

**Developing Vehicle-Based Advanced Warning
System for Driver Drowsiness Based on a Hybrid
Algorithm**

A thesis
submitted in fulfilment
of the requirement for the degree
of
Doctor of Philosophy
at the
University of Technology, Sydney
by

MURAD A. KARRAR

University of Technology, Sydney
2010

Certificate of authorship

I certify that the work in this thesis has not previously been submitted for a degree, nor has it been submitted as part of requirements for a degree.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of Candidate

Production Note:
Signature removed prior to publication.

Acknowledgments

First and foremost I would like to thank God for giving me the strength to embark on the long journey that was this research and to see it to completion. I would like to deeply thank my principal supervisor Dr. Sara Lal of the University of Technology, Sydney for her continuous support and endless guidance and for the countless hours spent over both the phone and email correspondence that helped to bring this research to completion. I also owe a great gratitude to my industry supervisor Dr. Eugene Zilberg of Compumedics Ltd, who was a constant source of guidance, support and encouragement. I would like to also thank my other industry supervisor Dr. David Burton, CEO of Compumedics, for granting me the opportunity to conduct my research in such an innovative field and for providing me with the necessary support with both equipment and encouragement.

I would like to thank the staff and my fellow colleagues at Compumedics for their help and support throughout my candidature and a very special thanks to Dr. Ming Xu for his enormous guidance, endless technical advice and support.

I thank the staff at Monash University Accident Research Centre for all the initial work that was conducted in the background to obtain approval for the use of a car simulator, and for helping in the recruitment process. A special thanks to Nebojsa Tomasevic for technical support with the simulator.

I would like to thank the Australian Research Council (ARC) for the Australian Post Graduate Award Industry (APAI) support under the ARC Linkage grant (LP0347012). The research support helped me immensely in recruiting subjects for the experiments, hiring equipment and presenting findings at conferences.

I also thank Bruna Pomella for proofreading the thesis. I would like to thank all the participants in the study who had to endure close to 4 hours of experiment with all the electrode attachments and the long driving simulations.

My deepest gratitude is extended to my family for all their tireless support and endless encouragement. Finally, my thanks goes out to my extended family and friends, both in Melbourne and Sydney, whose constant enquiries about the status of my thesis gave me yet another reason to complete this undertaking.

Preface

The following publications were achieved during the doctoral research:

Book Chapter

ZILBERG, E., BURTON, D., XU, Z. M., **KARRAR, M.** & LAL, S. (2008) Methodology and initial analysis results for development of non-invasive and hybrid driver drowsiness detection systems. IN AGBINYA, J., SEVIMLI, O., LAL, S., SELVADURAI, S., AL-JUMAILY, A., LI, Y. & REISENFELD, S. (Eds.) *Advances in Broadband Communication and Networks*. Denmark, River Publishers.

Journal Publication

ZILBERG, E., XU, Z. M., BURTON, D., **KARRAR, M.** & LAL, S. (2009) Statistical validation of physiological indicators for non-invasive and hybrid driver drowsiness detection system. *African Journal of Information and Communication Technology*, 5, 75-83.

Refereed conference Proceedings

KARRAR, M., ZILBERG, E., XU, Z. M., BURTON, D. & LAL, S. (2009) Statistical comparison for a drowsiness detection system based on the spectral and alpha burst techniques. *4th International Conference on Broadband Communication, Information Technology & Biomedical Applications*.

LAL, S., HENDERSON, R., WATERS, S., JAP, B. T., BURTON, D., ZILBERG, E., **KARRAR, M.**, XU, M. & BEKIARIS, E. Differences in EEG hemispheric activity during fatigue. Proceedings of 2nd international conference of the EU 6th framework integrated project SENSATION, 4 - 5 June 2007 in Chania, Crete, Greece

ZILBERG, E., BURTON, D., ZHENG MING, X., **KARRAR, M.** & LAL, S. (2007) Methodology and initial analysis results for development of non-invasive and hybrid driver drowsiness detection systems. *The 2nd International Conference on. Wireless Broadband and Ultra Wideband Communications, 2007. AusWireless 2007*.

Refereed Conference Abstracts

KARRAR, M., XU, M., ZILBERG, E., BURTON, D. & LAL, S. (2009) Assessing associations between video drowsiness ratings and subjective measures of fatigue with lifestyle and behaviour: a driver study. *International Conference on Fatigue*

Management in Transportation Operations: A Framework for Progress. Boston, USA, March 24-26.

KARRAR, M., ZILBERG, E., XU, M., BURTON, D. & LAL, S. (2009) Detection of driver drowsiness using EEG alpha wave bursts – comparing accuracy of morphological and spectral algorithms. *International Conference on Fatigue Management in Transportation Operations: A Framework for Progress*. Boston, USA, March 24-26.

