Wearable Technologies for Smart Environments: A Review with Emphasis on BCI

Goran Udovičić, Ante Topić, Mladen Russo
FESB – Split, University of Split, Croatia
goran.udovicic@kron.hr, ante.topic@fesb.hr, mladen.russo@fesb.hr

Abstract— **In recent years, there has been a growing demand for the development of smart environments to improve quality of life. A major role in this process have wearable devices capable of monitoring and recording psychophysiological measures/signals required for variety of applications including remote health monitoring, physical activity monitoring and general user interaction. This paper surveys the current state of technology, models and requirements of wearable devices with emphasis on Brain Computer Interface (BCI). BCI technology is a rapidly growing scientific field with a number of practical applications providing useful and accurate information and has a promising future. The paper also summarizes the current applications of BCI and presents their limitations and signal-processing algorithms. This area will be the biggest challenge of future research and development process. Other challenges include connectivity, data input, security, design, robustness, low energy consumption and energy harvesting.**

Keywords— wearable devices, wearable interfaces, Brain-Computer Interface, ambient energy harvesting, smart environments

I. INTRODUCTION

Wearable computers started to gain commercial and research interest in early 1990s. In these years, on-body computer solutions were often derived from standard computing components available at the time. In the past few years, improvements in miniature devices resulted in a huge growth of interest for wearable technology. As more integrated sensors became available, the view on market opportunities shifted to fitness, sports, and the quantified self. [1]. Due to a tremendous increase in research, wearables are now evolving into reliable and accurate devices, and are becoming a part of our daily lives.

This paper surveys the current state of technology, models and requirements of wearable devices with emphasis on BCI. BCI technology is a rapidly growing scientific field with a lot of advantages which will surely change our daily lives. So far many studies have been conducted in areas of driver's safety, gaming industry and medicine. Besides making our everyday lives easier, this technology is especially important to disabled people as it will be able to replace, restore, improve and extend bodily functions.

This paper is organized as follows. Section 1 gives a short introduction to wearable technology and the reasons for developing it. Section 2 presents a review of wearable devices with brief descriptions of Body Area Networks (BAN), garment and accessory based wearables, power supply and energy harvesting issues. The comprehensive overview of BCI devices is given in Section 3. Materials and methods used in BCI systems are discussed in Section 4. Finally, Section 5 concludes the paper.

II. A REVIEW OF WEARABLE DEVICES

There are many definitions of the wearable devices. One of the simplest is that a wearable device is any body-worn computer that is designed to provide useful services to end user regardless of its activity[1]. According to [2] a wearable computer is a computer that is subsumed into the personal space of the user, controlled by the user, and has both operational and interactional constancy, i.e. is always on and always accessible. Also wearables can be thought of as a system of various sensors attached on human body which keep track on some human activity or physiological functions. Collected data can be stored locally or transmitted to remote device such as smart phone or laptop via Bluetooth or Wifi technology. Electronic devices that add features to wearable systems, including computing, sensors, etc., must be unobtrusively embedded in users' outfit as a piece of clothing and accessories. Consequently, wearables become part of a regular garment or accessory that is already used in real life. All these devices have similar requirements including connectivity, data input, security, design, robustness, low energy consumption and energy harvesting.

A. Body Area Networks (BAN)

Before some time, a wearable device was able to perform only one action, due to technology or power requirements. Today, they are used for multiple operations or as a system of sensors. If these sensors are placed on the human body, then we can speak of Body Area Networks. Although sensors are usually placed on the human body, recently with the advance of nanotechnology, wearables could be put inside the human body. There are still discussions related to questions about privacy and other security issues.

One of the pioneer articles in Internet era is published by MIT researchers R. W. Pickard and J. Healey in 1997 [3]. They constructed the term "Affective wearable" as a wearable system equipped with sensors and tools which enable recognition of its wearer's affective patterns. Affective patterns include expressions of emotion such as glad smile, an

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irate gesture, a strained voice or a change in autonomic nervous system (ANS) activity such as heart rate or increasing skin conductivity. One part of this review is based on the thoughts that lot of physiological data can interpret some emotional state that person is feeling. This data can be very useful in human computer interaction since the idea is that machine can interpret what person is feeling based on its look, behavior or physiological response.

A nice survey was also done by K. Wac and C. Tsiourti in [4]. Their article represents wearables summary up to 2013. Survey is based on wearable BAN systems for psychophysiological measurements.

