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Physiological signal based detection of driver hypovigilance using higher order spectra

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ABSTRACT

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. 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. 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 higher order spectral features. The features were classified using k Nearest Neighbor, Linear Discriminant Analysis and Quadratic Discriminant Analysis. 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%. A number of road accidents can be avoided if an alert is sent to a driver who is drowsy or inattentive.

1. Introduction

According to available statistical data, over 1.3 million people die each year on the road and 20–50 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 100,000 vehicle crashes each year are the direct result of driver drowsiness. These crashes have resulted in approximately 1550 deaths, 71,000 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 fall 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, Dingus, Neale, Sudweeks, & Ramsey, 2006).

The term 'hypovigilance' is derived from two words 'hypo' and 'vigilance'. The word 'hypo' originates from the Greek language meaning 'diminished' and 'vigilance' means 'alertness'. So, 'hypovigilance' together means 'diminished alertness', and can be defined as anything that causes a decrease in paying close and continuous attention. Impairment of alertness in a driver may be due to prolonged sleepiness (drowsiness) or short term inattention (distraction) which includes cognitive and visual 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 monitored.

One of the challenges in developing an efficient hypovigilance detection system using physiological signals is to obtain proper drowsiness as well as inattentive data. Due to safety reasons, drowsiness cannot be manipulated in a real environment; thus, the drowsiness detection system has to be developed and tested in a laboratory setting. However, in a laboratory setting, the most reliable and informative data that pertains to driver drowsiness relies only on the way in which the driver falls into the drowsy state. Driver drowsiness mainly

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depends on (i) the quality of the last sleep, (ii) the circadian rhythm (time of day) and (iii) the increase in the duration of the driving task (Ingre, ÅKerstedt, Peters, Anund, & Kecklund, 2006; Kokonozi, Michail, Chouvarda, & Maglaveras, 2008; Vitaterna, Takahashi, & Turek, 2001). Researchers observed that there is a very high probability of a partially sleep-deprived driver to become drowsy when driving in a monotonous environment at a constant speed for 2 h during a time when their circadian rhythm is low. To manipulate cognitive distraction the drivers were asked to attend a call while driving and they were asked to answer basic, logical, simple mathematics and ambiguous questions. If the answer given by the driver was wrong then the questions were would be asked again (Avinash, Dvijesh, & Ioannis, 2010; Harbluk, Noy, Trbovich, & Eizenman, 2007). Visual distraction was manipulated by asking the drivers to respond to a text message on their mobile phone (Avinash et al., 2010). Researchers have attempted to determine driver hypovigilance using behavioral measures (Xiao, Bao-cai, & Yan-feng, 2009; Yin, Fan, & Sun, 2009; Zhang & Zhang, 2010), vehicle based measures (Forsman, Vila, Short, Mott, & Van Dongen, 2012; Liu, Hosking, & Lenné, 2009) or physiological measures (Akin, Kurt, Sezgin, & Bayram, 2008; Chuang, Huang, Ko, & Lin, 2015; Guosheng, Yingzi, & Prabir, 2010; Khushaba, Kodagoda, Lal, & Dissanayake, 2011; Kokonozi et al., 2008; Liang, Yuan, Sun, & Lin, 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 8–64 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 to measure ECG are expected to become feasible in the near future (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.