Table of Contents

Certificate of authorship	ii
Acknowledgments	iii
Preface.....	v
Table of Contents	vii
List of Illustrations.....	xiii
List of Tables	xxi
Glossary	xxvii
Abstract.....	xxx
Chapter 1	
Review of the literature and aims of the study.....	1
1.1 Introduction	1
1.2 Causes of fatigue/drowsiness	4
1.2.1 Sleep-related factors.....	5
1.2.2 Monotony.....	6
1.2.3 Cultural factors	6
1.3 High Risk Categories of drivers	7
1.3.1 Young Drivers.....	7
1.3.2 Shift Workers and professional drivers	8
1.3.3 Drivers who use Alcohol and other drugs.....	9
1.3.4 Drivers with sleep disorders.....	10
1.4 Indicators of Fatigue	10
1.4.1 Physiological indicators and measures of fatigue	11
1.4.1.1 Electroencephalography	11
1.4.1.2 Electrooculography (Eye Movement)	14
1.4.1.3 Piezofilm Movement Sensors and Strain Gauge Pressure Sensors	15
1.4.2 Self report and behavioural tests and scales.....	16
1.4.3 Driving Performance and driving tests	17
1.4.3.1 Driving Performance	17
1.4.3.2 Lane Deviation and steering wheel position.....	18
1.4.4 Video Analysis	20
1.5 Fatigue/Drowsiness Detection and Countermeasure Systems.....	21

1.5.1	<i>Current Proposed Countermeasures</i>	23
1.5.1.1	<i>Engine Driver Vigilance Telemetric Control System (EDVTCS):</i>	23
1.5.1.2	<i>Alertness and Memory Profiler (AMP)</i>	24
1.5.1.3	<i>ARRB Pro-Active Fatigue Management System</i>	25
1.5.1.4	<i>ETS-PC Eye tracking system</i>	27
1.5.1.5	<i>NOVAlert</i>	28
1.5.1.6	<i>Copilot PERCLOS Monitor</i>	29
1.5.1.7	<i>ZZZZAlert</i>	30
1.5.1.8	<i>SafeTRAC</i>	31
1.5.1.9	<i>MicroNod Detection System (MINDS™)</i>	32
1.5.1.10	<i>Eyegaze</i>	33
1.5.1.11	<i>SafetyScope</i>	35
1.5.1.12	<i>FaceLAB</i>	36
1.5.1.13	<i>Optalert</i>	38
1.5.1.14	<i>Tact (InSeat Solutions, LLC)</i>	40
1.5.1.15	<i>Driver Drowsiness Systems Comparisons</i>	40
1.5.2	<i>Practical countermeasures</i>	41
1.5.2.1	<i>Naps</i>	41
1.5.2.2	<i>Rest Breaks</i>	41
1.5.2.3	<i>Caffeine</i>	41
1.5.2.4	<i>Food Intake</i>	42
1.5.2.5	<i>Sound</i>	42
1.5.2.6	<i>Temperature</i>	43
1.6	Limitation and problems with existing studies and countermeasures	43
1.7	General Aim	44
1.8	Specific Aims	44
 Chapter 2		
	Experimental procedures and techniques	45
2.1	Introduction	45
2.2	Participants	45
2.3	Physiological Signals	47
2.3.1	<i>EEG Signals</i>	48
2.3.2	<i>EOG</i>	52
2.3.3	<i>Eyelid movement sensor</i>	53
2.3.4	<i>Movement and Pressure sensors</i>	54
2.4	Video Signals	60
2.4.1	<i>PERCLOS Data</i>	63
2.5	Data Acquisition	64
2.5.1	<i>Siesta (Compumedics, Ltd)</i>	64
2.5.2	<i>Laptop</i>	66
2.6	Software	67

2.6.1	<i>NetBeacon</i>	67
2.6.2	<i>PSG Online</i>	69
2.6.3	<i>Profusion PSG</i>	70
2.7	Lifestyle and Behavioural (self-report) measures	71
2.8	Design and experimental procedure	72
 Chapter 3		
Initial Determination of statistical associations between observed driver drowsiness, body movement and physiological measures.....		
		76
3.1	Introduction	76
3.2	Feature extraction	77
3.2.1	<i>Seat Movement Sensors</i>	77
3.2.2	<i>Steering Wheel Sensors</i>	79
3.2.3	<i>Eye Movements</i>	82
3.2.4	<i>Electroencephalography (EEG)</i>	82
3.3	Video-based rating of drowsiness as “gold standard”	85
3.3.1	<i>PERCLOS</i>	85
3.3.2	<i>Trained Observer Rating</i>	86
3.3.3	<i>PERCLOS versus Observer Rating</i>	88
3.3.4	<i>Examples of correlation between observer drowsiness rating and physiological signal patterns</i>	91
3.4	Determination of episodes of transition to drowsiness episodes	94
3.5	Statistical analysis methodology	96
3.6	Estimation of time courses of physiological indicators during episodes of transitions to drowsiness	99
3.6.1	<i>Piezofilm seat movement sensors – data description and transformation</i>	99
3.6.2	<i>Piezofilm seat movement sensors – correlation between observations</i>	101
3.6.3	<i>Piezofilm seat movement sensors – selection of regression models</i>	108
3.6.4	<i>Piezofilm seat movement sensors – regression estimates</i>	112
3.6.5	<i>Electroencephalography (EEG) – data description and transformation</i>	118
3.6.6	<i>EEG – regression estimates</i>	122
3.6.7	<i>Eye movement duration</i>	123
3.6.8	<i>Combined seat movement sensor, eye movement duration and EEG results for individual subjects</i>	125
3.6.9	<i>Steering wheel data</i>	128
3.6.10	<i>Eyelid versus EEG derived eye movement duration</i>	130
3.6.11	<i>Conclusions</i>	132
3.7	Logistic regression models for the associations between drowsiness indicators and probability of drowsiness	134
3.7.1	<i>Model description</i>	134
3.7.2	<i>EEG Models</i>	138
3.7.3	<i>Piezofilm seat movement sensors</i>	142

