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Mini-Symposia Title:

Driver Drowsiness: Causes, Detection, Prediction and Alert

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Theme:

- ( ) 01. Biomedical Signal Processing
- ( ) 02. Biomedical Imaging and Image Processing
- ( ) 03. Micro/Nano-bioengineering; Cellular/Tissue Engineering &
- ( ) 04. Computational Systems & Synthetic Biology; Multiscale modeling
- (•) 05. Cardiovascular and Respiratory Systems Engineering
- ( ) 06. Neural and Rehabilitation Engineering
- ( ) 07. Biomedical Sensors and Wearable Systems
- ( ) 08. Biorobotics and Biomechanics
- ( ) 09. Therapeutic & Diagnostic Systems and Technologies
- ( ) 10. Biomedical & Health Informatics
- ( ) 11. Biomedical Engineering Education and Society
- ( ) 12. Translational Engineering for Healthcare Innovation and Commercialization

Mini-Symposia Synopsis— Max 2000 Characters

Driver drowsiness has been a vastly underestimated cause of traffic accidents due to the difficulty in establishing whether a driver involved in a crash was drowsy. A recent report from the AAA estimates that almost ten percent of vehicle accidents involve drowsy driving, while another survey from the German ADAC has found out that one fourth of car drivers and almost half of the truck drivers have fallen asleep during driving. The European Respiratory Society has established a Task Force to address the topic of sleep apnea, sleepiness and driving. The planned session will start dealing with the causes of driver drowsiness. Different techniques for real-time monitoring of fatigue-related parameters will be presented and it will be discussed whether the standard sources of information used to detect drowsiness can also be used to predict when a given drowsiness level will be reached. Finally, the session will discuss current approaches to alert drivers about their drowsiness while driving.

Secure Data Encryption for Sleep Medicine Data Transmission Between Sleep Centers (ASCLEPIOS) for Sleepiness Evaluation*

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***Abstract*— Sleep disorders and sleep problems might lead to non-restorative sleep and in consequence to excessive daytime sleepiness. Excessive daytime sleepiness impairs performance and may cause accidents when driving. Therefore, whenever an accident occurred related to sleepiness, an assessment for sleep disorders is recommended. Often patient files needs to be reviewed by another sleep expert. A secure exchange of patient files and sleep recordings are required. In the project described here, a secure and safe encrypted data transmission is developed for both, patient data, and sleep signal data transmission between expert sleep medicine centers. This sleep medicine demonstrator is evaluated in a pilot study between two accredited centers with experience in sleep medicine. The exchange with encryption and decryption was implemented successfully. The implementation could be integrated in corresponding platforms for exchanging sleep medicine data.**

I. INTRODUCTION

The exchange of medical data between physicians and experts is needed in several scenarios. It is needed for getting a second opinion, it is needed in case of quality control for medical records and recorded raw data [1], and it is needed in case of law suits and evaluation by external reviewers. Sleep disorders, especially sleep apnea have a very high prevalence [2]. Sleep apnea can be the cause for excessive daytime sleepiness and needs to be diagnosed and treated adequately in order to avoid consequences such as accidents due to falling asleep at the wheel [2].

II. METHODS

In order to allow an exchange of sleep medicine data, a common data format and a common nomenclature needs to be defined. This data format based on the European Data Format (EDF) and enriched with a nomenclature, as published in the IEEE 11073 specification forms the basis to provide data exchange for a sleep medicine demonstrator [3].

III. RESULTS

The exchange of raw data including a viewer for raw data of sleep recordings was implemented and tested between sleep medicine centers [1]. The exchange of data using a secure cloud service with encryption was tested for simulated patient records using SSE encryption technique [4].

IV. DISCUSSION & CONCLUSION

After a successful testing of the sleep medicine data demonstrator, the encryption software needs to be implemented in the appropriate medical data exchange platforms. The more extensive testing needs to be performed by additional independent authorities and by users with different hardware and software at the user end.

ACKNOWLEDGMENT

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A machine learning pipeline approach detecting driver fatigue based on EEG signals

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Abstract— **Drowsiness driving is dangerous and causes multiple accidents each year, including fatal accidents. Current integrated systems use driver behavior parameters to detect indications of fatigue. New methods are available to measure fatigue with biosignals obtained with wearable devices. New low-cost EEG devices can record brainwaves, from which the level of fatigue can be read from a person. This approach examines how driving drowsiness can be detected with supervised machine learning classifiers trained with EEG signals.**

I. Introduction

Statistics from the German Automobile Club (ADAC) have shown that about 26% of drivers have already fallen asleep at the wheel. However, the number of unreported car accidents due to fatigue is estimated to be much higher. This is since the accident statistics refer to the driver's statements when determining the accident's cause. To avoid (partial) feelings of guilt, it can often happen that the driver states another cause of the accident [1]. The European Society for Sleep Research dealt with the frequency and causes of sleep-related accidents. The study was conducted in 19 European countries with more than 12,700 road user surveys: More than 42% of the respondents who caused an accident by falling asleep while driving stated that they had slept the night badly before [2, 3, 4]. Mortality from road traffic accidents is a global public health problem that costs an estimated 1,5 million lives each year [5]. This work aims to show how fatigue can be detected and evaluated with machine learning, whereby classifiers are created with state of the art tools and trained with EEG signals. The goal is to answer the question of whether it is possible to detect fatigue and show the accuracy of different models.

