Physiological measurements for determining driver's state and behavior

Timotej Gruden, Grega Jakus, Jaka Sodnik
University of Ljubljana, Faculty of Electrical Engineering, Ljubljana, Slovenia
timotej.gruden@fe.uni-lj.si, grega.jakus@fe.uni-lj.si, jaka.sodnik@fe.uni-lj.si

Abstract— **In the article we present physiological signals that can be measured on drivers with the purpose of determining drivers' state and behavior. The results of the analysis can be used in various fields of research including automated driving, driving simulations and driver profiling. Physiological signals of drivers can be divided into ten groups corresponding to ten major organ systems of the human body. Most important signals include ECG (electrocardiograph) and PPG (photoplethysmograph) from cardiovascular system, EGG (electrogastrograph) from digestive system, and EEG (electroencephalograph), GSR (galvanic skin response) and pupil diameter from nervous system. GSR and eye tracking have recently gained in popularity. EGG signal analysis also seems promising.**

I. INTRODUCTION

In the era of digital transformation, information and communication technologies (ICT) have become a part of almost every research field where automotive industry is not an exception. With the increase of wearable sensors' availability, rapid improvements in machine-to-machine (M2M) communication and the introduction of automated and connected vehicles, research that focus mainly on drivers has gained in popularity.

The purpose of this article is to explain different physiological signals that can be measured while driving and expose those that are most valuable in terms of determining driver's state and behavior. The results of such measurements are especially beneficial to the research fields described in the continuation of this section.

A. *Automated vehicles*

Before the means of transport become fully autonomous, more and more semi-automated vehicles will be available to consumers. If automated vehicles would be able to monitor drivers and their attributes (e.g. drowsiness, distraction, stress, etc.), they could provide customized feedback and/or warnings, such as DAISY (Driver Assisting System) does [1]. The recent ADASs (Advanced Driver Assistance Systems) tend to provide warnings by monitoring driver drowsiness either by image recognition techniques [2] or by eye tracking [3]. The take-over control of the vehicle could also be initiated by the vehicle in cases where driver is unable to safely operate it.

The vehicle automation is rapidly evolving. However, in order for automated vehicles to be introduced into practical use, various algorithms need to be developed. In fact, many artificial intelligence algorithms for autonomous driving are based on human-like driving [4]–[6]. To authentically imitate human drivers, we need to measure their moves, actions, decisions, different behaviors and the correlation between them. Common examples of algorithms that use driver data include driving style analysis [7].

B. *Driving simulators*

Algorithms, based on drivers' behavior, can not only be used in autonomous driving, but also in driving simulators, to make the behavior of the traffic more realistic [5], [6]. Besides bringing the driver a better user experience while practicing driving (e.g. in driving schools) or during driving just for entertainment (gaming industry), having realistically simulated traffic extends the ability of a simulator to test newly developed algorithms for automated driving, since the interaction of such vehicles with other vehicles can be more accurately evaluated.

C. *Driver profiling*

In order to develop new such algorithms or to evaluate how accurately the existing ones imitate human behavior, driver profiling is required. From the captured signals, we first have to determine what kind of behavior is typical for individual driver profile and then try to profile drivers based on observations of their behavior.

Profiling can be used for providing drivers their driving scores for self-evaluation [8] and training. Insurance companies often use driver profiling to detect risky drivers and adjust the insurance premium [9]. Modern use cases of recognizing driving behaviors and driver profiling based on measurements also include vehicle anti-theft protection [10].

In order to get the desired data for determining driver's state and behavior, we need to understand the responses of the human body to specific driver's states and behavior. Therefore, we present key physiological signals for driver analysis, their meaning and different ways of measuring them. More precisely, we will address the following two research questions in the article:

- Which physiological signals are important for a holistic representation of drivers' state and behavior?
- How can these physiological signals be measured?

