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Using EEG spectral components to assess algorithms for detecting fatigue

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Abstract

Fatigue is a constant occupational hazard for drivers and it greatly reduces efficiency and performance when one persists in continuing the current activity. Studies have investigated various physiological associations with fatigue to try to identify fatigue indicators. The current study assessed the four electroencephalography (EEG) activities, delta (δ), theta (θ), alpha (α) and beta (β), during a monotonous driving session in 52 subjects (36 males and 16 females). Performance of four algorithms, which were: algorithm (i) $(\theta + \alpha)/\beta$, algorithm (ii) α/β, algorithm (iii) $(\theta + \alpha)/(\alpha + \beta)$, and algorithm (iv) θ/β, were also assessed as possible indicators for fatigue detection. Results showed stable delta and theta activities over time, a slight decrease of alpha activity, and a significant decrease of beta activity ($p < 0.05$). All four algorithms showed an increase in the ratio of slow wave to fast wave EEG activities over time. Algorithm (i) $(\theta + \alpha)/\beta$ showed a larger increase. The results have implications for detecting fatigue.

Impact on industry: The results of this research have the implication for detecting fatigue and can be used for future development of fatigue countermeasure devices.

Keyword: EEG spectra; Driver fatigue; Fatigue countermeasure; Algorithms; EEG ratios

1. Introduction

Fatigue is a constant occupational hazard for any long-distance or professional driver, and can affect one's judgement of his or her suitability to continue driving (Brown, 1997). Efficiency and performance can be impaired during fatigue when an individual persists in continuing the current activity as normal (Brown, 1994). Lamond and Dawson (1999) reported that a driver who has remained without sleep for 24 h has reduced driving skills, and is comparable to driving with illegally high blood alcohol concentration of 0.10%. Fatigue is independent of energy consumption and cannot simply be measured by performance impairment (Brown, 1994). Hence, the need for physiological fatigue countermeasures arises to prevent fatigue related accidents.

In the recent years, researchers have investigated different types of fatigue countermeasure technologies, which include development of electroencephalography (EEG) algorithms to detect fatigue (Eoh, Chung, & Kim, 2005; Lal, Craig, Boord, Kirkup, & Nguyen, 2003), facial movement and feature detectors (Gu, Ji, & Zhu, 2002), and PERCLOS, which detects the percentage of eye closure (Wierwille, Ellsworth, Wreggit, Fairbanks, & Kim, 1994). However, Artaud et al. (1994) found that EEG is one of the most reliable indicators of fatigue, and hence, seems to be a promising fatigue countermeasure approach (Lal et al., 2003).

Fatigue countermeasure devices ought to have high reliability standard. Brown (1997) argued that factors other than fatigue also influenced the changes in driving performance, such as vehicle steering. A number of false alarms

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may occur if the countermeasure device has small reliability level. Therefore, reliability is one of the most important factors of future fatigue countermeasure devices (Brown, 1997). EEG has been shown to have a good test and retest reliability and high reproducibility for the delta and theta bands (Lal & Craig, 2005; Pollock, Schneider, & Lyness, 1991), as well as the alpha activity (Gasser, Bacher, & Steinberg, 1985; Tomarken, Davidson, Wheeler, & Kinney, 1992).

Four frequency components can be obtained from EEG recordings, which are delta (δ) ($\pm$0 to 4 Hz), theta (θ) (4–8 Hz), alpha (α) (8–13 Hz), and beta (β) (13–20 Hz), and these can be measured to detect the current state of a driver (Åkerstedt, Kecklund, & Knutsson, 1991). Delta activity is high during sleep. Early stage of drowsiness can be indicated by an increase in theta activity (Åkerstedt & Gillberg, 1990). Alpha activity reflects a relaxed wakefulness state, and decreases with concentration, stimulation or visual fixation (Stern & Engel, 2005). However, other researchers have also found an increase in alpha activity in train drivers who were sleepy enough to fall asleep while driving (Åkerstedt & Gillberg, 1990; Torsvall & Åkerstedt, 1987). Furthermore, increased beta activity has also been related to the alertness level, and decreases during drowsiness (Eoh et al., 2005). Torsvall and Åkerstedt (1987) believed that alpha activity was the most sensitive measure that could be used in detecting fatigue, followed by theta and delta activities. However, delta activity is more related to occurrence of sleep proper (Torsvall & Åkerstedt, 1987). Lal and Craig (2002) have also shown changes in brain wave activity with fatigue during driving.

