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A Light on Suitability of Physiological Sensors for Efficient Driver Drowsiness Detection System

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Abstract: The significant advance in bio-sensor technologies hold promise to monitor human physiological signals in real time. In the context of public safety, such technology knows notable research investigations to objectively detect early stage of driver drowsiness that impairs driver performance under various conditions. Seeking for low-cost, compact yet reliable sensing technology that can provide a solution to drowsy state problem is challenging. While some enduring solutions have been available as prototypes for a while, many of these technologies are now in the development, validation testing, or even commercialization stages. The contribution of this paper is to assess current progress in the development of bio-sensors based driver drowsiness detection technologies and study their fundamental specifications to achieve accuracy requirements. Existing market and research products are then ranked following the discussed specifications. The finding of this work is to provide a methodology to facilitate making the appropriate hardware choice to implement efficient yet low-cost drowsiness detection system using existing market physiological based sensors.

Keywords: Driver fatigue, Drowsiness detection, Measurement, Sensors, Physiological signals.

1. Introduction

Till now, the total number of serious car crashes is still increasing regardless of improvements in road and vehicle design for driver safety. Reduced mental alertness due to drowsy state has been identified as the greatest safety danger and the major cause of road traffic accidents [1].

While each day in the United States 80,000 individuals fall asleep behind the steering wheel (American Academy of Sleep Medicine, 2005), 25-30 % of driving accidents in the UK are drowsiness related [2], about 35 % drivers in the Netherlands and 70 % drivers in Spain have reported falling asleep while driving [3].

The measure of human physiological parameters allows evaluating objectively cognitive-attentive indicators, in reaction to external perceptual stimuli. The study of human physiology has showed that monotone driving task and nocturnal driving mostly lead to sleep deprivation, lacking sleep, and being in a state of low energy [3]. These symptoms decrease cognitive abilities and make driver more prone to fatal errors. Many drowsiness measurement technologies have been developed to monitor driving behaviour and alert drivers when drowsy.

Recently, with the remarkable advance in sensing and communication technologies, Low-cost wearable devices are fast becoming a key instrument on bio-sensors based applications and they have been applied in many fields including industrial, transportation, medical, daily-life, sport, etc. There are a number of tentative promoted by shift-work industries to monitor cognitive state of human-being using these emerging technologies since they hold the promise of being objective compared to other measuring technologies. These bio-signals based technologies make it possible to alert driver at earlier stages of drowsiness and thereby prevent many drastic accidents providing a solution to the driver drowsy problem [4].

In this study, we focus in assessing recent development of bio-sensors technologies in the market that are currently underway to address driver drowsiness issue, and provide a concise hardware specification mechanism to design efficient system with better accuracy. In the following, the key drowsiness detection technologies are presented in Section 2. The presented sensor technologies are then evaluated in terms of detection accuracy in Section 3. Next, the general architecture of bio-sensor based driver drowsiness monitoring system with different modules is explained in Section 4. Main performance characteristics that must be met by a drowsiness monitoring technology are discussed in Section 5. Section 6 is devoted to review potential market physiological sensors products. Ranking methodology is described in Section 7 providing a tool to make the appropriate hardware choice of existing products. Finally, Section 8 concludes the paper.

2. Drowsiness Detection Technologies

A plethora of driver fatigue researches exist spanning different measurement technologies. The most commonly used measurement can be categorized upon the monitoring instrument into:

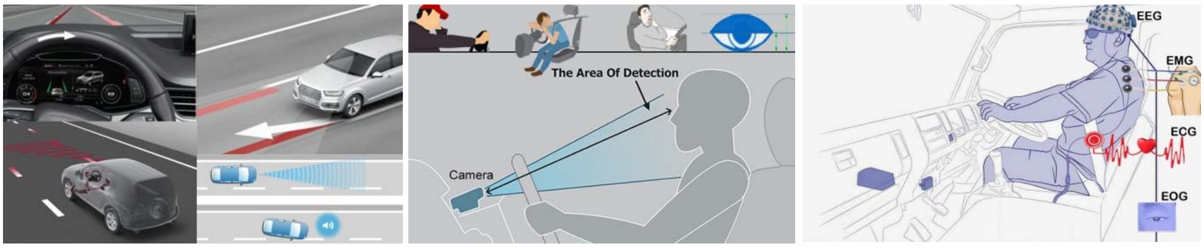
1) Vehicle-based sensors,
2) Video-based sensors,
3) physiological signals sensors such as electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), and electroencephalography (EEG) signals where the latter is the most used [4], [5].

2.1. Vehicle-Based Sensors

In-vehicle measurement sensors are deployed to collect a number of indicator metrics used to determine alertness/drowsiness level of driver through driving behavior as illustrated in Fig. 1(a). This approach focuses mainly on tree main aspects related to the vehicle and its environment:

1) Steering Wheel Movement;
2) Vehicle deviation and position;
3) Vehicle speed and acceleration.

The two most commonly adopted methods in industrial products are the steering wheel movement (SWM) and the standard deviation of lane position (SDLP).



(a) (b) (c)

Fig. 1. Illustration of (a) vehicle behavioural sensors; (b) driver behavioural sensors; (c) physiological signals sensors for fatigue and drowsiness detection.

