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Hypovigilance detection using energy of electrocardiogram signals

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Driver drowsiness and driver inattention are the major causes for road accidents leading to severe traumas such as physical injuries, deaths, and economic losses. This necessitates the need for a system that can alert the driver on time, whenever he is drowsy or inattentive. Previous research works report the detection of either drowsiness or inattention. In this work, we aim to develop a system that can detect hypovigilance, which includes both drowsiness and inattention, using Electrocardiogram (ECG) signals. Fifteen male volunteers participated in the data collection experiment where they were asked to drive for two hours at 3 different times of the day (00:00 – 02:00 hrs, 03:00 – 05:00 hrs and 15:00 – 17:00 hrs) when the circadian rhythm is low. The results indicate that the energy feature of ECG is efficient to detect hypovigilance with a maximum accuracy of 98%. The two types of inattention namely visual and cognitive are also analyzed in this work.

Keywords: hypovigilance, electrocardiogram, signals, NSF

Introduction

According to the statistics released by the World Health Organisation more than 1.2 million people die each year on the world's roads, and between 20 and 50 million suffer non-fatal injuries due to road accidents[1]. The National Highway Traffic Safety Administration (NHTSA), USA conservatively estimated 100000 police reports on vehicle crashes each year which were the direct results of driver drowsiness. Such accidents also result in approximately 1550 deaths, 71000 injuries and $12.5 billion in monetary losses [2]. The National Sleep Foundation (NSF) reported that in 2009, 54% of adult drivers had driven a vehicle while feeling drowsy and 28% had actually fallen asleep[3]. Driver inattention includes concentrating on secondary tasks like using cell phone, music player, etc while driving. In the year 2008, NHTSA estimated 5870 deaths, 350,000 injuries and 745,000 property damages due to driver distraction (NHTSA's National Centre for Statistics and Analysis, America, 2009 report) In US alone, damages of $43 billion per year has been estimated due to cell phone related crashes [4]. A naturalistic driving study found that 78% of crashes and 65% of near-crashes included inattention as a contributing factor [5]. According to the 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 their region per year. They also conclude that more than 85% of the causalities due to road accidents are from the developing countries [6]. All these statistics convey that driver hypovigilance, which includes both driver drowsiness and driver inattention is one of the main factors for road accidents throughout the world. Most of these accidents can be avoided, if the drowsy or distracted driver is alerted on time. This requires an efficient hypovigilance detection system that can detect both drowsiness and inattention to be developed.

Definition

The term 'Hypovigilance' is derived from two words 'Hypo' & 'Vigilance'. 'Hypo' originates from a Greek word meaning 'diminished' and 'vigilance' means 'alertness'. So, 'hypovigilance' together means 'diminished alertness,' and can be defined as anything that causes a decrease in paying a close and continuous attention. Impairment of alertness in a driver may be due to prolonged sleepiness or short term inattention. It may lead the driver to lose control of the vehicle which in turn can lead to accidents like crashing of the vehicle onto other vehicles or stationary surroundings. In order to prevent these devastating incidents, the state of the driver should be continuously monitored. There is no much difference between inattention and distraction. According to Hedlund et al. "Distraction involves a diversion of attention from driving, because the driver is temporarily focusing on an object, person, task, or event not related to driving, which in turn reduces the

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Table 1—Measures of drowsiness or inattention

References	Measures	Parameters	Advantages	Limitations
10,14,45-47	Vehicle based measures	• Deviation from the lane position • Deterioration in acceleration pressure • Loss of control over the steering wheel movements	Nonintrusive	Unreliable
12-14,46	Behavioral Measures	• Yawning • Eye closure • Eye blink • Head pose	Non intrusive; Ease of use	Lighting condition; Background
23,27,34,48	Physiological measures	Statistical & energy features derived from • ECG • EoG • EEG	Reliable; Accurate	Intrusive

awareness, decision-making, and/or performance of the driver, leading to an increased risk of corrective actions, near-crashes, or crashes” [7]. Since distractions may not produce immediate consequences, it would be better if a driver who is distracted is alerted on time. Researchers have mainly dealt with two types of distraction namely: cognitive distraction (e.g., talking in the cell phone) and visual distraction (eg. Texting a sms) [8-11]

Measures

In general any one of the following measures has been used for measuring either drowsiness or distraction as shown in Table 1.

