ASSESSING DRIVERS' FATIGUE STATE UNDER REAL TRAFFIC CONDITIONS USING EEG ALPHA SPINDLES

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Summary: The effectiveness of EEG alpha spindles, defined by short narrowband bursts in the alpha band, as an objective measure for assessing driver fatigue under real driving conditions was examined using an algorithm for the identification of alpha spindles. The method is applied to data recorded under real traffic conditions and compared with the performance of the traditional EEG fatigue measure alpha band power. Statistical analysis revealed significant increases from the first to the last driving section of alpha band power; with larger effect sizes for the alpha spindle based measures. An increased level of fatigue for drop-outs, as compared to participants who did not abort the drive, was observed only by means of alpha spindle parameters. EEG alpha spindle parameters increase both fatigue detection sensitivity and specificity as compared to EEG alpha band power. It is demonstrated that alpha spindles are superior to EEG band power measures for assessing driver fatigue under real traffic conditions.

INTRODUCTION

Extensive research has identified fatigue as a major problem in safety critical work situations as well as in public traffic (Dinges, 1995; Folkard, 1997). Despite the methodological difficulties of reliably assessing the causes for fatal traffic accidents, various studies conclude that 15-20 % of all fatal traffic accidents are caused by driver fatigue (Hell and Langwieder, 2001; Connor et al., 2002). The automotive industry follows various approaches to increase traffic safety by assessing driver fatigue and by taking corresponding actions, e.g. informing and warning the driver accordingly. Based on the assumption that fatigue is accompanied by behavioral correlates reflected in the driver's vehicle control, currently available in-vehicle fatigue detection systems are based mainly on driving performance data, e.g. steering wheel activity, lane keeping performance, etc. However, under real world traffic conditions, changes in driving performance measures are the result of multitude causes such as changes in road condition, traffic density, workload, fatigue, etc. In order to develop a dedicated driver fatigue related assistance system it is necessary to disambiguate these factors and to determine only those behavioural changes in driving performance which are caused solely by driver fatigue. We present a generic method for the measurement of fatigue under real operational conditions which we used to optimize and validate the driver assistance system "Attention Assist" (Mercedes-Benz). Fatigue measurements rely mostly on participants' self reports based on various single- and multi-item questionnaires which have been developed and correlated with both physiological and performance measures (i.e. Karolinska Sleepiness Scale "KSS"; Åkerstedt and Gillberg, 1990). Although of great value for studying the acceptance of a fatigue detection system, drivers' subjective rating scales exhibit limited objectivity as they are vulnerable to manipulation, to memory effects or to insufficient self introspection skills. Furthermore, subjective measures embrace an irresolvable trade-off between retrieval frequency and interference with the fatigue process under observation. Additionally, several on-road and simulator studies have shown that fatigue self assessment might be inaccurate in certain situations (Belz et al., 2004; Moller et al., 2006; Schmidt et al., 2009). Alternatively, secondary task performance measures have been proposed to assess fatigue. However, there is contradictory evidence whether such performance measures accurately render the fatigue process. In contrast, neurophysiology based measures can provide an objective and direct characterization of the driver's cognitive state with high temporal resolution (Lin et al., 2005; Trejo et al., 2007; Shen et al., 2008). Currently, advances in technology and in signal processing enable real-time measurements of drivers' cognitive states under real traffic conditions (Kohlmorgen et al., 2007; Dixon et al., 2009). We now propose an electroencephalography (EEG) based fatigue measure that largely fulfills the requirements formulated above and outperforms traditional EEG-based fatigue measures with respect to sensitivity and noise susceptibility.

