



Cairo University

AUTOMATIC DETECTION OF DRIVER DROWSINESS DURING SIMULATED DRIVING USING BRAINWAVES CHANGES AS INDICATOR

By

Ahmed Abdelhamid Mohamed Torki

A Thesis Submitted to the
Faculty of Engineering at Cairo University
In Partial Fulfillment of the
Requirements for the Degree of
DOCTOR OF PHILOSOPHY
In
Biomedical Engineering & Systems

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
GIZA, EGYPT
2018



Cairo University

AUTOMATIC DETECTION OF DRIVER DROWSINESS DURING SIMULATED DRIVING USING BRAINWAVES CHANGES AS INDICATOR

By

Ahmed Abdelhamid Mohamed Torki

A Thesis Submitted to the
Faculty of Engineering at Cairo University
In Partial Fulfillment of the
Requirements for the Degree of
DOCTOR OF PHILOSOPHY
In
Biomedical Engineering & Systems

Under the Supervision of

Prof. Dr.

Ayman M. Eldeib

Professor of Systems & Biomedical Engineering
Faculty of Engineering, Cairo University

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
GIZA, EGYPT
2018



Cairo University

AUTOMATIC DETECTION OF DRIVER DROWSINESS DURING SIMULATED DRIVING USING BRAINWAVES CHANGES AS INDICATOR

By

Ahmed Abdelhamid Mohamed Torki

A Thesis Submitted to the
Faculty of Engineering at Cairo University
In Partial Fulfillment of the
Requirements for the Degree of
DOCTOR OF PHILOSOPHY
In
Biomedical Engineering & Systems

Approved by the
Examining Committee

Prof. Dr. Ayman M. Eldeib

Main Thesis Advisor

Prof. Dr. Ahmed M. Albialy

Internal Examiner

Prof. Dr. Mohamed I. Aladawy

External Examiner

Faculty of Engineering, Helwan University

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
GIZA, EGYPT
2018

Engineer's Name: Ahmed Abdelhamid Mohamed Torki
Date of Birth: 02./10/1978
Nationality: Egyptian
E-mail: Engr.ahmed.torki@gmail.com
Phone: 01061178995.
Address: 17 Ramw Building-6th of October-Giza.
Registration Date: 01./10./2009..
Awarding Date:/....../2018
Degree: Doctor of Philosophy
Department: Biomedical Engineering & Systems



Supervisors:

Prof. Dr. Ayman M. Eldeib

Examiners:

Prof. Dr. Ayman M. Eldeib (Thesis Main Advisor)

Prof. Dr. Ahmed M. Albialy (Internal examiner)

Prof Dr. Mohamed I. Aladawy (External examiner)

Faculty of Engineering, Helwan University

Title of Thesis:

Automatic Detection of Driver Drowsiness During Simulated Driving Using Brainwaves Changes As Indicator

Key Words:

Driver drowsiness detection; Electroencephalogram; Simulated Driving

Summary:

Driver drowsiness contributes widely in vehicle accidents. Studies assessed drowsiness indicators at different driving setups. The first objective was to establish an experiment to obtain generic datasets of brainwaves epochs recorded by electroencephalogram (EEG) at forehead sites labeled with alertness and drowsiness for subjects using facial expressions recorded by videos. Subjects perform simulated driving for two hours after 6 PM. The second and third objective were to extract and select significant features that yield to highest classification accuracy between alert and drowsy using statistical and classification methods. The results showed the classification accuracy was 85.8 %.

Acknowledgments

I wish to express my deepest appreciation and sincere gratitude to Prof. Dr. Ayman M. Eldeib for his supervising and his great helpful advice and valuable guidance in this investigation.

The experiment was held in the rehabilitation laboratory in Systems and Biomedical Engineering department, Faculty of Engineering, Cairo University. The laboratory was partly funded by a grant from the Science and Technology Development Fund (STDF), Egypt.

I wish to express my deepest appreciation and sincere gratitude to Prof. Dr. Ahmed Badawy, Chairman of Systems and Biomedical Engineering Department for his support to overcome any obstacle to hold my experiment in the rehabilitation laboratory in Systems and Biomedical Engineering department, Faculty of Engineering, Cairo University.

My Deepest gratitude to Dr. Mona Foad Taher, Associate Prof. at Systems and Biomedical Engineering Department, Cairo University, for strong assistance throughout the experiment in the rehabilitation laboratory in Systems and Biomedical Engineering department, Faculty of Engineering, Cairo University.