A number of methods for fatigue detection using EEG have been proposed, such as detection of alpha spindles by Tietze (2000), and an algorithm that utilises the combination of all frequency components of EEG to signify level of alertness by Lal et al. (2003). Other studies have proposed two algorithms, which were $(\theta + \alpha)/\beta$ and β/α, that can be used as a fatigue detection technique (Brookhuis & Waard, 1993; Eoh et al., 2005). Delta activity was excluded from and not investigated in the study by Eoh et al. (2005) since it reflected the sleeping state of a person, and was not expected to show high activity during the driving activity. Eoh et al. (2005) believed that the first algorithm, $(\theta + \alpha)/\beta$, was a more reliable fatigue indicator since it showed a clear indication of increasing fatigue as the ratio between the slow wave and fast wave activities increased.

The current study investigated the performance of different algorithms, which had the potential to function as a fatigue indicator. The two algorithms studied by Eoh et al. (2005), $(\theta + \alpha)/\beta$ and β/α, were compared with another two new proposed algorithms, $(\theta + \alpha)/(\alpha + \beta)$ and θ/β. However, since the current study intended to investigate the ratio between slow and fast wave activities over time, hence, the second algorithm by Eoh et al. (2005), β/α, was denoted as α/β. The four frequency components in the EEG recording, delta, theta, alpha and beta, were also investigated in the analysis to understand each EEG band separately.

2. Materials and methods

Fifty-two non-professional drivers (36 males and 16 females), aged 20–70 years (mean: 28 ± 10 years), were recruited to perform a monotonous driving simulator task. The average body mass index (BMI) was 23 ± 7 kg/m^2 (normal range: 18.50–24.99 kg/m^2 (World Health Organization, 2007)). All participants provided informed consent prior to participating in the study. Lifestyle appraisal questionnaire was used as a selection criteria, which required participants to have no medical contraindications such as severe concomitant disease, alcoholism, drug abuse, and psychological or intellectual problems likely to limit compliance (Craig, Hancock, & Craig, 1996).

This study had the institute's Human Research Ethics Committee approval, and was conducted around noon $\pm$1.5 h in a temperature-controlled laboratory. Participants were asked to refrain from consuming caffeine, tea or food as well as smoking approximately 4 h before the study and alcohol 24 h before, and reported compliance with these instructions.

Grand Prix 2 (version 1.0b, 1996, Microprose Software Inc., USA) was used as driving simulator software. The video display from the software showed other cars, the driving environment and the current speed and other road stimuli. The driver simulator equipment consisted of a car frame with an in-built steering wheel, brakes, accelerator, and gears.

Participants completed 2 driving sessions for the purpose of the current study. The initial driving session was approximately 10–15 min of alert driving, which would serve as a baseline measure. During the alert driving session, participants were provided a track involving many cars and stimuli on the road. Following the alert driving session was the monotonous driving session, in which participants were required to drive continuously between 60 and 80 km/h for approximately 1 h. This session involved the participants driving with very few road stimuli.

Simultaneous physiological measurements were recorded during the driving sessions. The NeuroScan system (Compumedics, Australia) was used to record the physiological data. Thirty channels of electroencephalography (EEG) was measured simultaneously while participants were driving. The 10–20 international standard of electrode placement was applied (Fisch, 2000; Stern & Engel, 2005). A referential montage was used with the reference point located at the centre of the head, between the midline central electrode (Cz), and the midline central parietal electrode (CPz). Vertical electrooculogram (EOG) was also recorded, and later used to identify blink artefacts from the recorded EEG data. The EEG and EOG data was sampled at 1000 Hz. Blood pressure and heart rate were collected before and after the driving task. Video data of the driving and participants' faces, linked with the physiological measures in real time, were collected to identify physical signs of fatigue and to serve as an independent variable for fatigue assessment (Gu et al., 2002).

All 30 channels of the EEG data were then sectioned into 1-s epochs, and were subjected to fast Fourier transform (FFT) using in-house software, developed using LabVIEW programming language (National Instrument, version 8.2), to derive the four frequency components of interest, which were delta (0–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–35 Hz) (Rowan & Tolunsky, 2003). Delta and theta are considered slow wave activities, whereas alpha and beta are the fast wave activities (Fisch, 2000). The FFT analysis generated spectra magnitude (microvolts). Area under the curve of the spectra magnitude was computed for each frequency band of interest to derive a single power value (microvolts^2) for each of the frequency components.