3.7.4	<i>Eye movement duration</i>	146
3.7.5	<i>Combination of eye movement duration and seat movement magnitude</i>	149
3.7.6	<i>Combination of EEG and seat movement magnitude</i>	152
3.7.7	<i>Combination of EEG and eye movement duration</i>	153
3.7.8	<i>Combination of EEG, eye movement duration and seat movement magnitude</i> .	155
3.7.9	<i>Statistical analysis summary</i>	157
3.8	Discussions and conclusion	159
Chapter 4		
Detection of driver drowsiness based on spectral and morphological electroencephalography signal analysis		
		162
4.1	Introduction	162
4.2	Processing Techniques for EEG Signals	163
4.2.1	<i>EEG Power Spectral Analysis</i>	166
4.2.2	<i>Alpha burst Analysis</i>	168
4.2.2.1	<i>Characterization of Alpha Burst</i>	170
4.2.2.2	<i>Criteria of an alpha burst</i>	171
4.3	Statistical Analysis of associations between video based drowsiness ratings and EEG based measures of drowsiness	172
4.3.1	<i>Statistical model</i>	172
4.3.2	<i>Outcomes of linear regression for drowsiness detection based on spectral analysis of the EEG</i>	175
4.3.2.1	<i>Outcomes of linear regression of detection based on EEG alpha burst analysis</i>	183
4.4	Development of an algorithm for detecting driver drowsiness from EEG	193
4.4.1	<i>Drowsiness state detection</i>	193
4.4.1.1	<i>Driver's drowsiness assessment according to video image ratings</i> ..	193
4.4.1.2	<i>Automatic detection algorithm based on Spectral EEG analysis</i>	194
4.4.1.3	<i>Automatic detection algorithm based on Alpha burst</i>	196
4.4.2	<i>Algorithm Inputs</i>	200
4.4.2.1	<i>Number of Waves (burst_min_waves_count)</i>	200
4.4.2.2	<i>Noise Effect (burst_smoothing_coefficient_flag)</i>	201
4.4.2.3	<i>Amplitude Effect (burst_peaks_amplitude_variance_flag)</i>	201
4.4.2.4	<i>Period Effect (burst_waves_duration_variance_flag)</i>	201
4.5	Performance results for the EEG based drowsiness detection algorithms	202
4.5.1	<i>Drowsiness state and Transition Point</i>	202
4.5.2	<i>Algorithm Performance measurement</i>	203
4.5.3	<i>Receiver Operator Characteristic (ROC) graphs</i>	205
4.5.3.1	<i>Initial Average Set-up Time</i>	206
4.5.3.2	<i>Number of waves (burst_min_waves_count)</i>	208
4.5.3.3	<i>Effect of Amplitude Index (burst_peaks_amplitude_variance)</i>	209
4.5.3.4	<i>Effect of noise tolerance (burst_smoothing_coefficient)</i>	210
4.5.3.5	<i>Effect of Duration factor (burst_waves_duration_variance)</i>	211
4.5.3.6	<i>Effect of all the parameters versus no parameters</i>	212

4.5.3.7	<i>Automatic Detection Results</i>	213
4.6	Discussion and conclusions	217
Chapter 5		
Role of non-intrusive body movement sensors in the detection of driver drowsiness ...222		
5.1	Introduction	222
5.2	Measures of body movements and their relationships with drowsiness level	223
5.2.1	<i>Objectives of the statistical analysis</i>	225
5.3	Statistical Analysis of associations between video based drowsiness ratings and body movement sensor measurements	226
5.4	Statistical analysis of associations between video-based drowsiness ratings and a combination of body movements and EEG	241
5.4.1	<i>Outcomes of linear regression based on hybrid body movement sensor and EEG spectral analysis in predicting drowsiness</i>	242
5.4.1.1	<i>Outcomes of linear regression of detection based the hybrid body movement and EEG alpha burst analysis with the minimum number of 4 alpha waves</i>	247
5.4.2	<i>Outcomes of linear regression of detection based on the hybrid body movement and EEG alpha burst analysis with the minimum number of 6 alpha waves</i>	253
5.4.3	<i>Conclusion of the statistical analysis</i>	258
5.5	Hybrid Automatic Detection Algorithm	259
5.5.1	<i>Introduction</i>	259
5.5.2	<i>Alpha Burst Detection</i>	262
5.5.3	<i>Body movement Detection</i>	263
5.5.4	<i>Calculation of the Body movement Signal input parameter for the new hybrid model</i>	263
5.5.5	<i>Threshold for the body movement signal parameters</i>	266
5.5.6	<i>Definition of the Algorithm</i>	266
5.6	Performance evaluation of the hybrid algorithm	268
5.6.1	<i>Hybrid versus 'EEG only' algorithm</i>	269
5.6.2	<i>Number of Waves (burst_min_waves_count):</i>	271
5.6.3	<i>Effect of burst period variance (burst_waves_similairty_coefficient)</i>	272
5.6.4	<i>Effect of burst pattern smoothing index (burst_smoothing_coefficient)</i>	273
5.6.5	<i>Effect of Burst Pattern Amplitude Index (relative_burst_peaks_amplitude)</i>	274
5.6.6	<i>Effect of including EEG alpha burst parameters</i>	275
5.7	Discussion and conclusion	280
Chapter 6		
Lifestyle and behavioural association to video indicators of drowsiness282		
6.1	Introduction:	282