2.1.1. Steering Wheel Movement

Monitoring the Steering Wheel Movements (SWM) (Fairclough and Graham [6]; Fukuda, *et al.* [7]; Thiffault and Bergeron [8]; Borghini, *et al.* [9]; Eskandarian and Mortazavi [10]) can be an effective way to asses driving behaviour. In fact, certain unnatural manipulation of steering wheel is caused by non-alerted driver and can be an indication of driver fatigue and drowsiness. This approach measures steering behaviour using an angle sensor mounted on the steering axis. A number of metrics can be employed to measure abnormal driving which include number of steering wheel reversals, periods of steering correction and jerky motion of vehicle (Dong, *et al.* [11]). Sayed, *et al.* [12] recorded the steering angle patterns of the vehicle and used ANN (Artificial Neural Network) to classify them into drowsy- and non-drowsy-driving intervals.

2.1.2. Vehicle Deviation & Position

Position of the vehicle is another indication of driver fatigue and drowsiness. In fact, this approach relies on metrics such as the vehicle's position with respect the road's middle lane or also known as the standard deviation of lane position (SDLP) (Ingre, *et al.* [13]; Peng, *et al.* [14]), the car's deviation from lateral lane (Forsman, *et al.* [15]), vehicle yaw deviation (Furugori, *et al.* [16]), and vehicle heading difference (Morris, *et al.* [17]).

2.1.3. Vehicle Speed & Acceleration

Vehicle speed and yet a way to detect unnatural driving behaviour. Research has indicated that acceleration and vehicle speed has a relation with alertness level of driver and drowsy driver usually increases it acceleration. This approach relies on metrics such as speed of vehicle (Arnedt, *et al.* [18]; Fairclough and Graham [6]), acceleration rate (Chen, *et al.* [19]), and pressure on acceleration pedal (Furugori, *et al.* [16]).

2.2. Video-Based Sensors

Instead of focusing on vehicle movements, driver behaviour is monitored to collect a number of indicator metrics that can be used to determine alertness/drowsiness level of driver as illustrated in Fig. 1(b). The behaviour of the driver is mainly monitored through a camera and thus this approach is known as video-based measure. Visible symptoms of fatigue and sleepiness can be observed when driver becomes drowsy through measuring its abnormal behaviours. Research on fatigue and drowsiness detection using driver behavioural monitoring focused on three main measures:

1) Eye movement;
2) Face expression;
3) Head position.

2.2.1. Eye Movement

This measure focuses on eye monitoring through rate of eye blinking (Papadelis, *et al.* [20]), slow eye movements (SEM) (Shin, *et al.* [21]), and eye closure activities including PERCLOS metric which measures the percentage of eyelid closure (Xia, *et al.* [22]; Wang, *et al.* [23]), and the average eye closure speed (AECS) that characterizes eye movement (Ji, *et al.* [24]). The non-usual eye blink and closure reflect an indicator of drowsiness.

2.2.2. Face Expression

Drowsy driver shows some expressions on his face which can be used to measure the drowsiness level of driver. The measure of face expression and actions include inner and outer brow rise, yawning, jaw drop as well as lip stretch (Lew, *et al.* [25]; Xiao, *et al.* [26]; Abtahi, *et al.* [27]; Yin, *et al.* [28]).

2.2.3. Head Position

The position of head is yet another indicator of fatigue and drowsiness. Drowsy driver usually experiences head scaling down or head nodding (Brandt, *et al.* [29]), which happens in advanced stages of drowsiness.

2.3. Physiological Signals Sensors

Physiological signals of the driver can be used to measure his vigilance level since these signals originated from human organs such as brain, eyes, muscles, and heart that can indicate the fatigue and alertness level in real-time as depicted in Fig. 1(c). Physiological measures can be recorded from different organs that show visible correlation with the wakefulness/drowsiness state of a person. This includes:

- **Brain activity**: this can be captured by electroencephalography (EEG) or Near Infrared Spectroscopy (NIRS).
- **Ocular activity**: this is measured by electrooculography (EOG).
- **Muscle Tone**: This can be recorded using electromyography (EMG) signal.
- **Cardiac activity**: it is monitored through electrocardiography (ECG) and Blood Pressure signals.
- **Respiration**: by measuring respiratory effort, Nasal and oral airflow, Blood gas, and Snoring noise of sleeping.
- **Gastro intestinal parameters**: obtained by recording the esophageal pH.
- **Electro dermal activity**: measured by the galvanic skin response and through skin resistance and conductance.
- **Core temperature**: gives insights on the actual circadian phase of the person.

3. Technologies Evaluation

An evaluation is conducted to assess different sensor technologies. The methodology was based on a compilation of product evaluations gathered from literature searches of technical and scientific journals, review of experts on alertness/fatigue technologies as well as the Internet, on-site visits and technical demonstrations. The presented evaluation investigates the intrusiveness, the accuracy and suitability for adoption in real conditions of sensor technology.

Vehicle sensor technologies, which have been adopted by many car manufacturers, measure driving patterns such as steering wheel angles and reversals, car position with respect the road's middle lane and the standard deviation of lane position (SDLP), etc. This technology is non-invasive, but it presents a number of limitations and works in very specific situations [4]. The reason is that it can operate reliably only at particular environments depending on the geometric characteristics of the road and on the vehicle movement [30] and they are easily influenced by other factors such as road conditions, lighting and traffic conditions. For example, Sahayadhas, *et al.* [31] reported that the SDLP is purely dependent on road marking, climatic and lighting conditions. Based on literature reviews, lane tracking technology has relatively high false alarm rates (e.g., 14 % in [32]).