The total EEG data for the monotonous driving session was segmented into 10 consecutive equal time sections. Three lots of 30 epochs were averaged in each of the alert and the 10 sections of monotonous driving sessions to obtain one value for each section. The data from the 10 consecutive sections of the monotonous driving session was then compared to the alert baseline.

For the current study, four different EEG algorithms, together with delta, theta, alpha and beta activities, were computed during the data analysis to assess fatigue effects. The first two algorithms, algorithm (i) $(\theta+\alpha)/\beta$ and algorithm (ii) α/β, had previously been proposed to detect fatigue (Eoh et al., 2005). The other two algorithms tested were algorithm (iii) $(\theta+\alpha)/(\alpha+\beta)$, and algorithm (iv) θ/β. Algorithm (iii) $(\theta+\alpha)/(\alpha+\beta)$ had a ratio nearly similar with algorithm (i). Algorithm (iv) θ/β was chosen for the ratio between theta power and beta power. The algorithms being tested are the ratio between slow wave and fast wave activities. Algorithms (iii) and (iv) were included to test two further ratios of EEG activities.

Analysis of variance (ANOVA) analysis was performed to identify significant differences between the 10 time points during the monotonous driving and the alert baseline. This analysis was performed for each of the four algorithms and for delta, theta, alpha, and beta activities separately for the entire brain average, and also for five specific brain sites (central, frontal, occipital, parietal, and temporal). Results are reported as mean ± standard deviation (SD). Significant level is reported at $p < 0.05$.

3. Results

The total average time for the driving session was 63 min ± 12 min. From the study by Gillberg, Kecklund, and Åkerstedt (1996), 30 min of monotonous driving activity has been found to induce fatigue during driving. The average pre-study systolic blood pressure (SBP) was 118 ± 11 mmHg and diastolic blood pressure (DBP) was 75 ± 9 mmHg. The average post-study SBP was 114 ± 13 mmHg and DBP was 71 ± 17 mmHg. The average pre-study heart rate was 72 ± 10 beats/min and 65 ± 9 beats/min for the post-study heart rate. Student *t*-test analysis was performed on the pre-study and post-study blood pressure and heart rate data. Table 1 shows that SBP and heart rate reduced significantly after the driving test. There was a trend for post-study reduction in DBP.

Table 1
t-Test result for difference between pre- and post-measurements of blood pressure and heart beat (significant *p*-value italicised)

	Difference (pre- minus post-study)	SD of difference	t	p
SBP (mm Hg)	4.1	10.92	2.8	*0.01*
DBP (mm Hg)	4.6	16.83	2.0	0.05
Heart rate (beats/min)	5.9	8.03	5.4	*<0.001*

SBP = systolic blood pressure; DBP = diastolic blood pressure.
SD = standard deviation.

Fig. 1 shows an example of brain topography indicating delta, theta, alpha, and beta activities for one of the volunteers. High activity is indicated by the red-shaded areas[1], whereas low activity is indicated by the blue-shaded areas. Delta activity increased in the frontal area as driving progressed, and decreased towards the end of the driving session (time sections 8–9). Unlike delta activity, theta activity increased steadily, in the frontal region (time section 3). Theta was higher in the frontal, temporal, and occipital sites towards the end of the session (time section 10). Alpha activity had increased in the occipital region towards the end of the driving session (time sections 8 and 9). Beta activity was high during the early stages of driving (time sections 1 and 2), especially in the temporal and frontal sites, and had decreased by the end of the driving session.

ANOVA result for the algorithms revealed some significant differences between the alert baseline and the 10 time points during monotonous driving. These significant differences were found at temporal sites for algorithm (i) ($F = 2.7$, $p = 0.003$), algorithm (ii) ($F = 2.6$, $p = 0.01$), algorithm (iii) ($F = 2.7$, $p = 0.003$), and algorithm (iv) ($F = 2.5$, $p = 0.01$) (refer to Table 2). No significant differences were found at other sites.

Result for the four EEG frequency components revealed several significant differences. Delta activity was significantly different from the alert baseline for the entire brain average ($F = 2.3$, $p = 0.01$), and frontal site ($F = 3.5$, $p < 0.001$). Theta showed significant differences for the entire brain average ($F = 2.4$, $p = 0.01$), central ($F = 2.3$, $p = 0.01$), frontal ($F = 2.3$, $p = 0.01$), and parietal sites ($F = 3.6$, $p < 0.001$). Alpha ($F = 2.0$, $p = 0.03$) and beta activities ($F = 2.3$, $p = 0.01$) both showed significant

[1] For interpretation of colour in figures, the reader is referred to the Web version of this article.