There are various psychophysiological measures/signals that can be recorded by modern electronic devices. Actigraphy is a method of monitoring human rest and activity cycles. Accelerometer data can be used for mobility and posture detection provided by sensors that detect acceleration(s) in one to three orthogonal planes (anteroposterior, mediolateral, and vertical). Actigraph unit is typically placed on left thigh (above the knee) or chest and uses piezoelectric sensors [5].

Arterial blood pressure (BP) is one of the most important clinical parameters, and it is widely measured in and out of the medical environment. Ambulatory assessment refers to the use of computer-assisted methodology for self-reports, behavior records, or physiological measurements, while the participant undergoes normal daily activities. Due to the large number of measurements ambulatory recording provides a reliable estimate of a person's blood pressure [6].

The Electrocardiogram ECG is the process of recording the electrical activity of the heart over a period of time. Using twelve electrodes attached on to the chest, ECG provides monitor the Heart Rate(HR) as the number of heartbeats per unit of time, and the variation between the beats (HRV). Another parameter measured by the ECG is respiratory sinus arrhythmia—the natural variation in heartbeats that occurs during a breathing cycle.

Electrodermal activity (EDA) is a sensitive index of sympathetic nervous system activity. The most common measures of EDA are the skin conductance level (SCL) and the skin conductance response (SCR). Changes in skin conductance at the surface may affect to cognitive states, arousal, emotion and attention. That activity can be monitored using electrodes at palm of hand in laboratory environments [7].

Impendance cariography (ICG) is a feasible and accurate method for noninvasive measurements of stroke volume (SV) and the cardiac output (CO). With measured HR and BP different hemodynamic parameters are derived; the volume of blood ejected from one ventricle of the heart in one contraction known as stroke volume (SV), the cardiac output (CO), aortic valve opening to closing interval time (LVET) and time for ECG Q-wave to opening of aortic valve (PEP). ICG can identify patients at increased near-term risk of recurrent decompensation [8].

Skin surface electromyography (EMG) is a method used to record electric signal which produced by human muscle and detected by surface electrodes. In [9], an effective EMG-based impedance control method for an upper-limb power-assist exoskeleton robot is proposed.

Pulse oximetry is a noninvasive method for monitoring a patient's oxygen (O_2) saturation. In [10] authors developed algorithms for automated quality assessment for pulse oximetry and BP signals in a home environment.

Another biosignal that can be acquired with modern psychophysiology monitoring devices is temperature. Human body temperature comprises temperatures of the core body and peripheral. This is important in the study of human temperature regulation in daily life [11].

An electroencephalogram (EEG) is also a noninvasive measure used to monitor physiological state of humans based on recordings of electrical signals produced by brain. Measuring brain activity, EEG can be used to recognize emotions. Considering cumbersome EEG systems used mostly in clinical practice today, there is a need to propose intelligent wearable, wireless, convenient, and comfortable lifestyle solutions that provide high signal quality [12]. EEG, if it were connected to provide real-time monitoring, would be called a BCI. BCIs are discussed in section 3.

B. *Garment-based wearables*

There are various garment-based wearables which can be placed on different location of human body including head, neck, torso, arms, hands, legs and feet. Garments need to provide cover and protection from environmental effects, such as water, temperature, and fire, when adding wearable computing. Examples include shirts, gloves, pants, and shoes. Garment-based wearable computers have been designed and implemented for a variety of applications, including remote health monitoring, physical activity monitoring, and general user interaction. Nevertheless, most garment-based wearable computers include the key components for sensing, computing, user interface, data transmission, and power supply.

The wearable healthcare system should be not only small and easy for users to wear them, but also accurate in measuring physiological signals in daily life without any inconvenience. U-healthcare system [13] presented a headband to measure HR and accelerometer for step and fall detection, including a pulse oximeter at the forehead, microcontroller for signal preprocessing, ZigBee module for wireless data transfer, and a rechargeable battery for supply.

A European-integrated project, called ProeTEX (Protection e-Textiles: Micro-Nano-Structured fiber systems for Emergency-DisasterWear) [14] represents a new generation of "smart" garments for emergency-disaster personnel. They used three garment parts: T-shirt, jacket and a pair of boots. The system enables detection of health-state parameters of the users (HR, breathing rate, body temperature, blood oxygen saturation, position, activity, and posture) and environmental variables (external temperature, presence of toxic gases, and heat flux passing through the garments). The boots included CO2 sensors and a ZigBee module. Electronic communication and alarm modules were attached for transmitting useful information to the operation manager and providing visual and acoustic warnings when dangerous situations were detected.