6.2 Methods	283
6.2.1 <i>Life style Questionnaire</i>	284
6.2.2 <i>Profile of Mood States Questionnaire</i>	284
6.2.3 <i>The State Trait Anxiety Questionnaire</i>	286
6.2.4 <i>Control Efficacy</i>	286
6.2.5 <i>Fatigue Questionnaire</i>	286
6.2.6 <i>The fatigue state likert question</i>	287
6.3 Statistical analysis	288
6.4 Results	289
6.4.1 <i>Video observer rating of drowsiness versus lifestyle and psychological data</i> ...	294
6.5 Discussion and conclusions	295
6.5.1 <i>Lifestyle factors and drowsiness</i>	297
 Chapter 7	
Conclusions and future directions	299
7.1 Introduction	299
7.1.1 <i>Chapter 1</i>	300
7.1.2 <i>Chapter 2</i>	301
7.1.3 <i>Chapter 3</i>	301
7.1.4 <i>Chapter 4</i>	302
7.1.5 <i>Chapter 5</i>	304
7.1.6 <i>Chapter 6</i>	306
7.2 Future Directions	306
Appendix A: Consent Form	309
Appendix B: Simulator Track	311
Bibliography	312

List of Illustrations

Figure 1.1: EDVTS parts, the wrist watch, portable unit and the stationary unit. (J-S Co. NEUROCOM, Russia).....	23
Figure 1.2: The Fatigue Monitoring Unit of the AMP system (Advanced Brain Monitoring, USA).....	24
Figure 1.3: The fatigue monitoring panel (shown next steering wheel) (Australian Coal Association Research Programme (ACARP), Australia).....	26
Figure 1.4: ETS-PC Eye tracking system in a field trial (Applied Science Laboratories (ASL), UK).....	27
Figure 1.5: NOVAAlert personal wrist unit (Atlas Researchers Ltd (ARL), Israel).....	28
Figure 1.6: The Copilot camera and integrated DSP (Driving Research Center, USA).....	29
Figure 1.7: SafeTRAC System (left) Processing algorithm (right) (AssistWare, USA)	31
Figure 1.8: MINDS in laboratory settings (Advanced Safety Concepts, Inc. USA)	32
Figure 1.9: The Eyegaze System, the computer with video, the calculation procedure, infra-red view of the eye (LC Technologies, Inc., USA).....	34
Figure 1.10: A factory worker testing the SafetyScope System (Eye Dynamics, Inc., USA)	35
Figure 1.11: The two cameras associated with the FaceLAB system and the supporting the software (Seeing Machines, Australia)	37
Figure 1.12: The frame of the Optalert glasses that houses the data collection unit, the glasses are removed in this picture for a better view of the IR transceiver (Figure adapted from the Optalert website).	39
Figure 1.13: The setup of the Optalert system inside the vehicle, complete with the glasses and the vehicle system (Figure adapted from the Opalert website)	39

Figure 2.1: Electroencephalography (EEG) gold-plate cup electrodes (Grass Electrodes, Grass Technologies, Astro-Med, Inc., USA) 47

Figure 2.2: Ag/AgCl electrodes (Kendall-Meditrace, Tyco Healthcare, USA)..... 48

Figure 2.3: The 10/10 electrode placement system. Electrodes shown in black are the ones used in the current experiment. Adapted from (Oostenveld and Praamstra, 2001)..... 50

Figure 2.4: Electrooculography (EOG) electrode placement (Figure adapted from *Siesta User Guide*, 2003)..... 52

Figure 2.6: Placement of eyelid movement sensor (adapted from Respirationics (2004))..... 53

Figure 2.7: Piezoelectric film sensor (DT2-052K/L, Measurement Specialties, Inc, USA) 54

Figure 2.8: Strain gauge (Foil Strain Gauges, RS Components Pty Ltd, Australia) 54

Figure 2.9: Movement and Pressure Sensors Set-up 56

Figure 2.10: Position of the movement sensors on the seat and the steering wheel..... 57

Figure 2.11: The seat cover used to conceal the seat movement sensors. 57

Figure 2.12: Steering wheel cover used to conceal the steering wheel movement and pressure sensors..... 58

Figure 2.13: The enclosure of the amplifier box 59

Figure 2.14: The inner circuitry of the amplifier box..... 59

Figure 2.15: Video system setup..... 60

Figure 2.16: Kramer Video signal amplifier (Kramer Electronics, Israel)..... 61

Figure 2.17: Grand Magic Guard III (video signal multiplexer) (GrandTec, Taiwan) 61

Figure 2.18: Belkin USB Videobus capture card (Belkin, USA) 62

Figure 2.19: Four Images displayed from the Multiplex Video Signal. 62

Figure 2.20: Proxim Harmony OpenAir USB LAN (Proxim Wireless Corporation, USA).	65
Figure 2.21: NetBeacon Software (Compumedics, Australia)	68
Figure 2.22: Polysomnography (PSG) Online (Compumedics, Australia)	69
Figure 2.23: Profusion polysomnography (PSG) (Compumedics, Australia)	70
Figure 2.24: The simulator room and image viewed by the participants	73
Figure 2.25: The control room from where the investigator monitored the study and associated equipment.	74
Figure 3.1: The measurements from the seat sensor signals as the driver's body moves over the sensors (measures in volts). a) The raw seat sensor data has both positive and negative values. b) The same measurement as a) except that the absolute value of the measurements is taken. c) The seat movement signals after being processed by averaging the peak-to-peak values of movement sensors of 2-second intervals with an increment of 1 second.	78
Figure 3.2: The signal from one of the steering wheel movement sensors (piezoelectric sensors) for a given 100 seconds. a) Shows the raw steering wheel movement signal before the processing. b) The steering wheel signal after the processing stage, where the average of the peak-to-peak values over 1 second periods with 0.5 second increments were obtained.	80
Figure 3.3: The signal from one of the wheel pressure sensors (strain gauge) for a given 100 seconds. a) Shows the raw measurements from steering wheel pressure sensors; the signal has a DC offset of around 0.4 Volts, which increases the values by 0.4 Volts. b) The steering wheel signal after applying a low pass filter to the signal which removed the DC offset. c) The signal after the processing stage, where the minimum value averaged over 1 second periods with 1 second increments were obtained.	81
Figure 3.4: The EEG signal. a) Unfiltered EEG signal from the O2 (occipital) channel, b) Signal from the O2 after passing through a high pass filter. c) The reference	