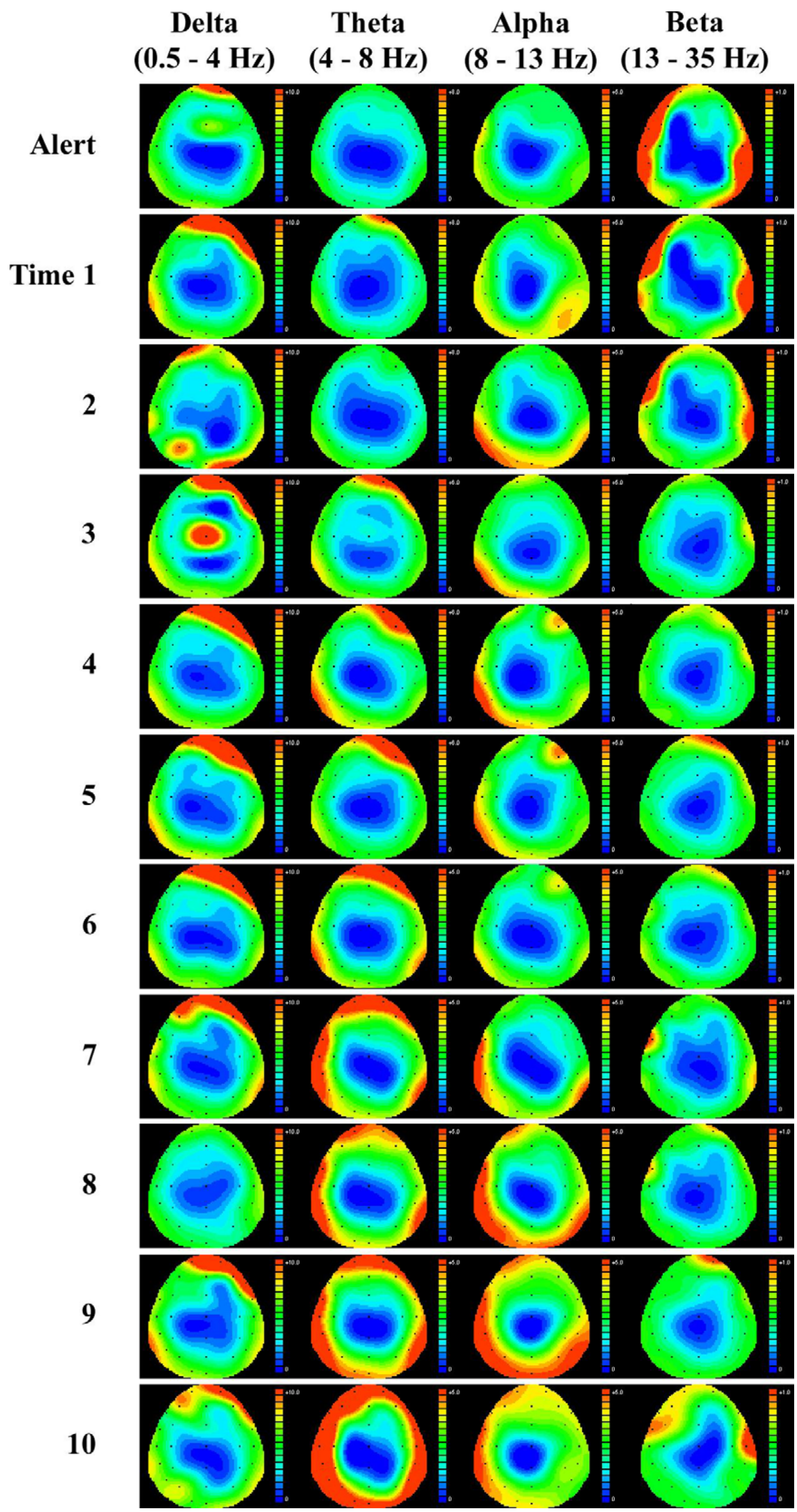


Fig. 1. Brain topography of alert baseline and 10 time sections during monotonous driving.

differences at the temporal site only. Summary of significant ANOVA result is provided in Table 2.