Another article [15] presents the design and development of STants, a low-cost, wearable system for monitoring lower body movements in long-term training sessions. They proposed a customized energy-efficient firmware design with multiple miniaturized inertial measurement units (IMUs) integrated into a pair of pants and socks using textile cables. IMUs are located at pelvis, upper legs and lower legs. The result is a light-weight, configurable platform with high wearing comfort for daily use.

Lots of articles are dealing with fall prevention in elderly subjects. The EU project "Self Mobility Improvement in the eLderly by counteractING falls" (SMILING project) [16] aimed to improve age-related gait and balance performance during walking through motorized shoes. Authors describes the shoe-worn inertial module and the gait analysis method needed to control in real-time the shoe insole inclination during training. It was possible to change the insole inclination at each stance to better stimulate the motor learning process during walking.

C. Accessory-based wearables

Application areas of accessory-based wearable computers largely overlap with those of garment-based systems. Some of examples include smart glasses, rings, and belts.

The rapid development of wearable technology has led to several research projects related to applications of smart glasses in healthcare. In [17], the authors proposed a general architecture of the system for the person recognition using integrated data from several sources. Smart glasses integrate data obtained from central health care information systems, from devices connected to the patient and from the patient. They evaluated three identification methods based on face recognition and using the recognition of graphical markers (i.e. QR-codes and proposed color-based codes). Considering the results of the developed methods system provides reliable and fast recognition results.

Recently, the Google Glass was used in teletoxicology during toxicology consultations [18].The consulting toxicologist viewing the video stream found the quality of audio and visual transmission usable in 89% of cases, and six patients received antidotes they otherwise would not have.

A user's wrist has become a perfect place for wearables due to the easy access and visual effects. Many researchers focused their design and development toward bracelet-based systems. One of them [19] presents device which is worn on the wrist and finger with integrated sensors to monitor physiological parameters such as skin temperature, HR, and body impact. The data from the sensors are integrated and processed. As the authors stated in the article a prototype of the device has been fabricated and extensively tested with very good results.

Along with a wrist, an interesting location for wearables is also a waist. In [20], the authors presented a wearable heart rate belt for ambulant ECG monitoring which can be comfortably worn on the chest or the waist. The system provides a transfer HR data to a sport watch for displaying. According to results ECG signals with reasonably good quality were recorded in rest and walking situations when wearing on the waist.

D. Power supply and energy harvesting for wearables

Battery supply is the most common type of powering wearable technology. They use different types of batteries including lithium-ion, thin-film and graphene batteries because of their size, weight and maintenance. One of the main issues with wearables is energy consumption. Despite the fact that wearable devices use the ultra-low power consumption they still need to be charged frequently. Therefore, energy harvesting offers a great potential for wearables. There are many benefits to the end user, including reduced dependency on battery power, reduced installation and maintenance costs and environmental protection. Instead of charging wearables wired or wirelessly, new wearables could self produce the energy they need from the light, heat, human motions or vibration in their surroundings. Types of ambient sources used for energy harvesting are wind, solar, vibration, electromagnetic, temperature gradient, thermoelectric, Radio Frequency (RF), acoustic etc.

Harvesting solar energy is probably the oldest way for powering of electronic devices. Low-power indoor devices such as remote sensors, supervisory and alarm systems, distributed controls, and data transfer system are suitable for photovoltaic (PV) harvesting system. Especially because of their maintenance and accessibility [21].

Thermoelectric harvesting transforms heat into electric energy using a physical principle known as Seebeck effect. Because the human body is a permanent source of heat, it might be used as a one side of system (hot side) while the surroundings can represent the other side (cooler side). The amount of energy that can be produced depends on the delta between the high and low temperatures. One of the major benefits of thermoelectric harvesting is that the energy is always available, both indoors and outdoors. The study of thermoelectric energy harvesting on people shows that although power generation is affected by many factors such as ambient temperature, wind speed, clothing thermal insulation, and a person's activity, it does not directly depend on metabolic rate [22].

Another energy harvesting technique using the Electromagnetic (EM) energy specifically Radio Frequency (RF) signals transmitted from TV, Radio, wireless LAN, mobile phone, etc. Authors in [23] present a possibility of GSM energy harvesting using a rectifying antenna and an application of its usage in increasing the communication range between Radio Frequency Identification (RFID) reader and battery free passive RFID tags.