signal A1 d) The signal O2 after the reference signal A1 was subtracted from it (O2 minus A1).....84

Figure 3.5: Examples of observer rating and PERCLOS estimates for two participants90

Figure 3.6: Observer ratings versus peak-to-peak values of movement signals on the seat. The first column displays the observer ratings versus the 5 movement sensors placed on the back section of the seat. The second column displays the observer ratings versus the signals from the movement sensors placed on the bottom section of the seat. In both columns (but more evident in the movement sensors on the back) there is a larger change in the signal from the movement sensors towards the end of the study thus corresponding to the drowsiness stage as indicated by the observer ratings.92

Figure 3.7: Observer ratings versus eye movement duration93

Figure 3.8: Observer rating versus alpha percentage.....93

Figure 3.9: Example of selection of episodes based on observer ratings for transition to drowsiness. The sections in red denote the transition to drowsiness episodes 96

Figure 3.10: Trajectories of piezofilm movement sensor signal of the first sensor in the back section of the seat for all the subjects..... 100

Figure 3.11: Logarithmic representation of the trajectories of piezofilm movement sensor signal for a given transition to drowsiness period for all the subjects 101

Figure 3.12: Scatter plot of normalised seat movement sensors across 11 time points..... 103

Figure 3.13: Scatter plot of normalised seat movement sensors across the 10 seat sensors 105

Figure 3.14: Estimated standard error as a function of 30-second intervals..... 107

Figure 3.15: Estimated autocorrelation matrix of the normalised seat movement signals across the 10 seat sensors 107

Figure 3.16: Trajectories of the reversed time course of the central EEG against the 10-second interval number for all the subjects..... 119

Figure 3.17: Trajectories of the reversed time course of the central EEG against the logarithm of the 10-second interval number for all the subjects.....	120
Figure 3.18: Predicted trajectories of the reversed time course of central EEG with and without logarithmic transformation of 10-second interval number for all the subjects.....	121
Figure 3.19: Means of regression residuals of central with and without transformation of 10-second interval number for all the subjects.....	121
Figure 3.20: Fitting binary logistic regression model for association between alpha band percentage for the central EEG derivation and odds of drowsiness.....	136
Figure 3.21: Receiver Operator Characteristic (ROC) curve for the parsimonious model with the central and occipital EEG sensor signals as parameters.....	142
Figure 3.22: Receiver Operator Characteristic (ROC) curve for the parsimonious model with the seat movement sensor signals as parameters.....	146
Figure 3.23: Receiver Operator Characteristic (ROC) curve for the parsimonious model with eye movement duration data as parameters.....	149
Figure 3.24: Receiver Operator Characteristic (ROC) curve for the parsimonious model with eye movement duration and seat movement data as parameters.....	150
Figure 3.25: Receiver Operator Characteristic (ROC) curve for the parsimonious model with EEG alpha percentage and seat movement data as parameters.....	153
Figure 3.26: Receiver Operator Characteristic (ROC) curve for the parsimonious model with EEG alpha percentage and eye movement duration data as parameters.....	155
Figure 3.27: Receiver Operator Characteristic (ROC) curve for the parsimonious model with EEG alpha percentage, eye movement duration and seat movement data as parameters.....	157
Figure 4.1: Strong association between observer ratings and alpha bursts	164
Figure 4.2: Weak association between observer ratings and alpha bursts. There are periods of significant drowsiness with little increase in alpha bursts	165

Figure 4.3: Weak association between observer ratings and alpha bursts, with a large number of waves in the alpha bursts but no corresponding high levels of drowsiness	166
Figure 4.4: An example of alpha burst EEG waveform. (a) 10 second EEG data recorded from a participant, which consists of two alpha burst waveforms. (b) A closer look at the section boxed in (a) showing the parameters of the alpha bursts..	169
Figure 4.5: Examples of alpha bursts from the C4 site that display the difference between alpha bursts that would produce different values of <i>Coeff(burst_smoothing_coefficient)</i> . a) shows an alpha burst that will be weighted very highly because it has a resemblance of a smooth alpha burst. b) shows an example of alpha burst that will be weighted low due to the sharp edges at its maximums and minimums	198
Figure 4.6: The time course of the drowsiness score from a participant. Three alert to drowsiness transition points are shown.	203
Figure 4.7: Effect of changing the reference length from 10 minutes to 15 minutes (parameters: wave count = 3, amplitude factor = off, noise factor = off, duration factor = off).	206
Figure 4.8: Effect of changing the reference length from 10 minutes to 15 minutes (parameters waves count = 6, amplitude factor = off, noise factor = off, duration factor = off)	207
Figure 4.9: Effect of changing the wave count on the outcome of the detection algorithm on the ROC curve, the spectral-based algorithm is also plotted here.	208
Figure 4.10: Effect of the amplitude parameter on the outcome of the EEG alpha bursts algorithm on the ROC curve. Section highlighted in (a) is magnified in (b)..	209
Figure 4.11: Effect of adding the noise parameter to the EEG alpha bursts algorithm on the ROC curve. (b) is a magnified section of the ROC curve in (a).	210
Figure 4.12: Effect of adding the period parameter to the EEG alpha bursts algorithm on the ROC curve. (b) is a magnified section of the ROC curve in (a).	211

