to 4–5 h per night. Sleep 20, 267–277.
Doppelmayr, M., Finkenzeller, T., Sauseng, P., 2008. Frontal midline theta in the pre-shot phase of rifle shooting: differences between experts and novices. Neuropsychologia 46 (5), 1463–1467.
Dureman, E.I., Boden, C., 1972. Fatigue in simulated car driving. Ergonomics 15, 299–308.
Dussault, C., Jouanin, J.C., Philippe, M., Guezennec, C.Y., 2005. EEG and ECG changes during simulator operation reflect mental workload and vigilance. Aviation, Space, and Environmental Medicine 76, 344–351.
Dutch Safety Board, 2010. Crashed during approach, Boeing 737-800, near Amsterdam Schiphol Airport, 25 February 2009. Final report of Dutch Safety Board, May 2010.
Eggemeier, F.T., Biers, D.W., Wickens, C.D., Andre, A.D., Vreuls, D., Billman, E.R., Schueren, J., 1990. Performance assessment and workload evaluation systems: analysis of candidate measures. Technical Report No. HSD-TR-90-023. Brooks Air Force Base, Armstrong Aerospace Medical Research Laboratory, TX.

Endsley, M.R., 1995a. Measurement of situation awareness in dynamic systems. Human Factors 37 (1), 65–84.
Endsley, M.R., 1995b. Toward a theory of situation awareness in dynamic systems. Human Factors 37 (1), 32–64.
Endsley, M.R., Garland, D.J., 2000. Pilot situation awareness training in general aviation. In: Proceedings of 14th Triennal Congress of the International Ergonomics Association and the 44th Annual Meeting of the Human Factors and Ergonomics Society.
Eoh, H.J., Chung, M.K., Kim, S.H., 2005. Electroencephalographic study of drowsiness in simulated driving with sleep deprivation. International Journal of Industrial Ergonomics 35, 307–320.
Fairclough, S.H., Venables, L., 2006. Prediction of subjective states from psychophysiology: a multivariate approach. Biological Psychology 71 (1), 100–110.
Fairclough, S.H., Venables, L., Tattersall, A., 2005. The influence of task demand and learning on the psychophysiological response. International Journal of Psychophysiology 56 (2), 171–184.
Fournier, L.R., Wilson, G.F., Swain, C.R., 1999. Electrophysiological behavioral, and subjective indexes of workload when performing multiple tasks: manipulations of task difficulty and training. International Journal of Psychophysiology 31, 129–145.
Fu, J.W., Li, M., Lu, B.L., 2008. Detecting drowsiness in driving simulation based on EEG. In: Autonomous Systems – Self – Organization Management and Control, pp. 21–28.
Gale, A., Davies, R., Smallbone, A., 1977. EEG correlates of signal rate time in task and individual differences in reaction time during a five-stage sustained attention task. Ergonomics 20, 363–376.
Gander, P.H., Nguyen, D., Rosekind, M.R., Connell, L.J., 1993. Age, circadian rhythms, and sleep loss in flight crews. Aviation, Space, and Environmental Medicine 64 (3), 189–195.
Gevins, A., Smith, M.E., 2003. Neurophysiological measures of cognitive workload during human-computer interaction. Theoretical Issues in Ergonomic Sciences 40 (1), 79–91.
Gevins, A.S., Cutillo, B.A., Bressler, S.L., Morgan, N.H., White, R.M., Illes, J., Greer, D.S., 1989. Event-related covariances during a bimanual visuomotor task II. Preparation and feedback. Electroencephalography and Clinical Neurophysiology 74, 147–160.
Gevins, A.S., Bressler, S.L., Cutillo, B.A., Illes, J., Fowler-White, R.M., 1990. Effects of prolonged mental work on functional brain topography. Electroencephalography and Clinical Neurophysiology 76, 339–350.
Gevins, A., Leong, H., Du, R., Smith, M.E., Le, J., DuRousseau, D., 1995. Toward measurement of brain function in operational environments. Biological Psychiatry 43, 145–152.
Gevins, A., Smith, M.E., McEvoy, L., Yu, D., 1997. High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. Cerebral Cortex 7, 374–385.
Gevins, A., Smith, M.E., Leong, H., McEvoy, L., Whitfield, S., Du, R., Rush, G., 1998. Monitoring working memory load during computer-based tasks with EEG pattern recognition methods. Human Factors 40 (1), 79–91.
Gevins, A., Le, J., Leong, H., McEvoy, L.K., Smith, M.E., 1999. Deblurring. Journal of Clinical Neurophysiology 16, 204–213.
