# Wearable, Wireless EEG Solutions in Daily Life Applications: What are we Missing?

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***Abstract*—Monitoring human brain activity has great potential in helping us understand the functioning of our brain, as well as in preventing mental disorders and cognitive decline and improve our quality of life. Noninvasive surface EEG is the dominant modality for studying brain dynamics and performance in real-life interaction of humans with their environment. To take full advantage of surface EEG recordings, EEG technology has to be advanced to a level that it can be used in daily life activities. Furthermore, users have to see it as an unobtrusive option to monitor and improve their health. To achieve this, EEG systems have to be transformed from stationary, wired, and cumbersome systems used mostly in clinical practice today, to intelligent wearable, wireless, convenient, and comfortable lifestyle solutions that provide high signal quality. Here, we discuss state-of-the-art in wireless and wearable EEG solutions and a number of aspects where such solutions require improvements when handling electrical activity of the brain. We address personal traits and sensory inputs, brain signal generation and acquisition, brain signal analysis, and feedback generation. We provide guidelines on how these aspects can be advanced further such that we can develop intelligent wearable, wireless, lifestyle EEG solutions. We recognized the following aspects as the ones that need rapid research progress: application driven design, end-user driven development, standardization and sharing of EEG data, and development of sophisticated approaches to handle EEG artifacts.**

***Index Terms*—Daily life EEG, EEG, EEG system development requirements, electroencephalography (ECG), intelligent systems, wearable EEG, wireless EEG.**

## I. Introduction

BESIDES the numerous benefits that the technological inventions brought to the healthcare domain, especially in surgical and monitoring applications within hospitals, they also facilitated raised awareness of people about their own health. Promoting health is crucial not only for the younger generation if they would like to have a prosperous and long life, but also for the elderly if they would like to live independently and to stay mentally fit for a longer period [1]. Today, more and more people try not to only maintain their health status and prevent illness, but also to improve their quality of life by promoting their health in various ways. This group of people forms a large community that is currently ‘underserved’ in the health device market space [2]. Having technology that will enable monitoring and characterizing human health is a prerequisite for the next (r)evolution in the healthcare arena—empowered users that will take care of their own health and that will assist healthcare providers in interpreting and improving users conditions [3]. However, transferring the technology used in hospitals to users’ homes proves to be challenging. Most in-hospital solutions for monitoring and managing health are by design too cumbersome or too complex to be used outside hospitals and require expert assistance. The only solutions available on the market that entered users’ homes are weight scales, blood pressure monitors, and activity monitors (i.e., advanced accelerometers).

However, to have a more holistic view of someone’s health, users would need to be aware of more aspects of their health status other than their weight, blood pressure, and activity. Attempts to bring more sophisticated technologies that can estimate human health metrics, such as electrocardiography (ECG) and electroencephalography (EEG), have been addressed in the research community in recent years. These systems are placed in a completely uncontrolled environment, outside of the experts’ hands and eyes and specially designed rooms. On the one hand, recordings with such systems have limited or no use to health care practitioners. Experts are neither confident in the quality of acquired data nor in the sources of physiological changes that are recorded by such devices. On the other hand, the users have neither sufficient knowledge to ensure proper usage of devices nor to interpret the extracted information in the correct way. Therefore, substantial development efforts are required to bridge this gap.

Among noninvasive daily life brain activity monitoring modalities, EEG is the only one that uses sensors and mounting capabilities such that it can be worn during free locomotion. It is superior to functional near infrared spectroscopy (fNIR) in terms of temporal resolution and brain areas that can be monitored [4]. Namely, fNIRs can only be used at the forehead (regions not covered with hair) and detect the blood oxygenation level (similar to fMRI) which cannot capture fast changes in the brain. Other modalities, such as fMRI and positron emission tomography (PET) and magnetoencephalography (MEG) either have low temporal resolution or are impractical to be adapted for daily life recording. Despite the many uses of EEG in the clinical domain, EEG is rarely brought outside hospitals and is considered to be too noise prone to be used in daily life applications [5].

While current research efforts on understanding our brain mainly focus on invasive EEG recordings, mostly in animals and occasionally in humans, there is still a lot to be learned

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from noninvasive EEG monitoring [6]. The main obstacle for utilization of noninvasive EEG in daily life situations seems to be rooted in the inadequacy of solutions used to acquire and process brain signals and ineffectiveness of the feedback information. Standard practice in EEG monitoring (in hospitals) requires a cumbersome and lengthy preparation procedure which can also lead to painful and unpleasant experiences. It involves skin preparation and gel-electrode application, mounting a number of wired sensors and connecting electrodes to the main acquisition unit and a PC. This is far from being user-friendly, comfortable, and convenient, and also result in stigmatization of users and limits the use to clinical or controlled (ambulatory) environments. As such, it is used only in a limited number of clinical applications where no alternatives exist, such as epilepsy prediction and monitoring [7] and monitoring brain recovery after injury [8].

Such issues indicate that we need substantial progress in developing technology for convenient, wireless, wearable EEG monitoring on one hand and in developing applications that can utilize the developed technology and foster the making of a database of knowledge in different brain research areas on the other. Several research centers have recognized this need and engaged in either developing lifestyle EEG solutions or technology to be used in such solutions [9]–[12]. A few such developments also lead to commercially available EEG systems: Neurosky's MindWave, MindSet and Necomimi [13], Emotiv Epoc headset [14], InteraXon Muse [15], g.tec gSahara [16], Quasar DSI 10/20 [17], Mindo Sepia, Trilobite and Coral [18], Neuroelectrics Enobio [19], and Cognionics 16 to 64 channel headsets [20]. Also, within Holst Centre/imec, an EEG monitoring headset with four active sensor chips is available [21].