Figure 4.13: Comparison of adding the parameters one at a time on the ROC curve. (b) is a magnified section of the ROC curve in (a).	212
Figure 4.14a) and b): The averaged alpha burst duration per minute from the alert period and pre-transition period for the central (C4) and the occipital sites (O2), respectively. * denotes a statistically significant difference between the numbers of alpha burst duration from the Alert period and from the Pre-transition period ($p < 0.05$).	214
Figure 4.15: Receiver operating characteristic (ROC) curves for alpha burst detection method and spectral analysis method.	215
Figure 4.16: Receiver operating characteristic (ROC) curves comparing changing parameter setting in alpha burst algorithm and spectral analysis. The rank number for displayed individual ROC curve was derived from the results of Table 4	215
Figure 5.1: Changes in the body movements reflect changes in observer-rated drowsiness levels.	224
Figure 5.2: Changes in the body movements is not reflected in the observer rated drowsiness	224
Figure 5.3: True positive drowsiness episode based on the EEG alpha burst algorithm. There is alpha burst in one of the EEG channels (C4) and minimal changes in the movement sensors on the back and bottom of the seat.	260
Figure 5.4: False positive based on the EEG alpha burst algorithm. The hybrid approach will help to improve the specificity of the algorithm. There are alpha bursts in data from both O2 and C4 EEG channels, but there is also much movement on the back and bottom seat sensors.	261
Figure 5.5: A small alpha burst episode is present in the C4 channel only (highlighted by the first grey bar). This would have been considered as a false negative based on the EEG alpha burst algorithm only. Whereas in the hybrid algorithm (EEG plus movement sensors) approach, this period would have been identified as a true positive (drowsiness) based on the reduction of activity shown in the movement sensors (highlighted by the second grey)	262

Figure 5.6: ROC from Hybrid EEG-Body movement vs. EEG-Only, (b) is a magnified section of the ROC curve in (a).....	270
Figure 5.7: The effect of varying the number of waves on the ROC curve.....	271
Figure 5.8: The effect of including the duration factor on the ROC curve. (a) is the entire ROC curve, (b) is a magnified section of the ROC curve in (a).	272
Figure 5.9: The effect of including the smoothing factor on the ROC curve. Section highlighted in (a) is magnified in (b)	273
Figure 5.10: The effect of including the amplitude factor on the ROC curve. Section highlighted in (a) is magnified in (b)	274
Figure 5.11: The effect of the factors on the graph. Section highlighted in (a) is magnified in (b).	275

List of Tables

Table 1.1:	Driver performance variables collected in a driver drowsiness study (Wierwille et al., 1996; Tijerina et al., 1999)	19
Table 1.2	A summary of some of the Drowsiness Detection System that were excluded in the study review by TRL Ltd and QinetiQ (Wright et al., 2007).....	40
Table 3.1:	Observer drowsiness scale based on the video analysis (modified from the Wierwille scale) (Wierwille and Ellsworth, 1994).....	87
Table 3.2:	Estimated autocorrelation matrix for normalised movement sensors across the same 11 time points (a matrix of autocorrelation coefficient)	104
Table 3.3:	Estimated autocorrelation matrix for normalised movement sensors across the 10 seat sensors for the same time points	106
Table 3.4:	Estimates of time course of the seat movement signals for different correlation models (asterisks relate to robust estimates of variance, values in brackets are for reduced dataset without non-random observations)	113
Table 3.5:	Estimates of correlation coefficients of the seat movement signals for different regression models and correlation assumptions	115
Table 3.6:	Estimates of time course of the seat movement signals for individual sensors and different correlation models.	117
Table 3.7:	Estimates of time course of the EEG alpha percentages for different EEG derivations and correlation models	122
Table 3.8:	Estimates of time course of the eye movement durations for different correlation models	124
Table 3.9:	Estimates of time courses of different EEG and seat movement signals for individual subjects (statistically significant positive associations highlighted, non-robust estimates for the GEE method marked with asterisks)	126
Table 3.10:	Estimates of time course of the piezofilm movement and strain gauge pressure sensors signals in the steering wheel for different correlation models	129

Table 3.11:	Estimates of time course of the eye movement durations measured with frontal EEG versus eyelid movement sensor for different correlation models.....	131
Table 3.12:	Univariate binary logistic regression for central and occipital EEG derivations as covariates and log odds of drowsiness outcome with different correlation assumptions	140
Table 3.13:	Parsimonious binary logistic regression models for central and occipital EEG derivations as covariates and log odds of drowsiness outcome with different correlation assumptions.....	141
Table 3.14:	Univariate binary logistic regression for a selected seat movement sensor as a covariate and log odds of drowsiness outcome with different correlation assumptions	143
Table 3.15:	Multivariate binary logistic regression for different combinations of seat movement sensor as covariates and log odds of drowsiness outcome with different correlation assumptions	144
Table 3.16:	Parsimonious binary logistic regression models for movement sensor as covariates and log odds of drowsiness outcome with different correlation assumptions	145
Table 3.17:	Univariate binary logistic regression for the most recent and preceding measures of eye movement durations as covariates and log odds of drowsiness outcome with different correlation assumptions	147
Table 3.18:	Parsimonious binary logistic regression models for eye movement duration data as parameters and log odds of drowsiness outcome	148
Table 3.19:	Parsimonious binary logistic regression models for a combination of eye movement duration and movement sensor signals as covariates and log odds of drowsiness outcome with different correlation assumptions	151
Table 3.20:	Parsimonious binary logistic regression models for a combination EEG alpha band percentages and movement sensor signals as covariates and log odds of drowsiness outcome with different correlation assumptions	152