In the next section, we provide a framework for classifying the signals and list physiological signals with different possibilities of measuring them. We describe each measurement and its specifics. A brief discussion about the usage and signal usefulness is provided in section III.

II. SIGNALS AND MEASUREMENTS

The physiology of the human body is divided into ten different organ systems, based on the functions they perform [11]. In the continuation, the physiological signals that can be measured and are important for driver analysis are presented according to organ systems they belong in. They include:

- *Cardiovascular (circulatory) system:* heart, blood propagation, blood vessels, etc.
- *Digestive (excretory) system:* stomach, liver, pancreas, food consumption and excretion, etc.
- *Endocrine system:* hormones that drive (signal) the body, and glands, that release hormones
- *Immune system:* defending mechanism of the body, white blood cells, antibodies, etc.
- *Muscular system:* muscle definitions, normal condition and evolution
- *Nervous system:* senses, memory, emotion, thinking process, divided to central (brain and spinal cord) and peripheral nervous system
- *Renal (urinary) system:* kidneys, bladder, urine excretion
- *Reproductive system:* sex organs, period, pregnancy, fetus growth, birth
- *Respiratory system:* nose and lungs, main function is providing oxygen.
- *Skeletal system:* bone marrow, red blood cells, body structure, calcium and phosphate storage

A. Signals

Table I presents important physiological signals in terms of representing drivers' state and different methods for measuring them. Signals are divided into the organ systems where their functionality is most noticeable, although many of the signals also provide useful information about some other organ systems (e.g. the functionality of autonomous nervous system can be measured with electrocardiography). Some signals (i.e. heart rate) can be measured directly or extracted from the others.

TABLE I.
PHYSIOLOGICAL SIGNALS IN TERMS OF REPRESENTING DRIVERS' STATE AND DIFFERENT METHODS FOR MEASURING THEM CATEGORIZED BY ORGAN SYSTEMS

Signal	***Organ system***	***Measurement***
Electrocardiograph (ECG)	Cardiovascular	Electrodes / capacitive sensors
Photoplethysmograph (PPG)	Cardiovascular	Detecting light absorption / reflection
Heart rate variability (HRV) *	Cardiovascular	Electrodes / through ECG or PPG
Heart rate (HR) *	Cardiovascular	Electrodes / IR / light absorption
Electrogastrograph (EGG)	Digestive	Electrodes on abdomen
Body temperature	Immune	Thermometer / IR
Electromyograph (EMG)	Muscular	Electrodes / pressure and force sensors
Electroencephalograph (EEG)	Nervous	Headset of electrodes
Galvanic skin response (GSR) / Electrodermal activity (EDA)	Nervous	Nearby electrodes for conductiveness measurements
Gaze point (GP)	Nervous	Eye tracking
Pupil diameter (PD)	Nervous	Eye tracking
Breathing	Respiratory	Accelerometer
Lung capacity	Respiratory	Spirometry
Air flow speed	Respiratory	Spirometry

*The signal is usually measured indirectly / extracted from another one.

No important or widely used signals measured on drivers have been found in endocrine system, renal system, reproductive system and skeletal system.

B. Measurements and interpretation

Electrocardiography *(ECG)* measures electrical activity of human heart during contractions. Depending on heart characteristic one would like to measure with ECG (i.e. different types of arrhythmias), different peaks or intervals in the ECG signal are used and different electrode placements with different number of electrodes (lead systems) have been proposed [12].

The simplest, 3-electrode bipolar monitoring, uses two of the electrodes in one of the configurations (right arm – left arm (Lead I), right arm – left leg (Lead II) or left arm – left leg (Lead III)) and the third as the grounding electrode. Common methods use 5-electrode monitoring (see Figure 1), where Leads I–III are measured simultaneously. However, a two-channel ECG (Lead I and Lead III) is sufficient since Lead II can be calculated by adding the other two [13]. Wearable devices usually measure only one lead. Some modern devices provide contactless ways of measuring ECG, e.g. seats with capacitive electrodes [14].