Although some of these devices have been available for a number of years, none of them has achieved larger penetration in the EEG application market so far. They are used in research laboratories around the world for brain–computer interface (BCI) investigations or for gaming applications built using BCI technology [22]. Based on this niche usage of EEG devices, one might argue that there is no need for daily life EEG monitoring. Although it might seem that this is the case today, we believe that the rising trend of users concerned with their mental health and the increased prevalence of mental disorders, such as depression and burnout will change this status [2]. Furthermore, due to safety concerns on roads and the severe impact of human error in critical jobs, monitoring mental state using such technology might also be included in legislation [23]. Finally, assessing conditions of people after a traumatic event (e.g., brain injury and stressful events) [24] and improving the condition of healthy subjects and people with cognitive problems through the usage of neurofeedback [25], [26] (e.g., peak performance training and ADHD treatments) are among the few application areas that start to explore the usage of lifestyle EEG solutions.

The aim of this paper is to sketch a number of reasons behind the failure of the current lifestyle EEG devices in penetrating one of the mentioned application areas and to provide suggestions and guidelines how these obstacles can be overcome in the future. The question that we would like to answer can be formulated as follows: *What is required to make an EEG solution intelligent in terms of acquiring superior signal quality across different real life use cases, while at the same time providing comfort and convenience, being of assistance to users and providing meaningful information to them*?

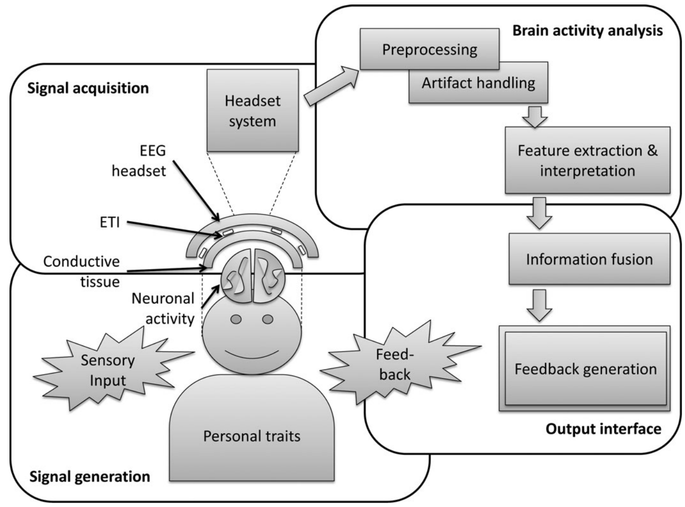



Fig. 1. Aspects that should be considered when designing and developing intelligent wireless, wearable EEG solutions for daily life applications.

We took a more holistic approach than in the two recent overviews of wireless EEG systems [27], [28]. The work by Casson *et al.* [27] focuses on power consumption and compression requirements, while Lee *et al.* [28] puts the emphasis on dry electrode development and deficiencies of signal processing approaches. We looked at aspects ranging from brain signal generation to end user applications. These aspects are depicted in Fig. 1 and include the following:

1) personal traits, previous and current environmental stimuli, and knowledge on how EEG signals are generated and transmitted through biological tissue;
2) capturing EEG signals from electrodes and low-power, miniaturized technology used for acquiring, amplifying, processing, and transmitting EEG signals;
3) algorithms and methods used for EEG signal preprocessing, artifact handling, feature extraction, and feature interpretation;
4) methods to process and present fusion of context-related brain activity.

In the sections to follow, we discuss the state-of-the-art in EEG solutions keeping these aspects in mind, identifying the areas that require fast progress in the coming years. Wherever possible, we highlight directions which could advance the state-of-the-art for these different aspects. We discuss each of the listed aspects in detail in Sections II to V. Then we discuss the overall design and development requirements for a daily life EEG system, focusing on the identified critical areas, in Section VI. These critical areas include the application- and user-driven design and development, standardization and sharing and handling real-life artifacts. The paper is concluded in Section VII.

## II. Source Features and Signal Generation

### A. Personal Traits

Electrical activity of the brain evolves with the maturation and aging of the brain and is heavily impacted by a number of personal traits. We can learn a lot about our development and cognitive evolution by monitoring our brain activity. However, due to the cumbersome and impractical procedure of EEG monitoring, EEG has never made it as a part of routine health checks and has also never been included in systematic research on human health status. No large EEG studies exist that look into the impact of demographics (age, gender, and race/ethnicity) on EEG and there is a lack of studies that look into the association between personal traits and EEG in normal healthy adults, children, and elderly.

Only a handful of studies discuss the gender differences, typically focusing on network or spectral maturation in children [29], [30], or adult sleep related rhythms [31], [32]. We are not aware of any systematic study that looks into EEG differences with respect to race. Only recently, there is more attention to monitoring children's EEG activity as an indication of proper development [33] and to monitoring cognitive decline in the elderly [34]. This was mainly motivated by the increased prevalence of conditions such as attention-deficit hyperactivity disorder (ADHD) or autism spectrum disorders (ASD) among children [35] and indications that EEG changes can help in extracting early markers of Alzheimer's disease and dementia [36]. Furthermore, there are no large publicly available databases that contain EEG activity of the normal healthy population. Neither is there a consensus on how to store the EEG information and the context in which it is recorded, nor on what features to extract from EEG signals for characterizing mental traits and states of a person.

Having EEG systems that will enable daily life measurements of electrical brain activity would facilitate the possibility to monitor larger populations with diverse personal traits and hence would enable generation of large databases. However, knowing what useful information can be extract from the recordings stored into the database would in a great sense determine whether the users would embrace the wireless EEG technology. Therefore, data collection and understanding of EEG features across different user traits have to go hand in hand. This would also call for standardization in terms of recording and exchange formats, as well as integrating EEG information with information from other sensors that can capture the context that a user is currently in. Furthermore, including information on demographics of users would be required.