On the other hand, video sensors technology is non-intrusiveness and user friendly and cab be mounted comfortably in various areas inside a vehicle. The common limitation is lighting. High detection rates have been reported in simulated environment with PERCLOS and Eye Blink (Bergasa, *et al.* [33]; Liu, *et al.* [34]). However, the detection rate decreases significantly when the experiments are carried out in a real environment (Philip, *et al.* [35]) and they are considered as less accurate and less stable compared to physiological sensors such as EEG and ECG. For instance, the detection rate of camera based eye tracking is just 59 % compared to 85 % and 97.5 % of EEG and ECG respectively (Sanjaya, *et al.* [5]). Golz, *et al.* [36] reported that the detection accuracy using PERCLOS signals was around 74 % and 66 % (errors between 26 % and 34 %) compared to the results from EEG/EOG signals which were 87 %.

Physiological sensors make it possible to alert driver at earlier stages of drowsiness and thereby prevent many drastic accidents [4]. Researchers observed via EEG that drivers had sleep bursts accompanied by theta waves and K-complexes while they still had their eyes open, something video-based monitoring might have missed. Physiological measures have been shown to be reliable and accurate since they are less impacted by environmental and road conditions and thus may have fewer false positives [37]. However, such methods are more invasive and intrusive. When compared to methods such as video-based (PERCLOS) and vehicle-based measures including SWM, the obtrusiveness of electrode-based methods becomes a concern. Several wireless dry-sensor devices have been developed to circumvent the invasiveness issue. These devices are low cost and promising, but their current versions have compromised accuracy and noise sensitivity.

Table 1 shows the evaluation results of the three above described drowsiness measure technologies.

The (+) symbol represents the rating level (either positive or negative) for a given criteria. This ranking is based on our study of drowsiness monitoring technologies and we believe that it is not the only evaluation method to access the performance of such technologies.

Table 1. Evaluation of existing technologies.

Sensor	Vehicle	Video	Physiological
Intrusiveness	+	+	+++
Artefacts/Noise	+	++	+++
Ease of Use	++	+++	+
Accuracy	+	++	+++

4. Bio-Sensors System Architecture

Due to the increasing interest in the use of wearable physiological or bio-sensor systems, many communication architectures have been proposed depending on the target application [38]. The general architecture of bio-sensor system is composed by three main modules:

1) Signal acquisition;
2) Data processing;
3) Control modules [46] as depicted in Fig. 2.

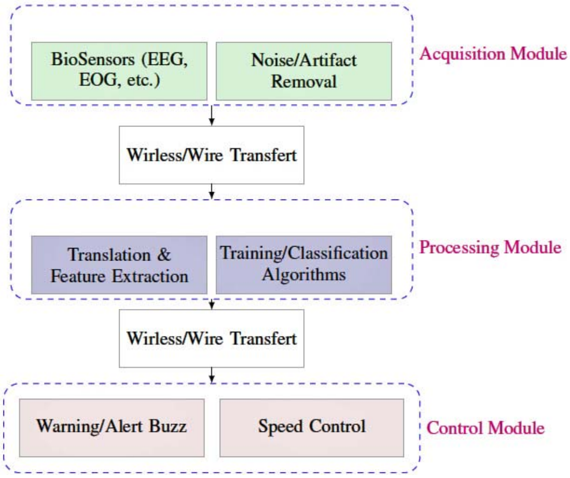


Fig. 2. Logical view of different system modules.

4.1. Acquisition Module

This module is composed of different physiological wearable sensors such as EMG, ECG, EOG, EEG, etc. attached to the body which measure physiological signals. These sensors form a network and communicate with the network coordinator to send data. The measured signals are then filtered and transformed to remove any noise and artifact that may affect the quality of sensed data values.

4.2. Processing Module

Signals are received from acquisition module after filtering noise and removing artefacts. As second stage, signals are processed to extract the main features that reflect different states of the target application (e.g. the cognitive states of driver). These features are then passed to the training and classification algorithms to determine the new measured states. As for driver drowsiness, the features can be used to determine in which level of alertness the driver is.

4.3. Control Module

Driver alertness is monitored in real time using acquisition and data processing modules. Whenever a drowsy state is identified, the detection event is then triggered by the control module to make the appropriate action in time. This action may be an alarm or buzz inside the vehicle to alert or wake-up the driver. The action may take control of the vehicle in order to speed-down or stop the vehicle.

Many portable systems propose to incorporate the acquisition and the processing modules into the same component to compact the system. Hence, there is a serious issue with the battery lifetime. In the context of driver drowsiness detection, the acquisition module is attached to the driver and the processing module is installed on the vehicle which has sufficient power supply. This allows extending the battery lifetime and keep monitoring for long periods.

The control module is mounted on the vehicle to trigger warning messages and sound alerts. This module can be even enabled to control some actions of the vehicle such as acceleration and speed. The system can be extended to support multi-tiers cloud-based architecture [39].