II. Methods

The experiments were done in a self-created driving simulator based on openDS. The EEG has been recorded with the Muse S, a low-cost EEG recording device. The video of the subject, the heart rate, and the driving simulator's data has been recorded during the driving experiment. Before and after the driving experiment, an oddball auditory task (P300 test) was done. With the P300 test, the subject's state could have been verified to know if the subject got fatigued after the 40-minute drive. Additionally, an online dataset of EEG signals from an experiment on driver fatigue has been used. Different machine learning pipelines have been applied.

III. Results

The approach reached an accuracy of max. 78% using a support vector machine and frequency features. With the same data but with entropy features, a random forest classifier achieved an accuracy of 66%. When using the online data and frequency features, an accuracy of 67% was achieved using a k-nearest neighbor classifier, and with entropy features, an accuracy of 76% was achieved using a support vector machine.

IV. Discussion & Conclusion

Fourteen subjects experimented, but one subject had to abort due to a sickness feeling from the driving simulator. Finally, 13 subjects remained in the dataset (10 male and three female), with an average age of 27.4 years with a standard deviation of 2.24. With the experiment data, higher accuracy was achieve than with the online data. The support vector machine realized the best result compared to all other trained classifiers.

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The Added Value of Personalisation in Driver Fatigue Detection

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Abstract— **Many fatigue detection systems have difficulties to provide timely warnings, especially for new drivers and new datasets. One idea to overcome these generalisation issues is to use personalised algorithms, and the topic of this presentation is to illustrate how much we can gain by using personalized instead of generic algorithms. An indicative number is a performance increase of about 20%. The obvious disadvantage with personalised algorithms is reduced applicability since the models must be adapted to each driver.**

I. INTRODUCTION

Driver fatigue detection systems often show high accuracies well above 90%, but at the same time, these systems often fail to detect fatigue on individual drivers at finer temporal resolutions than about 30 minutes [1]. There are several possible reasons for this discrepancy: (i) many machine learning-based systems use random partitioning to split data into a training set and a test set, ignoring the fact that the underlying time-series data are autocorrelated. This results in an underestimation of predictive error. (ii) there is a lack of open access high validity driver fatigue datasets. While it is commendable that the National Tsuing Hua University shared their dataset [2], the widespread use of this dataset is unsettling since the experiment was not conducted in an actual car and the participants were simply asked to act out facial expressions of fatigue rather than actually being fatigued. This will result in detection systems that detects stereotypical behaviours but fails to generalise to real-world settings where fatigued drivers are struggling to stay awake. (iii) most driver fatigue studies have high levels of experimental control. The restrictions imposed by the study design limits generalizability, especially if the system will later be used in a naturalistic setting in the presence of various confounding factors. (iv) if evaluations are based on group level results, individual differences and confounding factors are not considered properly as they are reduced by averaging. If one or several of these issues are not considered when designing a fatigue detection system, it is very likely that system performance underestimates the true prediction error. One idea to improve the performance of fatigue detection systems is to use personalised algorithms. Fatigue indictors vary between individuals and over time within individuals, depending on both internal and external factors. Although personalised algorithms will not resolve issues with confounders or with within-individual variability, they may reduce the impact of between-individual variability. The potential gain is large since between-individual phenotypic factors account for 50%–95% of the variance [3]. The aim of this presentation is to illustrate the added value of personalised driver fatigue detection algorithms.

II. METHODS

Results from two studies with 20 sleep deprived drivers driving on a real-world motorway will be presented. In experiment 1, ECG and EOG data were used to classify driver fatigue with an SVM. Four different cross-validation techniques were used [4], (i) leave one participant out (LOO), (ii) LOO, but injecting 10% of the data from the left-out participant in the training set, (iii) LOO, but injecting 30%, and (iv) random split of all data into a training set and a test set. In experiment 2, video data were used for fatigue classification based on a deep learning approach [5]. A generic algorithm was compared to a personalised algorithm.

III. RESULTS AND DISCUSSION

Experiment 1: The detection rate of sleepy drivers increased from 44% for LOO to 58% with 10%-injection, to 61% when injecting 30%. Random partitioning showed a detection rate of 81%. Experiment 2: The personalised classifier showed an accuracy of 92% whereas the generic classifier had an accuracy of 72%.