My Deepest gratitude to Eng. Khaled Sayed, Eng. Yasen Khalifa, Eng. Mohamed Hisham and Eng. Mohamed El Bialy, teaching assistant at Systems and Biomedical Engineering Department, Cairo University, for their close guidance and strong assistance throughout the experiment.

My Deepest gratitude to Eng. Eman Magdy for support in the simulating software.

My Deepest gratitude to all subjects who accepted my invitation to perform the simulated driving task for their patience and positive attitude.

My Deepest gratitude to Eng. Ahmed Atef and Eng. Marwa Ahmed who accepted my invitation to be the two observers who assessed the video epochs for their time and efforts.

My Deepest gratitude to Prof. Dr. Sameera Ezzat who supported me a lot in statistical studies.

My Deepest gratitude to Prof. Dr. M.Hany Hussein and all my former directors for their continuous support and concern during the period of doctoral study.

Finally, I wish to thank all my family, friends, colleagues for their support and patience during all the period of the study.

Dedication

I wish to dedicate this thesis to my father and mother who raised me well and supported me all my life. Also I wish to dedicate it to all who believed in me my wife, son, sister, and my wife's parents and all my friends who supported me all over the years.

Publications

The following publications were achieved during the doctoral research

Torki, A.A. and ELDEIB, A.M., “Driver Drowsiness Detection Using Forehead Brain Signals”, Journal of Engineering And Applied Science, Vol. 63, No. 4, pp. 293 – 310, 2016.

Table of Contents

ACKNOWLEDGMENTS.....	I
DEDICATION	II
PUBLICATIONS.....	III
TABLE OF CONTENTS.....	IV
LIST OF TABLES.....	VI
LIST OF FIGURES.....	VIII
ABSTRACT	X
CHAPTER 1 : INTRODUCTION	1
1.1. INTRODUCTION	1
1.2. OBJECTIVE	1
1.3. ORGANIZATION OF THE THESIS	2
CHAPTER 2 : BACKGROUND AND LITERATURE REVIEW	3
2.1 INTRODUCTION	3
2.2 DRIVER DROWSINESS DETECTION	3
2.2.1 Driver Drowsiness Detection Overview	3
2.2.2 Driver Drowsiness Assessment using Subject's Behavior.....	8
2.2.3 Driver Drowsiness Detection using Brainwaves.....	9
2.2.4 Driver Drowsiness Detection using Brainwaves at Forehead.....	11
2.3 BACKGROUND.....	13
2.3.1 Electroencephalography (EEG)	13
2.3.1.1 Basics and Acquisition.....	13
2.3.1.2 The Mobile Electroencephalogram System	15
2.3.2 Simulated Driving Task using Open Driving Simulation (Open DS)....	16
2.3.3 Machine Learning	17
2.3.3.1 Discrete Wavelet Transformation	17
2.3.3.2 Power spectral density estimates using periodogram.....	18
2.3.3.3 Support Vector Machine	18
2.4 SUMMARY	22
CHAPTER 3 : METHODS.....	23
3.1. INTRODUCTION	23
3.2. BRAINWAVES AND DRIVING BEHAVIOR DATA ACQUISITION	23
3.2.1. Experiment Setup.....	24
3.2.2. Subjects Selection	25
3.2.3. Monotonous Driving Simulation Task.....	26
3.2.4. Subjects' Brainwaves EEG Recording.....	28
3.2.5. Subjects' driving behavior Video Recording	29
3.3. EEG SEGMENTATION AND LABELING	30
3.4. COMPARISON OF LABELED EEG EPOCHS DATASETS	38

3.5.	FEATURES EXTRACTION OF LABELED EEG EPOCHS DATA SETS.....	39
3.6.	REGRESSION ANALYSIS OF EXTRACTED FEATURES.....	44
3.7.	CLASSIFICATION OF EXTRACTED FEATURES	46
3.8.	SUMMARY	47
CHAPTER 4 : RESULTS		49
4.1	INTRODUCTION	49
4.2	PLOTS COMPARISON OF LABELLED EEG EPOCHS DATASETS	49
4.3	SIGNIFICANT FEATURES BY BINARY LOGISTIC REGRESSION.....	63
4.4	SINGLE AND COMBINED FEATURES CLASSIFICATION RESULTS.....	69
4.2.1.	Single Features Classification Test Results	69
4.2.2.	Combined Features in Groups Classification Test Results	77
4.5	SUMMARY	85
CHAPTER 5 : DISCUSSION AND CONCLUSIONS.....		87
5.1.	DISCUSSION	87
5.2.	CONCLUSION.....	91
5.3.	STUDY DRAWBACKS AND FUTURE WORK	92
REFERENCES		93