III. BRAIN - COMPUTER INTERFACE DEVICES

Brain Computer Interface is a revolutionary technology that can change the people's lives in a way that will give dozens of new possibilities where people will be able to control devices only by thoughts. These days, BCI is able to replace, restore, improve and extend bodily functions which is especially important to disabled people. Some of these projects are TOBI [24] and MoreGrasp[25] project. Because of its importance, we describe it separately from all the other wearable devices.

A. The human brain – the most complex signal processing machine

Morphologically speaking, the brain is a part of the central nervous system, specialized in the collection, distribution, storage and processing of information and it is the most complex signal processing machine. The human brain can process and transform variety of environmental signals and extract information from these disparate signal streams to enable behavior, cognition and actions. Neurons, which are the basic signal processing elements of the brain transmit information about 10^6 times slower compared to transistors. But the advantage of the brain is that it has a huge number of neurons which are operating in parallel and a highly distributed memory system of synapses (over 100 trillion in the cerebral cortex). [26].

The cerebral cortex is divides in six zones and different parts of the cortex have different functions. With it, human beings perceive the environment, think, speak, socialize and perform complex mechanical actions. During the life cycle, the brain tissue changes the structure and function through interaction with the environment.

B. Brain waves

Neurons in cerebral cortex are interconnected in networks and they communicate with each other. Nerve impulses or brainwaves make electrical activity which is always present, even during sleep. Basically, any process that changes human perception changes his brainwaves. Brainwaves are divided into bands according to their frequency which is changing according to what we are doing and feeling. When person feels tired or dreamy the slower brainwaves are dominant which is the opposite of hyper-alert state when the higher frequencies are dominant.

In normal adult person there are five typical brainwaves based on the frequency range between 1 and 100 Hz designated as [27]:

- Δ (0,5 – 4 Hz) – Delta brainwaves have low frequency and they are generated in deepest meditation and dreamless sleep.
- θ (4 – 8 Hz) – Theta brainwaves are also generated in deep meditation but mostly occur in daydreaming and sleep.
- α (8 – 13 Hz) – Alpha brainwaves occur during mentally relaxed states and in some meditative states. These brainwaves bridge the gap between conscious thinking and subconscious mind.
- β (13 – 30 Hz) – Beta brainwaves are presented in conscious thoughts, situations of alertness, engagement in problem solving, decision making and other mental activity and cognitive tasks.
- γ (30 – 100 Hz) – Gamma brainwaves have the highest frequency and relate to simultaneous processing of information from different brain areas. Gamma waves are important for learning, memory and information processing.

An example of alpha waves recorded with our OpenBCI Ultracortex KIT is presented in Fig. 1.

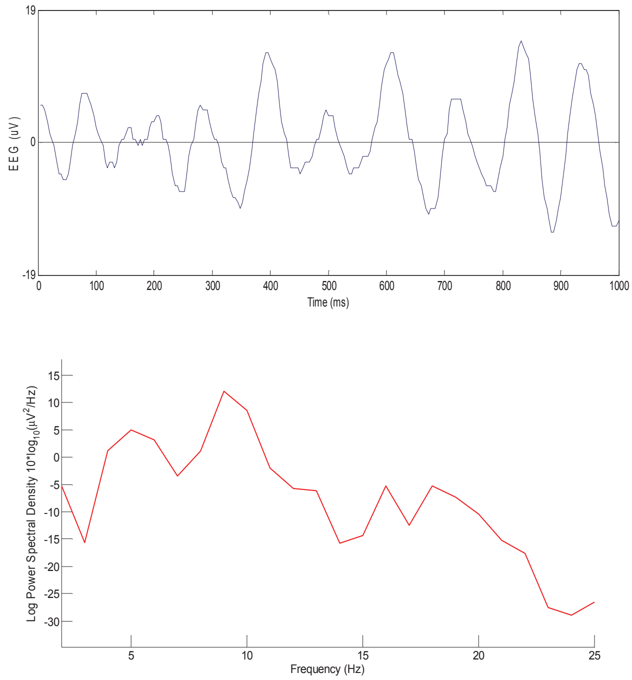

Fig. 1. Alpha waves

Brain activity can be measured based on how the neural signals are collected. Invasive systems relying on implanted arrays of electrodes are common in experiments involving rodents and nonhuman primates [28], and are well suited for decoding activity in the cerebral cortex.

Such systems provide high signal-to-noise ratio (SNR) measurements and enable decoding of spiking activity from small populations of neurons. The current challenge with such systems is that electrodes need to be implanted in humans, with their functional lifetime limited to roughly a year.