Performance increased with about 20% when using personalised algorithms. Future work includes developing prototype groups that each individual can be assigned to, with the goal to sidestep the training stage for each individual user.

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The influence of sleeping on driving behavior: Do drivers with poor sleep quality exhibit a more aggressive driving style?

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Abstract— **Driving is a very complex task that requires high cognitive ability. This ability can be affected by multiple factors that occur before, during, and after driving. A reduction in the cognitive capacity of the driver increases the probability of suffering traffic accidents and worsens energy efficiency.**

I. INTRODUCTION

Driving behavior and driving stress are influenced by multiple elements. There are factors that happen while driving, such as a pedestrian crossing the street incorrectly. However, there are also other factors unrelated to the moment of driving that strongly influence this activity, such as sleep, working hours or chronic stress.

Focusing on sleep, both a lack of it and its poor quality are associated in many studies with an increase in lateral deviations and reaction times [1]. Other effects that have been observed to be brought on by drowsiness are a decrease in the ability to predict traffic, for decision making, vigilance, and hazard perception [3].

II. METHODS

An experiment was carried out to analyze the effects of poor sleep quality on driving and variability. A total of 20 drivers participated in the experiment. The participants completed a survey about their characteristics (gender, age, and driving experience) and sleep quality. Sleep quality was indicated by drivers using a Likert Scale between 1 and 5 with 1 indicating that the driver usually sleeps very well and 5 that he or she often sleeps poorly.

The participants drove for 25 minutes, with both their heart signal and driving behavior being monitored. The drivers had to complete the routes proposed by the GPS of the driving simulator. The driving simulator assigned points to the participant at the beginning of the route. Points are deducted each time an infraction is committed. If the score reaches zero, the route must be repeated. This allows the participant to focus on the driving task as if in a real environment.

III. RESULTS

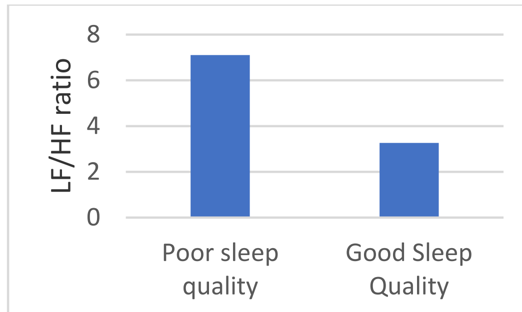

Figure 1. LF/HF ratio grouped by sleep quality.

IV. DISCUSSION & CONCLUSION

Figure 1 captures the LF/HF ratio obtained from participants while driving. The results show that the drivers who presented poor quality of sleep were those who obtained a higher value in the LF/HF ratio during driving. A high value in this ratio involves a higher stress level. Drivers who suffered from poor sleep quality obtained an LF/HF value twice as high as those with good sleep quality. There was a significant difference in the LF/HF ratio for poor sleep quality (M=7.11, SD=1.36) and good sleep quality (M=3.26, SD=2.14). The result of Wilcoxon's test is $Z = 1.789$, $p < 0.05$.

Regarding driving behavior, we also observe worse results for drivers who suffer from poor sleep quality. The Positive Kinetic Energy (PKE) value is higher than that of drivers who sleep well. A high PKE value means that the driver is driving with an aggressive driving style. The differences between the two groups are significant. The result of Wilcoxon's test is $Z = 2.236$, $p < 0.05$.

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Unobtrusive Vital Sign Monitoring in Automotive Environments

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***Abstract*— Classical methods to measure vital signs typically require close physical interaction with the patient (cables, electrodes, cuffs, pneumatic lines, etc.). This limits its usability for applications in automotive environments. Therefore, technologies for unobtrusive and contact-free monitoring of vital signs of the driver have attracted a lot of attention in recent years. This presentation will describe such technologies and will give an overview about their demonstration in cars.**

I. Introduction

From a practical perspective, cable-bound solutions are not an option for driver state monitoring outside experimental trials. Hence, unobtrusive and non-contact driver state monitoring using physiological information is currently gaining increasing attention. However, while simple schemes like the analysis of steering patterns to assess driver state have already been commercialized by several car manufacturers, the analysis of true physiological information coming from ECG, EEG and photoplethysmography (PPG) sensors still is in the research stage.

II. Unobstrusive Sensor Techniques

To assess the state of a patient, clinicians typically employ four primary vital signs for monitoring at the bedside: pulse (heart rate, HR), breathing rate (respiratory rate, RR), blood pressure (BP), and body (core) temperature (BT). Usually, oxygen saturation (SpO2) is added as a fifth vital sign. Since no attempts have been conducted to equip cars with unobtrusive BP monitoring, this vital sign will not be further addressed in this paper. Figure 1 covers unobtrusive sensors and the underlying physiological effects in general. Correspondingly, the presentation will cover the historical developments and the state-of-the art of these technologies in more detail, but specifically illuminates the current state of unobtrusive sensing inside a car. Table 1 compares different technical aspects of these sensors including the question of active energy injection and allowable distance between subject and device.