List of Tables

Table 2.1. The Mother wavelet families [55].	17
Table 3.1. The Main Data of the Included Subjects in the Experiment	26
Table 3.2. Illustration of Symptoms of Alertness and Drowsiness Levels	31
Table 3.3. Illustration of the Observers' Decisions and Their Count for Each Subject	33
Table 3.4. The Data Sets According To Labeling Postulates	37
Table 3.5. Statistical Features Extracted From EEG Signal Directly	39
Table 3.6. Statistical Features of Power Spectral Density (PSD)	39
Table 3.7. Features of Energies and Coefficients at different Levels Using Discrete Wavelet Transformation (DWT)	43
Table 3.8. Data Sets Used In Testing Single Features	46
Table 3.9. Data Sets Used In Testing Features in Groups	46
Table 4.1. The Indicators (Features) With Their Coefficients in the Forward Binary Logistic Model for the data set indexed "(1) Train" for "Group A"	64
Table 4.2. The Indicators (Features) With Their Coefficients in the Forward Binary Logistic Model for the data set indexed "(1) Train" for "Group B"	64
Table 4.3. The Indicators (Features) With Their Coefficients in the Forward Binary Logistic Model for the data set indexed "(3) Train" for "Group A"	65
Table 4.4. The Indicators (Features) With Their Coefficients in the Forward Binary Logistic Model for the data set indexed "(3) Train" for "Group B"	65
Table 4.5. The Indicators (Features) With Their Coefficients in the Forward Binary Logistic Model for the data set indexed "(4) Train" for "Group A"	66
Table 4.6. The Indicators (Features) With Their Coefficients in the Forward Binary Logistic Model for the data set indexed "(4) Train" for "Group B"	66
Table 4.7. The Indicators (Features) With Their Coefficients in the Forward Binary Logistic Model for the data set indexed "(6) Train" for "Group A"	67
Table 4.8. The Indicators (Features) With Their Coefficients in the Forward Binary Logistic Model for the data set indexed "(6) Train" for "Group B"	67
Table 4.9. Comparison between All the Models According To the Data Set and Group of Features	68
Table 4.10. The Three Highest Accuracies of Single Features at Delta Frequency Range Using DWT.	69
Table 4.11. The three highest accuracies of Single features at Theta frequency range using DWT.	70
Table 4.12. The three highest accuracies of Single features at Alpha frequency range using DWT.	71
Table 4.13. The three highest accuracies of Single features at Beta frequency range using DWT.	71
Table 4.14. The three highest accuracies of Single features ratios between different energies using DWT.	72
Table 4.15. The three highest accuracies of Single Features Statistical Features of EEG Signal.	73
Table 4.16. The three highest accuracies of Single features at Delta frequency range using PSD.	73
Table 4.17. The three highest accuracies of Single features at Theta frequency range using PSD.	74

Table 4.18. The three highest accuracies of Single features at Alpha frequency range using PSD.....	74
Table 4.19. The three highest accuracies of Single features at Beta frequency range using PSD.....	75
Table 4.20. The three highest accuracies of Single features ratios between different powers using PSD.	76
Table 4.21. The groups of Combined Features.	77
Table 4.22. The three highest accuracies of Combined Features for “(1) Train” and “(1) Test”.....	80
Table 4.23. The three highest accuracies of Group Features for “(1) Train” and “(2)”.	80
Table 4.24. The three highest accuracies of Group Features for “(3) Train” and “(1) Test”.....	81
Table 4.25. The three highest accuracies of Group Features for “(3) Train” and “(3) Test”.....	81
Table 4.26. The three highest accuracies of Group Features for “(4) Train” and “(4) Test”.....	82
Table 4.27. The three highest accuracies of Group Features for “(4) Train” and “(5)”.	83
Table 4.28. The three highest accuracies of Group Features for “(6) Train” and “(6) Test”.....	84
Table 4.29. Best Features’ Groups for Different Data Sets Interchanged in Training and Testing SVM Model.....	84
Table 5.1. The Main Difference between Previous Studies and the Presented Study....	90