Table 3.21:	Parsimonious binary logistic regression models for a combination of EEG alpha band percentages and eye movement durations as covariates and log odds of drowsiness outcome with different correlation assumptions	154
Table 3.22:	Parsimonious binary logistic regression models for a combination EEG alpha band percentages, eye movement durations and seat movement signals as covariates and log odds of drowsiness outcome with different correlation assumptions	156
Table 3.23:	Summary of parsimonious binary logistic regression models for different combinations of EEG alpha band percentages, eye movement durations and seat movement signals.....	158
Table 4.1:	Results of linear regression of the EEG channels O2, C4, and the combination of the two channels (C4 & O2) as predictors of average drowsiness based on the spectral method.....	177
Table 4.2:	Results of linear regression of the EEG channels O2, C4, and the combination of the two channels (C4 & O2) as predictors of average drowsiness based on the spectral method when correlation within individual subjects is taken into account	179
Table 4.3:	Results of linear regression of the EEG channels O2, C4, and the combination of the two channels (C4 & O2) as predictors of maximum drowsiness based on the spectral.....	181
Table 4.4:	Results of linear regression of the EEG channels O2, C4, and the combination of the two channels (C4 & O2) as predictors of maximum drowsiness based on the spectral method when correlation within individual subjects is taken into account	182
Table 4.5:	Comparison of the R^2 values for the different combinations of the alpha burst-based algorithm with wave count of 4 (the strongest association is bolded) .	184
Table 4.6:	Comparison of the R^2 values for the different combinations of the alpha burst-based algorithm with wave count of 6 (the strongest association is bolded) .	185

Table 4.7:	Comparison between the regression models of the adjusted average and the correlated alpha bursts values with wave count 4	187
Table 4.8:	Comparison between the significant variables of regression models of the average for the alpha burst-based algorithm with wave count of 4	189
Table 4.9:	Comparison between the regression models of the adjusted average and the correlated alpha bursts values with wave count 6	190
Table 4.10:	Comparison between the significant variables of regression models of the average for the alpha burst-based algorithm with wave count of 6	192
Table 4.11:	Results of changing the different parameter settings	216
Table 5.1:	Parameters of linear regression model for average and maximum drowsiness predicted from 10 body movement sensor signals located at the bottom and back section of the car seat.....	229
Table 5.2:	Parameters of linear regression model for average and maximum drowsiness predicted from body movement sensor signals at the bottom section of the car seat.....	232
Table 5.3:	Parameters of linear regression model for average and maximum drowsiness predicted from body movement sensor signals at the back section of the car seat.....	233
Table 5.4:	Parameters of parsimonious linear regression models for average and maximum drowsiness predicted from body movement sensor signals	235
Table 5.5:	Parameters of linear regression model for average and maximum drowsiness predicted from body movement sensor signals taking correlation into account	238
Table 5.6:	Parameters of parsimonious linear regression model for average and maximum drowsiness predicted from body movement sensor signals taking correlation into account	239

Table 5.7:	R^2 values for linear regression models for combinations of body movement sensors and different spectral EEG measures	244
Table 5.8:	Parameters of parsimonious linear regression model for average drowsiness predicted from a combination of the body movement sensor measurements and spectral EEG measures for cases when correlation between observations for the same subject is not taken into account and when correlation is taken into account	246
Table 5.9:	R^2 values for linear regression models for combinations of body movement sensors and alpha burst measures with wave count set to 4.....	249
Table 5.10:	Parameters of parsimonious linear regression model for average drowsiness predicted from a combination of the body movement sensor measurements and alpha burst measures for cases when correlation between observations for the same subject is not taken into account and when correlation is taken into account with wave count of at least 4 waves	251
Table 5.11:	R^2 values for linear regression models for combinations of body movement sensors and alpha burst measures with wave count set to 6.....	254
Table 5.12:	Parameters of parsimonious linear regression model for average drowsiness predicted from a combination of the body movement sensor measurements and alpha burst measures for cases when correlation between observations for the same subject is not taken into account and when correlation is taken into account with wave count of at least 6 waves	256
Table 5.13:	The ranking of the detection algorithms based on the Area Under the Curve value	277
Table 5.14:	Comparing performance between Hybrid and EEG-Only Algorithms and ranking based on the difference between the Hybrid and EEG-Only algorithms	279
Table 6.1:	Average scores for self-rated fatigue and psychological factors (values in bold are greater than the normative average)	290

Table 6.2:	Lifestyle factors data.....	292
Table 6.3:	Average scores for the video rated drowsiness variables	293
Table 6.4:	Multiple regression analysis of self-rated and psychological variables association with Drowsiness count	295