The behavior of the driver, including yawning, eye closure, eye blinking, head pose, etc., is monitored through a camera and the driver is alerted if any of the drowsiness or inattention symptoms are detected [12-14]. Vision-based measures are an efficient way to detect hypovigilance and some real-time products have been developed such as Seeing Machines [15] and Lexus [16]. 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 [17]. Vehicle based measures are useful to measure hypovigilance when the driver’s lack of vigilance has an effect on vehicle control or deviation. However, in some cases there is no impact on vehicle based parameters even if the driver was drowsy [18]. This makes vehicle based drowsiness detection system unreliable.

Though intrusive, physiological signal based measures are reliable and accurate as they provide the true internal state of the driver. Electrooculogram (EoG) signal measures the electric potential difference between the cornea and the retina by generating an electrical field in context to the orientation of the eyes [19-22]. Researchers have used EoG to track the eye movement, which is then used to detect drowsiness or inattention. Electroencephalogram (EEG) signal has various frequency bands such as the delta band (0.5–4 Hz) corresponding to the sleep activity, the theta band (4–8 Hz) related to drowsiness, the alpha band (8–13 Hz) corresponding to relaxation and creativity, and the beta band (13–25 Hz) corresponding to activity and alertness [23,24]. Inattention is related to Beta band and drowsiness is related to theta band. Many researchers have extracted features from these bands and have classified drowsiness or inattention[23-26]. Heart rate and Heart Rate Variability (HRV) signals that are derived from Electrocardiogram (ECG) signals, is also found to vary significantly during the different states of the driver such as alertness, drowsiness and inattentiveness [10,27-29].

Among the physiological parameters such as EEG, EOG and ECG, ECG can be measured in a less intrusive manner. The EEG signals require a large number of electrodes to be placed on the scalp of the driver and the electrodes for measuring EoG signal have to be placed near the eye which can hinder vision when driving. Several researchers have used non intrusive means to measure ECG by placing electrodes in the steering wheel [30] or on the driver’s seat [31] (Yu X, University of Minnesota, Duluth report 2009, Personal Communications). By considering the advantages of physiological measures over the other measures and the availability of non

Fig 1—Our experimental setup

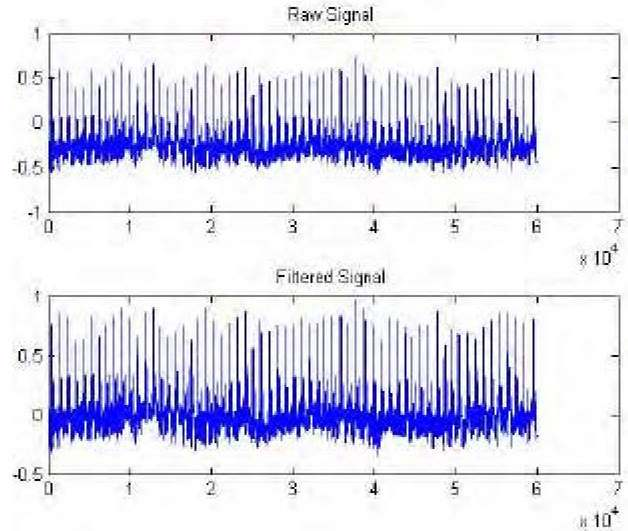

Fig 2—Raw signal and Preprocessed signal

Table 2—Protocol of our system

Driving	SMS (Have to respond) + Driving	Driving	Questions via cell phone + Driving	Driving
	Q1 Q2 Q3 Q4		Q1 Q2 Q3 Q4	
15	5	5	5	90

intrusive measurement modalities, ECG signals are chosen to detect hypovigilance in this work.

Most of the researchers have worked on HRV signals that are derived from ECG and analyzed features such as RR Interval (RRI) to detect driver drowsiness or inattention [26,28,32-34]. Also by extracting and analysing the Low-Frequency (LF) (0.04Hz - 0.15Hz) and High-Frequency (HF) (0.15Hz - 0.45Hz) components, they have found the ratio of the LF to HF to decrease progressively as driver moves from alert to drowsy state [35,36]. Researchers have also observed the heart rate (HR) to vary significantly during the different states such as inattention and drowsiness [10,27,37].