### B. Sensory Input

An EEG signal is a result of a number of concurrent neuronal activities occurring in our brain. They include our current mental state (changes) and cognitive processes, various external inputs to our senses and various internal inputs and outputs to our internal organs [37]. For example, a person having his/her eyes closed (i.e., preventing visual input) results in a completely different EEG signature all over the brain compared to the same person having his/her eyes open [38]. Therefore, knowing the current status and the history of information coming from our senses and traveling back and forth in our body, is important for understanding EEG activity at a certain moment.

Current solutions for monitoring EEG, as well as the existing data formats, do not support integration of such information sources in daily life. Only supported use cases are related to monitoring evoked responses during a defined task (sensory evoked potentials or event-related potentials—ERPs) with clearly specified event markers [39]. This is expected given that the EEG monitoring was predominantly done in a controlled lab environment with detailed specification of recording protocols. These protocols include a fixed set of context and sensory inputs. However, as soon as the EEG equipment moves into an uncontrolled daily life environment, monitoring the contextual information and especially the sensory input, would become an important design requirement.

Lifestyle EEG devices of the future have to be open for integration with sensors that can capture other physiological signals (e.g., ECG, GSR) or contextual information (cameras, GPS locators). Furthermore, formats used for storing EEG have to be somehow extended or have the possibility to be linked to the data incoming from these auxiliary sensors. Similarly to capturing and storage of personal traits, this also calls for standardizing contextual information capturing and storing, for the purpose of proper documentation and exchange.

### C. Neuronal Activity

Noninvasive EEG is the electrical potential measured on the scalp. It stems from neuronal activity below the scalp area where an electrode is placed. As the electrical potentials generated by neurons have to travel a relatively long distance through the surrounding tissue to the scalp surface and due to sheer number of neurons within different brain regions, surface EEG cannot record the activity of individual neurons. Rather, it represents the summation of electrical activity of thousands to millions of spatially aligned neurons [6]. As such, EEG provides poor spatial resolution, compared to modalities that monitor blood oxygenation, such as fMRI and fNIRs. However, EEG can provide high temporal resolution—to a millisecond range, similar to MEG. As MEG is not suitable for daily life monitoring, EEG is the optimal choice for studying dynamic processes and coupling of different regions in the brain during challenges imposed in our daily life.

Furthermore, by using novel techniques, such as different variants of nonparametric low resolution brain electromagnetic topography (LORETA) [40] and other parametric source localization methods (for a recent review we refer to [41]), spatial localization of brain activity becomes possible. To apply those methods, high density EEG recordings (i.e., larger number of EEG electrodes) are required, as well as the head/brain template. Due to the sheer number of available MR recordings and/or derived head models the latter is not an issue today. Also nowadays, the former can be realized with dry electrode solutions [20]. Although the resolution of these spatial maps cannot be compared to the resolution of fMRI, in contrast to fMRI, EEG is able to monitor brain activity during daily routines. While fNIRS also provide higher spatial resolution, the difficulty of applying this technology through hairy regions and the low temporal resolution of the signal, makes them only usable as an add-on to the EEG devices that would provide high spatial resolution at the frontal brain regions.

With further understanding on how synchronous activity of neurons results in EEG patterns [42] and how cortical fields are generated [43], we can expect that monitoring of neuronal population activity in real-life EEG applications would become possible. More concurrent EEG and fMRI recordings [44] that can be used to both correlate the temporal and spatial activities on one hand and estimate the precision of EEG source localization methods on the other, are needed. As this is a research field that is experiencing large expansion, we can expect substantial progress in this area. The only remaining question is in designing and developing EEG acquisition systems that would provide sufficient signal quality required for precise temporal and spatial characterization of brain activity (discussed in Section III).

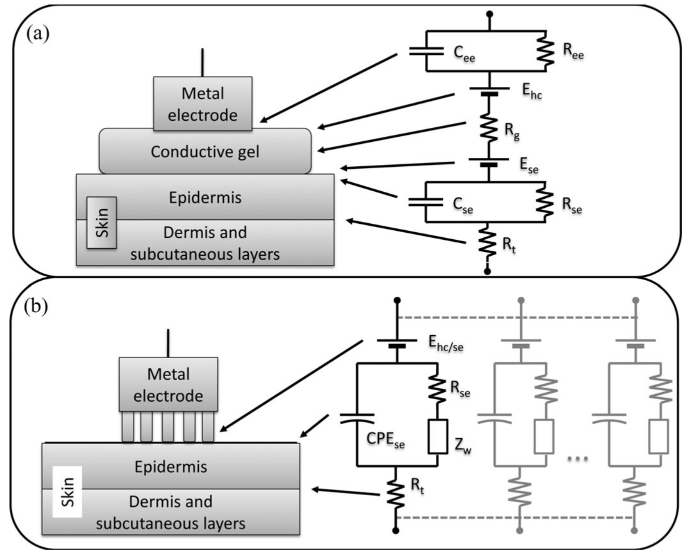



Fig. 2. Modeling electrode–skin contact when using a) electrodes with conductive gel and b) dry electrodes with pins.

### D. Conductive Tissues

In EEG measurements, we assume that the tissue between the source of the electrical signals (neurons) and an EEG sensor that captures the brain activity merely 1) smears the signal coming from a large population of neurons and 2) attenuates it due to the conductive properties of different tissue layers. Nevertheless, inhomogeneities of skin, skull, dura mater, cerebrospinal fluid (CSF), and pia mater, can have substantial impact on EEG [45]. The conductivity of the skull has the largest impact on the overall conductivity and yet it is poorly understood [46]. Furthermore, although neglected in the EEG monitoring, CSF might have a large effect on the recorded EEG scalp magnitude. It can lead to increased or decreased spatial blurring of the EEG signals, which can also be modified due to the head position and movement [47]. Understanding these properties is of particular importance for longitudinal monitoring (over a lifespan) that might involve constant changes in the conductive tissue properties of a person. At a young age and with brain atrophy due to normal aging or neurodegenerative diseases, assessing these properties becomes crucial as the brain tissue volume changes.