As depicted in Fig. 3, some of data can be transmitted via 3G/4G/LTE connections to the remote servers where data analytic algorithms can be used to train and extract new knowledge. This enables monitoring cognitive states during real driving tasks from large number of drivers and may be explored by the research community to enrich training sets and improve the accuracy of existing detection algorithms.

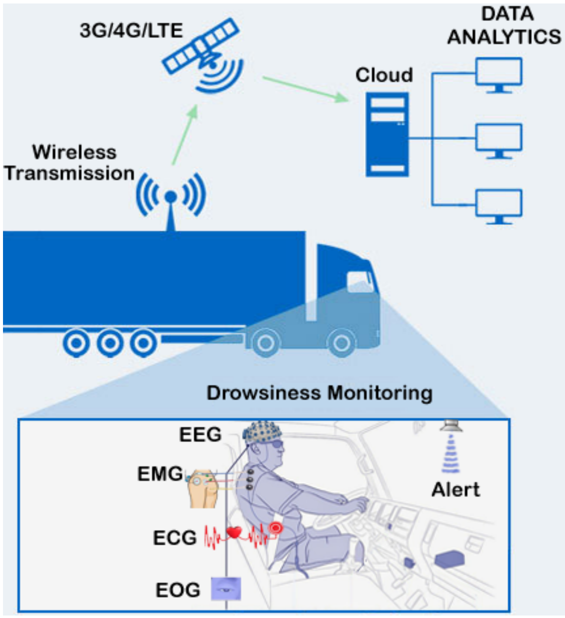


Fig. 3. Bio-Sensors Based Driver Drowsiness Detection System Architecture.

5. Performance Requirements

If any bio-sensors system is to prove suitable for detecting driver drowsiness, it must meet some performance specifications. These specifications are essential in making the appropriate bio-sensors hardware choice for design consideration. We presented in our previous work [46] the major requirements for an efficient bio-sensor drowsiness detection system which are discussed in the following:

5.1. Multi-Sensors Support

Single signal measurement such as EEG may necessitate dense electrode placement in different locations to accurately capture cognitive states. Hybrid signal acquisition through simultaneous recording of different bio-signals can yield higher accuracy of the system. Combination of multiple bio-signals measurements, such as ECG, EMG, EOG with EEG, the system can measure not only brain waves but also heart rate, eye movements, etc. Research results have showed that adding either EOG or ECG measurements, there is further improvements in reduction of error rates in drowsy state detection [40].

5.2. Type of Electrodes

The choice of electrode technology is very important since it represent the sensing component. With respect EEG measurement, wet electrodes known as silver-chloride electrodes (Ag/AgCl) are widely used by current market products. These electrodes are low-cost, and have low contact impedance, and good stability in time. Wet electrodes requires removing outer skin layer of the scalp and filling a special conductor gels which take long time to prepare and are uncomfortable to users.

Dry electrodes are other technology which does not need to use gel and skin cleaning. However the bad signal quality is their main disadvantage. Fig. 4 shows an example of dry and wet electrodes available in the market.

(a) (b)

Fig. 4. Dry electrodes (a) vs. Wet electrodes (b).

5.3. Electrode Placement

Capturing data from strategic locations, to pinpointing drowsy related cause, is critical. For each bio-signal, there exists suitable locations where may be placed to efficiently measure signal reflecting the drowsy state of driver. For EOG, electrodes are attached to the eye skin (up/down/left/right) whereas for EMG, they may be placed on the left bicep, right bicep, left forearm flexor, right forearm flexor, frontal muscles, or on the deltoid, trapezius Hostens and Ramon [41]. While 5 & 12 lead electrode placements are generally used for ECG recording.

For EEG, the electrode placement according to the 10-20 Standard defines which brain location that serves a specific function (as shown in Fig. 5). More specifically: Prefrontal Cortex (Fp) for emotional inhibition and attention; Frontal Lobes (F) for working memory, metaphorical thinking, sustained attention and judgment; Central Strip (C) for sensory-motor functions; Temporal Lobes (T) for language comprehension and long-term memory; Parietal Lobes (P) for language processing and procedural memory; Occipital Lobes (O) for visual processing. Thus, locations concerning various forms of attention which reflect alertness/drowsiness states must be covered by the hardware.

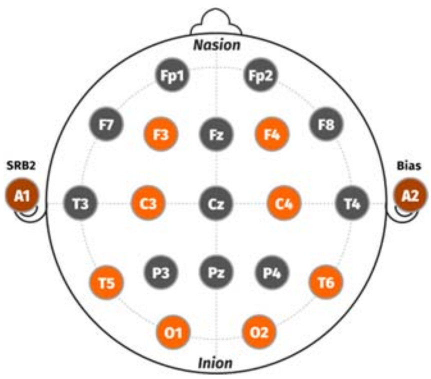


Fig. 5. The 10-20 system of EEG electrode placement.

5.4. Number of Channels

An electrode capturing bio-signal activity is called a channel. Typical Bio-sensor systems can have as few as a single channel to as many as channels (256 for EEG) depending on the required density. The system must trade-off between capturing as much as bio-activities with some performance metrics. For instance, increasing the number of channels will have significant delay for data processing. Second, more channels mean higher costs and more difficult experimental setups. Lastly, by increasing the number of channels, the huge amount of signals will be transmitted that impairs reliability and battery usage especially for mobile and low-power systems. On the other hand, very few channels impair the accuracy of detection.