Gillberg, M., Keeklund, G., Akerstedt, T., 1996. Sleepiness and performance of professional drivers in a truck simulator – comparison between day and night driving. Journal of Sleep Research 5, 12–15.
Grandjean, E., 1979. Fatigue in industry. British Journal of Industrial Medicine 36, 175–186.
Grandjean, E., 1988. Fitting the Task to the Man. A Textbook of Occupational Ergonomics. Taylor & Francis, London.
Grossman, P., Karemaker, J., Wieling, W., 1991. Prediction of tonic parasympathetic cardiac control using respiratory sinus arrhythmia: the need for respiratory control. Psychophysiology 28, 201–216.
Hakkanen, H., Summala, H., 2000. Sleepiness at work among commercial truck drivers. Sleep 23, 49–57.
Hamblin, P., 1987. Lorry driver's time habits in work and their involvement in traffic accidents. Ergonomics 30 (9), 1323–1333.
Hameroff, S., 2010. The conscious pilot–dendritic synchrony moves through the brain to mediate consciousness. Journal of Biological Physics 36, 71–93.
Hankins, T.C., Wilson, G.F., 1998. A comparison of heart rate, eye activity, EEG and subjective measures of pilot mental workload during flight. Aviation, Space, and Environmental Medicine 69 (4), 360–367.
Hanson, E.K.S., Bazanski, J., 2001. Ecological momentary assessments in aviation: the development of a Pilot Experience Evaluating Device (PEED) for the in-flight registration of flight phases, mental effort, and reaction time. In: Fahrenberg, J., Myrtek, M. (Eds.), Progress in Ambulatory Assessment Computer Assisted Psychological and Psychophysiological Methods in Monitoring and Field Studies, pp Measurements. Hogrefe & Huber, Seattle, pp. 477–492.
Hare, T.A., Camerer, C.F., Rangel, A., 2009. Self-controlin decision-making involves modulation of the vmPFCvaluation system. Science 324, 646–648.
Harris, W., Mackie, R.R., Abrams, C., Buckner, D.N., Harabedian, A., O'Hanlon, J.F., Starks, J.R., 1972. A study of the relationship among fatigue, hours of service and safety of operations of truck- and bus-drivers. Human Factors Research Inc. California, Report No. 1727-2.
Hart, S.G., Staveland, L.E., 1988. Development of NASA-TLX (Task Load Index) results of empirical and theoretical research. In: Hancock, P.A., Meshkati, N. (Eds.), Human Mental Workload. North Holland Press, Amsterdam.
Haworth, N.L., Heffernan, C.J., Horne, E.J., 1989. Fatigue in truck accidents. Victorian Road Freight Industry Council. Australia, Report No. 3.
He, B., Lian, J., 2002. Spatio-temporal functional neuroimaging of brain electric activity. Critical Reviews in Biomedical Engineering 30, 283–306.
Hirvonen, K., Hasan, J., Häkkinen, V., Värri, A., Loula, P., 1997. The detection of drowsiness and sleep onset periods from ambulatory recorded polygraphic data. Electroencephalography and Clinical Neurophysiology 102 (2), 132–137.
Holm, A., 2010. Developing neurophysiological metrics for the assessment of mental workload and the functional state of the brain. Doctoral dissertation for the degree of Doctor of Philosophy. Aalto University School of Science and Technology (Espoo, Finland), 12th of May 2010.
Holm, A., Lukander, K., Korpela, J., Sallinen, M., Müller, K.M.I., 2009. Estimating brain load from the EEG. The Scientific World Journal 9, 639–651.
Hori, T., Hayashi, M., Morikawa, T., 1994. TopographicEEG changes and the hypnagogic experience. In: Ogilvie, R.D., Harsh, J.R. (Eds.), Sleep Onset: Normal and Abnormal Processes. American Psychological Association, Washington, pp. 237–253.
Horne, J.A., Baulk, S.D., 2004. Awareness of sleepiness when driving. Psychophysiology 4, 97–110.
Horne, J.A., Reyner, L.A., 1995. Sleep related vehicle accidents. British Medical Journal 310, 565–567.
Horváth, M., Frantik, E., Kopriva, K., Meissner, J., 1976. EEG theta activity increase coinciding with performance decrement in a monotonous task. Activitas Nervosa Superior 18 (3), 207–210.
Hu, S., Zheng, G., 2009. Driver drowsiness detection with eyelid related parameters by Support VectorMachine. Expert System with Applications 36, 7651–7658.
