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Development of an algorithm for an EEG-based driver fatigue countermeasure

Saroj K.L. Lal[a,*], Ashley Craig[a], Peter Boord[a], Les Kirkup[b], Hung Nguyen[c]

[a] Department of Health Sciences, University of Technology, Sydney, Floor 14, Broadway, Sydney, 2007, NSW, Australia
[b] Department of Applied Physics, University of Technology, Sydney, NSW, Australia
[c] Faculty of Engineering, University of Technology, Sydney, NSW, Australia

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Abstract

Problem: Fatigue affects a driver's ability to proceed safely. Driver-related fatigue and/or sleepiness are a significant cause of traffic accidents, which makes this an area of great socioeconomic concern. Monitoring physiological signals while driving provides the possibility of detecting and warning of fatigue. The aim of this paper is to describe an EEG-based fatigue countermeasure algorithm and to report its reliability. *Method:* Changes in all major EEG bands during fatigue were used to develop the algorithm for detecting different levels of fatigue. *Results:* The software was shown to be capable of detecting fatigue accurately in 10 subjects tested. The percentage of time the subjects were detected to be in a fatigue state was significantly different than the alert phase ($P < .01$). *Discussion:* This is the first countermeasure software described that has shown to detect fatigue based on EEG changes in all frequency bands. Field research is required to evaluate the fatigue software in order to produce a robust and reliable fatigue countermeasure system. *Impact on Industry:* The development of the fatigue countermeasure algorithm forms the basis of a future fatigue countermeasure device. Implementation of electronic devices for fatigue detection is crucial for reducing fatigue-related road accidents and their associated costs.

Keywords: Fatigue; Drivers; Electroencephalography; Countermeasures; Road safety

1. Introduction

Driver fatigue is a significant cause of traffic accidents (Lal & Craig, 2001a, 2001b) and is believed to account for 20–30% of all vehicle accidents (The Parliament of the Commonwealth of Australia, 2000). Experts agree that this is a conservative estimate and that the actual contribution of fatigue to road accidents may be much higher. In addition to having potentially catastrophic personal consequences, fatigue-related accidents are a substantial financial burden on the community. Statistical analysis of accident data suggests that fatigue is implicated in road accidents, particularly at night (Haworth, Heffernan, & Horne, 1989; Mackie & Miller, 1978) and in situations in which driving hours are very long and varied (Åkerstedt, 1995; Hamelin, 1987; McDonald, 1984). Any activity, if pursued long enough, will render a person unable to maintain skilled performance; this is as true for driving as any other skill and is a precursor for accidents (Dinges, 1995; Horne & Reyner, 1995).

In our recent review papers on the issue of driver fatigue, we identified the importance of developing driver fatigue countermeasure devices in order to help prevent driving accidents and errors (Lal & Craig, 2001a, 2001b). Evidence from the scientific literature suggests reasons for giving serious consideration to the implementation of technological countermeasures for driver fatigue. These are:

1. Fatigue is a persistent occupational hazard for professional or any long-distance drivers who have schedules to maintain and who may be involved in shift-work.
2. Fatigue impairs cognitive skills; hence, it can adversely affect the drivers' ability to assess their level of alertness in order to continue driving safely (Brown, 1997).

In response to these serious issues, on-line monitoring of fatigue/drowsiness while driving has the potential to detect, in real time, dangerous behaviors that are related to fatigue,

* Corresponding author. Tel.: +61-2-9514-1592; fax: +61-2-9514-1359.
E-mail address: sara.lal@uts.edu.au (S.K.L. Lal).

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such as eye-closing, head nodding, and brain activity changes during deteriorations in alertness. To date, most fatigue countermeasure devices measure some physiological response in the driver such as the electroencephalogram, electrooculogram (EOG), respiratory signals, behavioral recordings such as analysis of the video film of a driver's face (Artaud et al., 1994) or changes in the driver's alertness through steering behavior (Yabuta, Iizuka, Yanagishima, Kataoka, & Seno, 1985), and adaptive driver systems (Michon, 1993). While a variety of potential countermeasures to fatigue have been developed, the effectiveness of these devices in preventing deterioration in driving performance is disappointing (Desmond & Matthews, 1997). This outcome may be attributable to the failure to take into account the variation of fatigue effects with changing task demands (Desmond & Matthews, 1997).