Glossary

Acronyms	Detailed
802.11	a set of standards for wireless networks
ABM	Advanced Brain Monitoring
ACARP	Australian Coal Association Research Programme
AFM	Advanced Fatigue Management
AMP	Alertness and Memory Profiler
ANOVA	analysis of variance
APSR	averaged power spectrum ratio
ARL	Atlas Researchers Ltd
ARRB	Australian Road Research Board
ASL	Applied Science Laboratories
AUC	area under the curve
B&W	Black & White
BFM	Basic Fatigue Management
BMI	body mass index
BP	Blood Pressure
C4	Central EEG measurements
CAM	Video camera
CRF	Fiat Research Centre
DARPA	Defense Advanced Research Projects Agency
DC	direct current
DFFT	discrete fast Fourier transform
DSP	Digital Signal Processing
ECG	electrocardiogram
ECU	Engine Control Unit
EDA	electrodermal activity
EDR	electrodermal response
EDVTCS	Engine Driver Vigilance Telemetric Control System
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
ESS	Epworth Sleepiness Scale
ETS	Eye tracking system
FFT	Fast Fourier Transform

Acronyms	Detailed
Fp1, Fp2	Frontal Polar EEG measurements
g	Grams
GB	Gigabyte
GEE	generalised estimating equations
GHz	Giga Hertz
HFLC	high-fat/low carbohydrates
HREC	Human Research Ethics Committee
Hz	Hertz
IrDA	Infrared Data Association
kg	Kilogram
LAN	local area network
LCB	Locus-of-control
LED	light emitting diodes
LFHC	low-fat/high carbohydrates
LOC	left outer canthus
MB	Megabyte
MBDAR	The maximum of the MBIARs of the 10 values
MBIAR	Maximum Body movement Increase Amplitude Ratio
MFMC	medium-fat/medium carbohydrates
mg	milligram
MINDS	MicroNod Detection system
ml	millilitre
MMBDAR	Maximum Body movement Decrease Amplitude Ratio
MMBIAR	The maximum of the MBIARs of the 10 values
MPEG4	Moving Picture Experts Group-4
MPSR	maximum power spectrum ratio
msec	milliseconds
MSLT	Multiple Sleep Latency Test
MUARC	Monash University Accident Research Centre
NCSDR	National Center on Sleep Disorders Research (USA)
NHTSA	National Highway Traffic Safety Administration (USA)
NREM	non rapid eye movement
NSW	New South Wales
NTC	National Transport Commission (Australia)
O2	Occipital EEG measurements

Acronyms	Detailed
PAL	Phase Alternating Line
PC	Personal Computer
PERCLOS	percentage of eyelid closure
POMS	Profile of Mood States
PS	Power Spectral
PSG	Polysomnography
RAM	Random-access memory
REM	Rapid Eye Movement
RF	radio frequency
RLL	Residual log-likelihood
ROC	right outer canthus
ROC	Relative Operating Characteristic
RPSR	relative frequency band power spectrum ratios
RTA	Road and Traffic Authority, NSW (Australia)
SAS	statistical analysis software
SD	Standard Deviation
SE	Standard Error
sec	Seconds
SEM	Slow Eye Movement
Sen	Sensitivity
Spec	Specificity
SSS	Stanford Sleepiness Scale
TAC	Transport Accident Commission, Victoria (Australia)
TBIAR	Test Body movement Increase Amplitude Ratio
UK	United Kingdom
US	United States
USA	United States of America
USB	Universal Serial Bus
USD	United States Dollar
UTS	University of Technology, Sydney
VAS	Visual Analogue Scale
VRTC	Vehicle Research & Test Center (USA)
Wi-Fi	Wireless LAN (Local Area Network)

Abstract

Fatigue is a major public health issue causing substantial emotional and financial burden on society. Driver fatigue is identified in nearly 20-30% of road fatalities, and can cost around AUD 3 billion per year. Providing drivers with early warning systems for fatigue could minimise fatigue-related road accidents. A car driving simulator study was conducted and physiological data such as electroencephalography (EEG), eye activity, movement sensor data, video and questionnaire information were obtained for the purposes of developing a drowsiness detection algorithm. The study was conducted at the Monash University Accident Research Centre (MUARC) where sixty non-professional drivers aged between 20-60 years were recruited. The study was conducted in the afternoon and the driving sessions lasted up to 3 hours of monotonous day and night driving scenarios with realistic scenery.

The preliminary analysis identified sections of data where clear episodes of drowsiness were evident. The analysis revealed that it was possible to detect drowsiness from a combination of physiological signals consisting of EEG, car seat movements and eye activity. Once the association between episodes of drowsiness and various signals were established, statistical analysis was performed on the entire data set. Two types of EEG processing were employed at this stage based on EEG alpha power and alpha burst analysis. A significant association was established between the probability of drowsiness and EEG alpha activity, with alpha burst duration resulting in a better association. Drowsiness detection algorithms based on these two methods were then developed.

The association established between drowsiness and the seat movement signals was far less than that between drowsiness and the alpha signals. The seat movement signals were then combined with both methods of alpha analysis. Adding seat movement signal to either of the two EEG methods resulted in improved associations with drowsiness with alpha burst association still being superior. The algorithm based on the combinations of alpha burst and seat movements formed the basis for the new hybrid algorithm.

Subjective measures of drowsiness, lifestyle and behaviour were also examined in this research and validated against video ratings of fatigue. It was shown that increased anxiety, anger and an unhealthy diet were associated with an increased probability of drowsiness.

The findings of this research can serve as a foundation for designing future vehicle-based fatigue countermeasure devices as well as highlight potential difficulties and limitations. Such driver fatigue studies will also benefit from further investigations of driver lifestyle and behavioural factors.