Development of decision algorithms in the driver fatigue monitoring and prediction system based on a wireless multisensor device

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Abstract. This paper presents the system for the continuous monitoring of the physiological state of the vehicle driver. The developed system allows to make adequate decisions and forecast the situation on the basis of the driver fatigue monitoring data. Identification of drowsiness, state if carried out on the basis of blinking duration and frequency analysis. The neural network is used to detect blinking patterns. Signal acquisition and processing are performed on the wearable multisensor microcontroller-based device.

1. Introduction

According to the Global status report of the World Health Organization [1], over 1.2 million people die on the roads each year, and up to 50 million suffer non-fatal injuries. AAA Foundation reports that about 9% of all road accidents and 11% of serious crashes were caused by driver’s loss of concentration induced by fatigue or drowsiness [2]. Because of this, development of the automated system performing continuous monitoring of driver’s physiological state and alerting before a potentially dangerous situation occurs is of immediate interest.

This paper is devoted to designing a system for real-time detection of transitional state, when the driver is losing control of a situation. It’s called a lapse of responsiveness [3]. This state is characterized as temporal sensorimotor and cognitive systems dysfunction for a period of 0.5 to 15 seconds. Drowsiness state is associated with a set of physiological and behavioral signs, which can be automatically detected by a monitoring system [4]. The rest of the paper covers the development of the algorithms for such system and presents a wearable device designed for real-time driver state monitoring.

SleepAlert is a wearable device for driver’s drowsiness detection. It measures EEG (electroencephalogram) signal using a set of three active dry-contact electrodes. In addition, this device obtains pulse wave signal with a pair of non-contact active electrodes. Also the device contains
an inertial sensor, tracking user’s head movements. Since individual signal may suffer from temporal quality degradation, the variety of sensors may potentially enable reliable detection of drowsiness.

The drowsiness detection system requires a set of sophisticated algorithms, designed for processing input signals and making decisions based on processing results. Multisensor nature of the system entails potentially high efficiency of simultaneous processing of data from different sensors, like EEG and head movement. The proposed operation scheme of the system is as follows:

- EEG signal contains EMG (electromyographic) artifacts mostly associated with eyes movement and blinking, that used as primary source of information about the driver’s state.
- EEG spectrum is analyzed in order to determine a relation between high-frequency and low-frequency components. Prevalence of lower band signals indicates a drowsy state [5].
- Pulse wave signal is used to identify user’s heart rate
- Head movement data is used to improve error rate of previous algorithms and as an additional source of information, such as presence of monotonic movements.

In this paper we primarily discuss the blinking analysis algorithm. In section 2 we provide a review of existing approaches towards EMG analysis. Section 3 presents the algorithm development of the drowsiness detection system. Section 4 contains a description of training data collection and evaluation process. Some details about hardware implementation are given in section 5, and section 6 gives a conclusion.

2. Review

The task of detection drowsiness stage is studied in various ways. Subjective evaluation techniques for drowsiness states detection are based on self-assessment of the driver's condition and are formalized in the form of a certain scale. These technics allow to describe drowsiness states in detail, but it can’t covered transition between the states of alertness and sleep.

The driver’s state can be determined by a number of typical facial expressions: frequent or constant blinking, nodding and rocking the head and frequent yawning. PERCLOS [8] - percentage eyelid closure. Despite the fact that some researchers claim to have 100% and 98% accuracy when using PERCLOS indicators and blink frequency [7], the situation changes greatly when the driver wears glasses and the lighting changes (by remote monitoring).

The other type of indicators, physiological indicators, are more suitable for the solution of this article’s problem, as they begin to change right in the early stages of sleep. Physiological indicators are EOG, ECG, EMG and EEG signals [6, 9].

The EOG signal, the field created by the potential difference between the cornea and the retina, is sometimes used to determine sleep by the movements of the eyes [7, 10]. The ECG and Heart Rate Variability (HRV) are also utilized [8, 10, 11]: this signs are the basis for calculating the indicator characterizing the transition from wakefulness to sleep [12].