Post hoc Bonferroni analysis was performed for each ANOVA result that was significantly different to identify the exact time points at which these differences existed. Using algorithm (i), significant differences were found in activities at the temporal site between alert baseline and time sections 2 ($p = 0.03$), 5 ($p = 0.04$), 6 ($p = 0.02$), 7

Table 2
Significant ANOVA result for algorithms (i)–(iv), delta, theta, alpha, and beta activities

	EB	C	F	O	P	T
A (i) $((\theta+\alpha)/\beta)$	–	–	–	–	–	0.003
A (ii) (α/β)	–	–	–	–	–	0.01
A (iii) $((\theta+\alpha)/(\alpha+\beta))$	–	–	–	–	–	0.003
A (iv) (θ/β)	–	–	–	–	–	0.01
Delta	0.01	–	<0.001	–	–	–
Theta	0.01	0.01	0.01	–	<0.001	–
Alpha	–	–	–	–	–	0.03
Beta	–	–	–	–	–	0.01

Note: Shows results with significant p-values (<0.05). EB = entire brain average, C = central, F = frontal, O = occipital, P = parietal, T = temporal.

($p = 0.02$), 8 ($p = 0.02$), 9 ($p = 0.01$), and 10 ($p = 0.001$). With algorithm (ii), significant differences were found between the alert baseline and time section 2 ($p = 0.04$), time section 5 ($p = 0.03$), time section 7 ($p = 0.03$), time section 8 ($p = 0.03$), time section 9 ($p = 0.01$), and time section 10 ($p = 0.001$). Using algorithm (iii), significant differences were found between the alert baseline and time section 2 ($p = 0.02$), time section 6 ($p = 0.03$), time section 7 ($p = 0.03$), time section 8 ($p = 0.02$), time section 9 ($p = 0.01$), and time section 10 ($p = 0.001$). With algorithm (iv), significant differences were found between the alert baseline and time section 2 ($p = 0.04$), time section 6 ($p = 0.03$), time section 7 ($p = 0.045$), time section 8 ($p = 0.03$), time section 9 ($p = 0.02$), and time section 10 ($p = 0.004$) (refer to Table 3).

Post hoc Bonferroni analysis for delta activity at the frontal site revealed significant differences between the alert baseline and time section 1 ($p < 0.001$), and time section 2 ($p = 0.02$). Time section 1 was significantly different to time section 4 ($p = 0.02$), time section 5 ($p = 0.02$), time section 8 ($p = 0.01$), time section 9 ($p = 0.04$), and time section 10 ($p = 0.03$). Significant difference between the alert baseline and time section 2 was found for theta activity for the entire brain average ($p = 0.01$), central ($p = 0.01$), and frontal sites ($p = 0.01$). Theta activity in the parietal site was significantly different between the alert baseline and time section 2 ($p < 0.001$), and between time sections 2 and 4 ($p = 0.03$), 2 and 5 ($p = 0.02$), 2 and 6 ($p = 0.04$), 2 and 7 ($p = 0.048$), 2 and 8 ($p = 0.04$), 2 and 9 ($p = 0.02$), and 2 and 10 ($p = 0.02$). Post hoc Bonferroni analysis for beta activity revealed only one significant difference between alert baseline and time section 10 ($p = 0.03$). Result for alpha revealed no significant differences at any time sections. Refer to Table 3 for summary of post hoc Bonferroni analysis.

Fig. 2 shows an example of the temporal activity for the four algorithms plotted over time. It shows a gradually increasing trend over time, which indicates one of the following possibilities: increasing trend of slow wave activity over time, and decreasing trend of fast wave activity over time, or both possibilities. Fig. 2a $((\theta+\alpha)/\beta)$ shows a greater increase from the alert baseline to the tenth time section, while Fig. 2b (α/β) shows the smallest increase.

The plots shown in Fig. 3 show the changes for delta, theta, alpha and beta activities over time. The slow wave EEG activities show an initial increase followed by a decrease, and then is steady over time (Fig. 3a and b). Whereas the fast wave EEG activities show a general decrease over time, indicated by a slight decrease of alpha activity, and a steeper decrease for beta activity (Fig. 3c and d).