Furthermore, understanding conductive properties provides essential information for the source localization type of applications, where small model errors can lead to inaccurate source localization [48]. Hence, better understanding of the conductive behavior of the tissues beneath the scalp will ensure more accurate source estimation and also comparability of EEG activity measured at the surface of the scalp. Together with the more accurate model for the electrode–skin contact conductivity (see next section), they should facilitate superior brain activity monitoring. Better cataloging of brain and skull models is required for precise evaluation of the impact of conductive tissues on the acquired brain signal. Also, large comparative studies that look into how properties of the tissue layers impact the propagation of the electrical brain activity would yield useful information.

## III. Signal Acquisition

### A. Electrode–Tissue Interface

EEG recordings in clinical applications are typically performed with the use of silver/silver-chloride (Ag/AgCl) electrodes that are in contact with the scalp through electrolytic gel. The electrolyte serves two purposes, 1) it bridges the ionic current flow from the scalp and the electron flow in the electrode and 2) it increases adhesion of the electrode to the scalp [49]. To further improve signal quality, the scalp is frequently cleaned and, especially in clinical applications, skin on the scalp is abraded. Such well-prepared electrode–tissue interface (ETI) results in a fairly stable electrical contact that can be modeled as a series of two resistors-capacitor (RC) circuits, two resistors, and two potential sources [50], as shown in Fig. 2(a). The RC circuits depict resistive and capacitive components at the electrode–electrolyte ($C_{\mathrm{ee}}$) and at the skin–electrolyte ($C_{\mathrm{se}}$) interface. The resistors represent electrolyte ($R_g$) and tissue ($R_t$) resistances, or the ones characterizing electrode–electrolyte ($R_{\mathrm{ee}}$) and skin–electrolyte ($R_{\mathrm{se}}$) resistive properties. The two potential sources represent electrode–electrolyte half-cell potential ($E_{\mathrm{hc}}$) and skin–electrolyte potential difference ($E_{\mathrm{se}}$). When skin is properly prepared and electrodes are properly applied, this model represents quite accurately the interface. Furthermore, the typical impedance magnitudes at the frequency of interest (below 100 Hz) are lower than 10 k$\Omega$ and the conductive properties of the interface (i.e., contact potentials) remain stable [51] at least until the electrolyte starts to dry out.

However, the abrasion process, as well as the use of conductive gel makes the whole EEG setup inconvenient for practical applications, especially in daily life settings. The application of electrolyte and the electrodes, even when simple EEG caps are used, requires expert assistance. The setup process is lengthy as it includes preparing the skin, applying the gel, positioning the electrodes (or the cap), and ensuring that the EEG signal quality level is acceptable. Additionally, the user (or expert) has to remove the electrolyte and clean the user's head afterward and also clean and dry the electrodes (and the cap) that were used. This takes time and requires additional effort. That is why recent technological developments are focusing on sensors that do not use conductive gel and skin preparation. These are so called dry (or dry-contact) electrodes and typically for EEG applications they include pins to penetrate the hairy regions [52].

Such solutions are already available, offered by imec [21], gTec [16], Quasar [17], Mindo [18], and Cognionics [20]. Electrodes provided are either Ag/AgCl or gold-plated. To improve user comfort and electrode-skin contact, electrodes with spring-loaded pins are sometimes used [53]. These dry electrodes can be reused until the top conductive layer wears off. While dry electrode systems demonstrate short setup time and increased user comfort, they are faced with decreased signal quality compared to ambulatory EEG systems [54]–[56] (although some publications claim similar signal quality to gel-based systems [11], [52], [53]). The decrease of the signal quality is caused by the fragile and complex ETI.

When using dry electrodes, the absence of electrolyte makes the transition of ionic tissue currents to electrode electron currents much more complex. This results in more dominant capacitive components and in the increase of impedance at the interface. The interface requires larger stabilization time and is more prone to noise and disturbances [56]. Also, the frequency response of the ETI over the frequencies of interest might vary and can be unstable over time [57]. Such dry ETI cannot be modeled by the same way as the electrolyte ETI and just removing the components related to electrolyte, as proposed in [52], does not yield good modeling results [58]. To provide a more accurate model of the interface, special components need to be introduced. These include 1) the Warburg element ($Z_w$) that models the ion diffusion and 2) the constant phase element ($\mathrm{CPE_{se}}$) that models the double layer at the contact interface. This is illustrated in Fig. 2(b), where we present a hypothetical model of the contact between the skin and dry electrode with a number of pins.

Furthermore, forces applied by the electrode support structure (e.g., headset) on the dry electrodes can vary and as there is no adhesion between the electrode and the skin, dry electrodes can glide over the skin surface and can produce various deformations of the skin beneath the electrodes. While this is not so pronounced in flat or ring electrodes, it has large impact in dry electrodes with pins [57]. In real life situations, when a person is freely moving, the artifacts stemming from movements can be substantially enlarged (see Section IV). Therefore, continuously monitoring contact properties in terms of, e.g., ETI, can be of great importance in estimating the EEG signal quality [21]. In summary, we know little about the dry electrode–skin model and especially how changes over time impact contact properties. Therefore, to provide a full understanding of measured EEG signals, we urgently have to apply our knowledge to dry ETI. Besides several studies that address this issue [56]–[58], there is not much focus on this aspect. We believe that rapid progress is required if we are going to see dry electrodes replace the conductive gel ones in the future.

