Various Approaches to Driver Fatigue Detection: A Review

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Abstract – **Drowsy driving is considered one of the most serious causes of fatal traffic accidents, especially for long distance drivers who struggle significantly during monotonous driving conditions. As a result, various types of warning systems have been proposed among other preventive measure against drowsy driving. These systems issue a warning upon detecting a decline in driving performance as indicated by a significant lane departure or fluctuation in headway distance, or upon detecting unsafe driver behavior such as prolonged eye closure time, or increased head sway, among other signs. Because these systems usually detect such behavior after drivers have already become drowsy, they may not provide sufficient active safety performance, and may not contribute significantly in decreasing related fatalities. Therefore, there is a need to pursue alternative ways for an earlier detection of drowsy driving. The main contribution of this work is the development of a new method for appropriate prediction of drowsy driving. The proposed method combines different approach… e.g. seismocardiography, adaptive driver's model etc.**

Keywords – Biosignals, driver, fatigue detection, adaptive control, steering wheel.

I. Introduction

In recent years, driver drowsiness and distraction have been important factors in a large number of accidents because they reduce driver perception level and decision making capability, which negatively affect the ability to control the vehicle. One way to reduce these kinds of accidents would be through monitoring driver and driving behavior and alerting the driver when they are drowsy or in a distracted state. In addition, if it were possible to predict unsafe driving behavior in advance, this would also contribute to safe driving. In this paper, we will discuss various monitoring methods for driver and driving behavior as well as for predicting unsafe driving behaviors. In respect to measurement methods of driver drowsiness, we discussed *visual and non-visual features of driver behavior*, as well as driving performance behaviors related to vehicle-based features. Visual feature measurements such as eye related measurements, yawning detection, facial expression are discussed in detail. As for non-visual features, we explore various physiological signals and possible drowsiness detection methods that use these signals. As for vehicle-based features, we describe steering wheel movement and the standard deviation of lateral position. To detect driver distraction, we describe head pose and gaze direction methods. To predict unsafe driving behavior, we explain predicting methods based on facial expressions and car dynamics. For a driver monitoring system, two issues such as driver fatigue measurement and distraction detection should be solved. Usually, driver fatigue or drowsiness may be related with symptoms including eye movement, facial expression, heart and breathing rate, and brain activity [1]. To detect driver drowsiness, visual features such as eye movement and facial expression are very important. Yawning measurement is also good indicator of a driver's drowsiness [2]. As non-visual features, heart rate variability (HRV), galvanic skin response (GSR) and conductivity, steering-wheel grip pressure, and body temperature are possible candidates for estimating the driver's fatigue level indirectly [2]. Electroencephalogram (EEG) and Electro-oculogram (EoG) give additional psychophysiological information about drowsiness or emotional reactions [3]. Driving behavior information such as steering wheel movement, lane keeping, acceleration pedal movement and braking, etc., should also be considered to detect driver drowsiness.

By carefully monitoring driver and driving performance behavior, it is possible to predict minor and major accidents. In particular, the progress of pervasive computing technology with integrated sensors and networking has made it possible to build an ideal platform to predict accidents.

The organization of this paper is as follows: Section 2 discusses driver drowsiness estimation and method and sensor for drowsiness detection, section 3 describes electromagnetic compatibility in vehicle while the driver model approach is described in section 4.

II. Drowsiness Estimation

The word "drowsy" simply refers to an inclination to fall asleep. A drowsy driver who falls asleep at the wheel can be characterized by diminished alertness compared to a normal state. Sometimes a driver experiences sleep for a few seconds and may not even realize it. This is called micro-sleep. The duration of micro-sleep can last between a few seconds and as

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long as 30 seconds or even more. This is sufficient time to drift out from one's traffic lane and crash into a tree or another car. Therefore, the driver's drowsiness state, in which a transition occurs from awake to asleep, should be monitored. To detect the drowsiness level of the driver, we have to extract *driver behavior* information as well as *driving behavior* information.

