International Journal of Psychophysiology 121 (2017) 12–17

Contents lists available at ScienceDirect

International Journal of Psychophysiology

journal homepage: www.elsevier.com/locate/ijpsycho

Performance of an automated algorithm to process artefacts for quantitative EEG analysis during a simultaneous driving simulator performance task

András Szentkirályi[a,b,c], Keith K.H. Wong[a,d], Ronald R. Grunstein[a,d], Angela L. D'Rozario[a,b,c,d,*,1], Jong Won Kim[a,e]

[a] CIRUS, Centre for Sleep and Chronobiology, Woolcock Institute of Medical Research, The University of Sydney, PO Box M77, Missenden Road, 2050, NSW, Australia
[b] Institute of Epidemiology and Social Medicine, Westfälische Wilhelms-University of Münster, Domagkstraße 3, D-48149 Münster, Germany
[c] Department of Respiratory and Sleep Medicine, Royal Prince Alfred Hospital, PO Box M30, Sydney Local Health District, Missenden Road, Sydney 2050, NSW, Australia
[d] School of Psychology, Brain and Mind Centre and Charles Perkins Centre, The University of Sydney, Sydney, NSW, Australia
[e] Department of Healthcare IT, Inje University, Inje-ro 197, Kimhae, Kyunsangnam-do 50834, Republic of Korea

ARTICLE INFO

Keywords:
EEG artefact processing
Power spectral analysis
Obstructive sleep apnea
Neurobehavioral function
Drowsiness

ABSTRACT

Background: Artefact removal from noisy EEG signals is cumbersome, and often requires manual intervention. We tested the performance of an automated method to detect and remove artefacts from EEG recorded during a driving simulation task.

Methods: Five patients with obstructive sleep apnea (OSA) and five healthy controls were randomly selected from 17 participants undergoing a 40-h extended wakefulness study with 2-hourly 30-minute simulated driving tasks with simultaneous EEG. Two EEG recordings from each individual were studied. EEG data was first processed by independent component analysis (ICA). The accuracy of the automated algorithm (AA) to detect residual EEG artefact was evaluated against a reference-standard (RS) of visually identified artefact-contaminated epochs. EEG spectral power was calculated using 1) the RS method, 2) the AA, and 3) raw data without any artefact rejection (ICA only).

Results: The algorithm showed good sensitivity (median: 83.9%), excellent specificity (91.1%), and high accuracy (87.0%) to detect noisy epochs. Cohen's κ indicated a substantial agreement between the two methods (0.72). EEG spectral power calculated using the RS and the AA did not differ significantly, while the power of the raw signal was significantly higher than those produced by any artefact rejection method. Increased EEG delta and theta power were significantly correlated with poorer driving performance.

Conclusions: These preliminary findings demonstrate an effective automated method to process EEG artefact recorded during driving simulation. This approach may facilitate the routine application of quantitative EEG analyses in future studies and identify new markers of impaired driving performance associated with sleep disorders.

1. Introduction

Motor vehicle accidents are the ninth leading cause of death globally, responsible for most deaths among young people aged 15–29 (WHO, 2011). According to the latest WHO report, 1.26 million people died on the roads worldwide in 2011 (WHO, 2011).

Driver fatigue contributes up to 20% of serious motor vehicle highway accidents (de Mello et al., 2013). Obstructive sleep apnea (OSA) is a common sleep disorder, which often leads to severe fatigue, drowsiness, and impaired cognitive functioning (Aloia et al., 2004). Individuals with OSA have an elevated risk (ranging from 1.2 to 4.9) of being involved in motor vehicle crashes (Tregear et al., 2009), and sleep deprivation has a more detrimental effect on driving in subjects with OSA than in good sleepers (Vakulin et al., 2007). Observational studies suggest that treatment with continuous positive airway pressure promptly improves driving performance in these patients (Tregear et al., 2010).