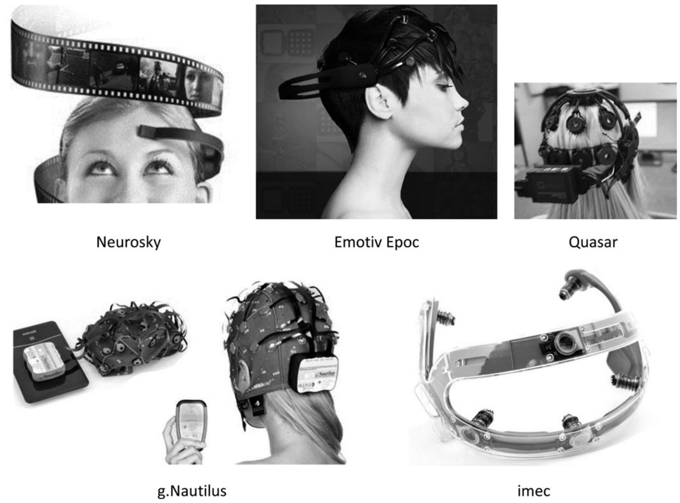



Fig. 3. Existing wearable wireless EEG devices.

### B. Miniaturized and Ergonomic EEG Headsets

In recent years, we have seen an increasing number of products and product concepts on the market that target EEG acquisition in a more convenient way than traditional systems, mainly using dry electrodes. Depending on the foreseen application, the mechanical designs may vary. In general, the mechanical design needs to keep the electrodes in place since gel or glue is not used in such devices. For long-term monitoring applications, for which usage during daily-life activities is foreseen, the design should be unobtrusive. For headsets that target the neuroscience community or medical diagnostics, speed of application and uncompromised signal quality are crucial. In these cases, the design will need to assist in capturing the highest possible signal quality. For serious games, based on BCI approaches, the design objective should not necessarily be unobtrusiveness, but user friendliness, ease of use, robustness, and 'fool-proof' designs.

Here we present a number of existing systems and we discuss how the different systems may be useful in different application spaces. Since the number of existing devices is too large to be discussed exhaustively here, we have selected devices that are commercially available and that vary greatly in the way how design tradeoffs are made. They are depicted in Fig. 3.

Neurosky's [13] product range is based on a one-channel measurement platform with dry electrodes. The single measurement channel is typically positioned at the forehead, which allows for frontal recordings. Patient ground and reference are positioned at the earclip. The dry electrode on the forehead is made of a stainless alloy. Data is wirelessly transmitted to a PC or a smartphone using Bluetooth (BT). Having the lowest price-tag of all products, it seems to target the low-end consumer market.

The Epoc (Emotive) [14] is amongst the most widely available and used devices. With 14 channels scattered around the head and low cost, it provides a flexible and versatile research platform. Data is wirelessly transmitted through a proprietary radio link. The system allows for 12-h continuous transmission. With a very attractive price-tag, the Epoc also targets the low-end consumer space. However, a substantially more expensive license is needed to get access to the raw EEG data and use the Epoc as a research vehicle.

Imec's headset [21] has four channels, based on an eight-channel wireless acquisition platform. It uses dry Ag/AgCl coated electrodes (Biopac EL120) with pins to move away hair and touch the bare skin. To increase user comfort and provide sufficient force at each electrode, they are mounted within spring-loaded holders. A proprietary protocol is used for wireless transmission of the data. The battery allows for 20 h of continuous transmission. The system is designed around low-power and integrated electronics, allowing for system miniaturization for systems having low number of channels and flexibility in headset solution designs.

Quasar's [17] DSI 10/20 is an EEG headset with 21 channels. The aim of the system is an ambulatory EEG recording and it includes mechanical and electrical mechanisms to reduce motion artifacts. Data is wirelessly transmitted through a proprietary system which requires a USB dongle. It allows continuous EEG transmission for 24 h. The focus of this device seems to be on achieving the highest signal quality possible but with a high price-tag.

A recent development is g.tec's [16] g.Nautilus platform. It can be combined with a cap system with active dry electrodes (g.Sahara) which allows for recordings according to the International 10–20 System. Dry electrodes are fabricated with gold-plated pins. The data is wirelessly transmitted through a proprietary radio link. The device can operate continuously for 8 h without charging.

A notable recent development is the in-ear EEG measurement platform developed by Imperial College [59]. It allows for unobtrusive EEG measurements. However, since the devices described in the publication are not available on the market and since the field of in-ear EEG measurements is unexplored to date, we do not discuss it further in this paper.

As indicated, these headsets are either designed or developed to serve the low-price market at a cost of compromising signal quality and/or robustness, or provide high quality EEG signal while having a much larger price tag. Irrespective of this, all these headsets are neither tailored to serve for a particular application, nor toward personal preferences of a designated user. Consequently, complaints can be heard about some of these solutions. These include headsets not fitting all user head shapes well, electrodes not covering the claimed locations on the head, or systems being too cumbersome or too uncomfortable to wear. This suggests that extensive effort has to be placed in designing the optimal headset that would be appreciated by users. For this task, e.g., designing a headset that covers only a certain brain region (required for the application), can be helpful. Furthermore, understanding the application, in terms of wearability and coverage of brain regions, is a first step in designing and developing novel, intelligent and wearable EEG headsets.

### C. Wireless and Wearable EEG System Designs

We compared the systems presented in the previous section along a number of characteristics, depicted in Table I. Values are only reported if disclosed by the manufacturer. A number of empty fields indicate that a large number of essential system characteristics are not disclosed for some systems, particularly for Emotiv and Neurosky. Among the reported characteristics, in this section, we discuss dc offset tolerance, ac or dc coupling, common-mode rejection (CMR), and wireless communication protocols. We believe that those aspects require further elaboration.

A dc offset between the potential of the patient and the potential at the inputs of the instrumentation can be the result of several mechanisms, such as charging of capacitance at the skin to electrode interface, ion diffusion, and charge distributions in the skin. It cannot be avoided and will depend, amongst others, on the electrode material and electrode design. The International Electrotechnical Commission (IEC) standard specifies a minimal dc tolerance of $\pm 300\ \mu$V. However, this requirement was probably defined with traditional (gel) electrodes and skin preparation in mind. It is therefore questionable whether this is still sufficient when using dry electrodes, or when other electrode materials are being considered.