The most commonly used physiological indicator for drowsiness detection is the EEG [13, 14, 15] - the recording of the oscillatory process of brain activity using electrodes placed on the head. In the classical EEG technique, up to 32 sensors are used, but as practice shows [6, 14], in some cases, several sensors are sufficient. Wearable applications, compared to standard clinical EEG, require special dry-contact or non-contact electrodes with strict positioning limitations induced by ergonomics considerations. Number of studies propose to calculate the EEG and EMG simultaneously to improve accuracy [6]. Electromyogram (EMG) allows determining the movement of muscles and localizing them to the EEG.

In research we decided to use physiological indicators - blink parameters, calculated by EMG, because it’s reliable detecting indicators and suitable for the applied task of wearable device development.

3. Methods

Drowsiness detection algorithm is currently based on detection of blinking patterns (figure 1) and evaluating statistical parameters of these signals. The preliminary research has shown that the artificial neural network (ANN) model has the best performance in terms of detection accuracy and computational complexity, since the signal processing has to be implemented in a wearable device.
Figure 1. An example of blinking signal on EEG recording of SleepAlert device

We use a focused time-delay ANN model. Two NNs are created to separately detect the beginning and end moments of a blink. Input signal, containing EMG component, is fed to the NN in a way that NN input windows width would be equal to the expected blink signal duration. In order to reduce the amount of memory required for storing the delayed input signal, it is decimated with a factor of 5. With input sampling frequency equal to 250 Hz and amount of inputs being 51, the time step between neural network input samples is 20 ms and total input window is 1 s. Moreover, the input signal is filtered and normalized.

NN has one hidden layer and one output layer. The hidden layer contains non-linear sigmoidal transfer functions. Best performance was achieved with 15 hidden neurons. The output layer is linear. Network output is rounded to values 0 and 1, where 1 indicates detection of blinking start or end and 0 represents absence of these events.

The post-processing of neural network output involves merging together events which occurred within a short interval of 100 ms (NN may output several similar events after one blink, so they will be treated as one). After that, blinking beginning and end from separate NNs are joined into one blinking event, if the end event occurred within 2 second interval of the corresponding start event. In addition, we measure blinking duration which can be used as a parameter for drowsiness detection.

Two statistical parameters of EMG signal are evaluated: mean amount of detected blinks per minute and mean duration of a blink per minute. We use the following procedure to determine driver’s condition based on given parameters. The lapse in responsiveness is detected if one of the conditions is met: blinking period is more than 600 ms; mean blinking frequency exceeds the average value by 70% or mean blinking frequency is 60% below the average.

4. Training and evaluation
In order to collect the required dataset for training and evaluating the blinking analyzer model, we have built up a test setup to imitate driving process and to continuously record data acquired by the SleepAlert device. This setup is based on a PC with a steering wheel controller (fig 2.). The SleepAlert device is connected to the PC using the Bluetooth 4.0 adapter. The PC monitor displays a track which is slowly scrolled down. The cursor is positioned in vertical center of a screen and a subject is asked to follow the track by the cursor, rotating the wheel and moving the cursor left and right in a way to position it as closely to the track as possible. The track was previously computed as a set of overlapping sinusoidal signals with frequencies from 0.02 to 0.2 Hz.
Assessment of subject’s physiological state, which was used as training and test data, was made based on the difference between the displayed track and the user’s cursor at every moment of sampling. In addition, the experiment was recorded on a video camera for subsequent manual analysis [16,17].

Experiments were conducted in the evening in a quiet room with ambient lighting. Duration of each experiment was one hour. All the data from SleepAlert sensors were recorded with timestamps, as well as the displayed track and the trajectory of user’s cursor. 15 subjects took part in data collection, 12 of them reported feeling drowsy and 3 fell asleep.