III. Discussion & Conclusion

In this presentation, special attention is given to unobtrusive and non-contact sensors for vital sign monitoring that can be placed inside the car, i.e., in the seat, the safety belt, the steering wheel or the cockpit. As there is no unobtrusive sensor technology that provides complete coverage, the future of in-car vital sign monitoring seems to lie in the fusion of several sensor channels and modalities.

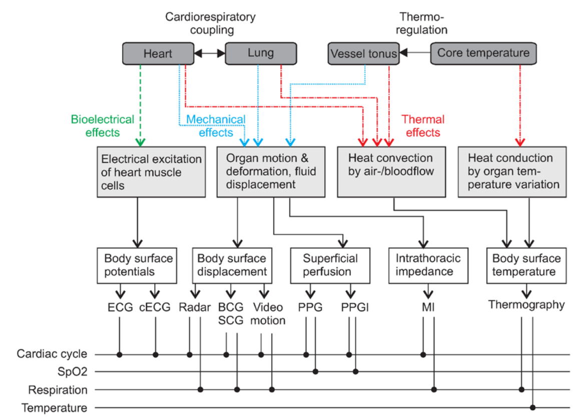

Figure 2. Overview of physiological sources, effects, unobtrusive and non-contact sensors, and obtainable vital signs [1].

TABLE I. Comparison of different unobtrusive cardiorespiratory monitoring techniques by their technical aspects [1].

Sensor Technique	*Type of Contact*	*Meas. Quantity*	*Energy Injection*	*Dist-ance*	*Sensi-tivity to position*
ECG (steering wheel)	galvanic	electric biopotential	no	0	+
cECG	capacitive	electric biopotential	no	mm	+
BCG	mechanical	displacement, force	no	0	–
Video motion	optical	displacement	no	m	–
PPG (steering wheel)	optical	photon absorption	yes	mm	o
PPGi	optical	photon absorption	yes	m	–
Thermogr aphy	optical	radiation temperature	no	m	–
MI	electro-magnetic	electric bioimpedance	yes	cm	o
Radar	electro-magnetic	displacement, velocity	yes	m	–

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Detecting Different Drivers' Fatigue Signals from the Face

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***Abstract*— Driver fatigue contributes to up to 20% of fatal and serious accidents. Drowsiness detector on a car can reduce numerous accidents. Non-intrusive techniques for detecting drivers' fatigue are easier to apply. This work presents two implemented approaches to extract different signals of drivers' fatigue from the face. One of the obvious signal are the eyes closure and yawning. The challenges are not just the detection of these signals; it is as well the detection in the context such as variation of light, or for faces of different ages, genders, wearing reading land marks, beard and moustache around their mouth. There are other signals of fatigue are eye-related cues such as red eyes and skin-related cues such as dark area under the eye. The incorporation of the both approaches can allow the identification of the level of the fatigue.**

I. INTRODUCTION

In Egypt, one of the main reasons of trucks' accidents is fatigue because truck drivers drive for continuous and long hours and they lack sleep. They lose track of the road while driving. There is no clear method to assess drivers fatigue by the police. There is also an absence of definitive criteria for establishing the level of fatigue that increases crash risk [1].

A few companies such as Ford [2], Volkswagen [3], and BMW [4] for some car models have embedded system in cars that detects drivers' fatigue and give feedback The challenge is to develop a low cost real time system that detects the drivers' fatigue.

II. METHODS

The core of this work uses image processing techniques like the Haar Cascade Classifier, local binary patterns (LBP), and histograms of oriented gradients (HOG) to detect the face and the eyes.

For the eye and mouth closure or opening, each has its algorithm and Support Vector Machine SVM model is developed to identify the fatigue state. For the other cues, the supervised anomaly detection algorithm is applied to recognize abnormality of the area under eyes and eye redness.

To evaluate the implementation, three studies were conducted. The first is for testing the light condition. it is done with a diver drove in different light conditions. Second had 10 participants to test the variation faces features of different ages, genders, wearing reading land marks, beard and moustache around their mouth [5]. The third is evaluated with seven participants in with different skin colors and various light conditions [6].

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III. RESULTS

The results of the three studies are promising as they have high accuracy percentages.

IV. DISCUSSION & CONCLUSION

After a successful implementation of these approaches of detecting fatigue drivers, the merge of both are required to identify the fatigue level. Moreover, integrating the intrusive system can support this identification to give the appropriate feedback to the driver in the right time. More and extensive testing of the implementation is required to gain confidence in the results.

ACKNOWLEDGMENT

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