The IEC standard specifies a minimum bandwidth of 0.5 to 50 Hz for EEG equipment. This may be sufficient to cover the most common diagnostic purposes, but extended bandwidth is required for certain paradigms (dc to 600 Hz). Especially when frequencies close to dc are being investigated, a dc-coupled system may be necessary. However, differential dc offsets may be in the order of hundreds of mV, which is an order of magnitude above the amplitude of the ac EEG signal. The amplification of these systems cannot be very high and therefore a very sensitive A/D convertor (typically 24 bits) is required. Hence, dc coupled systems typically require a higher number of ADC bits than ac coupled systems.

CMR was very important in the days of analog equipment, when EEG was still printed on paper without the possibility to properly filter the signal [60]. Power-line interference at 50 or 60 Hz and cable motion have been affecting the ability of the neurologist to evaluate the recordings. A high CMR ratio (CMRR) meant that power-line interference was reduced as much as possible. Nowadays, with digital signal processing techniques readily available on any PC software, the requirements for CMRR are much less stringent since power-line interference can be easily filtered out. Also, techniques such as driven right leg (DRL) circuitry [61] significantly reduce the impact of power line noise. Still, care should be taken not to let the power-line interference overload the amplifier, for which reduction of common-mode noise is still a useful technique.

Another way to avoid power-line interference and cable motion artifacts is the use of active electrodes [62]. While active electrode systems typically have lower CMRR (since the system is built using different components), it can be argued that lower CMRR can be tolerated, since power-line interference and cable motion artifacts hardly get a chance to enter the signal chain. CMRR is not very effective when the contact impedances of reference and channel electrodes differ [60], [63]. In case of traditional EEG recordings, the contact impedance is reduced to below 10 kΩ by skin abrasion. The application space considered here does not allow for skin abrasion and will therefore have to

TABLE I
COMPARISON OF AVAILABLE WEARABLE WIRELESS EEG DEVICES

| | NeuroSky | Emotiv Epoc | Quasar | g.Nautilus | imec | IEC Standard |
|---|---|---|---|---|---|---|
| CMRR | | | $>120$ dB | | | |
| Input impedance | | | 47 GΩ | | | |
| Bandwidth | 3–100 Hz | | 0.02–120 Hz | 0.1–40 Hz | 0.3–100 Hz | 0.5–50 Hz |
| Channel number | 1 | 14 | 12 | 32 | 8(4) | |
| Noise | | | 3 $\mu$Vpp | | 4 $\mu$Vpp | $<6$ $\mu$Vpp |
| Bit number | | | 16 | 24 | 12 | |
| Coupling | | | AC | DC | AC | |
| Dynamic range | | | 10 mVpp | | 1.6 mV | $>1.5$ mV |
| DC offset | | | $\pm$200 mV | | $\pm$500 mV | $\pm$300 mV |
| Electrodes | Dry | Wet | Dry | Dry | Dry | Gel |
| Wireless protocol | BT | Proprietary | Proprietary | Proprietary | BT | |

tolerate (significantly) higher contact impedances. As a result, the contact impedance difference between reference and channel electrodes (in absolute sense) will turn the common mode signal into differential signals, which will not be reduced by the CMR techniques.

Concluding, we can state that CMRR is not as important as it used to be thanks to digital signal processing techniques. At the same time it will become less effective when using dry electrodes without skin abrasion. Active electrodes may be a better way to prevent power-line interference from entering into the signal chain.

Wireless transmission solutions include either the use of Bluetooth (BT) technology or proprietary protocols for data transmission. While BT is widely used for data transfer, the sheer amount of raw data transmitted during an EEG recording makes this protocol quite power hungry. However, as most portable devices support BT, such a solution makes it portable and easily accessible by users. If longevity and independence are more important requirements for the design of an EEG system, other energy efficient solutions might be used. One option is Nordic radio [64] or ZigBee [65]. Also, if a system is designed for a specific application, a significant part of processing can be performed within a microprocessor, such that only relevant information is transmitted, making the use of BT low energy a more suitable option. However, note that BT low energy is not suitable for transmission of raw EEG data.

## IV. Brain Activity Analysis

### A. Signal Preprocessing

Before the analysis of EEG signals, a signal preprocessing step is performed. The preprocessing step can involve a number of procedures with the aim to trim EEG data such that noise and artifact components that entered the EEG system are reduced (i.e., ideally removed) and the EEG signal is prepared for analysis. Preprocessing can involve some or all of the following:

1) rereferencing of recorded signals;
2) band-pass filtering the signals;
3) resampling the signals;
4) signal epoching or segmentation;
5) selection of the clean EEG segments.

Most EEG systems collect a potential difference between a set of electrodes on the scalp (that capture local area EEG signal) and a common reference electrode positioned at a location where EEG activity is absent (a so-called monopolar montage). Due to difficulty in finding a ‘neutral’ EEG position on the head (especially in compact EEG headset solutions), an option where all electrodes are located over regions capturing brain activity might be more suitable (bipolar montage). In this case, potential difference between pairs of two electrodes is measured. Irrespective of the montage type, an application might require potential differences between arbitrary electrodes, hence rereferencing is often applied in the preprocessing step.

Techniques such as common average reference and Laplacian filtering are also often used in rereferencing with the goal of ‘simulating’ a neutral spot and minimizing the impact of noise and artifacts [6]. These methods give good results if the quality of the recorded EEG signal is high and similar across all electrodes. In real-life measurements with dry electrodes (see previous section), this might not be the case, hence using such (re-)referencing methods might not improve the signal quality. Furthermore, not knowing which channels and which signals are used for rereferencing, might pose serious problems when comparing signal analysis outcomes of different rereferencing methods. For lifestyle applications, where we can often expect a reduced set of electrodes to be used, proper referencing methods need to be carefully chosen for a specific application and they have to be properly documented.