5.5. Portability & Mobility

Conventional bio-sensors systems such as actiCHamp (Brain Products), Neuroscan NuAmps Express (Com-pumedics Ltd.), and EDVTCS (Neurocom) are wired. The acquisition part of wired systems generally comes with bulky and heavy amplifiers and pre-processing units. Connecting wires is usually complicated with a large number of cables between the electrodes and the acquisition part. For these reasons, preparation time for measuring signals is typically very long. In addition, user movement is limited due to cable constraints. Therefore, the application of drowsiness detection based on these systems is difficult to escape from laboratory scale experiments. With emerging wearable technologies, bio-potential measurements, such as EEG, ECG, EMG, and EOG can be delivered in real-time via wireless and Low-energy connections such as WiFi, Bluetooth, ZigBee, etc. Therefore, these provide the advantages of mobility and long-term monitoring. Portable systems facilitate the implementation of driver drowsiness detection systems and enable in-field experimentation instead of simulation environment. However, huge volume of signals may be sampled and need to be transmitted wirelessly in real-time. Hence, the system must prove energy-efficient operation for long period to be accepted for continuous monitoring. For example, compression algorithms can be used to alleviate big data transfer since it is time and energy consuming [42].

5.6. Artefact Removal

Bio-sensors are prone to various sources of noise and artefacts. Signal conditioning is essential to enable transmission of precise bio-signals. Many noise sources are likely present from physiological interference and power line noise. Physiological interference occurs between EEG, EMG, ECG, EOG and others. The amplitude of EMG, ECG and EOG is relatively lager around 50 uV and 20-30 mV while that of EEG is much smaller around 10 100 uV. Thus, the EEG signals are easily buried by these physiological signals unavoidably. Power line noise (Outlet, USB, etc.) can also contaminates the EEG signals in the range of 50 or 60 Hz. Furthermore, the measured bio-signals of mobile systems are also subject to heavy motion and vibration artefacts. Hence, the presence of noise and artefact removal mechanism is essential in such systems.

5.7. System Autonomy

Another important specification is the need of energy-efficient and long-term wearing system. For systems that use battery powered bio-sensors, the lifetime of the system is the critical challenge to ensure continuous driver monitoring. In fact, wireless transmissions consume the largest amount of device's energy. Indeed, the battery autonomy may go from 4 hours to 24 hours or even more depending on the wireless technology (e.g. Bluetooth, WiFi, etc.) and on the sampling rate. The system must be designed with efficient usage of sensory and radio components to ensure reasonable monitoring lifetime.

5.8. Software

The software is one of the main parts of the system. Thus it is fundamental to have access to data in order to manipulate and/or analyse the recorded signals. The market product may provide software development kit

(SDK) as bio-signal acquisition software or an application programming interface (APIs) compatible with some known commercial or open source bio-signals software platforms (e.g. BCI 2000, OpenVibe, LabVIEW, etc.). This facilitates and speeds-up the development of efficient detection algorithms.

5.9. Product Cost

Making a choice between products must trade-off system performance with its cost. Many of existing market devices are designed for clinical and research purpose and provide multi-sensor acquisition with a large number of electrodes/channels and with incredible sensitivity. The cost of such systems is visibly high due to the full provided functionality. Depending on the application need like driver drowsy detection, the system cost may be reduced and can be determined by the performance specifications such as number of channels, sensors' type, portability, wireless technology, flexibility, and comfort.

6. Market Bio-Sensors Platforms

Researchers have made use of a wide variety of physiological signal receivers to collect and amplify signals.

Conventional physiological signal systems such as actiCHamp system (Brain-Products, Gilching, Germany), Neuroscan NuAmps Express system (Compumedics Ltd., VIC, Australia), or EDVTCS Engine Driver Vigilance Telemetric Control system (Neurocom, Russia) are wired. The acquisition module in such systems comes with bulky and heavy amplifiers and preprocessing units. Connecting wires is usually complicated with a large number of cables between the electrodes and the acquisition part. For these reasons, preparation time for measuring signals is typically very long. In addition, user's movement is limited due to cable constraints. Therefore, the application of drowsiness detection based on these systems is limited to in-lab only experiments. Furthermore, the cost of such systems is visibly high, around 100 Ke, but they can be used to provide reference measurements and validate those of low cost systems. Nowadays, more smart, compact and user-friendly products have been increasingly introduced to the market, which bring physiological signal readings into in-field experiments.

6.1. General Use Platforms

Most of existing physiological signal measuring products provides specific monitoring functionality of human physiological states and the majority of these platforms are intended for general measurement usage. For example, MySignals [43], Shimmer [44], and Bitalino [45] provide e-Health platform that measures several signals such as ECG, EMG, EEG, and EDA (one-channel each).

ActiCHamp cap from Brain Products is destined for EEG signal acquisition. ActiCHamp exists with different channel and sampling rate configurations ranging from 32 to 160 channels and from 10 to 100 kHz receptively. ActiCAP express is light head cap version with 16 channels and active electrodes. Biosemi developed Active Two which is an 8/16/32 channels acquisition cap system with wet electrodes. The eego/rt sports from ANT Neuro is a portable head cap with up to 64 channels for rehabilitation mental states studies, and can work without conductive gel electrodes. NeXus-32 and Nexus-4 (Mind Media) are 32 channels (heavy) and 4 channels (portable) bio-sensors head cap with wet electrodes.