Noninvasive systems are better suited for situations in which a surgical implementation is not possible or warranted and thus have a much wider field of application.

Electroencephalography (EEG) is the most commonly used measurement modality for noninvasive recordings. The challenge with EEG is typically a low SNR [26]. Using noninvasive methods for collecting brainwave signals, the sensors usually record a very low signal (range 5-10 μV), while the noise interference is between 10 and 20 times greater than the brain signals measured on the skull, which is the greatest disadvantage of these methods [29].

C. International 10-20 system

The International 10-20 system is a method which describes the location of EEG electrodes on the head. Each position of electrode is matched with specific area of cerebral cortex. The numbers 10 and 20 mean the distance in percentage between adjacent electrodes (see Fig. 2). It is possible to add extra electrodes in empty spaces existing in 10-20 system and then it is called a 10-10 system. Positions of electrodes are named according to the region of the brain they records: frontal, central (sulcus), parietal (crown), temporal and occipital. Often an electrode is placed on the ear lobe as a reference or a "grounding" point.

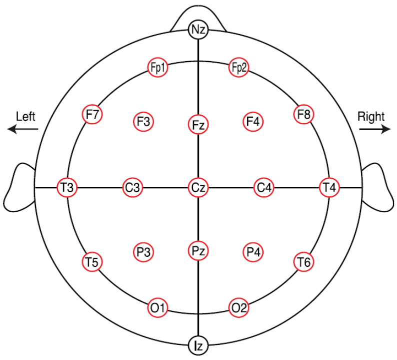

Fig. 2. 10-20 system electrode positions [30]

D. Brain-computer interfaces devices

A BCI interface, also known as a human-machine interface, provides an alternative method to control electronic devices by detecting the specific patterns in the electrical activity of the brain. The technology has many possible applications such as communication, computer access, cognitive effort detection and control of wheelchair or prosthetic arm or control of anything what is possible to control with a computer.

Human-machine interfacing (HMI) uses biological signals, such as brain signals, and translates them into control commands for external devices. Brain recordings can be performed noninvasively (surface EEG) by electrodes located on the scull / head to record the electrical activity of the brain. This recording modality has advantages compared to other HMI modalities such as reduced risks of infections and ethical constraints [31].

A BCI is a system that includes a means for measuring neural signals from the brain, a method/algorithm for decoding these signals and a methodology for mapping this decoding to a behavior or action.

BCI systems represent a new type of interface with which people, with otherwise normal neurological function, can interact with a computer/machine [26].

Components of a BCI system are given in Fig. 3:

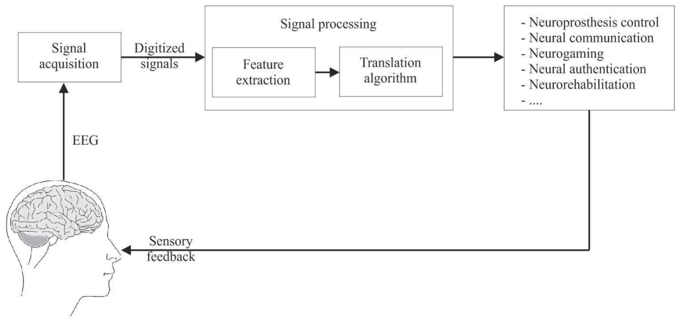

Fig. 3. Components of a BCI system

In Table 1, noninvasive BCI devices which are used to monitor or modulate the function of the nervous system are given [32].

There are many devices available on the market today, and their price ranges from few hundreds to few ten thousands dollars. The price is generally dependent on number and type of electrodes used, but is also very dependent on the fact if a device is certified for medical use. Devices used in medicine are much more expensive than consumer-grade systems.

Neuroelectrics' Enobio system is a popular product in scientific research (priced at 5.000 USD for an 8 electrode system and 20.000 USD for a 20 electrode system) as its specifications are comparable to even more expensive EEG systems. We also planned to use Enobio 8 system in our research, but have later decided for OpenBCI Ultracortex complete KIT which includes LulzBot Taz 5 3D Printer. We loosed the medical grade certification, but have gained the flexibility of designing our own headsets with 3D printer and a double number of electrodes than with Enobio 8 for practically the same price. OpenBCI EEG system is open source and is compatible with almost any type of electrode (dry/wet). Electrodes can also be very costly in proprietary systems, e.g. 800 USD for 8 dry Ag-AgCl electrodes for Enobio system, with only 100 usages.