In terms of drivers' physiological state analysis, reactions of the nervous system (increased or decreased activity, normal or abnormal activity) are usually observed through ECG.

Photoplethysmography *(PPG)* can (to some extent) provide the same results as ECG. It measures blood propagation through vessels which is the consequence of heart contractions. The output is commonly referred to as a blood volume pulse (BVP) signal.

PPG uses LEDs with different colors and detects changes in light, reflected from within the human tissue [15]. Different reflections present different blood volumes in vessels. The method is widely used in health monitoring wristbands.

With drivers, PPG can be used instead of ECG when the ease-of-use prevails over desired accuracy.

A variety of other variables can be extracted from ECG or PPG signal, e.g. ***heart rate*** *(HR)* and ***heart rate variability*** *(HRV)*. HRV can be used to measure vagal tone that represents parasympathetic nervous system [16].

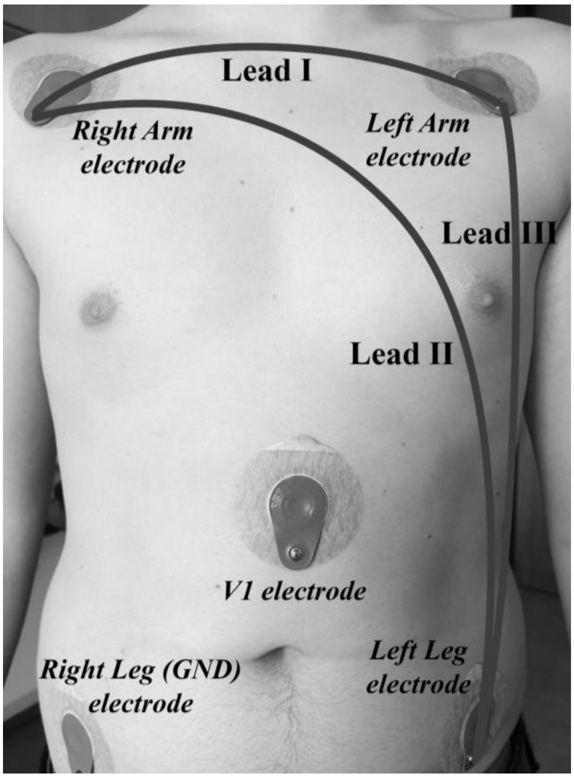

Figure 1. 5-electrode position for ECG measurement with Lead I–III**.**

It should be noted that some limitations exist when calculating HR or HRV from PPG in comparison to calculation from ECG. Studies showed that HRV can be accurately derived from PPG only during rest, but not during motion phases. During activity, stress changes the blood propagation speed that affects the PPG measurement [17]. HRV, measured with PPG, is commonly referred to as inter-beat interval (IBI). Acquiring only specific characteristic variables from ECG (i.e. heart rate) may be easily accomplished using wearable sensors instead of electrode sets. Sensors for contactless heart beat detection with image processing algorithms also exist.

Cutaneous ***electrogastrography*** *(EGG)* is a measurement of gastric slow waves and can be highly correlated to gastric motility. Validations of EGG method are performed with internal (intracellular) measurements of stomach.

The measurement is performed with electrodes, placed on the abdominal skin. The positioning of electrodes is not standardized, however there are recommendations to use five electrodes for a 3-channel EGG [18]. The common (reference) electrode is placed about 5 cm above the navel, all the channel electrodes are placed 5 cm away from the common one, above the stomach area, the grounding electrode is placed on the left side of the pelvic bone (see Figure 2). Single- or multi-channel EGG devices can be used. Since the signal is location dependent, a multi-channel measurement and analysis of the best channel is preferred [19]. The best channel was defined as the one with the most stationary dominant frequency during baseline (resting) measurement.

Measuring EGG is a time consuming task, since slow waves have a frequency of 0.05 Hz (3 cycles per minute). Therefore, the development of shorter EGG measuring methods is desired [20]. Another drawback of EGG is that measurement parameters are not standardized, so differences between studies may exist.