Although numerous physiological indicators are available to describe an individual's level of alertness, the EEG signal has been shown to be one of the most predictive and reliable (Artaud et al., 1994). However, very little evidence exists on the efficacy of incorporating EEG signal detection and analysis into a technological countermeasure device for fatigue. Researchers have suggested the possibility of using EEG grouped alpha waves and electrocardiogram in sleep detection systems (Fukuda et al., 1994; Ninomija, Funada, Yazu, Ide, & Daimon, 1993). However, no evidence exists for the efficacy of such a device. Other researchers suggest that EEG could be used to create an automated system that continuously tracks and compensates for variations in the alertness of a human operator (Gevins et al., 1995).

Due to the lack of an EEG-based fatigue detector, we assessed 35 (26 males, aged 34 ± 21 years) subjects during a driver simulator task with the aim to isolate EEG changes during early, medium, and extreme phases of fatigue during driving (Lal & Craig, 2002a). We found significant changes in slow wave activity such as delta and theta during the early phase, increases in beta during the medium phase, and further increases in delta, theta, and alpha during the extreme phase of fatigue. Using the data from the 35 subjects, we subsequently developed fatigue countermeasure software that could be used as the basis for a fatigue countermeasure device that is able to detect the three phases of fatigue based on EEG changes (described in the Methods section). The first aim of this study was to describe the development of an EEG-based fatigue countermeasure algorithm. The second aim was to test the reliability of this algorithm to detect different phases of fatigue in "off-line data analysis" mode.

2. Methods

2.1. Brief description of the EEG algorithm

From the data collected in 35 subjects in a previous study (reported in Lal & Craig, 2002a), an EEG fatigue algorithm was created. The EEG of drowsiness/fatigue was classified into transitional (early fatigue phase: between awake and presence of slow wave activity), transitional–posttransitional (medium fatigue phase: which has characteristics of both), posttransitional (extreme fatigue phase: early Stage 1 of sleep, dominated by slow wave activity), and arousal phases (emergence from drowsiness; Santamaria & Chiappa, 1987). The EEG changes observed during the alert, transitional, transitional–posttransitional, and posttransitional phases of fatigue were used to develop the algorithm that could detect a set of programmed changes that occur during different phases of fatigue. The average change in EEG for each of the fatigue phases was computed as the difference from the alert baseline.

The algorithm was developed using Lab View (version 5.1, National Instruments, USA). The software was designed to detect the abovementioned four different functional states of the brain. EEG data in these four phases were categorized into four channels represented in the software by color panels, which were green, yellow, orange, and red, respectively (see black/white version in Fig. 1). A color scale indicated green as a "safe" level (alert) and red as a "dangerous" level of fatigue (posttransitional phase). Yellow and orange denoted early (transitional phase) and medium (transitional–posttransitional phase) levels of fatigue, respectively.

The fatigue software was developed so that it was capable of analyzing EEG data in real-time as well as off-line analysis of previously acquired data. It is capable of acquiring two channels of EEG data. The software uses an FFT to transform raw EEG data into the frequency domain. The program then calculates the magnitude, for each second of data, in each of the delta (0–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–20 Hz) frequency bands (Fisch, 1991). The magnitude is calculated as the sum of the values (in microvolts) within a particular band of the EEG spectrum.

A section of the data is taken over a period of time that is representative of the individual's alert state. These data are taken from the beginning of the trial before the subject develops symptoms of fatigue. From this baseline data, the mean and standard deviation of the magnitudes in each frequency band are calculated for all three fatigue phases. Thus, for each channel, the following values are calculated by the program Dm, Dsd, Tm, Tsd, Am, Asd, Bm, and Bsd. Where D, T, A, and B represent the magnitude in the delta, theta, alpha, and beta bands, respectively, and m and sd represent the mean and standard deviation of those magnitudes. For each of the four phases mentioned above, specific coefficients are used to decide whether the data will be detected as being in the alert (green), transition to fatigue (yellow), transitional to posttransitional (orange), or posttransitional (red) phase. The software then allows baseline coefficients to be set in terms of the mean and standard deviation for each band, for example: $\mathrm{DT} = d_1 \times \mathrm{Dm} + d_2 \times \mathrm{Dsd}$, where DT represents a threshold in the