The presented models were evaluated on the test data acquired in the driving imitation experiment. The blinking detector training and testing additionally required manually marking input signal, indicating blinking moments as seen on figure 1. The performance of the blinking detector is shown in table 1. Results are presented for several individual subjects as well as for whole dataset. Significant difference in error rate is due to inherently different signal quality on different subjects.

| Test data | False positive error, % | False negative error, % |
|-----------|-------------------------|-------------------------|
| Subject 1 | 12.2                    | 8.5                     |
| Subject 2 | 14.2                    | 0                       |
| Subject 3 | 12.9                    | 19.8                    |
| Overall   | 16.9                    | 7.4                     |

Figure 3 presents an example of successful responsiveness lapse detection. Driver’s loss of concentration, indicated by a major difference in road and steering trajectories starting, is preceded by a rapid growth in blinking periods. The system reacts 15 seconds before actual loss of control.
Figure 4 is the time series plot of average blinking period (top) and relative trajectory tracking error (bottom) recorded during one hour driving imitation experiment. Dashed line shows the drowsiness state threshold. Generally, the correlation between high values of blinking period and major tracking errors is clearly visible. At 38 and 54 minutes there are the largest tracking deviations detected. In these moments the algorithm issued the warning about possible responsiveness lapse to the driver.

![Figure 4. One-hour experiment recording with drowsiness detection.](image)

5. Sleepalert device
The described signal processing for the drowsiness detection system is performed on a microcontroller-based wearable device. The form factor is a head band with five frontal dry-contact and non-contact active electrodes [18, 19]. The device acquires following signals:

- EEG signal using dry-contact electrodes with sampling rate of 1000 Hz. This signal also contains electromyographic artifacts such as blinking and eye movement.
- Pulse wave using non-contact electrodes with sampling rate of 1000 Hz
- Driver’s head movement signals using accelerometer and gyroscope IC with 125 Hz sampling rate

The mentioned signals are acquired and processed by microcontroller-based control system [20]. The board is equipped with STM32L431 MCU with ARM Cortex-M4 core and FPU coprocessor. Its advanced digital signal processing capabilities are used for on-board data processing, which involves digital filtering, vector and matrix operations and Fourier transform. The device also transmits raw and processed data via the Bluetooth 4.0 interface.

The microcontroller is running FreeRTOS operating system, and the signal processing is implemented as a task in this OS, taking data from input queue, processing it and putting results in output queue. Input sample rate is 250 Hz, since raw EEG signal is preliminary decimated and filtered using a FIR filter with 2-50 Hz bandpass.

Input signal is smoothed out with the 9th order Savitzky-Golay filter. This filter requires four previous samples and four following samples of input signal for every output point. Because of this, the output is delayed by 4 samples. In addition, to reduce the amount of RAM required by smoothing and neural network algorithms, input signal is decimated by a factor of 5. We employ a certain technique to optimize the filtering and decimation operation. It is illustrated on figure 5. Columns represent memory array cells and rows represent steps. Vertical arrow show the windows used by filter. The first smoothing filter window is processed on step 9, it’s center is 4th point. The next window is processed on 14th step, centered at 9th point. The next window, taken on 19th step, again is centered in 4th point. To make a new filter window ready by this moment, steps 11th to 14th require an additional copy to cells 0 to 3.
Decimated and smoothed signal is then transferred to the ANN input. Network output evaluation is implemented as matrix multiplication and addition operations. Microcontroller implementation of algorithm was tested to provide the same output on the same test data compared to modelling version. In addition, blinking detector was tested in natural environment.

6. Conclusion
In this paper we described the development of the driver drowsiness detection system. This system’s operation is based on the blinking detector, employing artificial neural network algorithm to detect blinks in the EEG signal and measure their period and duration. These parameters allowed us to estimate subject’s current physiological condition during the experiments with driving process simulation.

Embedded versions of these algorithms are designed for the wearable microcontroller-based device. System performance was tested to be suitable for real-time monitoring.

On the next stages of this research we are going to implement other algorithms utilizing all of the signals acquired by the device to improve the accuracy of drowsiness detection.

Acknowledgment
The work was carried out with the financial support of the FASIE, project №53GRNTIS5/26082 dated 22.12.2017 and grant from the Program Competitiveness Enhancement of Peter the Great St.Petersburg Polytechnic University, Project 5-100-2020.

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Figure 5. Buffer utilization scheme used by smoothing file.
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