Idogawa, K., 1991. On the brain wave activity of professional drivers during monotonous work. Behaviormetrika 30, 23–34.
Ishii, R., Shinosaki, K., Ukai, S., Inouye, T., Ishihara, T., Yoshimine, T., Hirabuki, N., Asada, H., Kihara, T., Robinson, S.E., Takeda, M., 1999. Medial prefrontal cortex generates frontal midline theta rhythm. Neuroreport 10, 675–679.
Jap, B.T., Lal, S., Fischer, P., Bekiaris, E., 2009. Using EEG spectral components to assess algorithms for detecting fatigue. Expert System with Applications 36, 2352–2359.
Johns, M.W., Chapman, R., Crowley, K., Tucker, A., 2008. A new method for assessing the risks of drowsiness while driving. Somnologie 12, 66–74.
Jones, R.D., Poudel, G.R., Innes, C.R., Davidson, P.R., Peiris, M.T., Malla, A.M., Signal, T., Carroll, G.J., Watts, R., Bones, P.J., 2010. Lapses of responsiveness: characteristics, detection, and underlying mechanisms. Conference Proceedings IEEE Engineering in Medicine and Biolology Society, 31, pp. 1788–1791.
Jung, T.P., Makeig, S., 1994. Estimating level of alertness from EEG. Engineering in Medicine and Biology Society 2, 1103–1104.
Jung, T.P., Makeig, S., Stensmo, M., Sejnowski, T.J., 1997. Estimating alertness from the EEG power spectrum. IEEE Transactions on Biomedical Engineering 44 (1), 60–69.
Kalauzi, A., Vuckovic, A., Bojić, T., 2012. EEG alpha phase shifts during transition from wakefulness to drowsiness. International Journal of Psychophysiology (May) [Epub ahead of print].
Kecklund, G., Åkerstedt, T., 1993. Sleepiness in long distance truck driving: an ambulatory EEG study of night driving. Ergonomics 36 (9), 1007–1017.
Khushaba, R.N., Kodagoda, S., Lal, S., Dissanayake, G., 2011. Driver drowsiness classification using fuzzy wavelet-packet-based feature-extraction algorithm. IEEE Transactions on Biomedical Engineering 58 (1), 121–131.
Klimesch, W., 1999. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Research Reviews 29, 169–195.
Klimesch, W., Doppelmayr, M., Schimke, H., Ripper, B., 1997. Theta synchronization and alpha desynchronization in a memory task. Psychophysiology 34 (2), 169–176.
Kohlmorgen, J., Dornhege, G., Braun, M., Blankertz, B., Müller, K.-R., Curio, G., Hagemann, K., Brun, A., Schrauf, M., Kincses, W., 2007. Improving human performance in a real operating environment through real-time mental workload detection. In: Toward Brain-Computer Interfacing. MIT press, Cambridge, MA, pp. 409–422.
Kong, J., Wang, C., Kwong, K., Vangel, M., Chua, E., Gollub, R., 2005. The neural substrate of arithmetic operations and procedure complexity. Cognitive Brain Research 22, 397–405.
Kothe, C.A., Makeig, S., 2011. Estimation of task workload from EEG data: new and current tools and perspectives. In: 33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, August 30–September 3.
Kramer, A.F., 1991. Physiological metrics of mental workload: a review of recent progress. In: Damos, D.L. (Ed.), Multiple Task Performance. Taylor & Francis, London.
Krebs, M.J., Wingert, J.W., Cunningham, T., 1977. Exploration of an Oculometer-Based Model of Pilot Workload. NASA Technical report CR-145153. Honeywell Systems & Research Center, Minneapolis, Minnesota.
Kriegeskorte, N., Simmons, W.K., Bellgowan, P.S.F., Baker, C.I., 2009. Circular analysis in systems neuroscience – the dangers of double dipping. Nature Neuroscience 12 (5), 535–540.
Lal, S.K.L., Craig, A., 2000. Psychophysiological effects associated with drowsiness: driver fatigue and electroencephalography. International Journal of Psychophysiology 35 (1), 39–47.
Lal, S.K.L., Craig, A., 2001a. Critical review of the psychophysiology of driver fatigue. Biological Psychology 55, 173–194.
Lal, S.K.L., Craig, A., 2001b. Psychological effects associated with drowsiness: driver fatigue and electroencephalography. International Journal of Psychophysiology 55, 183–189.
Lal, S.K.L., Craig, A., 2002. Driver fatigue electroencephalography and psychological assessment. Psychophysiology 39, 1–9.

