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Original Research Article

A physiological measures-based method for detecting inattention in drivers using machine learning approach

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ABSTRACT

Background: In recent years, as a result of the usage of electronic gadgets in vehicles, driver inattention has become one of the major causes of road accidents that lead to severe physical injuries, deaths and significant economic losses. Statistics ensure the need of a reliable driver inattention detection system that can alert the driver before a mishap happens.
Methods: In this work, we aimed to develop a system that can detect inattention using electrocardiogram (ECG) and surface electromyogram (sEMG) signals. Cognitive and visual inattention was manipulated by asking the driver to respond to phone calls and short messaging services, respectively. A total of 15 male subjects participated in the data collection process. The subjects were asked to drive for two hours in a simulated environment at three different times of the day. ECG, sEMG and video were obtained throughout the experiment. The gathered physiological signals were preprocessed to remove noises and artefacts. The inattention features were extracted from the preprocessed signals using conventional statistical, higher-order statistical and higher-order spectral features. The features were classified using *k*-nearest neighbour analysis, linear discriminant analysis and quadratic discriminant analysis.
Results: The bispectral features gave overall maximum accuracies of 98.12% and 90.97% for the ECG and EMG signals, respectively.
Conclusion: We conclude that ECG and EMG signals can be explored further to develop a robust and reliable inattention detection system.

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1. Introduction

In the year 2008, NHTSA (National Highway Traffic Safety Administration) estimated 5870 deaths, 350,000 injuries and 745,000 property damages due to driver distraction [1]. In the US alone, $43 billion per year in damages has been estimated to be due to cell phone-related crashes [2]. A naturalistic driving study found that 78% of crashes and 65% of near-crashes included inattention as a major contributing factor [3]. According to the United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP), approximately 1 million deaths, 23 million injuries and 10 million vehicles are exposed to road accidents in the ESCAP region each year. The commission concluded that more than 85% of the causalities due to road accidents occur in developing countries [4]. Driver inattention is one of the most prevalent reasons for road accidents and it needs to be addressed to prevent accidents and ensure safe travel. 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 reduces the driver's awareness, decision-making, and/or performance, leading to an increased risk of corrective actions, near-crashes, or crashes'' [5].

Because distractions need not produce immediate consequences, it would be ideal if a driver who is distracted is alerted on time. The researchers have noted that the sources of distraction may take four forms, namely visual distraction (e.g., looking away from the roadway), auditory distraction (e.g., responding to a ringing cell phone), biomechanical distraction (e.g., manually adjusting the radio volume), and cognitive distraction (e.g., being lost in thought) [1,6]. The driver usually engages with more than one of the above-mentioned components and thereby gets distracted while driving (e.g., visually searching for a control to manipulate). Most of the researchers have mainly dealt with cognitive distraction and visual distraction as the primary concern because the remaining types of distraction fall under these two broad components. To detect inattention on time, these two categories have to be understood, and based on our understanding of this process, a distraction detection protocol has to be developed.

To manipulate cognitive inattention, Harbluk et al. asked mental arithmetic questions, such as single-digit addition (easy task) and double-digit addition (difficult task), through a mobile phone, and the participants responded to the tasks through the mobile phone in the hands-free mode. The participants were asked to drive in a road with heavy traffic for 8 km while performing the following three tasks: easy task, difficult task and no task. The level of inattention of the participant was calculated through an eye tracker and by the way in which the brakes where applied [7]. In another experiment conducted by Itoh, the skin temperature was measured as a driver performed arithmetic tasks while driving [8]. Avinash et al. manipulated cognitive distraction by asking the driver to attend to a call while driving, and the subjects were asked to answer a pre-recorded set o f questions presented in two modules. One was a combination of basic, logical and simple mathematics, and the other set comprised ambiguous questions. If the driver answered incorrectly, the questions were asked again [9]. To manipulate visual distraction, the drivers were asked to visually see a touch screen placed in front of them and were asked to press the moving circle on the screen. Driver inattention was monitored by tracking the lane changes and eye movements [10]. In another experiment, visual distraction was monitored by asking the drivers to respond to a text message on their mobile phone. The researchers found an increase in the skin temperature (ST) of the participants when they were distracted [9].

When a driver is distracted, the vehicle may or may not leave the lane. Hence, it is not advisable to detect distraction based only on vehicle-based measures. Additionally, detection using vehicle measures and behavioural measures may occur too late to prevent accidents. To avoid this problem, researchers have used physiological signals, such as the heart rate, EEG and skin conductance, to detect inattention [11–13]. The power spectrum of the beta band of the EEG signal has been found to increase as the driver becomes inattentive [13]. Because of the intrusiveness of EEG, researchers have attempted to use ECG signals. The heart rate is easily determined through the electrocardiogram (ECG) signal and is used for detecting the in attention of a driver [14]. The heart rate increases due to acceleration of the sympathetic nerve when a driver is imposed with cognitive tasks while driving [15,16]. When a driver is in a state of cognitive distraction, the effects of conversation, thinking, or other factors in addition to driving has a significant impact on the heart rate and thereby decrease the R–R interval [11]. The surface EMG (sEMG) is a non-invasive index of the level of muscle activation [17]. Thinking or cognitive work activates the sEMG [18,19]. Because physiological signals can identify the actual attention state of a driver, they are reliable for detecting inattentiveness.

In our experiment, visual and cognitive inattention is identified using video recordings and ECG and sEMG data, which are split accordingly. The raw data are prone to artefacts and are thus preprocessed accordingly. The conventional statistical, higher-order statistical (HOS) and higher-order spectral features are extracted from the ECG and sEMG signals and are classified using the LDA, QDA and kNN classifiers. The accuracy suggests that the bispectral features contain information pertinent to the inattentiveness of drivers.

2. Materials and methods

2.1. Protocol

The simulator game TORCS, which is an open source tool for research purposes, was used to enable driving. A monotonous environment was created by setting the maximum driving speed to 70 km/h [20]. A schematic diagram of the protocol used in this work to obtain normal, drowsy, cognitive distraction and visual distraction data are shown in Fig. 1. The entire protocol was scheduled to last 2 h. During the first 15 min, normal signals were obtained from the subjects because they were driving without any distractions during this time. Then, to stimulate visual distraction, the subjects were asked to reply to four text messages that were sent during the next five minutes with questions related to their hobbies and general interests, such as food and sports. Cognitive distraction was stimulated by placing