Prediction of individual risk of road accidents in OSA is challenging,

Abbreviations: AA, automated algorithm; EEG, electroencephalogram; EOG, electrooculogram; FFT, fast Fourier transform; ICA, independent component analysis; OSA, obstructive sleep apnea; RS, reference-standard; SD, standard deviation; SDEA, standard deviation of EEG amplitude

* Corresponding author at: CIRUS, Centre for Sleep and Chronobiology, Woolcock Institute of Medical Research, PO Box M77, Missenden Road, Sydney 2050, NSW, Australia.
E-mail addresses: szentkir@uni-muenster.de (A. Szentkirályi), keith.wong@sydney.edu.au (K.K.H. Wong), ron.grunstein@sydney.edu.au (R.R. Grunstein), angela.drozario@sydney.edu.au (A.L. D'Rozario), jongwonkim@inje.ac.kr (J.W. Kim).
[1] Co-senior author.

http://dx.doi.org/10.1016/j.ijpsycho.2017.08.004
Received 22 December 2016; Received in revised form 1 July 2017; Accepted 14 August 2017
Available online 15 August 2017
0167-8760/

since many subjects do not show prominent daytime impairments and can drive safely. A further difficulty is that patients with OSA are often unaware of their sleepiness and impairment, or minimize the symptoms (Engleman et al., 1997). While some studies have found that OSA severity is associated with more motor vehicle crashes (George and Smiley, 1999; Teran-Santos et al., 1999), subjective and objective severity markers per se, including sleepiness or the respiratory disturbance index, are poor indicators of road accidents (Barbe et al., 1998). Driving simulators provide a relatively simple method to assess driving performance. Compared to normal controls, the overall performance of patients with OSA is worse on a driving simulator (Findley et al., 1995; George et al., 1996), but individual prediction of road accidents remains poor (Turkington et al., 2001).

Quantitative analysis of the wake electroencephalogram (EEG) can be utilized to monitor vigilance and neurobehavioral performance. Increased EEG spectral power within the alpha and theta frequency bands of continuously recorded EEG was shown to be a good indicator of night-time driving fatigue and, to a lesser extent, reduced performance among professional drivers in a field study (Kecklund and Akerstedt, 1993). Driving simulator studies provided similar results (Anund et al., 2008; Campagne et al., 2004; Zhao et al., 2012), and others found that spectral power within lower (delta) and higher (beta) frequency ranges may also reflect sleepiness and performance decrements (Lal and Craig, 2002; Phipps-Nelson et al., 2011). Quantitative analysis of the EEG involving other measures than the spectral power could be also promising. For example, EEG coherence between most brain regions is increased during driving-induced mental fatigue (Jap et al., 2010; Zhao et al., 2016).

Few studies have investigated the relationship between simultaneously recorded EEG and driving simulator performance in OSA patients. Risser et al. found that patients with OSA had impaired driving and more crashes compared to healthy individuals, and the OSA group also showed EEG-defined attention lapses to be more frequent and of longer duration (Risser et al., 2000). In a simulator study of medium traffic density, OSA patients demonstrated near normal driving performance with some difficulties in speed adjustment and a more cautious behavior than controls (Tassi et al., 2008). Interestingly, increased alpha and theta activity correlated with driving impairment only in the OSA group. Boyle et al. described significant deterioration of driving control during EEG-defined microsleep episodes compared to driving performance without microsleeps in patients with OSA (Boyle et al., 2008). While such methods could be utilized in monitoring and alerting systems, quantitative analysis of the resting awake EEG also has the potential to predict impaired simulated driving performance in patients with OSA (D'Rozario et al., 2013).

