TOWARDS A COUNTERMEASURE DEVICE TO DETECT FATIGUE IN DRIVERS

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ABSTRACT

Fatigue affects the drivers' ability to continue driving safely. Therefore, on-line monitoring of physiological signals while driving provides the possibility of detecting fatigue in real time. The EEG signal has been found to be the most predictive and reliable indicator. However, little evidence exists on implementing EEG into a fatigue countermeasure device.

The aims were to utilise EEG changes during fatigue for development of fatigue countermeasure software and to test the ability of such software in detecting fatigue. EEG was obtained in twenty truck drivers during a driver simulator task till subjects fatigued. Changes found in delta, theta, alpha and beta activity were used to develop algorithms for the software. The software was designed to detect an alert state and early, medium and extreme levels of fatigue. The software was tested in off-line mode in a group of ten truck drivers.

The software was capable of detecting fatigue accurately in all ten subjects. The percentage of time the subjects were detected to be in a fatigue state was significantly different to the alert phase ($p<0.01$). For 40% of the total driving time subjects were alert and for 60% of the time, the software detected one of the three fatigue states. In on-line analysis the software could alert the three stages of fatigue.

The software could detect fatigue accurately. This is the first countermeasure software that can detect fatigue based on EEG changes in all bands. Future field research is required with the fatigue software to produce a robust and reliable fatigue countermeasure system.

INTRODUCTION

Technological Countermeasures for Fatigue/Drowsiness

Research on Technological Countermeasure to Fatigue

Evidence from the scientific literature suggests reasons exist for giving serious consideration to the implementation of technological countermeasures for driver fatigue. These are:

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.

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 (1)).

Therefore, on-line monitoring of fatigue/drowsiness while driving provides in real time the possibility of detecting potentially dangerous behaviours that are related to fatigue, such as eye-closing, head nodding and deterioration in alertness. To date, most fatigue countermeasure devices measure some physiological response in the driver such as the electroencephalogram, electro-oculogram, respiratory signals, behavioural recordings such as analysis of the video film of driver's face (Artaud et al. (2)) or changes in the driver's alertness through steering behaviour (Yabuta et al. (3)).

Research has described how the analysis of a driver's breathing regularity can contribute to the prediction of deterioration in alertness (Artaud et al. (2)), however this approach has still not been confirmed in a real-driving situation. Others have described adaptive driver systems with telemetric applications in the car aimed at supporting the driver such as route guidance, anti-collision, etc (Michon (4)). These applications can distract the driver by presenting too much information. These types of applications lack driver acceptance because of inadequate warning thresholds (i.e. neither situation-specific nor driver adapted) and there is certainly no guarantee that the systems are designed intelligently to detect fatigue states (Onken & Feraric (5)). Even though 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 (6)). This outcome may be attributable to the failure to take into account the variation of fatigue effects with changing task demands (Desmond & Matthews (6)).

Although numerous physiological indicators are available to describe an individual's level of alertness, the EEG signal has been shown in the research presented in this paper and the research of others to be one of the most predictive and reliable (Artaud (2)). Generally there is a pronounced appearance of slow wave activity during fatigue. However, very little evidence exists on 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 (7)). However, no evidence exists on the implementation of such a device. An automated drowsiness detector based on ongoing EEG was also developed about twenty years ago by Gevins et al. (8). However, once again progress on the applicability of the device has not been reported. In spite of this, the same 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. (9)).

The aims of this study were:

- to utilise the EEG changes that occur during driver fatigue for the development of software to be incorporated into the development of a fatigue countermeasure device.

- to test the ability of such software to detect the transitional phase to fatigue, transitional-post transitional phase and the post-transitional phase in 'offline data analysis'.

METHODS

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. 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.

Study protocol

The study was conducted in a temperature-controlled laboratory as the subjects performed a standardised sensory motor driver simulator task. The driving task consisted of 10 minutes of active driving to familiarise the subject, followed by a two continuous hours of driving (speed < 80 km/hr) till the subjects showed physical signs of fatigue. Simultaneous EEG measures were obtained during the driving task. Nineteen channels of EEG were recorded according to the

International 10-20 system (Fisch (10)). Physical signs of fatigue were identified using a video image of the driver's face, linked in real time with the EEG measures.