METHODS

Alpha Spindle Detection

To account for non-stationary characteristics of the EEG as well as to facilitate a computationally efficient implementation for real-time applications, we use the short time Fourier transform (Oppenheim and Schafer, 1989) for the spectral decomposition of the EEG signal. Each EEG-channel is divided into segments of 1 s length with an overlap of 750 ms. Subsequently, each segment is made zero mean and multiplied with a Hamming window, the FFT is computed and the spectral amplitude density maximum between 3 and 40 Hz is identified. If this maximum lies within the alpha band (7–13 Hz), the *full width at half maximum* (FWHM) of the spectral peak is determined. If the FWHM is smaller than twice the bandwidth of the Hamming window (indicating a component of sufficiently narrow bandwidth to be considered oscillatory), the time segment undergoes further analysis. To account for the 1/f-like noise of EEG recordings (Pereda et al., 1998; Wagenmakers et al., 2004), each EEG channel has an exponential curve fitted to the mean amplitude spectrum obtained as the average across all single-segment amplitude spectra from the entire recording. This allows separating between "signal" (area above fitted curve) and "noise" (area below fitted curve). Adaptation to varying noise levels over time is achieved by multiplying the exponential fit with the ratio between the integrated spectrum of the current segment and the integrated mean spectrum. We consider alpha spindles to reflect periods of amplitude modulated cortical steady state activity which (a) can be detected above a certain signal-to-noise ratio (SNR), (b) can be restricted to single electrodes, (c) have a stable peak frequency and (d) can persist for up to several seconds. Consequently, for each EEG channel and for each one-second time epoch, we test whether the total area under the peak, bounded by the FWHM, is at least twice as large as the area in the same frequency interval below the fitted noise line (effectively establishing a signal-to-noise-ratio threshold). We call this ratio the *oscillation index*. Consecutive time segments fulfilling this criterion and having a peak frequency within a 10 % change to the previous segment are grouped to one alpha spindle. The *frequency* of an alpha spindle is calculated as the mean of the peak frequency of all contributing segments; the same applies to the *spectral amplitude*. The *duration* of a spindle is defined as the time span from the start of the spindle's first time segment to the end of its last segment. Since alpha spindles are discrete events characterized by their *duration, spectral amplitude* and *peak frequency*, we also use the moving average of these parameters over larger time windows to obtain continuous measures better suited to reproduce continuous fatigue changes. Additionally this enables us to count the occurrence rate of alpha spindles within the moving window. We call this parameter the *alpha spindle rate*.

Procedure

The subjects drove on a low-traffic German highway (A81) at a maximum speed of 80 mph. The ride usually took about 3.5 h and was performed during daytime between 1 p.m. and 5 p.m. While driving, the subjects performed an auditory oddball reaction time task, which is described elsewhere (Schmidt et al., 2009). Altogether, 10 out of 55 participants (6 male, 4 female; age: M = 27.5; range: 24-36) aborted their drive due to severe fatigue (average driving time: 2:23 h, SD: 0:38 h, range: 0:56 – 3:15 h), which provides the most objective fatigue criterion available. Hence, unless stated differently, we only used the data from these ten participants. Especially for these subjects, the contrast in driver fatigue between sections at the beginning and at the end of the drives should be maximal since the study was performed during daytime with participants well-rested at the start of their drive. This is also underlined by the results of the self rating on the KSS ranging from one (extremely alert) to nine (extremely sleepy, fighting sleep) that was assessed every 20 min throughout the drive. The average KSS value for the first 20 min was 4.3 (SD = 1.9) and increased to 8.5 (SD = .5) before break-off. We therefore used the first and the last 20 min period of each drive here.

Physiological Measures

EEG was recorded with BrainAmp hard- and software (Brain Products GmbH, Munich, Germany) with 64 electrodes and 500 Hz sampling rate. Electrode placement was based on the extended international 10-20 system, using the nose bridge as reference. Data were band-pass filtered from .5 Hz to 48 Hz and sampled down to 128 Hz. In order to minimize the influence of muscle activity, eye blinks and technical noise, we used the extended infomax ICA algorithm (Lee et al., 1999), available in the EEGLab toolbox (Delorme and Makeig, 2004), to reject artifactual components.

Data Reduction

In order to reject remaining artifacts after ICA correction, we applied an auto-regression based approach (see Schlögl, 2000 for details) to identify artifactual epochs which were then excluded from further analysis. Due to their proximity to muscular structures, we excluded all temporal and fronto-polar electrodes, resulting in 43 out of 62 EEG channels available for further analysis. Channels Cz and FC2 had to be excluded due to technical problems with the EEG hardware. The proposed algorithm for alpha spindle detection was used to identify alpha spindles and to calculate spindle rate, average spindle amplitude, duration and frequency for both 20 min driving sections. Alpha band power (7–13 Hz) was calculated using Welch's modified periodogram.