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Lal, S.K.L., Craig, A., Boord, P., Kirkup, L., Nguyen, H., 2003. Development of an algorithm for an EEG-based driver fatigue countermeasure. Journal of Safety Research 34 (3), 321–328.
Laube, I., Seeger, R., Russi, E.W., Bloch, K.E., 1998. Accidents related to sleepiness: review of medical causes and prevention with special reference to Switzerland. Schweizerische medizinische Wochenschrift 128 (40), 1487–1499.
Lebedev, M.A., Nicolelis, M.A., 2011. Toward a whole-body neuroprosthetic. Progress in Brain Research 194, 47–60.
Lehmann, D., Grass, P., Meier, B., 1995. Spontaneous conscious covert cognition states and brain electric spectral states in canonical correlations. International Journal of Psychophysiology 19, 41–52.
Leocani, L., Toro, C., Manganotti, P., Zhuang, P., Hallett, M., 1997. Event-related coherence and event-related desynchronization/synchronitazion in the 10 Hz and 20 Hz EEG during self-paced movements. Electroencephalography and Clinical Neurophysiology 104, 199–206.
Lin, C.T., Wu, R.C., Jung, T.P., Liang, S.F., Huang, T.Y., 2005. Estimating driving performance based on EEG spectrum analysis. EURASIP Journal on Applied Signal Processing 19, 3165–3174.
Lin, C.T., Ko, L.W., Chung, I.F., Huang, T.Y., Chen, Y.C., Jung, T.P., Liang, S.F., 2006. Adaptive EEG-based alertness estimation system by using ICA-based fuzzy neural networks. IEEE Transactions on Circuits and Systems 53 (11), 2469–2476.
Lundberg, J., 1999. Distributed Situation Awareness for the Civil Cockpit: Theory and Operationalisation. LIU-KOGVET-D-0013-SE. LinköpingsUniversitet, Linköping.
Luu, P., Tucker, D.M., Makeig, S., 2004. Frontal midline theta and the error-related negativity: neurophysiological mechanisms of action regulation. Clinical Neurophysiology 115, 1821–1835.
Lyznicki, J.M., Doege, T.C., Davis, R.M., Williams, M.A., 1998. Sleepiness, driving, and motor vehicle crashes. Council on Scientific Affairs, American Medical Association 279 (23), 1908–1913.
Mackie, R.R., Miller, J.C., 1978. Effects of hours of service, regularity of schedules and cargo loading on truck and bus driving fatigue. Human Factors Research Inc. CA, Technical report 1765-F.
Makeig, S.M., 1993. In low Lapses in alertness: coherence of fluctuations in performance and EEG spectrum. Electroencephalogy and Clinical Neurophysiology 86, 23–35.
Makeig, S., Jung, T., 1995. Changes in alertness are a principal component of variance in the EEG spectrum. Neuroreport 7, 213–216.
Mano, T., Shiozawa, Z., Amino, A., Nagasaka, T., Shindo, K., Nagasaki, H., Kobayashi, T., Mihara, K., 1995. EEG findings for drivers during driving in a highway. Electroencephalogy and Clinical Neurophysiology 97 (4), 149.
Mascord, D.J., Heath, R.A., 1992. Behavioral and physiological indices of fatigue in a visual tracking task. Journal of Safety Research 23, 19–25.
Matousek, M.I., Petersen, A., 1983. A method for assessing alertness fluctuations from EEG spectra. Electroencephalogy and Clinical Neurophysiology 55, 108–113.
McDonald, N., 1984. Fatigue, Safety and the Truck Driver. Taylor and Francis, London.
McEvoy, L.K., Pellouchoud, E., Smith, M.E., Gevins, A., 2001. Neurophysiological signals of working memory in normal aging. Cognitive Brain Research 11 (3), 363–376.
Menon, V., Rivera, S.M., White, C.D., Glover, G.H., Reiss, A.L., 2000. Dissociating prefrontal and parietal cortex activation during arithmetic processing. NeuroImage 12, 357–365.
Millán, J., Franzé, M., Mouriño, P., Cincotti, F., Babiloni, F., 2002. Relevant EEG features for the classification of spontaneous motor-related tasks. Biological Cybernetics 86, 89–95.
Moller, H.J., Kayumov, L., Bulmash, E., Nhan, J., Shapiro, C.M., 2006. Simulator performance, microsleep episodes, and subjective sleepiness: normative data using convergent methodologies to assess driver drowsiness. Journal of Psychosomatic Research 61 (3), 335–342.