Detection of drowsiness level based on driver behavior information uses two types of features – visual and non-visual.

A. *Visual features*

There are many visual features which correspond with drowsiness or tiredness level of driver. These features can be divided to three main groups which correspond with parts of faces which are inspected.

The first and most common group of visual features utilizes typical behavior of eyes during drowsiness and falling asleep. The method are based on measuring e.g. eye blinking frequency, degree of eyelid opening/closing, speed of eyelid or detection of gaze direction [4].

The second group of visual features focuses on detection of specific head pose or movements. Usually the methods detect head nodding which is terminated by waking head jerks.

The last group observes the facial expression esp. mouth movement and it is known as yawning detection [5].

B. *Non-visual features*

Non-visual features or physiological signals such as heart rate and brain activity are useful in predicting drowsiness, with fewer false positives compared to visual features because the determination of a drowsy state from visual features can be possible only after the driver is well on the way to sleep. In other words, the prediction of drowsiness based on these physiological signals makes it possible to warn a drowsy driver in a timely manner. Electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), electro-oculogram (EoG), and Photoplethysmography (PPG) may all be used as physiological signals [6, 7]. The properties of some biomedical signals are shown in Tab. I.

Driving behavior information includes deviations from lane position, vehicle speed, steering movement, pressure on the acceleration pedal, etc. [8].

TABLE I. PROPERTIES OF SOME BIOMEDICAL SIGNALS

Signal	Dynamic Range	Frequency Range
ECG	50 μV - 5 mV	0.05 - 100 Hz
EMG	1–10μV	500 Hz – 10 kHz
EEG	2–100 μV	0.5 – 100 Hz
EoG	10 μV–5 mV	dc – 100 Hz

From the ECG signal, heart rate (HR) can be extracted; the heart rate can be used to detect drowsiness because it varies significantly between alertness and drowsiness states [2]. Heart rate variability (HRV) which measures the beat-to-beat changes in the heart rate is also used to detect drowsiness. As the driver goes from an alert to a drowsy state, the ratio of low frequency to high frequency beats in the ECG signal progressively decreases [3]. One critical issue in handling physiological signals is to eliminate noise and artifacts inevitable in real environment driving conditions. Following effective filtering, various feature extraction techniques such as Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) are used. Then, the extracted features are classified using Support Vector Machine (SVM), Artificial Neural Networks (ANN), Linear Discriminant Analysis (LDA), etc. Even though the reliability and accuracy in detecting driver's drowsiness based on physiological signals is high when compared to visible features, an important limitation of physiological signal measurement is its intrusive nature. One possible way to solve this limitation is to use wireless technologies such as Zigbee and Blutooth for measuring physiological signals in a non-intrusive way by placing the electrodes on the steering wheel or in the driver's seat [8]. Finally, the signals are handled by smart phones and driver drowsiness is determined. However, this kind of non-intrusive system is less accurate compared to intrusive systems due to improper electrode contact.

To obtain reliable driver's drowsiness detection results, some attempts had been done to fuse various measurements [9]. A mixture blinks rate, maximum eye close duration and percentage of non-steering measures to detect drowsiness.

Driving behavior features or driving performance measures include steering wheel movement, lane keeping, acceleration pedal movement and braking, etc. [10]. These features correlate to vehicle type and variability among drivers in their driving habits, skills and experience (driver model). The two most commonly used driving behavior measures for detecting the level of driver drowsiness are the steering wheel movement and the standard deviation in lateral position. Steering Wheel Movement (SWM) is measured using steering angle sensor mounted on the steering column. When the driver is drowsy, the number of micro-corrections to the steering wheel, which are necessary in normal driving, is reduced [11, 12]. The driver's drowsiness state is determined from small SWM's of between ~0.5° and ~5°. Standard Deviation of Lateral Position (SDLP) is another sleepiness sensitive continuous performance measure. SDLP [13] is correlated with the Sleepiness Scale (KSS) [14], a nine-point scale that has verbal anchors for each step. However, SDLP is dependent on external factors such as road markings, lighting and climatic conditions. Sometimes, these driving performance measures are not specific to the driver's drowsiness. In particular, these kinds of driving behavior measures are dependent on the vehicle type, driver experience, and conditions of the road.