Statistical Analysis

Our main focus was on comparing the EEG parameters from the first and last 20 min driving sections, respectively. For each subject, spindle rate, mean spindle amplitude, duration and frequency as well as mean alpha-band power were obtained for each of the 20 min time segments and then averaged further within each of three channel groups: frontal, central and parieto-occipital, reference: nose. Thus, each parameter yielded 6 values for each subject (2 driving sections × 3 channel groups), which were analyzed using a 2-way repeated-measures design (separately for each parameter) with within-subject factors “driving section” and “channel group”. The repeated-measures design was implemented via a multivariate (MANOVA) approach in order to circumvent problems arising from violations of the sphericity assumption for the factor “channel group” (O’Brien and Kaiser, 1985). The test criterion reported is the (exact) F-statistic derived from Pillai’s trace; the level of α was set to .05 for all analyses. The partial η^2 is reported as a measure of relative effect size whenever H_0 had to be rejected. For statistically significant results of the main effect “channel group”, a post-hoc analysis was applied in which each factor level was compared to the previous level.

RESULTS

The results of the repeated-measures analysis of variance on the effects of driving section and channel group are summarized in Table 1. Figure 1 visualizes the results by showing the mean over all participants for each dependent measure, channel group and driving section.

Table 1. Statistical results for the repeated-measures analysis (MANOVA) of driving section and channel group for alpha spindle measures and alpha band power

	Main Effect						Interaction		
	driving section			channel group			driving section x channel group		
	F(1,9)	p	η^2	F(2,8)	p	η^2	F(2,8)	p	η^2
Spindle Rate	22,556	.001	.715	.803	.481	n.s.	.542	.601	n.s.
Spindle Duration	21,277	.001	.703	1,052	.393	n.s.	.646	.550	n.s.
Spindle Amplitude	9,667	.013	.518	1,569	.266	n.s.	.582	.581	n.s.
Spindle Frequency	.038	.849	n.s.	16,201	.002	.802	.600	.572	n.s.
Alpha Power	8,179	.019	.476	1,409	.299	n.s.	.476	.638	n.s.

All measures except spindle frequency showed significant differences ($p < .05$) between the first and last driving epoch. Spindle rate, spindle duration and spindle amplitude showed the highest differences between the two driving sections as reflected in the partial η^2-values, with the highest η^2-value (.715) for spindle rate.

Only spindle frequency showed a significant effect for the channel groups. Frontal channels had a lower frequency than central channels ($F(1,9) = 20.55$; $p = .001$; $\eta^2 = .695$) and central channels were lower in frequency than the parieto-occipital group ($F(1,9) = 19.62$; $p = .002$; $\eta^2 = .686$). Figures 1a-d indicate a tendency of increased alpha spindle activity going from anterior to posterior sites, reflected by a higher spindle rate and longer spindle duration.

No significant interaction between driving section and channel group was observed for any of the dependent measures, indicating similar changes in parameter values with increasing fatigue for all channel groups. Considering the relative increase of the fatigue measures from the first to the last driving section, spindle rate (Figure 1a) showed the highest dynamic with a 90% increase for all channels as compared to only a 32% increase for alpha power (Figure. 1e).