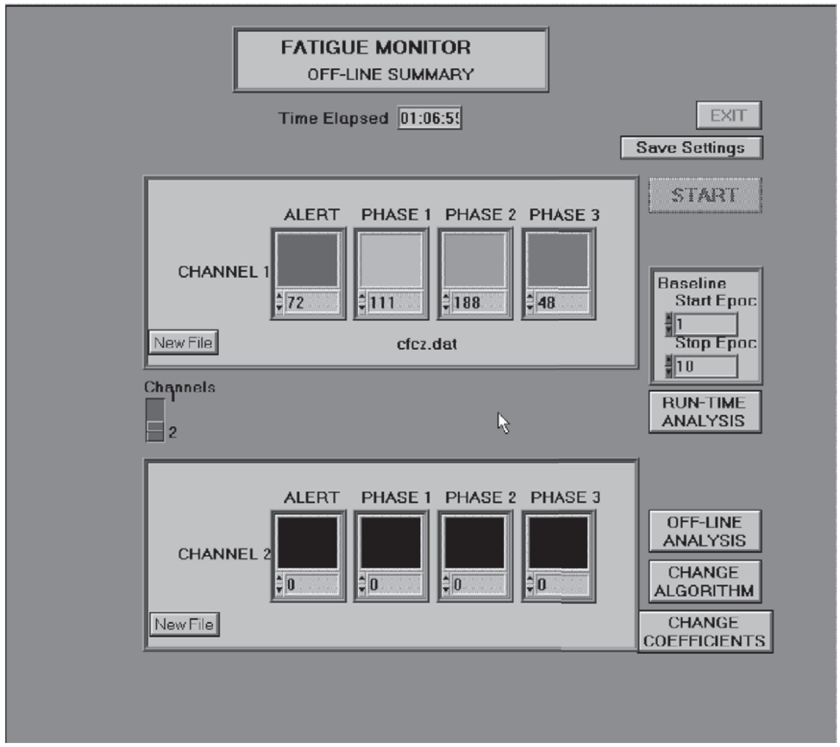

Fig. 1. The panel allocation of data into an alert (green), Phase 1: transition to fatigue (yellow), Phase 2: transitional–posttransitional phase (orange), and Phase 3: post-transitional phase (red). Note: An example of EEG data detection shown in one channel only [detected from one site on the brain, in this instance the Cz (central) site].

delta (D) band and d_1 and d_2 represent coefficients that define that threshold. Two thresholds can be defined in this way for each frequency band in each channel.

In addition, a third threshold defined in absolute values of magnitude allows the software to exclude outliers. The program then applies algorithmic Boolean logic to define the alert and three states of fatigue in terms of the instantaneous magnitude in each frequency band and the relation of those magnitudes to the thresholds. Based upon the data from the 35 subjects, a range of EEG magnitude (mean and S.D.) values for each phase were programmed into the software. This algorithm determines the percentage of EEG data that will be detected as an alert or one of the fatigue phases for each subject. The software can be programmed for average EEG effects in a sample or on an individual basis. The user is able to change the conditional and combinatorial logic; thus, the software allows different algorithms of fatigue detection to be tested quickly and easily. The following section describes the off-line testing of the efficacy of the algorithm.

2.2. Testing the fatigue countermeasure algorithm

2.2.1. Subjects

Ten male subjects who were licensed truck drivers were randomly recruited for the study. Subjects were aged 44 ± 11 years and all gave written consent for the study, which was approved by the institutional ethics committee. To qualify for the study, subjects had to have no medical contraindications such as severe concomitant disease, alcoholism, drug abuse, and psychological or intellectual problems likely to limit compliance. This was determined during the initial interview on a separate day prior to the study.