C. *Driver distraction detection*

Distraction is another important factor causing impairment of driver attention, involving a driver not paying sufficient attention to the road in spite of the presence of obstacles or other people. In particular, there is a trend toward increasing use of in-vehicle information systems, which also leads to driver distraction. To detect driver distraction, it is necessary to extract head pose or gaze information [15]. Head pose estimation provides a driver's field of view and current focus of attention. It is intrinsically linked to visual gaze direction. When the eyes are not visible, head pose is used to estimate the gaze direction.

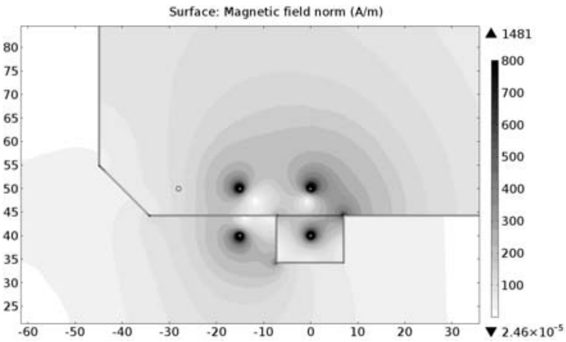

Fig. 1. Intensity distribution of the magnetic field [A/m] around the wires in various parts of the chassis

III. Electromagnetic compatibility in automotive engineering

Driver activity monitoring equipment is considered as a vehicle component. It is subject to the electromagnetic compatibility (EMC) norms and directives related to this field. The guidelines EU 2004/104/EC and CISPR 12, 25 are especially important. The international norms ISO 11451, 11452, 7637 and others deal with the electromagnetic susceptibility of automobiles and their subsystems. The manufacturer norms supplement determining the EMC of particular cars.

The devices can be considered as medical equipment too. Therefore, they should also partly conform to the norm EN 60601-1-2 that applies to the EMC of medical equipment. It is important to note that additional area of interference sources and receivers needs to be considered. It will be necessary to thoroughly eliminate any interference coupling. From the biomedical point of view, signals with amplitudes from units of µV to units of mV and the frequency range from 0 Hz to 100 Hz, rarely up to 20 kHz, are monitored. It is necessary to find an appropriate measuring method to determine the magnitude of interfering electromagnetic fields with very low intensities and low frequencies inside a car. When dealing with EMC of automobiles, it is also important to use appropriate modelling and simulation methods, allowing easy parametrisation of the model, excellent visualisation of the results, and a very good correspondence to the reality. An example can be the modelling of the intensity distribution of the magnetic field around four wires ($d = 0.5$ mm, $I = 1$A) passing through various parts of the car chassis (thickness 0.25 mm). It uses the finite element method (FEM) on a 2 dimensional field, see Fig. 1.

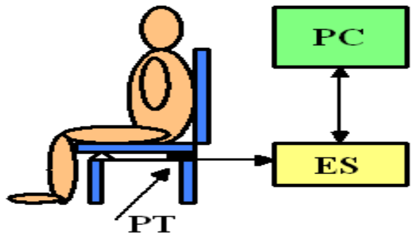

Fig. 2. Principle of the noninvasive BCG measuring: PT - piezoelectric transducer, ES - electronic system, PC - personal computer

IV. Some Non Contact Methods

Balistocardiography (BCG) is a noninvasive technique developed for recording and analyzing cardiac vibratory activity as a measure of cardiac contractile performance [15]. This new field of monitoring heart activity, enables determine both amplitude-force and time-frequency relationships, is termed [16]. Thus, one may determine the force-response of the cardiovascular system to changes in external stimuli, as well as the autonomous nervous system regulation of the circulation and the activity of the sympathetic and parasympathetic systems. The basic part of the BCG is a rigid piezoelectric force transducer resting on chair. The examined person sits on the seat placed on the transducer and force caused by the cardiovascular activity is a measured (Fig. 2). In Fig. 3 the ECG, BCG and ultrasound signals are shown, in Fig. 4 the example of BCG and BCG signal after filtration are displayed.