Usually, the dominant frequency (DF), spectral power shares and power of the DF are extracted from EGG and compared within-subject to observe bradygastria (lower DF than usual), tachygastria (higher DF than usual) and sickness (an increase in total signal power) during driving.

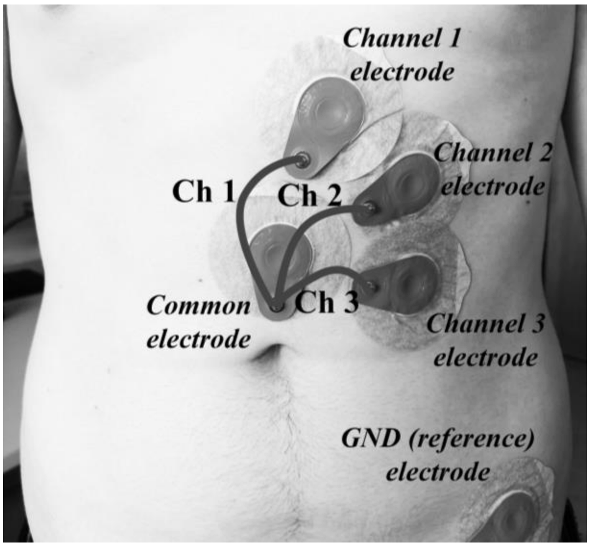

Figure 2. 5-electrode position for 3-channel EGG measurement.

Increased ***body temperature*** can be caused by an overloaded immune system. However, the reflection is subject to high delay.

Most modern thermometers use infrared sensors to determine body temperature because their reaction is really fast and accurate. However, older and slowly adaptable thermally sensitive resistors or mercury thermometers can still be used.

An increase of body temperature also appeared to be connected to driver drowsiness [21].

Electromyography *(EMG)* measures electrical activity of the muscles (direct assessment) as visible in Figure 3. It can be validated by pressure and force sensors, since they measure the results of muscle activity.

Driver’s most often used muscles are the ones that press clutch, break and throttle pedals. Therefore, EMG of the leg muscles can be used to detect how much effort in using the pedals does the driver need to take.

Electroencephalography *(EEG)* measures the most basic signals that can be acquired and directly represent brain activity. From the readings of electrical activity, specific frequency components of brain waves can be extracted. Alpha waves (8–13 Hz) are expressed when persons have their eyes closed or are relaxed. With the opening of the eyes or excessive mental workload, alpha waves disappear and beta waves (12.5–30 Hz) become more noticeable [23].

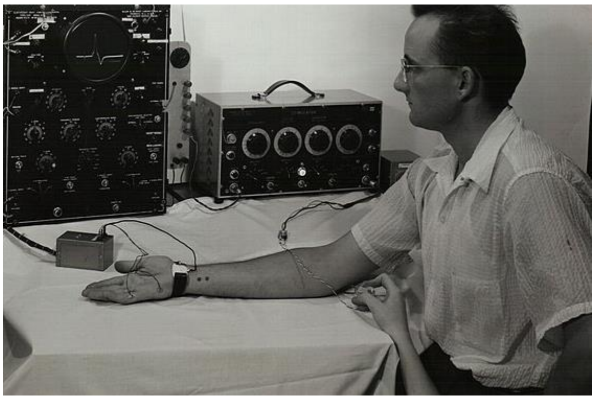

Figure 3. EMG measurement in one of the first researches on EMG [22]

With the detection of alpha waves, EEG can successfully measure driver drowsiness and relaxation. With the presence of beta waves, driver’s cognitive load can be measured.

EEG measurement requires a special helmet with many electrodes and wires (see Figure 4). It can be performed either in an intrusive way (electrodes directly on the skull) or in a non-intrusive way (with skin surface electrodes).