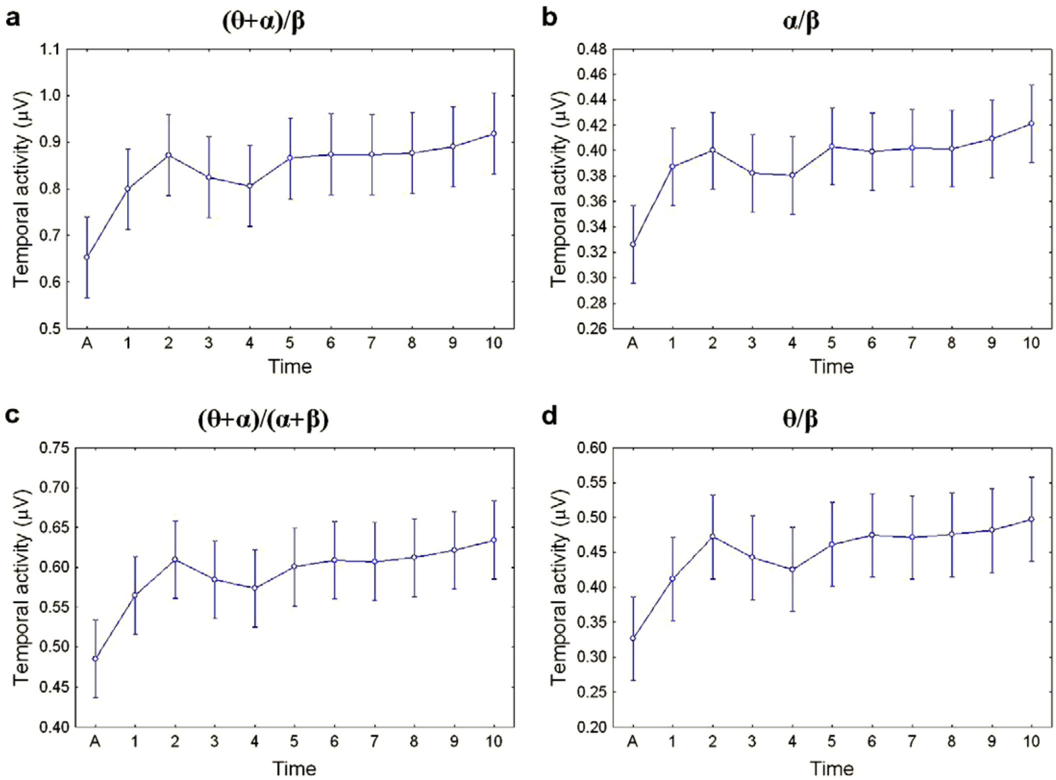
4. Discussion

Driver sleepiness is one of the main factors associated with road crash accidents (Horne & Reyner, 1995, 1999). Several factors have been studied to prevent fatigue or sleepiness during driving. For example, Reyner and Horne (2002) studied the effect of caffeine as fatigue

Table 3
Post hoc Bonferroni analysis for results showing significant p-value in ANOVA analysis