2.3. Study protocol

The study was conducted in a temperature-controlled laboratory as the subjects performed a standardized sensory motor driver simulator task. The driving task consisted of 10 min of active driving to familiarize the subject, followed by a maximum of two continuous hours of driving (speed < 80 km/h) until the subjects showed physical signs of fatigue. Simultaneous EEG and electrooculogram (EOG) measures were obtained during the driving task. Nineteen channels of EEG were recorded according to the International 10-20 System (Fisch, 1991), which spans the entire brain. A monopolar montage was used; that is, EEG activity was recorded in relation to a linked-ear reference. Left eye EOG was obtained with electrodes (Red dot, Ag/AgCl, Health Care, Germany) positioned above and below the eye with a ground on the masseter. The EOG signal was used to identify blink artefact in the EEG data as well as changes in blink types such as the small and slow blinks that characterize fatigue (Lal & Craig, 2002a).

2.4. Data acquisition and frequency domain analysis

The EEG and EOG data were acquired using a multichannel physiological monitor (Neurosearch-24, Lexicor, USA). An individual EEG data point was classified as an epoch; a basic unit for stored EEG data. Data were sampled at 256 Hz and the total sample time was individual dependent until arousal from fatigue by a verbal interaction from the investigator. A fast Fourier transform (FFT) was performed on the EEG data using a spectral analysis package (Exporter, Lexicor). The EEG was defined in terms of frequency bands including delta (0–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–20 Hz; Fisch, 1991). For each band, the average EEG magnitude (in microvolts) was computed as an average of the 19 channels (representative of the entire head). The EEG of fatigue was classified into the first appearance of transitional (between awake and absence of alpha), transitional–posttransitional (which has characteristics of both), and posttransitional phases (early Stage 1 of sleep), followed by self-arousals (alert states on emergence from fatigue; Santamaria & Chiappa, 1987).

For each phase, 30 successive EEG spectra were generated using FFT and were averaged to form 30 s means to derive the EEG magnitude in the four EEG bands. Previous studies report reliable changes during fatigue and brain functional states from EEG data spanning 15 s to 1 min (Gillberg, Kecklund, & Åkerstedt, 1996; Torsvall & Åkerstedt, 1987). During fatigue, many "microsleep" cycles spanning transitional through to posttransitional phases followed by self-arousal periods may occur. The first complete cycle constituting the three fatigue phases followed by a self-arousal phase was analyzed for each participant.

2.5. Validation of fatigue states

The alert phase and the three different fatigue phases were classified according to the simultaneous video analysis of facial features in the EOG outcomes, and a detailed account of the process was described in our previous study (Lal & Craig, 2002a). Physical signs of fatigue were identified using a video image of the driver's face, linked in real time with the physiological measures. The video analysis and the EOG served as independent variables for fatigue assessment. Specific facial features characteristic of fatigue observed during the driving task that were used to identify fatigue included changes in facial tone, blink rate, eye activity, and mannerisms such as nodding and yawning (Belyavin & Wright, 1987; Yabuta et al., 1985). The video image and the EOG, which showed these signs of fatigue, were used to validate the EEG changes in the different fatigue phases (as classified by Santamaria & Chiappa, 1987). Our previous study showed that identification of these physical signs of fatigue in this manner had excellent reliability demonstrated by a high interobserver and intraobserver agreement (88% between three trained observers; Lal & Craig, 2002a, 2002b). In our previous study (Lal & Craig, 2002a), we found that during an alert state, there were fast eye movements with conventional blinks of high amplitude. During the transitional stage of fatigue, the majority of subjects (67%) had minimal eye movement accompanied by yawning episodes (23%). In the transitional to posttransitional stage, small fast rhythmic blinks were observed (46%) as well as frequent nodding (23%). In the posttransitional stage, slow eye movements and slow blinks dominated (100%) and eyes were either closed or half closed (69%). On arousal, slow blinks disappeared to be replaced by conventional blinks (100%).

On appearance of fatigue as classified from the video and EOG measures (Lal & Craig, 2002a), 30 epochs that spanned the range of the alert and three fatigue phases were recorded to test the software's ability to allocate each epoch into the correct phase. Secondly, the software was tested for its ability to detect fatigue from a complete data set (all epochs) collected for each of the 10 individual subjects and to identify the proportion of time a subject may be in one phase or another. To achieve this, the total number of epochs collected for each subject (which were variable) were run through the algorithm to identify the percentage of time each subject was in a particular state during the study.