IV. BCI RESEARCH AREAS

There are many areas where BCI devices can be applied. In this paper we have decided to cover four important research areas. Probably the most important area for present and future research is the BCI use in medical science. Millions of people with neuromuscular disorders could have much easier lives if they would be given the ability to control prosthesis only with thoughts. Another interesting field is in biometrics, representing a new way of person identification and authentication with human thoughts. However, many more studies and improvements are required to make this useful in daily life. Research in the area of drowsiness and fatigue of drivers has been very well studied over the years. Driver drowsiness detection systems can be applied in today's cars. The last area covered in this paper is Neurogaming which means playing games with thoughts. Results of research studies are good but the technology is not yet applicable because the BCI reactions are very slow which means that some game genres like vehicle simulations or action games are not suitable for playing.

A. BCI in medicine (Doing by thinking)

One of the main aims in developing BCI devices is that people who are paralyzed or without limbs can live normally with prostheses that can be driven by thoughts. In this regard, researchers in University of Pittsburg [33] are investigating a human-machine interface technology that promises to allow people to operate a robotic arm, simply by thinking about whatever task that needs to be performed. They have done surgery in the regions of brain responsible for hand movements for person who is paralyzed from the neck down. With this invasive method the researchers have been able to increase the robotic arm's maneuverability from seven to ten dimensions over the past three years.

An excellent review of Brain Computer interfaces in medicine is given in [34] where is shown that BCI in medicine can help people disabled by neuromuscular disorders such as amyotrophic lateral sclerosis, cerebral palsy, stroke, or spinal cord injury. Also, BCI is helpful for rehabilitation after stroke and for other disorders. In a similar review [35], the researchers discuss the current status of BCI as well as the future expectations.

B. BCI in biometrics (authenticate / identify a person with BCI)

In the field of biometrics related to authentication, the primary targeted group are disabled persons who could improve life quality if there is a possibility to login on various services such as online banking.

In [36], Tulceanu proposed a new brainwave authentication scheme based on emotional responses. Using only the stable generic activation patterns for three users they get overall authentication success rate of 29.16% which is not so good result but shows potential of using emotions as credentials.

Similarly, authors in [37] used widely available and inexpensive Neurosky's MindWave EEG device to verify its capability for authentication. They developed a quite simple method that enables users to create stronger password with two phase authentication.

Researchers in [38] were dealing with person identification and authentication and they proposed the use of a statistical framework based on Gaussian Mixture Models and Maximum A Posteriori model adaptation. Biosemi system with 32 integrated electrodes was used on nine subjects during three days. They showed that there are some mental tasks that are more appropriate for person authentication than others. Also, the performance degrades over days but using training data over two days increases the performance. Finally, they conclude that there is a potential for incremental learning.

A good review of authentication of Brain-Computer interface users in network applications is presented in [39]. So far, retina scans and BCI technology are the best tools for authentication of users who cannot move or control their muscles. But, this way of authenticating is not yet completely secure and there is a lot of future work and development required.

C. Drowsiness and fatigue of drivers

Lots of researchers are dealing with a theme which is related to driver drowsiness because of many fatal accidents, injuries and property damages. So far, the most of developed prototypes for monitoring driver drowsiness base their detection on single driver characteristics (physiological measures) or on car performance measures. Very few attempts have been made on combining all above measures in a complementary way [40].

Authors in [41] used a driving simulator equipped with video cameras and Enobio to collect EEG data. Researchers proposed a new method in which the alert state data was obtained just prior to the drowsy state and computed the band powers in the alert and drowsy states to signify the drowsiness. Driver drowsiness detection system was developed using the power spectrum analysis of EEG signal. Additionally, they have also identified that occipital and parietal regions show more significant changes in the alpha and theta powers during the transition from alert to drowsy state as compared to other brain regions.

In [40], the authors presented a methodology to monitor the level of vigilance. Researchers performed an experiment on nine healthy subjects who have not slept the night before the real driving with instructor. They used a test car fully equipped for measuring lots of characteristics. Tested subjects told that the best warning, when the system predicted that the driver is in drowsy state, is vibration and the second best is sound.

Study [42] was performed to monitor the physiological changes that occur during driving. Subjects were driving in real life while multichannel EEG, EOG, EMG and ECG were recorded. The result was that before the driver started making driving errors, the alpha activity and alpha relative band ratio (RBR) was significantly increased in short hops. Quantitative EEG analysis revealed significant variations of RBR by driving time in the frequency bands of delta, alpha, beta, and gamma. Most of the estimated EEG statistics, such as the Shannon Entropy, Kullback–Leibler Entropy, Coherence, and Cross-Approximate Entropy, were significantly affected by driving time.