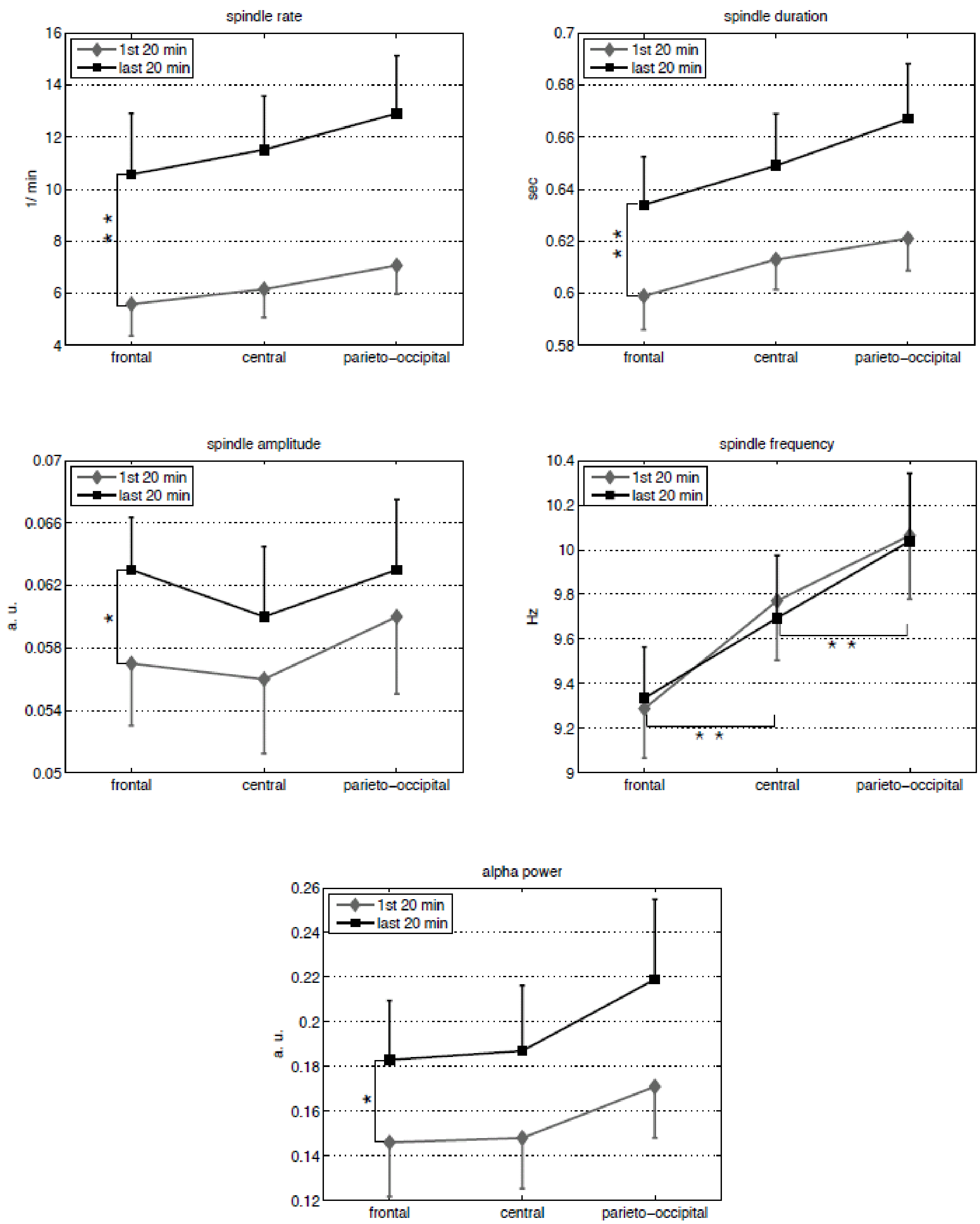

Figure 1. Comparison of the first and last section of the drive for three channel groups; values represent averages over all participants; error bars indicate the standard errors of the means (* p < .05, ** p < .01)

DISCUSSION

Statistical analysis of driving data revealed significant increases between the first (alert) and the last (drowsy) 20 min of the drive for all alpha spindle parameters except spindle frequency. For the same alpha spindle parameters, effect sizes were higher than for alpha band power (see Table 1). This confirms our hypothesis that alpha spindles are a more sensitive indicator of driver fatigue for real-traffic experiments than alpha power. On the group level, we found a significant increase of fatigue-related parameters in general, without being prominent at a particular site. This is in contradiction to studies which showed a prominent increase of alpha power over central and parietal sites, but not frontal sites (Lal and Craig, 2001 and Oken et al., 2006). However, one possible explanation is the different definition of frequency band boundaries. For example, fatigue related effects at frontal sites were reported for the theta band with an upper boundary of 8 Hz (Lal and Craig, 2002; Strijkstra et al., 2003), which overlaps our alpha band by 1 Hz starting at 7 Hz. Another reason could be the individual site with prominent alpha spindle activity ranging from parieto-occipital to frontal-midline. Cortical sites with significant differences that vary individually may result in reduced effects at all sites on the group level. One decisive difference between the above mentioned articles and our studies is represented by the fact that our measurements were performed under real driving and real traffic conditions as compared to measurements performed in driving simulators and often under sleep deprivation.

Our experimental setting does not allow quantifying the contribution of the secondary task on the EEG alpha activity. However, this influence is most probably - if at all - very small since we used an unattended odd-ball paradigm eliciting minimal to no higher cognitive, e.g. attentional load. This assumption is additionally supported by findings reported in various fatigue studies (Kecklund and Åkerstedt, 1993; Lal and Craig, 2002; Papadelis et al., 2007) that did not use any additional cognitive task and which found effects similar with regard to alpha band activity to those reported in this article.

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