Morrel, L.K., 1966. EEG frequency and reaction time – a sequential analysis. Neuropsychologia 4, 41–48.
Nählinder, S., 2004. ACES – air combat evaluation system. FOI-R–1368–SE. FOI Methodology Report. FOI, Linköping, Sweden.
Nählinder, S., 2009. Flight Simulator Training: Assessing the Potential Department of Management and Engineering. Doctoral thesis, Comprehensive summary.
Ninomija, S.P., Funada, M.F., Yazu, Y., Ide, H., Daimon, N., 1993. Possibility of ECGs to improve reliability of detection system of inclining sleep stages by grouped alpha waves. In: Proceedings of the 15th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 1410–1411.
O'Donnel, R.D., Eggemeier, F.T., 1986. Workload assessment methodology. In: Kaufman, B.K., Wiley, T.J. (Eds.), Handbook of Perception and Human Performance, Volume II, Cognitive Processes and Performance. New York, pp. 41–42.
Ohsuga, M., Shimono, F., Genno, H., 2001. Assessment of phasic work stress using autonomic indices. International Journal of Psychophysiology 40 (3), 211–220.
Okogbaa, O.G., Shell, R.L., Filipusic, D., 1994. On the investigation of the neurophysiological correlates of knowledge worker mental fatigue using the EEG signal. Applied Ergonomics 25 (6), 355–365.
Otmani, S., Pebayle, T., Roge, J., Muzet, A., 2005. Effect of driving duration and partial sleep deprivation on subsequent alertness and performance of car drivers. Physiology & Behavior 84, 715–724.
Pagani, M., Mazzuero, G., Ferrari, A., Liberati, D., Cerutti, S., Vaitl, D., Tavazzi, L., Malliani, A., 1990. Sympathovagal interaction during mental stress. Circulation Supplement 83, 11–19.
Papadelis, C., 2010. In: Verster, J.C., Charles, F.P.G. (Eds.), Brain Activity During Sleepy Driving. Sleep, Sleepiness and Traffic Safety. NOVA Science Publishers, pp. 93–108.
Papadelis, C., Kourtidou-Papadeli, C., Bamidis, P.D., Chouvarda, I., Koufogiannis, D., Bekiaris, E., Maglaveras, N., 2006. Indicators of sleepiness in an ambulatory EEG study of night driving. Conference Proceedings IEEE Engineering in Medicine and Biology Society, 1, pp. 6201–6214.
Papadelis, C., Chen, Z., Kourtidou-Papadeli, C., Bamidis, P.D., Chouvarda, I., Bekiaris, E., Maglaveras, N., 2007. Monitoring sleepiness with on-board electrophysiological recordings for preventing sleep-deprived traffic accidents. Clinical Neurophysiology 118 (9), 1906–1922.
Papadelis, C., Lithari, C., Kourtidou-Papadeli, C., Bamidis, P.D., Portouli, E., Bekiaris, E., 2009. Monitoring driver's sleepiness on-board for preventing road accidents. Studies in Health Technology and Informatics 150, 485–489.
Parasuraman, R., Jiang, Y., 2012. Individual differences in cognition, affect, and performance: behavioral, neuroimaging, and molecular genetic approaches. NeuroImage 59 (1), 70–82.
Parasuraman, R., Sheridan, T.B., Wickens, C.D., 2008. Situation awareness, mental workload, and trust in automation: viable, empirically supported cognitive engineering constructs. Journal of Cognitive Engineering and Decision Making 2 (2), 140–160.
Peiris, M.T., Davidson, P.R., Bones, P.J., Jones, R.D., 2011. Detection of lapses in responsiveness from the EEG. Journal of Neural Engineering 8 (1), 016003.
Pettyjohn, E.S., McNeil, R.J., 1977. Use of inspiratory minute volumes in evaluation of rotary and fixed wing pilot workload. In: Methods to Assess Workload, AGARD Aerospace Medical Panel Meeting, Cologne.
Pfurtscheller, G., Neuper, C., Mohl, W., 1994. Event-related desynchronization during visual processing. International Journal of Psychophysiology 16, 147–153.
Philip, P., 2005. Sleepiness of occupational drivers. Industrial Health 43, 30–33.
Postma, M.A., Schellekens, J.M., Hanson, E.K.S., Hoogeboom, P.J., 2005. Fz theta divided by Pz alpha as an index of task load during a PC-based air traffic control simulation. In: de Waard, D., Brookhuis, D., van Egmond, R., Boersma, T. (Eds.), Human Factors in Design, Safety, and Management. Shaker Publishing, Maastricht, pp. 1–5.
