PHYSIOLOGICAL SIGNAL BASED DETECTION OF DRIVER HYPOVIGILANCE USING HIGHER ORDER SPECTRA

by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
ANOVA	-	Analysis of Variance
ANS	-	Autonomous Nervous System
APS	-	Average Pupil Size
aVF	-	Augmented Voltage Foot
aVL	-	Augmented Voltage Left Arm
aVR	-	Augmented Voltage Right Arm
BD	-	Blink Duration
BR	-	Blink Rate
C	-	Center
CCD	-	Charge Coupled Device
CD	-	Cognitive Distraction
CMN	-	Common Mode Noise
DWT	-	Discrete Wavelet Transform
DVR	-	Deutscher Verkehrssicherheitsrat.eV
ECG	-	Electrocardiogram
EEG	-	Electroencephalogram
EMG	-	Electromyogram
EoG	-	Electrooculogram
ESCAP	-	Economic and Social Commission for Asia and the Pacific
FFT	-	Fast Fourier Transform

HASTE	-	Human Machine Interface And the Safety of Traffic in Europe
HF	-	High Frequency
HMM	-	Hidden Markov Model
HOS	-	Higher Order Statistical
HR	-	Heart Rate
HRV	-	Heart Rate Variability
IR	-	Infra Red
IVIS	-	In Vehicle Information System
kNN	-	k Nearest Neighbor
KSS	-	Karolinska Sleepiness Scale
LA	-	Left Arm
LDA	-	Linear Discriminant Analysis
LCD	-	Liquid Crystal Display
LED	-	Light Emitting Diode
LF	-	Low Frequency
LL	-	Left Leg
MIROS	-	Malaysian Institute of Road Safety
NHTSA	-	National Highway Traffic Safety Administration
NREM	-	Non Rapid Eye Movement
NSF	-	National Sleep Foundation
PCA	-	Principal Component Analysis
PERCLOS	-	Percentage Eye CLOSure
PRC	-	Percentage Road Centre
PSD	-	Power Spectral Density

QDA	-	Quadratic Discriminant Analysis
RA	-	Right Arm
REM	-	Rapid Eye Movement
RL	-	Right Leg
ROI	-	Region Of Interest
RRI	-	R-R Interval
RT	-	Reaction Time
SA	-	Sinoatrial Node
SC	-	Skin Conductance
SD	-	Standard Deviation
SDLP	-	Standard Deviation of Lane Position
SE	-	Steering Error
SEM	-	Slow Eye Movement
sEMG	-	Surface Electromyogram
SMS	-	Short Message Service
ST	-	Skin Temperature
SVM	-	Support Vector Machine
SWM	-	Steering Wheel Movement
TORCS	-	The Open Racing Car Simulator
ULF	-	Ultra Low Frequency
UNESCAP	-	United Nations Economic and Social Commission for Asia and the Pacific
VD	-	Visual Distraction
VLF	-	Very Low Frequency

VLP	-	Variation of Lane Position
WHO	-	World Health Organisation

Pengesanan Berasaskan Isyarat Fisiologi Untuk Hipo-Kewaspadaan Pemandu Menggunakan Spektrum Tertib Lebih Tinggi