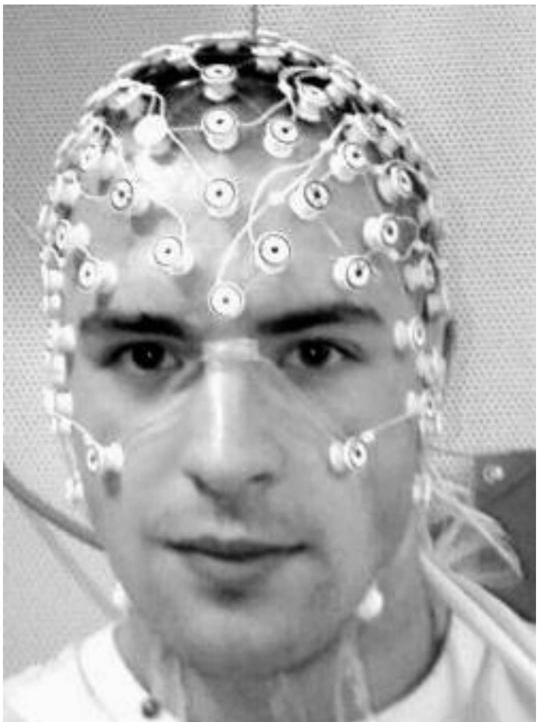

Figure 4. EEG measurement setup with electrode cap by Douglas Myers [25]

Galvanic skin response *(GSR)* or ***electrodermal activity*** *(EDA)*, as latest researches refer to it, is the physiological response of sweat glands (production of swear) which correlates to sympathetic nerve system activity [26]. The primary research focus is usually on induced sweat gland activity.

EDA can be measured with two nearby electrodes on a person's wrist or fingers. The measurement is simple and usually dry Ag electrodes are used.

Studies report that cognitive load, stress and arousal can be measured with GSR and that even better results can be obtained when combined with ECG, EMG and respiration activity measurements [27].

Eye tracking, as the name implies, refers to tracking eye position in real time, calculating gaze points and measuring other eye parameters (e.g. pupil diameter). Researches showed, that in setups with controlled brightness, cognitive load can be extracted from the pupil diameter [28].

Two kind of devices were identified for eye tracking. A standalone device in front of the participant or wearable glasses. The main advantage of glasses is, that eye tracking can be performed independent of participant’s head position and rotation. Fixations (eye focusing on particular view) and saccades (rapid eye movements) are then determined in post-analysis [29]. Eye tracking is also widely used in applications, studying neural system activity, since eye trackers present a nonintrusive contactless measurement in opposite to e.g. EEG or GSR.

Main point of eye tracking in terms of driver analysis is the measurement of (beside the gaze point itself) pupil diameter, through which cognitive load and arousal can be determined [28]. However, drivers’ gaze points measurements can be used to post-analyze their driving. In driving simulators, gaze point detection could be used to teach the drivers about the necessity of paying attention on the road.

Accelerations are most often the consequence of body movement. Accelerometers can also be used to detect chest movement from which breathing patterns can be extracted.

Algorithms for removing motion artefacts with the usage of accelerometers to detect the artefacts are also available and can be used in driving environments, where motion is always present. Most basic algorithms only perform (in)validation of samples of data signals due to excessive motion. They are commonly used with ECG recording [30].

Spirometry primarily measures how (flow speed) and how much (volume) air does a person inhale and exhale. Lung capacity and one’s ability to handle stress (to be able to inhale enough oxygen) can be concluded from spirometry results.

In laboratory environment it can be measured with continuous breathing through a device that measures air flow (see Figure 5). It is however not practical for use in real-life scenarios.

If spirometry is used for driver analysis, it is done prior to driving task. It is primarily used in researching driver drowsiness for the detection of respiratory disorders that cause the drowsiness [31].

C. Multi-signal measurements

When measuring multiple signals at once, usually a means for providing synchronization between them is necessary. Although, if the analysis is not going to involve multiple signals or differences between them, we do not need to provide synchronization, it is still highly recommended for possible future analysis decisions.