The fatigue anticipating software: towards a technological countermeasure against driver fatigue

The EEG changes that were found during fatigue were used as the basis of developing the fatigue-detecting software. To accomplish this, the EEG changes observed during the alert, transitional, transitional-post-transitional and post-transitional phases of fatigue were used to develop an algorithm that could detect a set of programmed changes that occur during different phases of fatigue. The software was developed using Lab View (version 5.1, National Instruments, USA). The software was designed to detect four different functional states and these are alert, transitional phase (early fatigue stage) of fatigue, the transitional-post transitional phase (medium levels of fatigue) and the post-transitional phase (extreme levels of fatigue) (the phases are described according to (Santamaria & Chiappa (11)). EEG data in the four phases were categorised into four channels represented by colour panels, which were green, yellow, orange and red respectively. As indicated by the colour scale, green is a 'safe' level (alert) and red is a 'dangerous level of fatigue (post-transitional phase). Yellow and orange denote early (transitional phase) and medium (transitional-post transitional phase) level of fatigue, respectively.

Data and statistical analysis

Different algorithms based on the EEG changes observed during fatigue were developed and tested. The fatigue software is capable of analysing EEG data in real-time as well as off-line analysis of previously acquired data. In real time and off line analysis, the fatigue software is capable of acquiring two channels of EEG data (i.e. data acquired from two different EEG sites on the brain) which has been sampled at 256 Hz during the driving task. For the purposes of this paper the results of testing the software on previously acquired EEG data will be reported and hence only the off-line analysis mode will be referred to.

The software performs a fast Fourier transform for spectral analysis of the acquired EEG data. The EEG is then 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, (10)). For each band the software computes the EEG magnitude (μV) which is the sum of all amplitudes of all data points within a band's frequency range.

The software computes a baseline mean from a section of data that represents the alert state of the individual. A range of randomly selected epochs, linked in real time to a video recording of the subject's alert state were chosen to represent the baseline. The mean and standard deviation of the EEG magnitude in this phase is then computed for all four frequency bands in the alert phase. The software allows a threshold coefficient to be defined for each of the frequency bands in terms of the mean and standard deviations that will determine a particular state of the individual i.e. alert or a fatigue state. For each of the four phases mentioned above, a different set of coefficients decides whether the data will be detected as being in the alert (green), transition to fatigue (yellow), transitional to post-transitional (orange) or post-transitional (red) phase. A range of EEG magnitude (mean and SD) values for each phase were programmed into the software. This algorithm determines the percentage of data that will be detected as an alert or one of the fatigue phases for each subject. Using the AND (&)/OR (|) logic an algorithm is defined for the alert and fatigue states. For example (D & T) & A | B indicates that the state of fatigue is indicated only if the delta and theta and either alpha or beta magnitude is within the defined range. This algorithm can be varied depending on the presence of the different EEG waves in a particular phase.

The EEG data collected in the ten truck drivers were analysed using offline analysis. Raw EEG time domain ASCII data was acquired using a physiological monitor (Neurosearch-24, Lexicor, America), were converted to real text format using a program modified from the Neurosearch-24 software, Lexicor, USA (E.exe). Using the previously recorded EEG data from another group of Thirty-five truck drivers four test algorithms were developed for the EEG changes that occur during the alert and the three fatigue phases (Lal & Craig (12)). The algorithm was tested for its capability to identify the proportion of data from the 10 subjects that was in the alert and fatigue states and allocate them to the colour panels described above. In off-line analysis mode, the data could also be viewed graphically with a line indicating in 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. Scheffé test then identified where the differences existed in the comparison of the means. The significance level was set at $p<0.05$ for all analyses performed.

RESULTS

The results of the off-line analysis using the fatigue detection software on EEG data of the ten truck drivers are shown in Table 1. The software categorised the data into an alert, transition to fatigue, transitional- post transitional and a post-transitional phase. Table 1 shows the percentage of fatigue status detected in the subjects. The ability of the software to detect fatigue (validated by the video and EOG analysis of fatigue; for details refer to Lal & Craig (12, 13)) was demonstrated by the fact that the software detected no false positives. In other words, the software did not detect fatigue when the subject was alert which was confirmed via simultaneous video and EOG analysis.

Table 1 **Showing the ability of the fatigue software to detect an alert or a fatigue state in each subject (detection shown as percentage values)**

Subject No	Alert	Transition to Fatigue	Transitional- post transitional	Post-Transitional
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 ± sd	39.6 ± 12.8	27.3 ± 10.4	17.7 ± 7.8	15.4 ± 8.0

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=0.0002). The post-hoc analysis identified that the percentage of time the subjects were detected to be in the transitional-post transitional and post-transitional fatigue phases were significantly different to the alert phase (p=0.003 and p=0.0009, 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. That is the subjects' were in the transitional phase of fatigue for a greater proportion of the time than in the transitional-post transitional or the post-transitional phases of fatigue. For almost 40% of the total driving time the subjects were in an alert state, while for the remaining 60% of the time, the software detected the subjects to be in one of the three fatigue states.