In this experiment, both drowsiness and distraction have been traced from ECG signals to check if there is significant difference between these states.

Materials and Methods

Protocol

Driver drowsiness mainly depends on the: (i) the quality of the last sleep, (ii) the circadian rhythm (time of day) and (iii) the increase in the duration of driving task [18,27,38]. Hence, the protocol was designed to take data during three different times of the day (00:00 – 02:00 hrs, 03:00 – 05:00 hrs and 15:00 – 17:00 hrs). The lighting conditions in laboratory were also simulated accordingly. A simulator game, TORCS, was used to enable driving and the maximum speed was set to 70 km/hr in order to create a monotonous environment [39]. The protocol used to obtain the data for normal, drowsy, cognitive distraction and visual distraction states in the driver is as shown in Table 2. The first 15 minutes were dedicated for normal driving. Then to stimulate visual distraction, the subjects were asked to reply the four text messages that were sent during the next five minutes, with questions related to their hobby. At the 25th minute a phone call was made to the driver and they had to respond to the arithmetic questions asked to them. This helped to simulate cognitive distraction. Then to simulate drowsiness, the subjects were asked to drive for an hour and half without any disturbance.

Subjects and Experimental setup

The experimental set up is as shown in Fig 1. A driving simulator was used to enable driving. Electrodes were placed in the arms and legs to measure ECG data. Power Lab Data Acquisition System, AD Instruments, Australia was used to collect the ECG data at a sampling frequency of 1000 Hz. The video of the subjects face while driving was also recorded for the entire 2 hour session using an IR camera (30 fps). 15 male volunteers in the age group of 23 to 32 years with a mean age of 25.6 participated in

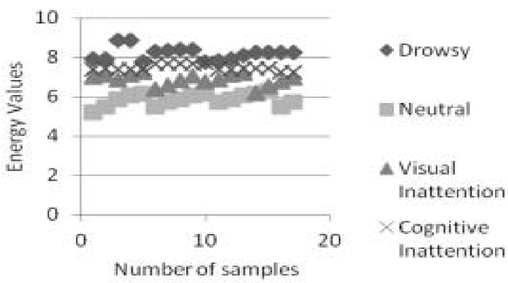

Fig 3a-03:00 – 05:00 hrs

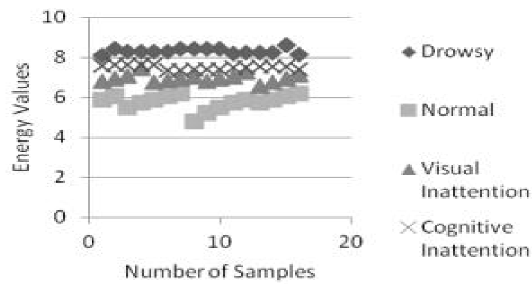

Fig 3b-15:00 – 17:00 hrs

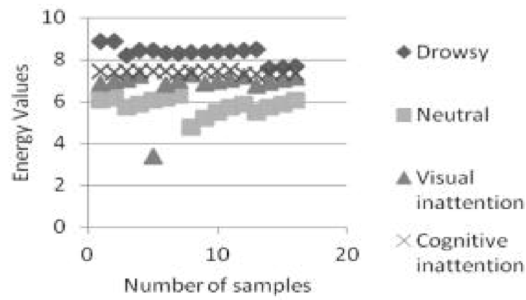

Fig 3c-00:00 – 02:00 hrs

Fig 3—Energy features derived for drowsy, neutral, visual and cognitive inattention during different times of day

the experiment. The recordings were performed after obtaining a written consent from the subjects.

Data Analysis

The ECG signals obtained during driving are highly prone to movement artifacts and removing these artifacts is one of the biggest challenges in data analysis. To remove these noises, the signal was normalized by subtracting mean value from original data and then filtering using Butterworth 6^{th} order filter [26]. The raw signal and the filtered signal are shown in Fig 2.