One of the major technical difficulties to extract meaningful physiological information from the EEG through quantitative analysis is that artefacts must be removed from the signal. In real-life situations such as driving, head and body movements, eye movements, blinks, environmental noise, etc. may substantially increase the proportion of EEG artefacts. Independent component analysis (ICA) is an efficient algorithm widely used to solve blind source separation problems (Hyvarinen et al., 2001). ICA can efficiently separate artefacts with stereotypic features, like blinks and eye movements from clear EEG signal during rest (Gao et al., 2010a; Gao et al., 2010b). However, artefacts with less stereotypic profile (e.g. due to movements or sweating) are much less likely to be separated by ICA, and therefore in addition, manual removal of residual noise remains necessary, especially in EEG recorded during activity. While some limited automated algorithms exist for artefact detection in the sleep EEG, in driving studies to date EEG artefacts have been processed manually, i.e. noisy epochs were visually identified by an expert and removed. Therefore, artefact processing is time-consuming and laborious, while subjective judgement due to the lack of standardized criteria reduces the reliability of results.

To address these problems, we developed a new and time-saving automated algorithm for residual artefact detection and removal following application of ICA in EEG data recorded during a driving task. We tested whether the automated algorithm is capable of detecting noisy epochs with high accuracy and agreement when compared to visual artefact recognition (reference-standard) in EEG signals recorded in patients with OSA and non-OSA controls. To evaluate the utility of the proposed method for subsequent quantitative EEG analysis in a research setting, we compared EEG power spectra generated using the automated algorithm and the reference-standard method. We further examined associations between the derived quantitative EEG measures and simulated driving performance.

2. Methods

2.1. Study design and participants

For this analysis, we used data collected from a previously published study (Wong et al., 2008). Patients with previously diagnosed OSA (apnea-hypopnea index > 10/h) from the Royal Prince Alfred Hospital sleep clinic and Hornsby Sleep Disorders and Diagnostic Centre in Sydney, Australia and non-OSA healthy controls recruited from the community were invited to participate in this extended wakefulness experiment. Participants were excluded if they had a major co-existing sleep, neurological, psychiatric, or serious medical disorder, excessive alcohol consumption ($>$ 40 g daily), had worked a night shift or travelled across more than two time zones in the previous two months.

The study was performed according to the Declaration of Helsinki, the Sydney South West Area Health Service Human Research Ethics Committee approved the protocol and all participants provided written informed consent (Australian and New Zealand Clinical Trials Registry No: ACTRN12606000066583).

2.2. Protocol and measurements

The detailed study protocol and some data have been published previously (D'Rozario et al., 2013; Wong et al., 2008). Participants attended the sleep laboratory for a 3-day/night protocol with a repeated-measurement within-subject design. Following a baseline night with polysomnography, every 2 h, 19 times across the 40 hour extended wakefulness period, participants underwent a 30-min simulated driving task (AusEd Driving Simulator, Woolcock Institute of Medical Research, Sydney, Australia) (Desai et al., 2007). EEG was continuously recorded during driving tasks (Alice-3; Respironics, Murrysville, PA, USA) using 6 referential derivations (C3-A2, C4-A1, Fz-A2, Cz-A1, Pz-A2, Oz-A1) plus left and right electrooculogram (EOG) at a sampling rate of 200 Hz. EEG was low pass filtered at 100 Hz for anti-aliasing and a 50 Hz notch filter was applied. A total of 315 EEG recordings from 17 participants were exported into standardized digital European Data Format prior to artefact detection and all subsequent analyses. Fig. 1 shows the number of participants and recordings at each stage of the study.

2.3. EEG preparation and artefact processing

The first six minutes of each 30-min EEG recording were discarded to allow familiarization with the driving simulator. The signal integrity for all EEG channels of each individual EEG recording was confirmed by preliminary visual inspection of a qualified sleep expert (AS). The Fz-A2 derivation was discarded from all analyses due to poor signal quality. Recordings with at least three out of the remaining five EEG channels with artefact-free signals for at least 75% of the time were included ($n = 210$). In order to analyze a representative subsample of this pool, two recordings from each of 10 participants were selected randomly (20 recordings, 5760 × 5-s epochs).

EEG was first processed using the FastICA algorithm (Hyvarinen et al., 2001) within each 5-s epoch. Separated sources that were highly correlated with EOG signals (threshold of 0.6) were removed. The EEG signals free of eye movement artefacts were subsequently reconstructed