List of Figures

Figure 1.1. Illustration of Forehead Positions Selected In This Study	1
Figure 2.1. Summary of European Road Safety Observatory Fatigue Report [1]	4
Figure 2.2. Sample of the Driving Simulator [4].....	5
Figure 2.3. Various Drowsiness Detection Techniques [6].....	6
Figure 2.4. Brain waves four basic groups [46]	13
Figure 2.5. Electrodes placement [46].....	14
Figure 2.6. EEGO Sport System [47]	15
Figure 2.7. Open DS simulated road [53].....	16
Figure 2.8. Linear SVM Classifier [57].....	19
Figure 2.9. The influence of Soft margin C value [57]	21
Figure 2.10. The influence of kernel parameters on decision boundary margin [57]	21
Figure 3.1. Experiment Setup	25
Figure 3.2. Sample of subject's approval on experiment consent.....	27
Figure 3.3. The Monitoring Impedance Dashboard of the EEG Recording System	28
Figure 3.4. The EEG recorded by eegosports (manufactured by ANT NEURO).	29
Figure 3.5. The Video Recording of Subject 1 with Very Sleepy Facial Symptoms.....	30
Figure 3.6. The Video Recording of Subject 6 with Different Facial Symptoms.	30
Figure 3.7. Sample of Assessment Sheet Filled By One of the Observers.	33
Figure 4.1. Comparison between 'Alert' (solid blue), 'Drowsy' (dash red), at Fp1, Data set "(1) Train", (a) Averaged Amplitudes, (b) Averaged PSD.	52
Figure 4.2. Comparison between 'Alert' (solid blue), 'Drowsy' (dash red), at Fp2, Data set "(1) Train", (a) Averaged Amplitudes, (b) Averaged PSD.	52
Figure 4.3. Comparison between 'Alert' (solid green), 'Drowsy' (dash black), at Fp1, Data set "(2)", (a) Averaged Amplitudes, (b) Averaged PSD.	53
Figure 4.4. Comparison between 'Alert' (solid green), 'Drowsy' (dash black), at Fp2, Data set "(2)", (a) Averaged Amplitudes, (b) Averaged PSD.	54
Figure 4.5. Comparison between 'Alert' (solid dark grey), 'Drowsy' (dash gold), at Fp1, Data set "(3) Train", (a) Averaged Amplitudes, (b) Averaged PSD.....	54
Figure 4.6. Comparison between 'Alert' (solid dark grey), 'Drowsy' (dash gold), at Fp2, Data set "(3) Train", (a) Averaged Amplitudes, (b) Averaged PSD.....	55
Figure 4.7. Comparison between 'Alert' (solid cyan), 'Drowsy' (dash magenta), at Fp1, Data set "(4) Train", (a) Averaged Amplitudes, (b) Averaged PSD.....	56
Figure 4.8. Comparison between 'Alert' (solid cyan), 'Drowsy' (dash magenta), at Fp2, Data set "(4) Train", (a) Averaged Amplitudes, (b) Averaged PSD.....	56
Figure 4.9. Comparison between 'Alert' (solid brown), 'Drowsy' (dash orange), at Fp1, Data set "(5)", (a) Averaged Amplitudes, (b) Averaged PSD.	57
Figure 4.10. Comparison between 'Alert' (solid brown), 'Drowsy' (dash orange), at Fp2, Data set "(5)", (a) Averaged Amplitudes, (b) Averaged PSD.	58
Figure 4.11. Comparison between 'Alert' (solid purple), 'Drowsy' (dash beach), at Fp1, Data set "(6) Train", (a) Averaged Amplitudes, (b) Averaged PSD.....	59
Figure 4.12. Comparison between 'Alert' (solid purple), 'Drowsy' (dash beach), at Fp2, Data set "(6) Train", (a) Averaged Amplitudes, (b) Averaged PSD.....	59
Figure 4.13. Comparison between 'Drowsy "(1) Train" ' (dash red), 'Alert "(2)"' (solid green), 'Alert "(3) Train"' (solid dark grey), at Fp1, (a) Averaged Amplitudes, (b) Averaged PSD.....	60

Figure 4.14. Comparison between ‘Drowsy “(1) Train” ’ (dash red), ‘Alert “(2)”’ (solid green), ‘Alert “(3) Train”’ (solid dark grey), at Fp2, (a) Averaged Amplitudes, (b) Averaged PSD.....	61
Figure 4.15. Comparison between ‘Drowsy “(4) Train” ’ (dash magenta), ‘Alert “(5)”’ (solid brown), ‘Alert “(6) Train”’ (solid purple), at Fp1, (a) Averaged Amplitudes, (b) Averaged PSD.....	62
Figure 4.16. Comparison between ‘Drowsy “(4) Train” ’ (dash magenta), ‘Alert “(5)”’ (solid brown), ‘Alert “(6) Train”’ (solid purple), at Fp2, (a) Averaged Amplitudes, (b) Averaged PSD.....	62

Abstract

Driver drowsiness contributes widely in the increase of possibility of vehicle accidents. Many studies assessed drowsiness indicators at different driving setups. Brainwaves recorded at different head sites resulted in better accuracies. The detection of drowsiness after normal working day with normal sleep habits was the main scope of this study.