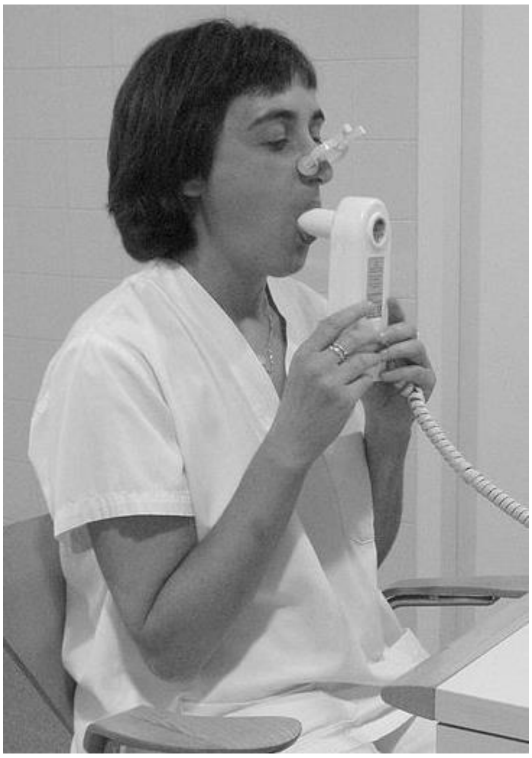

Figure 5. Performing spirometry in a laboratory [32]

Based on our experience, two methods for providing synchronization are proposed. First one is a using a synchronized system. This can be accomplished either by measuring all signals with the same system (a multi-purpose system, e.g. Biopac MP160 [33]) or by having multiple separate coherent systems with the ability to timestamp the recorded data. The same reference clock should be used for synchronizing separate systems (e.g. the same computer, GPS, etc.). The second method involves using a separate synchronization component that has to be present at every measurement. If supported by the sensors, an external triggering signal can be used in order to start (trigger) the measurement on all sensors / systems simultaneously. For the equipment that does not support external triggers, manual simultaneous signal modifications on all sensors can be performed. It is important that the modifications are not likely to occur during normal signal measuring (e.g. unusual amplitudes or patterns) and that they are as simultaneous as possible (e.g. pressing two buttons one with another). This method is however prone to inaccuracy.

One may also be interested in the desired accuracy of the synchronization between systems. It is safe to assume that the sampling frequency of the slowest sensor determines the required accuracy, since achieving higher accuracy does not bring any additional value. Therefore, the desired synchronization accuracy should be at least $1/f_s$, where f_s is the lowest sampling frequency used in the system.

III. Discussion and Conclusion

Different physiological measurements for determining driver's state and behavior appear to provide reliable results in terms of driver analysis. They can be used in a variety of automotive research fields, including autonomous driving, driving simulation development and driver profiling.

Among the mentioned psychological signals especially the analysis of GSR, eye movement and EGG signals seem to have an important potential. ECG is the most widely studied signal and therefore best understood by the research community.

GSR and eye tracking have gained in popularity in automotive industry because of the nonintrusive measurement process. If automated vehicles could predict the current state and cognitive load of drivers, vehicles could decide which tasks are drivers capable of completing and which should be done automatically.

In the field of driving simulators, simulation sickness is widely studied. Some implications exist, that EGG measurements could help detect individual's possibility for experiencing simulation sickness. Furthermore, the introduction of autonomous vehicles will reduce the need for drivers to monitor the outside environment and thus increase the possibility for motion sickness. Its early detection with combination of novel in-vehicle infotainment concepts could help minimize its effects.

Opened research questions include providing (developing) reliable means for measuring the signals in a driving environment, where movement will always be present. Another interesting research topic addresses the need for algorithms that could provide relevant descriptions of drivers' states and enable driver profiling based on multiple physiological signals measured.

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