Poythress, M., Russell, C., Siegel, S., Tremoulet, P., Craven, P.L., Berka, C., 2006. Correlation between expected workload and EEG indices of cognitive workload and task engagement. In: Schmorrow, D., Stanney, K., Reeves, L. (Eds.), Augmented Cognition: Past, Present and Future. Strategic Analysis, Inc, Arlington, pp. 32–44.
Riemersma, J.B.J., Sanders, A.F., Hildervanck, C., Gaillard, A.W., 1977. Performance decrement during prolonged night driving. In: Mackie, R. (Ed.), Vigilance: Theory, Operational Performance and Physiological Correlates. Plenum Press, New York, pp. 41–58.
Risser, M.R., Ware, J.C., Freeman, F.G., 2000. Driving simulation with EEG monitoring in normal and obstructive sleep apnea patients. Sleep 23 (3), 393–398.
Roscoe, A.H., 1987. In-flight assessment of workload using pilot ratings and heart rate. In: Roscoe, A.H. (Ed.), The Practical Assessment of Pilot Workload. , AGARDgraph No, 282.
Roscoe, A.H., 1992. Assessing pilot workload. Why measure heart rate, HRV and respiration? Biological Psychology 34, 259–287.
Roscoe, A.H., Ellis, G.A., 1990. A subjective rating scale for assessing pilot workload in flight: a decade of practical use. In: Tech. Report 90019. Royal Aerospace Establishment, Farnborough, England.
Roth, B., 1961. The clinical and theoretical importance of EEG rhythms corresponding to states of lowered vigilance. Electroencephalography and Clinical Neurophysiology 13, 395–399.
Ryu, K., Myung, R., 2005. Evaluation of mental workload with a combined measure based on physiological indices during a dual task of tracking and mental arithmetic. International Journal of Industrial Ergonomics 35, 991–1009.
Sammer, G., Blecker, C., Gebhardt, H., Bischoff, M., Stark, R., Morgen, K., Vaitl, D., 2007. Relationship between regional hemodynamic activity and simultaneously recorded EEG-theta associated with mental arithmetic-induced workload. Human Brain Mapping 28 (8), 793–803.
Santamaria, J., Chiappa, K.H., 1987. The EEG of drowsiness in normal adults. Journal of Clinical Neurophysiology 4, 327–382.
Sauseng, P., Klimesch, W., Freunberger, R., Pecherstorfer, T., Hanslmayr, S., Doppelmayr, M., 2006. Relevance of EEG alpha and theta oscillations during task switching. Experimental Brain Research 170 (3), 295–301.
Shen, K.Q., Li, X.P., Ong, C.J., Shao, S.Y., Wilder-Smith, E., 2008. EEG-based mental fatigue measurement using multi-class support vector machines with confidence estimate. Clinical Neurophysiology 119, 1524–1533.
Sheridan, T.B., Simpson, R.W., 1979. Toward the definition and measurement of the mental workload of transport pilots. In: FTL Report No. R79-4. Massachusetts Institute of Technology, Cambridge.
Simon, M., Schmidt, E.A., Kincses, W.E., Fritzsche, M., Bruns, A., Aufmuth, C., Bogdan, C., Rosenstiel, W., Schrauf, M., 2011. EEG alpha spindle measures as indicators of driver fatigue under real traffic conditions. Clinical Neurophysiology 122 (6), 1168–1178.
Slobounov, S.M., Fukada, K., Simon, R., Rearick, M., Ray, W., 2000. Neurophysiological and behavioral indices of time pressure effects on visuomotor task performance. Cognitive Brain Research 9 (3), 287–298.
Smith, A., Gevins, A., Brown, H., Karnik, A., Du, R., 2001. Monitoring task loading with multivariate EEG measures during forms of human-computer interaction. Human Factors 43 (3), 366–380.
Smith, M.E., McEvoy, L.K., Gevins, A., 2002. The impact of moderate sleep loss on neurophysiologic signals during working-memory task performance. Sleep 25 (7), 784–794.
Smulders, F.T., Kenemans, J.L., Jonkman, L.M., Kok, A., 1997. The effects of sleep losson task performance and the electroencephalogram in young and elderly subjects. Biological Psychology 45 (1–3), 217–239.