2.6. Statistical analysis

The 30 epochs identified as representing the alert and the three fatigue phases from the video and EOG measures were entered into the software in off-line analysis mode. The testing of the fatigue algorithm involved identifying the proportion of epochs that were in the alert and the three different fatigue phases and allocating the data to the color panels described previously. In off-line analysis mode, the data could also be viewed graphically with a line indicating which panel (i.e., alert or one of the fatigue states) a particular epoch had been allocated. A repeated measures ANOVA was performed to identify if differences existed in the means of the four states detected by the software. A Scheffé test then identified where the differences existed in the comparison of the means. The significance level was set at $P < .05$ for all analyses performed.

3. Results

The software categorized the simultaneous delta, theta, alpha, and beta data according to the algorithm into alert, transition to fatigue, transitional–posttransitional, and posttransitional phases. Figs. 2 and 3 show an example of EEG changes according to a topograph display in an individual subject. The topograph summarizes the EEG data in a color-coded map. In the topograph, the magnitude values are shown for defined frequency bands for the different electrode sites in areas of the scalp. The values are color coded

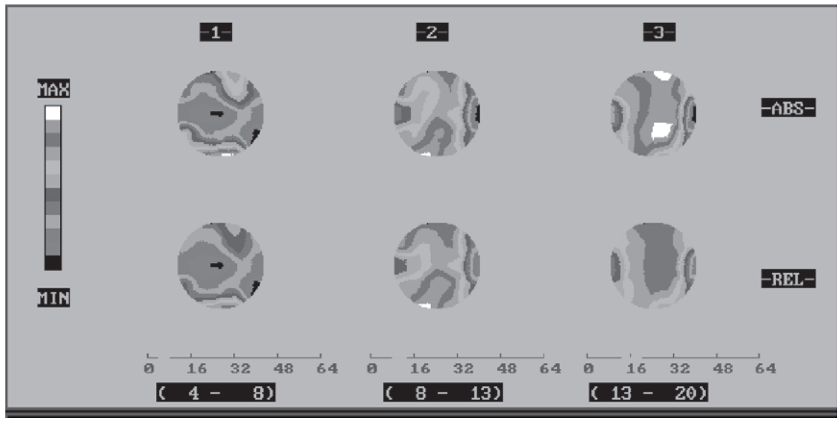

Fig. 2. Shows the topograph of EEG activity in the 1=theta, 2=alpha, and 3=beta bands during an alert state. Note: The darkest shade (specified by a red color) indicates more activity in the alpha and beta bands (2 & 3) and the gray shade (specified by a blue color) marked with arrows indicates a reduction or lack of activity in the theta band (1).

and plotted to produce a continuous color map. The bottom of each column shows the bandwidths, which are theta (4–8 Hz), alpha (8–13 Hz), and beta (13–20 Hz). Each oval topograph depicts a view of the head from above. The color scale displayed as a bar to the left of the ovals represents low (blue) to high power (red). The bottom row of the oval topograph is labeled "REL" (relative). This row maps the full color scale spectrum across the entire amplitude range of the three bands. Each topograph is color coded to indicate how much activity it contains relative to the other two topographs. The top row of the oval topographs is labeled "ABS" (absolute). When one band has less activity relative to another band, it is difficult to see the distribution of power in that band because of the few colors mapped into it. The absolute frequency measurement solves this problem by mapping the full color scale spectrum into each band. Fig. 2 shows the EEG activity of alertness, that is, the presence of alpha and beta activity (indicated by the presence of more red color in the alpha and beta band). Fig. 3 shows the topograph during fatigue showing an increase in slow wave activity, that is, theta in both relative and absolute cases (indicated by presence of more red color in the theta band). Note the simultaneous decrease in alpha and beta activity (indicated by a decrease in the red color in the alpha and beta bands).

The total epochs were distributed among each of the four phases. These epochs were validated according to the video and EOG analysis, which acted as the control against which the software allocation of the epochs was compared. The ability of the software to detect fatigue (validated by the video analysis of fatigue) was demonstrated by the fact that the software detected no false positives. A false positive was defined as detecting fatigue in the absence of facial/EEG signs of fatigue. Table 1 demonstrates the allocation by the software of the total number of epochs to the alert and the three fatigue phases for each subject.