ABSTRAK

Dalam tahun-tahun kebelakangan ini, hipo-kewaspadaan melibatkan pemandu yang mengantuk dan pemandu yang lalai adalah salah satu punca utama kemalangan jalan raya dan boleh menyebabkan kecederaan fizikal yang teruk, kematian dan kerugian ekonomi yang signifikan. Statistik menunjukan terdapatnya satu keperluan sistem pengesanan hipo-kewaspadaan pemandu dengan kebolehpercayaan tinggi yang dapat memberi amaran kepada pemandu sebelum sesuatu kejadian yang tidak diingini yang berlaku. Kajian sebelum ini hanya melaporkan tentang pengesan sama ada berkaitan dengan kemengantuk atau kelalaian. Dalam karya ini, kami berhasrat untuk membangunkan suatu sistem yang boleh mengesan hipo-kewaspadaan, yang melibatkan kedua-dua kemengantuk dan kelalaian, menggunakan isyarat Elektrokardiogram (ECG) dan Electromyogram (EMG). Penyelidik telah mencubaan untuk menentukan kemengantuk pemandu atau pemandu yang tidak memberi tumpuan menggunakan ukuran-ukuran berikuti: (1) ukuran-ukuran subjektif, (2) ukuran-ukuran berasaskan kenderaan, (3) ukuran-ukuran tingkah laku dan (4) ukuran-ukuran fisiologi. Satu kajian terperinci mengenai ukuran-ukuran ini berkenaan sensor yang digunakan, kelebihan dan kekurangannya pada setiap ukuran diberikan. Cara-cara yang berbeza di mana kemengantuk dan kelalaian telah dimanipulasikan secara eksperimen juga dibincangkan. Isyarat ECG dan EMG adalah kurang intrusif berbanding dengan isyarat fisiologi yang lain dan memberikan keadaan sebenar pemandu.Kemengantuk telah dimanipulasi dengan membenarkan pemandu untuk memandu pada kelajuan yang terhad dan membosankan untuk tempoh yang lama dan kelalaian telah dimanipulasi dengan meminta pemandu untuk berintraksi terhadap panggilan telefon dan khidmat pesanan ringkas. Sejumlah 15 subjek lelaki mengambil bahagian dalam proses pengumpulan data. Mereka memandu selama dua jam dalam persekitaran simulasi, pada tiga sela masa yang berlainan (00:00 - 02:00 jam, 3:00-5:00 jam dan 15:00 - 17:00 jam) iaitu apabila irama sirkadian mereka adalah rendah. ECG, EMG dan video telah dirakam pada keseluruhan eksperimen. Isyarat fisiologi yang diperolehi ini telah dipraproseskan untuk mengeluarkan hinggar dan artifak yang tidak diingini. Ciri-ciri hipo-kewaspadaan disari daripada isyarat praproses menggunakan ciri-ciri statistik konvensional, statistik tertib lebih tinggi dan spektrum tertib lebih tinggi. Perbezaan statistik yang signifikan dapat diperhatikan antara keadaan-keadaan kewaspada, kemengatukkan dan kelalaian pada kedua-dua isyarat fisiologi. Ciri-ciri yang telah diklasifikasikan menggunakan k nearest neighbor, analisis diskriminan linear dan analisis diskriminan kuadratik. Ciri-ciri tenaga isyarat ECG memberikan ketepatan maksimum 93,35%. Ciri-ciri dwispektrum memberikan ketepatan maksimum keseluruhan 96.75% dan 92.31% untuk isyarat ECG dan EMG masing-masing menggunakan validasi k fold. ECG dan EMG isyarat telah digabungkan dengan menggunakan analisis komponen utama untuk mendapatkan ciri-ciri pengabungan optimum dan ketepatan klasifikasi adalah 96%. Dalam kes kemengantukkan, pemandu perlu disedarkan pada masanya. Oleh itu, pelbagai peringkat kemengantukkan dikelaskan dengan ketepatan keseluruhan 71%. Menyedarkan pemandu pada peringkat awal kemengantukkan dapat mengurangkan kemalangan. Pada masa hadapan, prestasi sistem pengesanan hipo-kewaspadaan boleh dipertingkatkan dengan penggabungan ukuran-ukuran fisiologi dengan ukuran-ukuran berasaskan imej dari video dan ukuran-ukuran berasaskan kenderaan. Kami menyimpulkan bahawa dengan merekabentuk suatu sistem hibrid pengesanan kemengantukkan yang menggabungkan ukuran-ukuran fisiologi yang tidak intrusif dengan ukuran-ukuran lain dapat menentukan tahap kemengantukkan pemandu secara tepat. Banyak kemalangan jalan raya boleh dielakkan jika amaran dihantar kepada pemandu apabila dia dianggap mengantuk.

Physiological Signal Based Detection of Driver Hypovigilance using Higher Order Spectra

ABSTRACT

In recent years, driver hypovigilance which includes driver drowsiness and driver inattention is one of the major causes of road accidents and can lead to severe physical injuries, deaths and significant economic losses. Reliable driver hypovigilance detection system which could alert the driver before a mishap happens would ensure less road accidents. Previous research works have reported only on detecting either drowsiness or inattention. In this work, the focus is on developing a system that can detect hypovigilance, which includes both drowsiness and inattention, using Electrocardiogram (ECG) and Electromyogram (EMG) signals. Researchers have attempted to determine driver drowsiness or driver inattention using the following measures: (1) subjective measures, (2) vehicle-based measures, (3) behavioral measures and (4) physiological measures. A detailed review on these measures as to the sensors used, advantages and limitations associated with each measure is provided. The different ways in which drowsiness and inattention has been experimentally manipulated is also discussed. ECG and EMG signals are less intrusive as compared to other physiological signals and provide true state of the driver. Drowsiness has been manipulated by allowing the driver to drive monotonously at a limited speed for long hours and inattention was manipulated by asking the driver to respond to phone calls and short messaging services. A total of 15 male subjects participated in the data collection process and drove for two hours in a simulated environment, at three different times of the day (00:00 – 02:00 hours, 03:00 – 05:00 hours and 15:00 – 17:00 hours) when their circadian rhythm is low. ECG and EMG signals along with the video recording have been collected throughout the experiment. The gathered physiological signals were preprocessed to remove noise and artifacts. The hypovigilance features were extracted from the preprocessed signals using conventional statistical, higher order statistical and higher order spectral features. Statistically significant differences were observed between the alert, drowsy and inattentive states in both the physiological signals. The features were classified using k nearest neighbor, linear discriminant analysis and quadratic discriminant analysis. The energy feature of ECG signals gave a maximum accuracy of 93.35 %. The bispectral features gave an overall maximum accuracy of 96.75 % and 92.31 % for ECG and EMG signals respectively using k fold validation. The features of ECG and EMG signals were fused using principal component analysis to obtain the optimally combined features and the classification accuracy was 96%. In case of drowsiness, the driver has to be alerted on time. Hence, the different stages of drowsiness were classified with an overall accuracy of 71 %. Alerting the driver during initial stage of drowsiness would minimize accidents. In the future, the performance of hypovigilance detection system can be enhanced my merging these physiological measures with behavioral measures and vehicle based measures. A hybrid drowsiness detection system that combines non-intrusive physiological measures with other measures would accurately determine the drowsiness level of a driver. A number of road accidents can be avoided if an alert is sent to a driver who is drowsy or inattentive.