The energy of the filtered signal is obtained from equation (1).

$$\text{Energy} = \sum_{i=1}^{n} x_i^2 \qquad \ldots(1)$$

where x is the ECG samples and n is the total number of samples

The energy features were trained and classified using the Quadratic Discriminant Analysis (QDA) [40-42] and k-nearest neighbor (kNN) [40,43,44] classifiers. In both the cases, 70% of data is used for training, while the remaining 30% for testing.

Results and Discussions

The distribution of energy features for normal, drowsy, visual distraction and cognitive distraction states during different times of the day is shown in Fig 3. We can see a clear demarcation between drowsy, visual distraction, cognitive distraction and normal states. It can also be observed that the plots are consistent despite of variation in time of day. Also, from the figure, we can observe that during drowsiness, the energy levels vary from 7 to 9. This wide range of variation provides an avenue to investigate on the levels of drowsiness (highly drowsy, drowsy, and slightly drowsy). The energy features obtained during the various states of the driver were used to classify the drowsiness and inattentiveness using QDA and KNN classifiers.

Table 3—Classification: drowsy and normal

Classifier	Drowsy	Normal
QDA	100	97.91667
knn(1)	100	97.91667
knn(2)	100	97.91667
knn(3)	100	97.91667

Table 4—Classification: inattention and normal

Classifier	Inattentive	Normal
QDA	89.58333	97.91667
knn(1)	95.83333	100
knn(2)	95.83333	100
knn(3)	93.75	97.91667

Table 3 shows the results for classifying the drowsy and normal state of the driver. The classification of drowsiness is 100% for both QDA and KNN. However, the classification accuracy is 97.9% for normal state.

Table 5—Classification: Drowsy, Inattention and normal

Classifier	Drowsy	Inattention	Normal
QDA	96.20253	89.5833333	97.91667
knn(1)	96.20253	85.4166667	97.91667
knn(2)	97.46835	89.5833333	97.91667
knn(3)	98.73418	89.5833333	97.91667

These improved results indicate that an efficient non intrusive drowsiness detection system can be developed by extracting only energy features from ECG. Fig 3 also indicates a wide distinction between drowsy and non drowsy data.

The classification accuracies of inattentive and normal states of a driver is shown in table 4. The results indicate that this system can also detect inattention efficiently. The accuracy is 96% for inattention and 100% for normal data. Hence, from tables 3 and 4, we can find that ECG signal is an efficient tool to classify both drowsiness and inattention.

The performance of a hypovigilance system, which could detect both drowsiness and inattention from normal driving, is shown in Table 5. We get an accuracy of 98.7 % for drowsy, 89.5 % for inattention and 97.9 % for normal. In order to understand the characteristics of energy on inattention, the types of inattention – cognitive and visual was further investigated. The results of classifying the four states: drowsy, normal, visual inattention and cognitive inattention is as shown in Table 6. The maximum accuracy for the four states is 86%, 97.7 %, 84.2 % and 89.5 % respectively. These higher accuracy rates indicate that the energy features of the ECG signals are highly efficient in determining the hypovigilance in a driver.

Conclusion

Monitoring driver behavior is a much needed factor for safe driving as driver drowsiness and driver inattention are the major causes for road accidents. Though researchers have probed into either drowsiness or inattention, not one of them has worked on a universal system to detect both drowsiness and inattention. In this work, hypovigilance has been successfully detected using ECG signals. We have also worked specifically on different types of inattention (Visual and Cognitive). The energy feature of the heart signal has been classified into the various states such as drowsy, normal, visual inattention and cognitive inattention successfully with accuracy ranging between 84% and 98%. Based on the research study a non intrusive system to detect the levels of drowsiness and alert the driver can be worked out.

Table 6—Classification: Drowsy, Normal, Visual Inattention and Cognitive Inattention

Classifier	Drowsy	Normal	Visual	Cognitive
QDA	82.27848	97.91667	84.21053	87.5
knn(1)	86.07595	97.91667	78.94737	64.58333
knn(2)	83.5443	97.91667	84.21053	87.5
knn(3)	84.81013	97.91667	84.21053	89.58333

The ECG measure can also be fused with other measures such as behavioral measure for better detection.

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