The ANOVA showed that there was an overall difference in the comparison of the means of the four states ($F = 9.15$, $df = 3{,}27$, $P = .0002$). The post hoc analysis found that the percentage of time the subjects were in the transitional–posttransitional and posttransitional fatigue phases was significantly different to the alert phase ($P = .003$ and

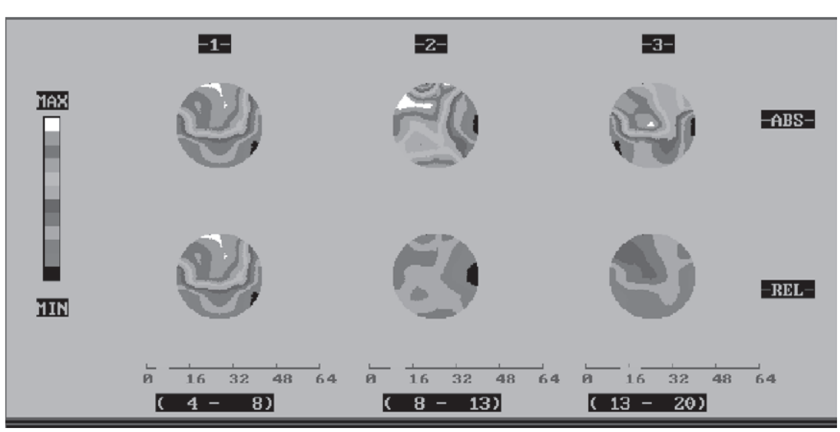

Fig. 3. Shows the topograph of EEG activity in the 1=theta, 2=alpha, and 3=beta bands during transition to fatigue phase. Note: ABS=absolute, REL=relative.
-The increase in 1=theta is shown by presence in the darker shade (specified by a red color) in the fatigue state.
-The reduction in 2=alpha and 3=beta is shown by the appearance of lighter shades (white-gray) in the fatigue state.

Table 1
Percentage of epochs detected in the different functional states of the brain

Subject No.	Alert	Transition to fatigue	Transitional–posttransitional	Posttransitional
1	37.2	27.7	22.0	13.1
2	36.3	14.3	29.4	20.0
3	35.9	22.5	23.7	17.9
4	18.9	27.2	27.7	26.1
5	34.3	46.9	12.6	6.2
6	46.5	28.8	16.8	8.0
7	29.6	39.6	16.6	14.2
8	65.9	16.1	9.1	8.9
9	39.7	17.3	13.1	29.9
10	52.0	32.4	6.0	9.6
Average ± S.D.	39.6 ± 12.8	27.3 ± 10.4	17.7 ± 7.8	15.4 ± 8.0

P=.0009, respectively). The software detected a larger proportion of epochs in the first fatigue state, that is, the transitional phase to fatigue, compared to the other two fatigue phases ($P < .01$). The number of epochs detected in the transitional to posttransitional and posttransitional phases was not significantly different. The video and EOG analysis had identified subjects as being in the alert phase for an average of 40% of the time, in the transitional phase for 25% of the time, in the transitional to posttransitional for 20%, and in the posttransitional state for 15% of the total study time. The percentage error of the algorithm detecting fatigue compared with video/EOG allocation of fatigue in the whole data set was as follows: alert = 1%, transitional = 9.2%, transitional to posttransitional = 11.5%, and posttransitional: 2.7%. The largest difference in the two methods of detection (i.e., video/EOG vs. the algorithm) was observed for the transitional and transitional to posttransitional phases with error rates of around 10%. We believe that the ability of the algorithm to detect the different phases at error rates of around 10% demonstrates impressively high reliability.

4. Discussion

This paper described a fatigue-detecting algorithm based on EEG changes and reports the ability of the algorithm to detect different phases of fatigue. The algorithm was developed in response to the EEG changes reported during driver fatigue in previously recorded data (Lal & Craig, 2002a). The results of testing the software in off-line mode found that the 10 truck drivers were in a fatigue state for at least 60% of the total time they spent driving in the simulator. This confirms our previous findings that drivers are at risk of driving in a fatigue state for a majority of time when the driving task is monotonous (Lal & Craig, 2002a). Experienced drivers know that they endanger themselves and others when they ignore the feelings of fatigue, where the natural end result is falling asleep. Various theories of fatigue have been explored previously, with driver fatigue being specifically defined as a state of reduced mental alertness, which impairs performance in a range of cognitive and psychomotor tasks, including driving (Williamson, Feyer, & Friswell, 1996). This theory has been supported in our previous studies in professional and nonprofessional drivers (Lal & Craig, 2002a, 2002b). During driver fatigue, we found increases in slow wave brain activity, specific changes in EOG, for example, slow eye blinks and behaviors such as nodding and yawning (monitored by video; Lal & Craig, 2002a).