In [43], a drowsiness estimation system was developed using EEG by combining Independent Component Analysis (ICA), power spectrum analysis, correlation evaluations, and linear regression model. The experimental results performed in driving simulator show that the proposed ICA-based method applied to power spectrum of ICA components can successfully detect the driver's fatigue.

In [44], an EEG based drowsiness detection approach that is subject and session independent was presented. The authors used thirteen subjects in experiment in virtual reality based driving environment. The subject's EEG power spectrum was analyzed using the Mahalanobis Distance (MD) and FFT windows. Results concluded that the power spectrum analysis of the alpha and theta bands was in correlation with driver drowsiness and can be used in its detection.

TABLE I. BRAIN-COMPUTER INTERFACE DEVICES

Company	Model	Price (USD)	Number of EEG sensors	Sensor type	Additional sensors	Sample rate (kHz)	Duration of portable use
Advanced Brain Monitoring	B-Alert X10	9.950	9 (head cap)	Wet	ECG, EMG, EOG (4 channels)	0,256	8+ hr (Bluetooth)
	B-Alert X24	19.950	20 (head cap)	Wet	ECG, EMG, EOG (4 channels)	0,256	8+ hr (Bluetooth)
Biosemi	Active Two	13.500 17.000 21.000 27.000 45.000 52.000 75.000	8 + 2 16 + 2 32 + 2 64 + 2 128 + 2 160 + 2 256 + 2 (head cap)	Wet	7 input channels available	adjustable by user: 2, 4, 8 or 16 kHz per channel	5 – 72 hrs for 256 – 16 channels (USB connection)
Brain Vision LLC	actiCap Xpress	11.375	16 + 2 (head cap)	Wet / dry	2 analog input channel available	2 – 20	n/a
	actiHamp	35.600 49.900 66.200 80.000 95.500	32 +1 64 + 1 96 + 1 128 + 1 160 + 1 (head cap)	Wet	Photo sensor, 8 analog input channel available	50 – 100 25 – 50 10 – 25 10 – 25 10 – 25	6hr (on battery, USB connection)
Cognionics	Dry EEG Head band	n/a	2-8 + 2 (head band)	Dry	Accelerometer (3-axis)	0,54	4+ hr (Bluetooth)
	Dry EEG Head set	26.500 or 42.600	16 + 2 24 + 2 32 + 2 64 + 2 (head set)	Dry	Accelerometer (3-axis)	0,3	6+ hr (Bluetooth)
	Dry EEG Visor Cap	n/a	16 + 2 (head cap)	Dry	Accelerometer (3-axis)	0,54	4+ hr (Bluetooth)
	Multi position band	1.800 – 3.800	2-8 + 2 (head cap)	Dry	Accelerometer (3-axis)	0,54	4+ hr (Bluetooth)
	Quick-20 Dry EEG Head set		20 + 2 (head set)	Dry	Accelerometer (3-axis)	0,3	6+ hr (Bluetooth)
Emotiv	EPOC	699	14 + 2 (head set)	Wet	Gyro (2-axis)	0,128	12hr (RF)
	EPOC+	799	14 + 2 (head set)	Wet	Gyro (3-axis) Accelerometer (3-axis) Magnetometer (3-axis)	0,128	12hr (RF) or 6hr (Bluetooth)
	Insight	299	5 + 2 (head set)	Dry	Gyro (3-axis) Accelerometer (3-axis) Magnetometer (3-axis)	0,128	4hr (Bluetooth)
InteraXon Inc.	Muse	299	5 + 2 (head set)	Dry	Accelerometer (3-axis)	0,22	5hr (Bluetooth)
Macrotellect Ltd.	BrainLink	373	1 + 2	Dry	n/a	n/a	4hr (Bluetooth)
Melon Inc.	Melon EEG head band	149	1 + 2 (head set)	Dry	n/a	0,25	8hr (Bluetooth)
Mind Media	NeXus-32	23.995	21 + 2c (head cap)	Wet	4 ExG 3 auxiliary channels	2.048	20+ hr (Bluetooth)
NeuroSky	Mind Wave Mobile	130	1 (head set)	Dry	Accelerometer (3-axis)	0,25	8 hr (RF)
Quantum Science and Applied Research Inc (QUASAR)	DSI 10/20	n/a	21 + 1 (head cap)	Dry	Accelerometer (3-axis) ECG EMG EOG Temperature	0,24 or 0,96	24 hr (Bluetooth)
NeuroElectrics	Enobio	4.995 14.495 24.995	8 + 2 20 + 2 32 + 2 (head cap)	Wet / dry	Accelerometer (3-axis) ECG EMG EOG GSR	0,25	8 hr (Bluetooth)
Compumedics NeuroScan	Quick Caps	54.300 55.076 81.396	12 to 256 (head cap)	Wet	ECG, EMG, EOG	n/a	n/s
OpenBCI	Ultracortex (Mark III) Supernova	Preassembled 1099.99	16 (head set)	Wet/Dry	EMG, ECG	0,25	26 hr (Bluetooth)
	Ultracortex KIT with 3D printer	3449,98	16 (head set)	Wet/Dry	EMG, ECG	0,25	26 hr (Bluetooth)