CHAPTER 1

INTRODUCTION

1.1 Background

According to available statistical data, over 1.3 million people die each year on the road and 20 to 50 million people suffer non-fatal injuries due to road accidents (WHO, 2009). Based on police reports, the US National Highway Traffic Safety Administration (NHTSA) conservatively estimated that a total of 100000 vehicle crashes each year are the direct result of driver drowsiness. These crashes have resulted in approximately 1550 deaths, 71000 injuries and $12.5 billion in monetary losses (Rau, 2005). In the year 2009, the US National Sleep Foundation (NSF) reported that 54% of adult drivers have driven a vehicle while feeling drowsy and 28% of them actually fell asleep (NSF, 2010). The German Road Safety Council (DVR) claims that one in four highway traffic fatalities are a result of momentary driver drowsiness (Fraunhofer-Gesellschaft, 2010). These statistics suggest that driver drowsiness is one of the main concerns worldwide that need to be addressed.

Similar to driver drowsiness, statistics of driver inattention reveals the seriousness of the need for driver hypovigilance system. In the year 2008, NHTSA estimated 5870 deaths, 350,000 injuries and 745,000 property damages due to driver distraction (NHTSA, 2009). In US alone, damages of $43 billion per year have been estimated due to cell phone related crashes (Cohen & Graham, 2003). A naturalistic driving study found that 78% of crashes and 65% of near-crashes included inattention as a major contributing factor (Klauer et al., 2006). According to United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP), around 1 million deaths, 23 million injuries and 10 million vehicles are exposed to the road accidents in ESCAP region per year. They conclude that more than 85% of the causalities due to road accidents are from the developing countries (UNESCAP, 2009).

Road accidents have become one of the top ten major factors of deaths in Malaysia. In the year 2008, the Royal Malaysian Police reported that, traffic accidents in Malaysia have been increasing at the average rate of 9.7% per annum over the last three decades (Abdullah & Zamri, 2010). Malaysian Institute of Road Safety (MIROS) in its statistics has found that in the year 2008, the country has recorded losses of RM 7.8 billion due to road accidents (Bernama, 2010). Driver hypovigilance, being one of the most prevalent reasons for road accident, needs to be addressed in order to prevent accidents and to ensure safe travel. The symptoms of driver hypovigilance have to be detected early enough and the driver has to be alerted accordingly, to avert an accident.

1.2 Problem statement and its significance

This thesis addresses the problem of driver hypovigilance (driver drowsiness and driver inattention) using physiological signals. Researchers have attempted to determine driver hypovigilance using the following measures:

1. Vehicle-based measures - A number of metrics, depending on vehicle movements, are constantly monitored while driving. This includes deviations from lane position, movement of the steering wheel, pressure on the acceleration pedal, etc. Any change in metrics that crosses a specified threshold indicates a significantly increased probability that the driver is drowsy or inattentive (Forsman et al., 2012; C. C. Liu et al., 2009).
2. Behavioral measures - The behavior of the driver such as yawning, eye closure, eye blinking, head pose, etc., is monitored through a camera and the driver is alerted if any hypovigilance symptoms are detected (Xiao et al., 2009; Yin et al., 2009; Zhang & Zhang, 2010).
3. Physiological measures - The correlation between physiological signals and driver hypovigilance has been studied by many researchers using signals such as electrocardiogram (ECG), electromyogram (EMG), electrooculogram (EoG) and electroencephalogram (EEG) (Akin et al., 2008; Guosheng et al., 2010; Khushaba et al., 2011; Kokonozi et al., 2008; W. Liang et al., 2009).