In the current study, the software was shown to be capable of detecting the three stages of fatigue reliably from changes in EEG, especially the slow wave variations, and was validated by video and EOG monitoring. However, it should be noted that these results represent an initial trial of the first prototype of the software and a larger study will be required to replicate these results. This is the first instance in which a fatigue-detecting software was shown to not only detect three different phases of fatigue but can also compute EEG changes simultaneously in the delta, theta, alpha, and beta bands. In addition, it has the capability to detect fatigue on an individual basis where an algorithm can be computed based on the individual's specific EEG changes during fatigue. As demonstrated in this study, it can also be programmed to detect fatigue based on the average changes that occur in a sample.

Other research has described how the analysis of a driver's breathing regularity can contribute to the prediction of deterioration in alertness (Artaud et al., 1994); however, this approach has still not been confirmed in an on-road context. Furthermore, videotaping the driver's face has also been reported to have a number of technical hurdles and little is known about the feasibility of this approach (Artaud et al., 1994). Others have described adaptive driver systems with telemetric applications in the car aimed at supporting the driver, such as route guidance and anticollision (Michon, 1993). However, these applications can distract the driver by presenting too much information. These types of applications can lack driver acceptance because of inadequate warning thresholds (i.e., neither situation-specific nor driver adapted), and there is certainly no scientific evidence presented that the systems are designed intelligently to detect fatigue states (Onken & Feraric, 1997).

To date, few researchers have investigated the use of EEG as a fatigue countermeasure. Some have developed a system that detects sleepy states of drivers using grouped EEG alpha waves and warns them of the dangerous state (Ninomija et al., 1993). They reported an error in their subsystem in the magnitude of 25–35%. In order to improve the reliability of their EEG-based system, these researchers suggest that they need to monitor the simultaneous electrocardiogram during driving. The disadvantage apparent in this system is the use of extra electrodes to monitor two separate physiological signals making it more cumbersome than having one recording system. The same investigators further describe a system based on detecting grouped alpha waves using a convolution with special weighting factors such as moving average methods (Fukuda et al., 1994). They reported that the system separates grouped alpha waves from various kinds of noise and detects low awakening levels as soon as grouped alpha waves appear. However, this group has not reported the further development of their system in a field condition. In our research, we found that even though alpha increases during drowsiness, the magnitude of change in the delta and theta waves are larger and easier to detect (Lal & Craig, 2002a). Furthermore, basing fatigue on one EEG variable cannot be as reliable as detecting the simultaneous changes that occur in all the frequency bands. This is the current sophistication of the software described in the current research. Since fatigue is a cortical deactivation that affects all brain waves in one way or the other, it can only be beneficial to record and detect changes in all bands in a future EEG-based fatigue-monitoring device.

5. Summary

Further research is required with the fatigue software to produce a real-time robust and reliable fatigue-detecting/alerting system. The need for future modifications of the software has become apparent in this research. In both real-time and off-line analysis mode, a "threshold" algorithm is required that can negate major artifacts in the EEG data that can occur due to coughing, sneezing, and any large extraneous movements as well as vibrational movements due to the car and the road surface. For example, individual algorithms need to be incorporated into the software that can detect head and body movements, large muscle potentials, and eye movement potentials referenced against an artifact-free calibration period. Such computer rejection of artifact has been described in previous research (Hamilton, Curley, & Aimi, 2000) and may form the basis of detecting and eliminating extraneous signals in the fatigue-detecting system described in the current research. Hardware, which is being developed in our unit together with the currently described software, will form a prototype fatigue-monitoring device. The software's ability to allocate the EEG data into the various color panels could be used in the future to alert drivers of their fatigue status. For example, yellow would indicate early fatigue and red would indicate extreme fatigue. Auditory feedback could replace the color feedback in the final commercial device. The next phase of our research will test the fatigue countermeasure software in real time in a laboratory and field driving trial.