EEG data is usually band-pass filtered before the analysis is performed. Depending on the frequency range of interest and the intended signal analysis, the filter characteristics can be quite different. They can include the use of high-pass filtering (e.g., 0.1 Hz) for event-related potential (ERP) studies or specific frequency band filtering used in spectral analysis, e.g., 8–13 Hz filtering for alpha activity monitoring. Also, a power line notch filter is almost always applied to remove artifacts stemming from electrical instruments in the vicinity. However, knowing only the frequency range of filters does not uniquely determine how the data is preprocessed. Additionally, improper filter implementations (i.e., filter type, infinite or finite response, order) can result in removing a portion of EEG activity [66]. Hence, filter implementation has to be carefully chosen and properly documented.

In general, EEG data is typically resampled for offline EEG analysis, since sampling frequencies of acquisition systems can be as high as 4 kHz. In the analysis of EEG, we are usually interested in frequencies lower than 100 Hz, hence resampling to 256 or 128 Hz is often used. Resampling can reduce noise and is useful for saving transmission power in case of real-time system design.

The analysis of EEG signals is typically performed per epoch, where epoch length can range from one second in case of ERPs, to one minute in case of sleep analysis. Furthermore, depending on the application and the type of analysis, overlap is introduced between these epochs. Selecting different epoch duration and epoch overlap percentage can result in different algorithm performance, e.g., on BCI communication speed [67]. All these steps have to be carefully selected and captured by the system (for recording or comparison purposes).

Finally, extracting clean EEG segments can be performed manually, automatically using signal processing methods, or as a combination of the two (semiautomatic). The most commonly used approach that precedes any signal analysis is visual inspection and manual removal of segments that are contaminated. In clinical practice this is done by clinicians experienced in EEG monitoring. Although this is considered the most robust solution, disagreements may exist between experts. Either establishing clear rules on how contaminated segments are identified by clinicians or providing clear documentation of the process, would help in repeatability of this manual step and support overall agreement. Such manual methods may be acceptable for off-line signal analysis application, however, they are not suitable for real-time lifestyle ones. For such applications, this step is based on signal processing methods that can extract signal features useful in separating 'clean' from contaminated EEG. These methods can be considered as part of the EEG artifact handling approach. As handling EEG artifacts is one of the main obstacles in real-life applications of wireless and wearable EEG solutions, we dedicated the next section to this topic.

### B. EEG Artifacts

In case of EEG, the term artifact denotes all the electrical signals produced by sources other than the human brain, but captured by an EEG acquisition system. There are several slightly different classifications of artifacts observed in EEG recordings, based on the sources or nature of the artifact. The classification used in this paper is derived from the ones discussed in papers by Geetha *et al.* [68] and Sweeney *et al.* [5], with the addition of motion artifacts. The five artifact classes identified are:

1) environmental artifacts;
2) EEG recording equipment artifacts;
3) artifacts due to improper EEG system usage;
4) systemic physiological artifacts; and
5) motion artifacts.

Here, we first introduce these artifacts and then discuss how they can be handled.

*1) Environmental Artifacts:* Environmental artifacts, also known as interference, encompass artifacts due to power lines that are in our environment (so called 50 or 60 Hz hum) and electromagnetic interference (EMI) that can be produced either in measurement cables, or in a human body (which acts as an antenna), emitted by an external source. These are the major sources of interference in the physiological measurements due to capacitive coupling of the measurement cables, mains supply, and other devices. However, as this interference is typically either outside the frequency range of interest for EEG (EMI), or at a fixed frequency (50/60 Hz), it can be easily removed by a proper EEG system design and/or by filtering them in the signal preprocessing step. The solutions involve hardware or software implementations of band pass filtering and using techniques such as CMR and DRL discussed in Section III. Such issues are minimized in wireless devices, due to low power, shorter cables, and the absence of grounding. Furthermore, this interference can be further reduced by shielding or twisting cables and using active sensor chips as described in Section III.

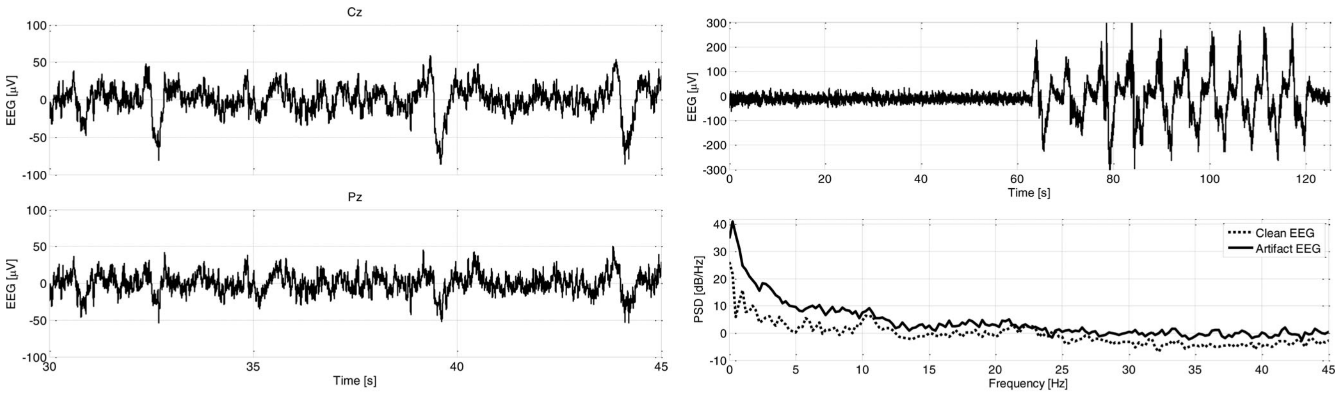
*2) EEG Recording Equipment Artifacts:* EEG recording equipment artifacts stem from EEG instrumentation and originate from the circuit components and communication lines. The former can usually be observed as a thermal noise, shot noise, or pink noise when recording the EEG signals. The latter typically results in spiky signal, cross-talk between different channels, or in enhancement of environmental artifact components. Usage of adequate components and proper system design and evaluation is required to eliminate or minimize such artifacts. Since lifestyle wireless EEG systems will be used in uncontrolled environments, a more versatile and more extensive battery of system tests is required (compared to what is required in IEC standard) to ensure this, as discussed in Section III.