D. Neurogaming (BCI games)

Neurogaming is a new field of gaming which uses non-invasive BCI in order to improve gameplay so that users can interact with a console without the use of a traditional controller. Inputs for this kind of gameplay can be various, like player heart rate, brain waves, pupil dilation, hand and body gestures and even emotions.

Researchers in [45] were already in 2010 asking questions why would a healthy person want to use BCI when it has still so many issues (delays, bad recognition, long training time, cumbersome hardware)? From that time till now, lots of issues have been improved so the neurogaming is now an important area in BCIs. Applications for healthy people are becoming more and more important in BCI research.

The number of BCI games papers produced increases by every year so researchers in [46] give a very good review of games which can be controlled by some BCI devices. They reviewed the games by genres and concluded that gameplay must be altered to achieve accurate control of the game and to make the game more enjoyable for the player. At the moment BCI reactions are very slow which means that some genres like vehicle simulations or action games are not suitable for playing. On the other hand, strategy games and puzzle games are perfect for BCI as there are normally no time constraints. Another survey about using BCI in gaming industry is presented in [47] and a review of multiplayer and multimodal BCI games based on EEG in [48].

Concept of Brain Machine Interface (BMI) for the purpose of gaming in real and virtual world with hand and wire free operations is given in [49]. The authors proposed a system where by using commercially available wireless EEG headset like NIA, Emotive EPOC and Mind flex, is possible to play games only using thoughts. Experiment was performed on three young healthy volunteers and researchers used an open source software BCI2000 [50]. Neural signal was preprocessed to boost up the SNR (signal to noise ratio) and that signal was extracted and used as control command in games. For extracting the specified component from signal and to remove non P300 ERP (Event Related Potential), a constrained independent component analysis (cICA) was used. Finally, it was realized that the BMI device is more efficient then the muscular controlled device.

In [51], Emotiv EPOC headset was used to collect EEG data which was then filtered to get separate frequency bands to train cognitive-affective classifiers with three classification techniques: Support Vector Machines (SVM), Naive Bayes (NB), and k-Nearest Neighbors (kNN). Conclusion and suggestion was to use a combination of classifiers to get better results.

V. CONCLUSION

In the last years, developments in smart environment technologies, especially BCIs, have made tremendous evolutional progress and ensure improvement of the quality of everyday lives. Wearable devices capable of monitoring and recording psychophysiological measures/signals have a major role in this process as well as BCI controlled applications. The BCI has tremendous potential as a technology and an enormous market potential as well and not only in the field of medicine but also in technology companies and the marketing sector to the aviation industry.

Some people with severe disabilities are already using BCI as assistive technologies for basic communication and control in their daily lives but BCIs are not yet ready for autonomous home use. The main features that BCIs must provide for achieving this goal are usability and reliability. Mostly, the current BCI systems are relatively complicated considering setup and manipulation of system and principally needs presence of technical experts. Therefore, BCIs have to be improved to provide simply use of system for end users and their caregivers. Researchers all around the world are developing new hardware and software for BCI systems which uses different brainwave signals, methods and signal-processing algorithms. The present technology still needs a huge advancement in each component of BCI, including signal acquisition, signal recording techniques, feature extraction and translation methods and end-user applications. BCI devices have to become faster, smaller, more reliable, easier to wear, more accurate, cheaper, etc. In several years, BCI could also become a standard in medical treatment and therapy and also in monitoring personal health.

The main technology challenges for wearables as well as BCIs includes power and energy efficiency, connectivity, data input and analytics, security, software development, design and robustness.

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