Cognionics developed 64 channels headset Dry electrodes for general signals measurement. Quick-20/30 is light version with 20 channels and possibility to integrate 8 channels from auxiliary EOG/ECG/EMG/PPG sensors. Cognionics also designed Sleep HeadBand with 10 channels for sleep monitoring. G.tec designed g.nautilus with 8/16/32 channels and wet/dry electrodes for clinical and research purpose. Quick Cap is 256 wet electrode head cap from NeuroScan capable of measuring EEG, ECG, EMG, and EOG signals. QUASAR designed DSI-10/20 head cap with 21 dry electrodes. While Enobio, from NeuroElectrics, is an acquisition head-cap with 8/16/32 channels. mBrainTrain designed 24 channels EEG wireless cap with wet electrodes as a research tool for psychology, sport, sleep, and serious gaming/VR studies. ABM realized B-Alert X10 (13 channels) and B-Alert X24 (24 channels) which are portable physiological sensor headsets that can measure EEG combined with some other physiological signals such as ECG and provide quick and valuable insight into the cognitive function and mental state of the user.

OpenBCI is an open-source sensor board capable of measuring EEG, EMG, and ECG signals. OpenBCI can support 4/8/16 and wet/dry electrodes which are sold separately. IMEC developed EEG headset with 8 channels to monitor Emergency Room and Intensive Care Unit patients. Omilex sold ModularEEG which is 2-channels open-source hardware known as OpenEEG. Neurosky designed MindWave; a single channel EEG using one dry electrode on the forehead (FP1) for everybody use. Emotiv is another company that developed mobile bio-sensors. EPOC+ is a 14 channels and Insight is 5-channels from Emotiv that use dry electrodes and are capable of providing the following metrics to the users:

1) Engagement/Boredom which reflects long-term alertness and task-relevant attention stimuli;

2) Excitement (Arousal) that reflects the instantaneous arousal towards stimuli associated with positive valence;

3) Stress (Frustration);

4) Meditation (Relaxation).

Versus is EEG headset with 5 channels and dry electrodes designed for athletic peak- performance neuro-feedback training through customized exercise protocols to improve mental acuity, concentration, and sleep management. Muse Headset from Interaxon is an easy-to-use 4 channels headband for concentration and meditation training. Melon is a slim EEG headset with 4 dry electrodes for focus neuro-feedback. iFocusBand is a headband with 3 flexible woven electrodes targeted primarily for sports performance training. Lee et al. [38] present a complete review of current portable BCI based systems with common architectures and applications.

6.2. Drowsiness Detection Platforms

Due to the obtrusiveness nature of physiological signal-based technologies, few drowsiness detection products exist in the market. With the growing progress in sensing technologies, less intrusive electrode technology has emerged with acceptable signal-to-noise level and makes it possible to develop reliable detection systems. For instance, Anti-sleep alarm Vigiton from Neurocom and StopSleep are products that recognize the loss of concentration and prevents micro-sleep by measuring the conductivity of the skin (electrodermal activity EDA). Fig. 6 illustrates existing market physiological measurement platforms. Table 2 provides a brief comparison of these platforms regarding their main specifications including the number of channels, type and electrode placement, data transfer technology and sampling rates as well as the battery autonomy and the corresponding cost whenever provided.

Fig. 6. View of market physiological based measurement platforms.

7. Products Ranking & Discussion

Notable efforts are taking place to promote bio-sensors technologies for pioneer applications. To our knowledge, there exist practically very few biosensors product intended for driver drowsiness detection on the market. Most of existing products provide bio-signals monitoring for general research usage or for medical and neuro-feedback applications such as training, sport, gaming, etc. In the context of driving monitoring, more efforts are needed to meet performance specifications to develop efficient drowsiness detection system. For instance, high precision products are bulky and rely upon a large number of channels (e.g., 64-256), which is cost non-effective and makes it difficult to do fast artefact removal. Furthermore, electrode placement is too technical due to the requirement for electrodes, gel, wiring, etc. The use of dry electrodes is promising to reduce the cost and time required for data collection but novel techniques are needed to improve the accuracy of measured signals. Lower cost products come with reduced resolution (e.g., 4-16 channels) but with increased portability. Although, these devices are cost effective and more comfortable, they either suffer from low accuracy or require additional signal inputs such as EOG, ECG, and EMG to maintain high accuracy.

Table 2. Review of existing Bio-Sensors market products with major specifications.