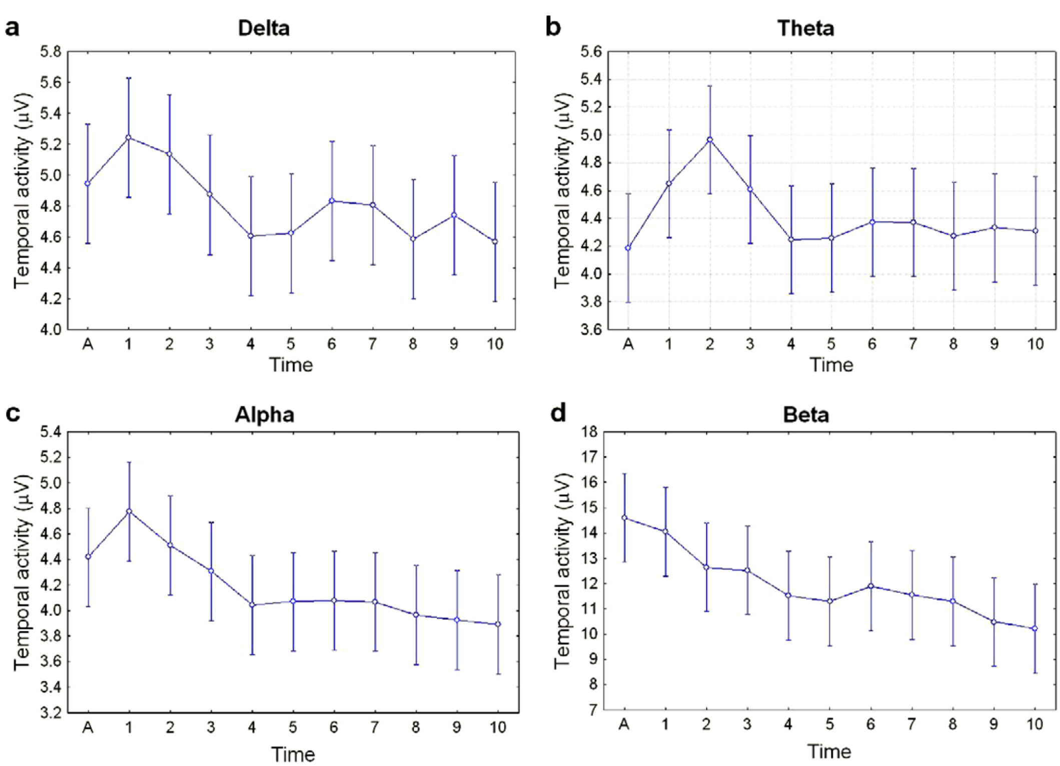
	Site	Comparator	Time sections									
			01	02	03	04	05	06	07	08	09	10
A (i) $((\theta+\alpha)/\beta)$	T	Alert	–	0.03	–	–	0.04	0.02	0.02	0.02	0.01	0.001
A (ii) (α/β)	T	Alert	–	0.04	–	–	0.03		0.03	0.03	0.01	0.001
A (iii) $((\theta+\alpha)/(\alpha+\beta))$	T	Alert	–	0.02	–	–	–	0.03	0.03	0.02	0.01	0.001
A (iv) (θ/β)	T	Alert	–	0.04	–	–	–	0.03	0.045	0.03	0.02	0.004
Delta	EB		–	–	–	–	–	–	–	–	–	–
Delta	F	Alert	<0.001	0.02	–	–	–	–	–	–	–	–
Delta	F	01		–	–	0.02	0.02	–	–	0.01	0.04	0.03
Theta	EB	Alert	–	0.01	–	–	–	–	–	–	–	–
Theta	C	Alert	–	0.01	–	–	–	–	–	–	–	–
Theta	F	Alert	–	0.01	–	–	–	–	–	–	–	–
Theta	P	Alert	–	<0.001	–	–	–	–	–	–	–	–
Theta	P	02	–		–	0.03	0.02	0.04	0.048	0.04	0.02	0.02
Alpha	T		–	–	–	–	–	–	–	–	–	–
Beta	T	Alert	–	–	–	–	–	–	–	–	–	0.03

Note: Shows significant p-values. EB = entire brain average, C = central, F = frontal, P = parietal, T = temporal.



Key: A = Alert
1 - 10 = 10 time points during monotonous driving

Fig. 2. Temporal activity plotted over time during driving for the four algorithms.



Key: A = Alert
1 - 10 = 10 time points during monotonous driving

Fig. 3. Temporal activity plotted over time during driving for delta, theta, alpha and beta.

countermeasure and the efficacy of caffeine in counteracting driver sleepiness. These authors found that caffeine was effective in reducing sleep-related vehicle accidents. Others studied technological fatigue countermeasures by assessing driving performance or physiological changes as potential indicators of fatigue (Williamson & Chamberlain, 2005). For example, some studies have suggested the use of artificial neural network algorithm in automatic detection of alertness and drowsiness level from EEG recordings (Vuckovic, Radivojevic, Chen, & Popovic, 2002). The result from the algorithm and independent human assessment was compared and had a 94% agreement, hence, the authors concluded that artificial neural network algorithm could be utilised to automatically detect drowsiness during driving from EEG recordings (Vuckovic et al., 2002).

The current study investigated EEG activity in separate frequency bands, delta, theta, alpha and beta, and four different algorithms, which were: algorithm (i) $(\theta+\alpha)/\beta$, algorithm (ii) α/β, algorithm (iii) $(\theta+\alpha)/(\alpha+\beta)$, and algorithm (iv) θ/β, at different brain sites and the entire brain average to assess the efficacy of these algorithms as fatigue detection techniques. All algorithms were denoted as the ratio between the slow wave and the fast wave EEG activity. The outcome of the study showed significant differences between the alert baseline and the 10 time sections at temporal sites for the four algorithms, and for alpha, and beta activities. Delta and theta showed significant differences at the central, frontal and parietal sites, including the entire brain average.