Stein, E.S., 1992. Air Traffic Control Visual Scanning. FAA Technical Report DOT/FAA/CT-TN92/16. US Department of Transportation.

Steptoe, A., 1985. Theoretical bases for task selection in cardiovascular psychophysiology. In: Steptoe, A., Ruddel, H., Neus, H. (Eds.), Clinical and Methodological Issues in Cardiovascular Psychophysiology. Springer Verlag, Berlin, pp. 6–15.

Sterman, M.B., Mann, C.A., 1995. Concepts and applications of EEG analysis in aviation performance evaluation. Biological Psychology 40 (1), 115–130.

Stern, J.A., 1993. The eyes: reflector of attentional processes. CSERIAC Gateway 4 (4), 7–12.

Togo, F., Takahashi, M., 2009. Heart rate variability in occupational health – a systematic review. Industrial Health 47, 89–602.

Torsvall, L., Åkerstedt, T., 1987. Sleepiness on the job: continuously measured EEG changes in train drivers. Electroencephalography and Clinical Neurophysiology 66, 502–511.

Tsai, Y.-F., Viirre, E., Strychacz, C., Chase, B., Jung, T.-P., 2007. Task performance and eye activity relating to cognitive workload. Aviation, Space, and Environmental Medicine 78 (5), B176–B185.

Tsuchida, A., Bhuiyan, M., Oguri, K., 2009. Estimation of drowsiness level based on eyelid closure and heart rate variability. In: Proceeding of the 31st Annual International Conference IEEE Engineering in Medicine and Biology Society (EMBS), pp. 2543–2546.

Urbano, A., Babiloni, F., Babiloni, C., Ambrosini, A., Onorati, P., Rossini, P.M., 1997. Human short-latency cortical responses to somatosensory stimulation. A high resolution study. Neuro Report 8 (15), 3239–3243.

Vidulich, M.A., Wickens, C.D., 1986. Causes of dissociation between subjective workload measures and performance. Applied Ergonomics 17, 291–296.

Vuckovic, A., Radivojevic, V., Chen, A.C., Popovic, D.B., 2002. Automaticrecognition of alertness and drowsiness from EEG by artificialneural networks. Medical Engineering & Physics 24 (5), 349–360.