Company	Product	Number of Channel	Electrode Type	EEG Locations	Bio Sensors	Data Transfer	Rate (kHz)	Battery Life	System Cost ($)
Brain Products	ActiCHamp ActiCap	160 128 96 64 32 16	Wet Wet Wet Wet Wet Wet/Dry	(Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O)	EEG EEG EEG EEG EEG EEG	USB USB USB USB USB USB	10-25 10-25 10-25 25-50 50-100 2-20	6 hr 6 hr 6 hr 6 hr 6 hr 6 hr	96,500 80,000 66,200 49,900 35,600 11,375
ANT Neuro	eego/rt sports	64+24	Wet	(Fp) (F) (C) (T) (P) (O)	EEG EMG EOG	USB	2.048	6 hr	>25,000
Biosemi	Active Two	256+7 160+7 128+7 64+7 32+7 16+7 8+7	Wet Wet Wet Wet Wet Wet Wet	(Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O)	EEG ECG EMG EEG ECG EMG EEG ECG EMG EEG ECG EMG EEG ECG EMG EEG ECG EMG EEG ECG EMG	USB USB USB USB USB USB USB	2-16 2-16 2-16 2-16 2-16 2-16 2-16	5 hr 5 hr 5 hr 5 hr 5 hr 5 hr 5 hr	75,000 52,000 45,000 27,000 21,000 17,000 13,500
Cognionics	Dry Head Set Quick-20 Sleep Headband	16+8 24+8 32+8 64+8 20+8 10	Dry Dry Dry Dry Dry Dry	(Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (T)	EEG ECG EMG EEG ECG EMG EEG ECG EMG EEG ECG EMG EEG ECG EMG EEG	BLE BLE BLE BLE BLE BLE	0.262 0.262 0.262 0.262 0.262 0.262	6 hr 6 hr 6 hr 6 hr 6 hr 6 hr	~15,500 ~20,500 26,500 42,600 20,600 3,800
G.tec	Sahara Nautilus	8 16 32	Wet/Dry Wet/Dry Wet/Dry	(Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O)	EEG EEG EEG	RF RF RF	0.25/0.5 0.25/0.5 0.25/0.5	8 hr 8 hr 8 hr	4,500 ~9,500 ≤25,000
QUASAR	DSI10/20	21	Dry	(Fp) (F) (C) (T) (P) (O)	EEG ECG EMG EOG	BLE	0.24/0.9	24 hr	22,500
NeuroElectrics	Enobio	8 20 32	Wet/Dry Wet/Dry Wet/Dry	(Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O)	EEG ECG EMG EOG EEG ECG EMG EOG EEG ECG EMG EOG	BLE BLE BLE	0.25 0.25 0.25	8 hr 8 hr 8 hr	4,995 14,495 24,995
AMB	B-Alert X10 B-Alert X24	9+4 20+4	Wet Wet	(F) (C) (P) (F) (C) (P) (O)	EEG ECG EMG EOG EEG ECG EMG EOG	BLE BLE	0.256 0.256	8 hr 8 hr	9,950 19,950
NeuroScan	Quick Caps	256	Wet	(Fp) (F) (C) (T) (P) (O)	EEG ECG EMG EOG	USB	02/0.5	0	81,396
Mind Media	NeXus-32	21	Wet	(Fp) (F) (C) (T) (P) (O)	EEG ECG EMG EOG	BLE	2.048	20 hr	23,995
mBrainTrain	EEG Cap	24	Wet	(Fp) (F) (C) (T) (P) (O)	EEG	BLE	0.25/0.5	5 hr	6,925
OpenBCI	Head Set	4 8 16	Wet/Dry Wet/Dry Wet/Dry	(Fp) (F) (C) (T) (Fp) (F) (C) (T) (P) (O) (Fp) (F) (C) (T) (P) (O)	EEG ECG EMG EEG ECG EMG EEG ECG EMG	RF/ BLE RF/ BLE RF/ BLE	0.20 0.25 0.25	26 hr 26 hr 26 hr	199+60 499+60 899+60
IMEC	EEG Headset	8	Dry	(F) (C) (T) (P)	EEG	BLE		22 hr	25,000
Olimex	OpenEEG	2	Wet/Dry	(Fp) (F)	EEG	USB	0.19/0.5	0	119
Emotiv	EPOC+ Insight	14 5	Wet	(F) (T) (P) (O) (F) (T) (P)	EEG	RF RF	0.128 0.128	12 hr 4 hr	799 299
NeuroSky	Mind Wave	1	Dry	(Fp)	EEG	RF	0.25	8 hr	130
Macrotellect	BrainLink	1	Dry	(Fp)	EEG	BLE	0.512	4 hr	373
InteraXon Inc.	Muse	5	Dry	(Fp) (P) (O)	EEG	BLE	0.22	5 hr	299
SensLabs	Versus	5	Dry	(F) (C)	EEG	BLE	0.25/1.28	5 hr	399
Melon Inc.	Head band	1	Dry	(Fp)	EEG	BLE	0.25	8 hr	149
Focus	IFocusBan	2	Dry	(Fp)	EEG	BLE	0.25	12 hr	500

In the context of driver drowsiness detection, it would be preferable that the bio-sensor system is less obtrusive and composed with multiple bio-sensors especially EEG and EOG [36], with few but sufficient number of channels, active electrodes, low-power communication technology with acceptable sampling rate and battery autonomy. To facilitate the choice of suitable hardware for drowsiness detection, we have ranked the reviewed bio-sensor products in Sec. 6 using the performance specifications discussed in Sec. 5. As multiple bio-sensors are needed, we ranked with (1, 2, 3, 4) whenever EEG, ECG, EMG, EOG are supported. Electrode type is ranked with 1 for wet and 2 for dry. Electrode placement is ranked only for EEG from 1 to 6 for (Fp) (F) (C) (T) (P) (O) locations. We ranked the number of channels with 1/2/3/4/5 for 64-256/32-64/16-32/8-16/1-8 channels. Portability is ranked following the data transfer technology as 1/2/3/4 for USB, WIFI, BLE[1], and RF[2]. Artefact removal is ranked with 0 or 1 for the existence of the mechanism. Battery lifetime is ranked as 1/2/3/4/5 for 1-4/4-8/8-12/12-16/16-24 hour's autonomy. The software is ranked with 0/1/2 when the signal processing software is provided and wither is commercial or open-source software. Finally, the cost is ranked with 1/2/3/4/5 for price ranging in [50k 100k]/[25k 50k]/[10k 25k]/[1k 10k]/[0 1k] $.