Comparison with a previous study by Eoh et al. (2005) reveals similar result for algorithm (i) $(\theta+\alpha)/\beta$, algorithm (ii) α/β, and beta activity. Algorithm (i) $(\theta+\alpha)/\beta$ showed an increasing slope as the driver became fatigued, whereas beta activity shows a decreasing trend. Algorithm (ii) α/β showed an increasing slope, and this is similar to the algorithm (β/α) by Eoh et al. (2005). Eoh et al. (2005) showed that the ratio between fast wave and slow wave activities (β/α) as fatigue progressed had a decreasing trend. However, when the ratio is inverted, the plot is also inverted, and should result in an increasing pattern, as shown in the present study by algorithm (ii) (α/β). Alpha activity showed the opposite trend when compared to the study by Eoh et al. (2005), where it had a slightly decreasing pattern, instead of an increasing slope. Other studies have also found an increasing alpha activity during fatigue (Åkerstedt & Gillberg, 1990; Kecklund & Åkerstedt, 1993).

From the plot of the four EEG frequency bands (see Fig. 3), it is clear that beta, which represents the alertness or arousal level (Lal & Craig, 2001; Stern & Engel, 2005), drops significantly towards the end of a monotonous driving task, where fatigue level would be higher. On the other hand, alpha and theta waves showed only small changes when compared to the alert state. Hence, this explains the increasing trend in the ratios between slow wave and fast wave activities, as shown in Fig. 2. The decrease of beta (fast wave) activity would increase the ratios in the algorithms, and although alpha activity, which represents the alert and relaxed state (Lal & Craig, 2001), is also considered as a fast wave activity, it has a small contribution towards changing the ratio. This indicates that alpha activity does reduce but less than beta activity during fatigue.

By observation, algorithm (i) has a greater increasing trend compared to the other three algorithms. As Eoh et al. (2005) explained, the algorithm $(\theta+\alpha)/\beta$ combined the power of theta and alpha together ‘‘during the repetitive phase transition between wakefulness and micro sleep’’, hence, mutual addition of alpha and theta shows a more significant effect compared to the alpha (algorithm (ii) α/β) and theta (algorithm (iv) θ/β) alone.

Belyavin and Wright (1987) observed an increase in delta and theta activities during fatigue, and a decrease of beta activity with worsening performance and reduced vigilance. Other research also shows an increase of theta activity during fatigue (Eoh et al., 2005; Subasi, 2005). Lal and Craig (2002) also found a significant increase of delta and theta activity, however with a smaller increase of alpha and beta activities during fatigue. In the current study, delta and theta activities increased at the beginning of the study and stabilised to the alert level throughout the rest of the monotonous driving session. According to Belyavin and Wright (1987), the most useful indicator for reduced vigilance is the sharp decrease of beta activity, which was also shown in the result of the current study. However, according to Torsvall and Åkerstedt (1987), the increase of alpha activity is the most sensitive indicator of fatigue. During alert wakefulness (with eyes open), alpha activity is normally low, unless the individual is currently fatigued, in which state alpha will start showing higher activity (Åkerstedt and Gillberg, 1990; Kecklund and Åkerstedt, 1993; Subasi, 2005). However, this trend was not observed in the result of the current study, which showed a slowly decreasing alpha activity over time.

Changes in the EEG components, such as in increase of theta and alpha activities or decrease of beta activity, during fatigue instigating driving session may be masked by one’s activities, such as head movement or listening to music, as one attempts to fight fatigue (Åkerstedt et al., 1991). Hence, combination of different algorithms in detecting fatigue may be required to ensure the reliability of the employed fatigue detection technique.

5. Conclusion

This study has investigated the four EEG frequency bands, delta, theta, alpha and beta, and four algorithms (algorithm (i) $(\theta+\alpha)/\beta$, algorithm (ii) α/β, algorithm (iii) $(\theta+\alpha)/(\alpha+\beta)$, and algorithm (iv) θ/β) to assess fatigue. Some significant differences were detected from the alert baseline over time, which were mostly in the temporal site, except for the delta and theta activities, which were also different in the central, frontal, parietal sites, as well as the entire brain. This study has also demonstrated a significant drop in beta activity as the alertness level decreases during the late stage of a monotonous driving task, which highly contributes to the increase of ratio between slow wave and fast wave activities in the four algorithms tested. A greater increase of ratio was found for algorithm (i) $(\theta+\alpha)/\beta$ at the end of the monotonous driving session, compared to the other three algorithms. The results have implications for the development of future fatigue countermeasures, which can reduce fatigue related accidents and greatly impact the industry in terms of socio-economic benefits, especially the transport industry.

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