Wang, Z., Hope, R.M., Wang, Z., Ji, Q., Gray, W.D., 2012. Cross-subject workload classification with a hierarchical Bayes model. NeuroImage 59 (1), 64–69.

Williamson, A.M., Feyer, A., Friswell, R., 1996. The impact of work practices on fatigue in long distance truck drivers. Accident Analysis and Prevention 28 (6), 709–719.

Wilson, G.F., 1993. Air-to-ground training missions: a psychophysiological workload analysis. Ergonomics 36 (9), 1071–1087.

Wilson, B.J., Bracewell, T.D., 2000. Alertness monitor using neural networks for EEG analysis. Proceedings of the 2000 IEEE Signal Processing Society, Workshop on Neural Networks for Signal Processing, 2, pp. 814–820.

Wilson, G.F., Eggemeier, F.T., 1991. Psychophysiological assessment of workload in multitask environments. In: Damos, D.L. (Ed.), Multiple Task Performance. Taylor and Francis Ltd, London, pp. 329–360.

Wilson, G.F., Fisher, F., 1991. The use of cardiac and eye blink measures to determine flight segments in F4 crews. Aviation, Space and Environmental Medicine 62, 959–962.

Wilson, G.F., Fisher, F., 1995. Cognitive task classification based upon topographic EEG data. Biological Psychology 40 (1–2), 239–250.

Wilson, G.F., Fullenkamp, P., 1991. A comparison ofpilot and WSO workload during training missions using psychophysiological data. In: Farmer, E. (Ed.), Proceedings of the Western European Association for Aviation Psychology. Avebury, Aldershot.

Wilson, G.F., Russell, C.A., 2003a. Operator functional state classification using multiplepsychophysiological features in an air traffic control task. Human Factors 45, 381–389.

Wilson, G.F., Russell, C.A., 2003b. Real-time assessment of mental workload using psychophysiological measures and artificial neural networks. Human Factors 45, 635–643.

Wilson, G.F., Russell, C.A., 2007. Performance enhancement in an uninhabited air task using psychophysiologically determined adaptive aiding. Human Factors 49, 1005–1018.

Wilson, G.F., O'Donnell, R.D., Wilson, L., 1982. Neurophysiological measures of A-10 workload during simulated low altitude missions. AFAMLR Technical Report No. 83-0003. Wright-Patterson AFB: Air Force Aerospace Medical Research Laboratory.

Wilson, G.F., Estepp, J., Christensen, J.C., 2010. How does day-to-day variability in psychophysiological data affect classifier accuracy. Human Factors and Ergonomics Society Annual Meeting Proceedings, 54, pp. 264–268.

World Health Organization, 2009. WHO. Preventing Road Traffic Injury: A Public Health Perspective For Europe, 2009.

Wright, N., Powell, D., Mcgown, A., Broadbent, E., Loft, P., 2005. Avoiding involuntary sleep during civil air operations: validation of a wrist-worn alertness device. Aviation, Space, and Environmental Medicine 76, 847–856.

Yamada, F., 1998. Frontal midline theta rhythm and eye blinking activity during a VDT task and a video game: useful tools for psychophysiology in ergonomics. Ergonomics 41 (5), 678–688.

Yeh, Y.Y., Wickens, C.D., 1988. Dissociation of performance and subjective measures of workload. Human Factors 30, 111–120.

Yeo, M.V., Li, X., Wilder-Smith, E.P., 2007. Characteristic EEG differences between voluntary recumbent sleep onset in bed and involuntary sleep onset in a driving simulator. Clinical Neurophysiology 118 (6), 1315–1323.

Zhao, C., Zhao, M., Liu, J., Zheng, C., 2012. Electroencephalogram and electrocardiograph assessment of mental fatigue in a driving simulator. Accident Analysis and Prevention 45, 83–90.

Zilberg, E., Xu, Z.M., Burton, D., Karrar, M., Lal, S., 2009. Statistical validation of physiological indicators for noninvasive and hybrid drowsiness detection system. African Journal of Information and Communication Technology 5 (2), 75–83.