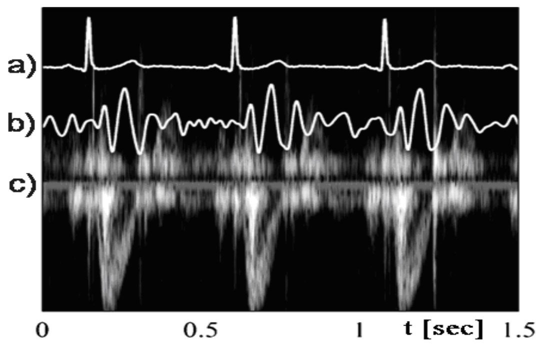

Fig. 3. Comparing of different biomedical signals. From top to bottom: ECG, BCG and Doppler ultrasound signals time evolution

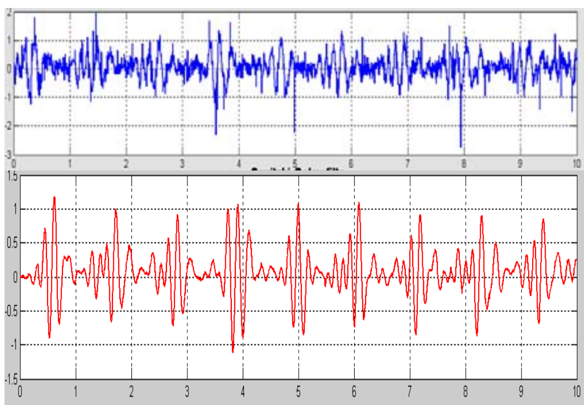

Fig. 4. Example of the time evolution of BCG signal, man, age 45 years, 78 kg,. Measured signal with noise (top), signal after lowpass and highpass filtration (bottom)

BCG signal is not possible measured when car is running, but is possible when car is stopped e.g. in vehicle queues on the road etc. The BCG method belongs to non-contact driver drowsiness detection.

We tested also ultrasound sensor system for head position and breathing detection. Result, shown breathing is in Fig. 5.

One of most promising method is steering behavior monitoring [17-19]. These systems measure continuously, cheaply, non-intrusively, and robustly even under extremely demanding environmental conditions. The expected fatigue induced changes in steering behavior are a pattern of slow drifting and fast corrective counter steering. Using steering wheel movement as an indicator for fatigue is more robust under these same operating conditions [20-22]. Collecting this data is favorable for fatigue detection since it is non-obtrusive and uses cheap, durable, and maintenance free sensors that are already integrated into the steering wheel system.

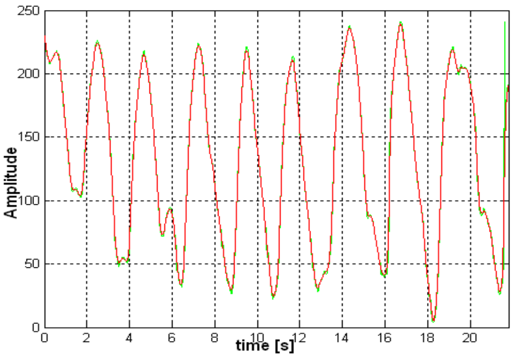

Fig. 5. Breathing detection based on ultrasound system. On the Y scale are samples values.

V. Conclusion

In this paper the review of various approaches to driver fatigue was presented. It look like that most promising will steering behavior monitoring which will described (with measuring results included) in next work.

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