Each of these methods used for detecting hypovigilance has its own advantages and limitations. Vehicle-based measures are useful in measuring drowsiness when a lack of vigilance affects vehicle control or deviation. However, researchers have identified cases where there is no impact on vehicle-based parameters when the driver were drowsy (Ingre et al., 2006). This makes a vehicle-based drowsiness detection system unreliable. Behavioral measures are an efficient way to detect drowsiness and some real-time products have been developed (Lawrence Barr et al., 2009). However, when evaluating the available real-time detection systems, Lawrence et al. observed that different illumination conditions affect the reliability and accuracy of the measurements (Lawrence Barr, et al., 2009). Physiological measures are reliable and accurate because they provide the true internal state of the driver. However attaching sensors to the body is intrusive. To reduce the intrusiveness, lesser number of sensors has to be used. Among all physiological parameters investigated, ECG and EMG can be measured using lesser number of sensors. EEG signals require 8 to 64 electrodes to be placed on the scalp which is intrusive. Similarly the electrodes used for measuring EoG signals are placed near the eye which can hinder driving. Non-obtrusive physiological sensors such as wearable sensors are expected to become feasible in the near future (B.-G. Lee & Chung, 2012; Sloten et al., 2009). The advantages of physiological measures and the increasing availability of non-intrusive measurement equipment paves way to explore the possibility of discriminating drowsy, inattentive and alert states from less intrusive physiological signals.

1.3 Research philosophy

In this thesis a few issues pertaining to hypovigilance has been addressed: First, it has to be understood if ECG and sEMG signals are reliable to detect hypovigilance. If the first hypothesis is true, the second goal is to probe into the signal and identify features that are indicative of hypovigilance. In real time applications, the symptoms of hypovigilance need to be detected to alert the driver on time before any tragedy or accident happens. Hence the next goal is to understand the different stages of hypovigilance from ECG signals. Using only one physiological signal may tend to provide unreliable results. Merging two signals may help the system to perform better.

So the final goal is to fuse the features of ECG and sEMG signals and observe if there is significant difference in the classification accuracy.

1.4 Research objectives

Our thesis focusses on detecting hypovigilance which includes both drowsiness and inattention using ECG and EMG signals. The objectives are explained below:

Objective 1: ***To develop a database of physiological signals (ECG & EMG) for driver hypovigilance research***

To develop an efficient hypovigilance detection system, reliable data is needed. Capturing spontaneous hypovigilance, especially drowsiness behavior is a challenging and laborious task because the driver has to be made sleepy. Researchers have observed that driver drowsiness mainly depends on the circadian rhythm (time of day) when the vigilance level is low (00:00 – 02:00 hrs; 03:00 – 05:00 hrs and 15:00 – 17:00 hrs) and the increase in the duration of the driving task (Ingre, et al., 2006; Kokonozi, et al., 2008; Vitaterna et al., 2001). It was also observed that, the possibility of getting drowsy is lesser during the other times of the day.

Hence for this work, a hypovigilance database comprising ECG signals, sEMG signals and video recording during drowsiness and inattention was created. This is mainly done because of the lack of dataset for the research community currently. The most challenging task in getting reliable data is to make the subjects fall asleep while driving. It is not safe to make drivers fall asleep on wheels due to safety reasons. So in this experiment, the subjects were asked to drive for two hours in a simulated environment during the three different times of the day when they tend to fall asleep. The simulated environment was replicated to that of a real world environment. A unique dataset of ECG, sEMG signals and video recording are collected from 15 male subjects during driving in alert, inattentive and drowsy conditions.

Objective 2: ***To classify the hypovigilance states of the driver from the ECG and EMG signals using statistical, higher order statistical and higher order spectral features***

Most of the research on drowsiness and inattention has focused mainly on behavioral techniques or vehicle based techniques and commercial products have been developed (Lexus, 2011; Mercedes-Benz, 2009). However vehicle based measures can function reliably only at particular environments and they depend too much on external factors like road marking, climatic and lighting conditions. Moreover it is highly subjective, as it varies from person to person. Although the behavioral method is not intrusive and will not cause annoyance to drivers, the hypovigilance detection is not so accurate, which gets severely affected by the environmental backgrounds, driving conditions, and driver activities. In addition, this approach requires the camera to focus on a relative small area around the eye. It also requires relative precise camera focus adjustment for every driver (X. Yu, 2009b). False alerts are also possible to a great extent, which will annoy the driver.

The reliability and accuracy of driver hypovigilance detection by using physiological signals is very high compared to other methods as the true state of the driver can be known. However, the intrusive nature of measuring physiological signals