Table 3 shows the results of existing bio-sensor products ranking [46].

Table 3. Bio-Sensors Platforms Ranking.

	Number of channel	Electrode Locations	Type of Electrodes	Multi-sensors	Portability	Artefact Removal	Battery Autonomy	Software	Cost	Ranking
ActiCHamp-64	2	6	1	1	1	1	2	2	2	18
ActiCHamp-32	3	6	1	1	1	1	2	2	2	19
ActiCap	4	6	2	1	1	1	2	2	3	22
eego/rt sports	2	6	1	3	1	1	2	1	2	19
Active Two-128	1	6	1	3	1	1	2	2	2	19
Active Two-64	2	6	1	3	1	1	2	2	2	20
Active Two-32	3	6	1	3	1	1	2	2	3	22
Active Two-16	4	6	1	3	1	1	2	2	3	23
Active Two-8	5	6	1	3	1	1	2	2	3	24
Cognionics-70	1	6	2	3	3	1	2	1	2	21
Cognionics-40	2	6	2	3	3	1	2	1	2	22
Cognionics-32	3	6	2	3	3	1	2	1	3	24
Cognionics-24	3	6	2	3	3	1	2	1	3	24
Quick-20	3	6	2	3	3	1	2	1	3	24
Sleep Headband	4	3	2	1	3	1	2	1	4	21
G.tec SAHARA-32	3	6	2	1	4	1	2	1	3	23
G.tec SAHARA-16	4	6	2	1	4	1	2	1	3	24
G.tec SAHARA-8	5	6	2	1	4	1	2	1	4	26
Q. DSI10/20	3	6	2	4	3	1	5	1	3	28
Enobio-8	5	6	2	4	3	1	2	1	4	28
Enobio-20	3	6	2	4	3	1	2	1	3	25
Enobio-32	3	6	2	4	3	1	2	1	3	25
B-Alert X10	4	3	1	4	3	1	2	1	4	23
B-Alert X24	3	4	1	4	3	1	2	1	3	22
Quick Caps	1	6	1	4	1	1	1	1	1	17
NeXus-32	3	6	1	4	3	1	5	1	3	27
mBrainTrain Cap	3	6	1	1	3	1	2	1	4	22
OpenBCI-4	5	4	2	3	4	1	5	2	5	31
OpenBCI-8	5	6	2	3	4	1	5	2	5	33
OpenBCI-16	4	6	2	3	4	1	5	2	5	32
IMEC	5	4	2	1	3	1	5	1	3	25
OpenEEG	5	2	2	1	1	1	1	0	5	17
Emotiv EPOC+	4	4	1	1	4	1	3	1	5	24
Emotiv Insight	5	3	2	1	4	1	1	1	5	23
NeuroSky	5	1	2	1	4	1	2	1	5	22
BrainLink	5	1	2	1	3	1	1	0	5	19
Muse	5	3	2	1	3	1	2	2	5	24
Versus	5	2	2	1	3	1	2	0	5	21
Melon	5	1	2	1	3	1	2	0	5	20
Focus	5	1	2	1	3	1	3	0	5	21

[1] BLE: Bluetooth Low Energy marketed as Bluetooth Smart.

[2] RF: Proprietary RF refers to any radio frequency specific to an original equipment manufacturer OEM and it is under 928MHz.

It can be observed that OpenBCI, Enobio, and DSI10/20 are the top ranked platforms that have met the required performance specifications among others. This ranking is based on our study of physiological based-sensors technologies and we believe that it is not the only evaluation and ranking method to access the performance of such technologies. Although some performance metrics were not taken into consideration in our ranking (e.g., device comfort), we think that the proposed ranking tool help in choosing the most appropriate hardware products to develop efficient drowsiness detection system.

8. Conclusions

Driver drowsiness poses a major danger for public safety. Monitoring driver's alertness is of high importance to prevent grand number of incidents. Existing drowsiness detection technologies such as vehicle and video-based have limited accuracy and work well in specific conditions. Recently, a number of portable bio-sensor devices have rapidly attracted the research interest to circumvent the drive drowsy problem under any condition. These promising devices can objectively capture the drowsiness state by monitoring physiological signals of drivers and alert them in real-time. However, the choice of the hardware must trade-off some performances such as signal quality and the cost. This paper highlights current progress in the development of bio-sensor based driver drowsiness detection systems and discusses a number of specifications required by such systems to achieve better accuracy. Existing market and research bio-sensor platforms are then evaluated and ranked following these specifications providing the research community with a tool to make the appropriate hardware choice for design consideration of efficient yet low-cost driver drowsiness detection. We plan to perform experimental comparison tests between some existent market platforms in our research agenda.

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