Only a few works have been carried out for detecting hypovigilance using ECG signals. Researchers have observed that the heart rate (HR) derived from ECG signals varies significantly during the drowsy state (Kokonozi et al., 2008). Heart Rate Variability (HRV) signals that are derived from Electrocardiogram (ECG) signals are also found to vary significantly during the alertness and drowsiness states of the driver (Kokonozi et al., 2008; Michail, Kokonozi, Chouvarda, & Maglaveras, 2008; Sloten et al., 2009) and is a passive means to quantify drowsiness (Mulder, 1992; Patel, Lal, Kavanagh, & Rossiter, 2011). The frequency domain spectral analysis of HRV shows that typical HRV in human has four frequency bands: high frequency band (HF) that lies in 0.15–0.4 Hz, low frequency band (LF) in 0.04–0.15 Hz, very low frequency (VLF) in 0.0033–0.04 Hz and ultra-low frequency in 0.0–0.0033 Hz (Camm et al., 1996; O'Hanlon, 1972). The ratio of LF to HF in HRV decreased progressively as driver moved from alert to drowsy state (Guosheng et al., 2010; Östlund et al., 2004). A number of HRV analyses during sleep suggest that the sleep frequency of HRV lies in the region of 0.05–0.15 Hz (Camm et al., 1996). In a recent experiment, the state of the subject (drowsy, fatigue or normal) was analyzed using 23 meaningful fuzzy rules which was framed based on the HRV signals (Malcangi, 2015). In an experiment conducted by Miyaji, Kawanaka, and Oguri (2009), the heart rate increased by 8 beats/min and the average value of heart rate RRI decreased significantly during cognitive distraction. Kawakita, Itoh, and Oguri (2010) also observed an increase in the heart rate when mental workload was added to driving. In a field experiment to detect visual and cognitive inattention, inter-beat intervals of the heart decreased significantly when the driver was distracted (Engström, Johansson, & Östlund, 2005). In another experiment, Yu, Sun, and Zhang (2011) observed that there was significant difference in the entropy of ECG signals with and without distraction. These suggest that the entropy of ECG signals either in time domain or in frequency domain is potential and significant metrics in measuring driver distraction.

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

Min

Fig. 1. Protocol of the system.

The surface electromyography (sEMG) is a non-invasive index of the level of muscle activation (De Luca, 1984). In recent years, more attention is focused on the analysis of EMG signals during sleep because of known aberrations during REM. Researchers have also attempted to quantify muscle activity from sEMG during sleep (Fairley, Georgoulas, Mehta, Gray, & Bliwise, 2012; Ferri et al., 2008). However, very few works have been done in the context of driver drowsiness. The muscle activity during simulated driving showed significant difference between 1st minute and 15th minute of driving (Balasubramanian & Adalarasu, 2007). sEMG was captured from trapezius and deltoid muscles during monotonous car driving and muscle fatigue was analyzed by Hostens and Ramon (2005). Researchers have investigated and proved that the sEMG variables of left biceps, right biceps, left forearm flexor, right forearm flexor and frontal muscles are valid and reliable indicators of muscular fatigue (Katsis, Ntouvas, Bafas, & Fotiadis, 2004). They recommended that analysis has to be made on different groups of muscles (i.e. latissimus dorsi, gluteus maximus, deltoid, and trapezius) to further verify whether the proposed metrics provide useful information about the fatigue level. Though sEMG has not been studied in the context of drowsiness, it would be significant to analyze the pattern of muscle fatigue during drowsiness. Akin et al. (2008) observed the success rate to be higher when using a combination of EEG and EMG signals as compared to using either one of signal in detecting drowsiness. This also indicates that sEMG can be used along with other physiological signals to enhance the performance of the system (Hu & Zheng, 2009; Kurt, Sezgin, Akin, Kirbas, & Bayram, 2009). Researchers have also found that thinking or cognitive work activates sEMG (Malmo & Malmo, 2000; Whitham et al., 2008). However, so far no research work has been done to correlate inattention and driving in the context of sEMG signals.

Drowsy, inattentive and normal ECG and sEMG data is collected from the subjects. Based on the video recording the data is split accordingly. The acquired ECG and sEMG signals are preprocessed by using various digital filtering methods to reduce the effects of noises and other interferences and the features are extracted from the processed signal by using higher order spectral techniques. The extracted features are then classified into three categories namely drowsy, inattentive (cognitive and visual) or normal, using Linear Discriminant Analysis (LDA) and k Nearest Neighbor (KNN) classifiers. The features from sEMG signals and the ECG signals are fused together using principal component analysis (PCA) to check if the accuracy of the combined signal is better than a signal analyzed alone.

2. Materials and methods

2.1. Protocol

A schematic diagram of the protocol used in this work to obtain normal, drowsy, cognitive distraction and visual distraction data is shown in Fig. 1. The entire protocol was scheduled to last for 2 h. In the first 15 min, normal signals were obtained from the subjects, as they were only driving without any distraction. Then in order to

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