As a result of this research, other parameters became apparent that need investigation for the feasibility of a fatigue-monitoring device in an operational setting. In the laboratory, restrictions on equipment size and weight were of little concern. However, in an applied setting, these restrictions can be important. Furthermore, real-time field trials of the fatigue-monitoring device are essential. More research also needs to be carried out on EEG-based electrodes. The electrodes used with the fatigue monitor should be easy to connect and able to monitor EEG changes accurately for long periods. Data reduction should also be quick in real time in order to manage the suddenly changing fatigue states. We envisage a device in the future that could be worn on the head in the form of a band that would detect brain activity changes of drivers during driving and warn of signs of fatigue using varying degrees of audible feedback for the three different levels of fatigue. Even though drivers usually know they are fatigued, few pay heed to their lapsing attention levels. It is believed that a device that can provide immediate and interactive feedback of the driver's fatigue state would be more effective in alerting the driver to take precautions. A device such as this would be useful in many areas of the transport industry that are prone to driver fatigue and sleepiness effects, such as in the commercial sector (National Transportation Safety Board, USA, 1995) as well as in drivers with clinical symptoms of sleep disorders and dementia, and in adolescents (Aldrich, 1989; American Thoracic Society, 1994; Carskadon, 1990; Findley, 1995; Hansotia, 1997).

As discussed previously, a valid measure of fatigue such as the EEG seems promising for the development of a fatigue countermeasure device. The fatigue countermeasure device must provide a valid indication of fatigue rather than some type of performance impairment (Desmond & Matthews, 1997). Furthermore, the stimulus delivered when the performance impairment due to fatigue is detected must successfully restore normal performance. In the future, such an enabling technology could be important in the transport environment that demands alertness and that involves multiple tasks competing for limited attention resources (Gevins et al., 1995). With the advances in miniaturization of equipment, the use of physiological parameters such as the EEG has become more feasible in operational settings (Rokicki, 1995). The use of simple on-line frequency domain analysis procedures to compute the spectral bands in the EEG forms the basis of the fatigue-detecting software described in this research. The initial aim would be to apply the countermeasure device in the commercial driving industry; however, it could also be important in preventing fatigue-related accidents in nonprofessional drivers.

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Dr Saroj KL Lal, BSc, MSc, PhD (Psychophysiology of fatigue), GCHE, MACRS, ASP. Dr Lal has previously been a Hospital Scientist researching in the area of psychophysiology research in sleep, hypertension, and cardiovascular diseases. Dr Lal is currently an academic and a National Health and Medical Research Council fellow in the Faculty of Science, University of Technology, Sydney (UTS), investigating driver fatigue, physiology, and behavior. Has published in areas of heart disease, fatigue, hypertension, and sleep in scientific and medical journals.

Professor Ashley Craig, BSc (Hons), PhD (Psychology), Hon. Doct., MAPS, MCCP. Research professor and currently Associate Dean (Research and Development) in the Faculty of Science, UTS. Published in areas of heart disease, neurophysiology, fatigue, and stuttering. Member of New York Academy of Sciences, Australian Psychology Society, College of Clinical Psychology, Australia, and the Ergonomics Society of Australia.

Peter Boord, BE (Hons) Elec. Previously a Professional Engineer (Defense Science Technology Organisation, SA) and a consultant engineer. Currently a doctoral student in the Faculty of Science, UTS. Publications in Technology and Disability and in Neural Networks.

Associate Professor Les Kirkup, BSc, MSc, PhD (Physics), MInstP, CPhys, MAIP. He holds the position of Associate Professor in Physics in the Faculty of Science. Previously, he held positions as lecturer in physics. He is a member of the Institute of Physics (UK) and the Australian Institute of Physics. Has published in various biomedical journals as well as books.

Professor Hung Nguyen BE, ME, PhD. He is Head of Mechatronics and Intelligent Systems Group, Director (Engineering) of Key Research Centre in Health Technologies, and Executive Director of AIMEDICS. He is well published in the area of biomedical engineering, advanced control and instrumentation, and artificial intelligence. He is a Fellow of the Institution of Engineers, Australia, and a Senior Member of the Institute of Electrical and Electronics Engineers.