DISCUSSION

The potential of the EEG detecting software

The fatigue detecting software described involved the development of algorithms that were designed to detect different states of fatigue i.e. transitional, transitional-post transitional and post-transitional phases of fatigue. The algorithms were based upon EEG changes reported during driver fatigue in data previously recorded from 20 subjects. The results of testing the software in offline mode on data from a different group of 10 subjects identified that these drivers were in a fatigue state for at least sixty percent of the total time they spent driving in the simulator. The software was capable of detecting the three stages of fatigue previously validated by video and EOG monitoring (Lal & Craig (12, 13)). The video image, which showed these physical and EOG signs of fatigue were used to validate the EEG changes associated with fatigue. The study was concluded when specific video signs appeared such as slow eye movement and slow blinks leading to eyes either half closed or fully closed together with mannerisms such as head drooped or continuous nods. The identification of these physical signs of fatigue from the video has been shown to have excellent reliability demonstrated by a high inter- observer and intra-observer agreement (Lal & Craig (12)).

However it should be noted that these results represent a pilot trial of the first prototype of the software and a replication study will be conducted in our unit in order to validate these results. This software is also unique in the sense that it can detect fatigue based on EEG changes occurring simultaneously in the delta, theta, alpha and beta bands (Lal & Craig, (14)). Furthermore, it has the capability to detect fatigue on an individual basis where an algorithm can be computed based on the individual's EEG changes during fatigue. It can also be programmed to detect fatigue based on the mean changes that occur in a sample.

Future research and development of the fatigue-detecting software

More research is required with the fatigue software to produce a robust and reliable fatigue detecting/alerting system. The need for some future modifications of the software has become apparent in this research. These are (1) In both the real-time and offline analysis mode a 'threshold' algorithm is required which can negate major artifacts in the EEG data that can occur due to coughing, sneezing and any large extraneous movements. 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 an on-line computer rejection of artifact has been described in previous research (Gevins (8)) and may form the basis of detecting and eliminating extraneous signals in the fatigue detecting system described in the current research. (2) Currently the software is only capable of specifying two fatigue levels as indicated in the threshold settings panel even though algorithms can be devised to detect three fatigue phases. The programming of algorithms can be made simpler by modifying the software to be able to set three threshold coefficients to detect the three fatigue states. Simultaneous development of the hardware (Biosync, Mind Switch Pty. Ltd., Sydney) is also occurring, which together with the software will form a fatigue countermeasure device. The software's ability to allocate the EEG data into the various colour panels could be used in the future to alert drivers of their fatigue status, for example, yellow indicating light fatigue and red indicating extreme fatigue, using varying levels of auditory feedback.

To date few researchers have investigated the use of EEG as a fatigue countermeasure. Ninomija et al. (15) developed a system which detects sleepy states of drivers using grouped EEG alpha waves and warns them of the dangerous state. 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 to detect fatigue. 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. (7)). 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 real 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. 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 countermeasure device.

As a result of this research other parameters became apparent that need investigation for the feasibility of a fatigue countermeasure 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 countermeasure device are essential. The system also needs to be shown to be reliable. Furthermore, more work needs to be carried out on EEG based electrodes. The electrodes used with the fatigue monitor should be easy to connect as well as be able to monitor EEG changes accurately for long periods. Data reduction should also be quick in real time to defeat the suddenly occurring fatigue states.

Therefore 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 (6)). 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. (9)). With the advances in miniaturisation of equipment, the use of physiological parameters such as the EEG has become more feasible in operational settings (Rokicki (16)). The use of simple on-line frequency domain analysis procedures to compute EEG alpha, theta, delta and beta bands form the basis of the fatigue detecting software described in this research.

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. This includes deriving fast real time data filtering and processing techniques that can be viable in a dynamic driving environment. Hardware being developed in our unit which together with the currently described software will form the basis of a fatigue countermeasure device. The software's ability to allocate the EEG data into the various colour panels could be used in the future to alert drivers of their fatigue status. For example, yellow would indicate light fatigue and red would indicate extreme fatigue. Auditory feedback could replace the colour 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.

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Therefore, 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 (6)). 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. (8)). With the advances in miniaturisation of equipment, the use of physiological parameters such as the EEG has become more feasible in operational settings (Rokicki, (16)). 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. Such a device could be important in preventing fatigue related accidents in the transport or heavy industry.

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