The first objective was to establish an experiment that can obtain a dataset of recorded brainwaves recorded at forehead sites (Fp1 and Fp2 with Fpz reference) and labeled with alertness and drowsiness states by assessing video recordings of subjects' behavior especially facial expressions. Forehead sites facilitates future practical implementation of drowsiness detection system. These recordings was achieved for subjects undergoing simulated monotonous driving task for two hours after 6 PM. Brainwaves were recorded via electroencephalogram (EEG) mobile system and facial expressions were recorded simultaneously using video webcam. Recorded data for all subjects were segmented into non overlapping five seconds epochs. Each epoch of EEG signals was labelled as alert or drowsy in accordance to subject's facial symptoms in video records. The comparison of labeled brainwaves datasets was performed to test the changes in EEG signal between the alertness and drowsiness states. Features were extracted out of EEG signals recorded at forehead sites by discrete wavelet decomposition and periodogram. The second objective was to model the features using statistical regression model to predict drowsiness state according to significant features. The selected model according to data was binary logistic regression model to predict the probability of drowsiness states according to the significant features. The third objective was to build drowsiness detection algorithm using support vector machine classifier.

The recommended data set and extracted features to build the drowsiness detection algorithm were selected according to the binary logistic regression and classification of combined features results. The recommended training data set was epochs labeled Alert without any accompanied movement head or sitting posture change and epochs labeled Drowsy with slightly drowsy to extremely drowsy without any accompanied movement head or sitting posture change. The recommended combined features group consists of energy of Alpha, energy of Beta and standard deviation of Level 4 detail coefficients (Beta range) for Fp1 and Fp2. These features were extracted using discrete wavelet transformation with mother wavelet Daubechies 6 (db6). This yielded to classification accuracy was 85.8 %. This accuracy was achieved from Support vector machine classifier setup was Gaussian radial basis function kernel (scaling factor equal 0.2). The results are very promising to use Fp1 and Fp2 EEG signals. This accuracy in comparison to other researchers' studies was satisfying. Many reasons can contribute in this variance of accuracy, the driving task setup, preparation of subject for driving, vigilance states labeling, and signal preprocessing.

Chapter 1 : Introduction

1.1. Introduction

Drowsiness of drivers has been observed as one of the most contributing factors in vehicle accidents in many countries. Drowsiness detection and alerting the driver were the scope of many researches since years to minimize the number of accidents. Detecting or predicting drowsiness is not a straight forward issue. Drowsiness symptoms can be confusing. Many researchers tested and examined many indicators to build detection or prediction systems. This study worked on forehead brainwaves as indicator to build drowsiness detection algorithm. The drowsiness detection system focuses on the driving after 6 PM normal working hours.

1.2. Objective

The first objective was to establish an experiment that can obtain generic datasets of non-overlapping five seconds epochs brainwaves at forehead sites (Fp1 and Fp2 with Fpz reference) labeled with alertness and drowsiness states for subjects undergoing simulated monotonous driving task for two hours after 6 PM. The brainwaves were recorded using electroencephalogram (EEG). Forehead sites facilitates future practical implementation of drowsiness detection system. Figure 1.1 showed an illustration of the selected forehead sites for brainwaves recording in this study. The labeling was done by assessing facial expression and observing sitting posture by two observers. The facial expression and sitting posture were recorded by video simultaneously with the EEG recordings.

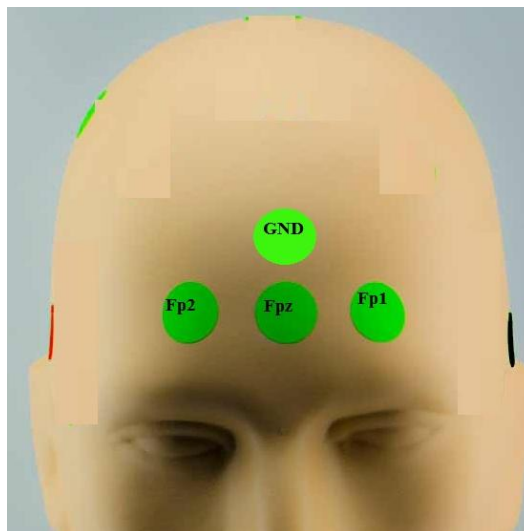


Figure 1.1. Illustration of Forehead Positions Selected In This Study