*3) Artifacts Due to Improper EEG System Usage:* Artifacts due to improper usage result in a measurement error. They stem from variations in the preparation and setup, as well as misuse of the measurement device. Although this problem is almost nonexistent in a clinical environment, for lifestyle applications it is a reality. Artifacts due to improper usage can be observed during the preparation/setup or in the early phases of monitoring. Improper positioning of the electrodes or the headset, as well as improper electrode (and skin) preparation are typical examples. Using dry electrodes integrated into the headset and having contact impedance and signal quality indication, is one option that helps mitigating the former problem, both at the start as well as during the measurement. Furthermore, having a user interface that would help in preparing, adjusting and testing the setup avoids such artifacts. Most existing solutions (including the ones discussed in previous sections) do not offer this way of assistance to users.

*4) Physiological Artifacts:* Physiological artifacts are the distortions in the signal of interest due to other physiological processes in the body. They can be classified into following categories:

1) Artifacts produced by eye movement and eye blinks.
2) Artifacts produced by muscle tension.
3) Artifacts produced by cardiac activities.

*a) EOG:* The most common artifacts in EEG recordings are eye blinks and eye movements. They have the highest impact in the frontal areas of the head. Changes in the resting potential of the retina during eye-blinks and eye-movements as well as




(a) (b)

Fig. 4. Artifacts produced by a) eye-blinks and b) head movements.

muscle activities of the eye lid during blinks produces disturbances in EEG. They can be measured with electrooculograph (EOG). These disturbances are mainly present in low frequency components of the EEG, i.e., up to 10 Hz. EOG artifacts can have amplitudes of up to 1 mV that attenuate with distance toward the occipital sites. By measuring EEG during eyes closed limits the impact to only eye movement. However, EOG signals are always present during EEG measurements. An example of eye blink artifacts can be seen in Fig. 4(a).

*b) EMG:* Jaw, facial, and neck muscles also produce electrical activity that can impact EEG. This activity can be measured using electromyograph (EMG) and it is most prominent over the temporal lobes. The largest EEG activity can be observed when jaw muscles are used (teeth clenching and chewing) and during head movements that involve neck muscles. Unlike EOG, EMG spreads over a wide frequency range, typically from 20 Hz to few hundred Hz. The amplitude of the EMG signal can be in the order of mV across the whole EEG spectrum. Since head muscle activations are an inherent part of normal daily routines, solutions that handle such artifacts have to be devised.

*c) ECG:* Heart also generates an electrical signal that can be recorded in numerous positions on a human body, including the head. The signal is called electrocardiograph (ECG). ECG artifacts influence the frequency content in the 0.5–40 Hz frequency range. Hence, it is important to recognize and handle situations where such a signal contaminates EEG. Similarly to EMG artifacts, methods for ECG artifact removal exist, but the topic is not fully explored [69]. The beating of the heart also produces artifacts that stem from voltage changes in the area near the blood vessels that contract and expand. They are strongest over temporal arteries and veins. Heart beats artifacts are low in amplitude and can have an impact in the lower frequency range (0.5–3 Hz). Therefore, they can impact the performance in systems for overnight recordings and especially in characterization of deep or slow-wave sleep (stage N3 of NREM) and K-complexes observed during stage N2 of NREM sleep.

*5) Motion Artifacts:* User motion results in the a) changes in the measurement geometry, b) coupling between sensors and the skin surface, and c) tissue deformation. Motion artifacts are complex artifacts that can impact all previously mentioned artifacts. The most dominant phenomena that contributes to the motion artifact is the change in relative position of electrode to the tissue (skin). It influences the size of the contact surface, introduces skin deformation and produces changes on the interface layer (due to changes in conductive gel thickness/amount or the amount of sweat), which in turn results in electrical coupling. As a result, there is significant electrical signal distortion. Movement artifacts produced during normal activities, including locomotion, can have amplitudes that are an order of magnitude larger than signals produced by brain activity, as illustrated in Fig. 4(b). They are larger when dry electrodes are employed instead of conductive gel ones, due to the more complex electrode–skin contact, as discussed in Section III. Unlike previously described artifacts which exhibit stereotypical behavior, motion artifacts are nonstationary time-varying electrical signals. This makes them more difficult to handle than other electrical disturbances. Therefore, the nonstationary EEG signal is mixed with the time-varying motion artifacts signal, as well as more stationary physiological artifact. Handling such artifacts is among the grand challenges for daily life EEG monitoring as the magnitude of these artifacts is huge and impact a wide frequency range.

*6) Handling Artifacts:* Most current EEG recording protocols rely on artifact avoidance and manual or semiautomatic artifact removal methods. While there is a substantial progress in automatic reduction of environmental and recording equipment artifacts, only a few solutions exist that offer fully automatic artifact handling methods for physiological and motion artifacts [5]. These are mostly focused on EOG artifact reduction for conductive gel recordings, as these artifacts are always present in EEG recordings and exhibit a clear pattern [see Fig. 4(a)].

Handling artifacts can be done either by artifact rejection or artifact reduction methods. In both cases, the first step is the detection of motion artifact in an EEG segment. Artifact rejection refers to the process of detecting artifacts and rejecting the complete recorded trials or EEG segments (i.e., epochs) contaminated by them. While for long-term EEG monitoring, rejecting a certain amount of EEG epochs contaminated by artifacts might be an accepted solution, it might also result in a substantial loss of data, leading to insufficient information for proper data analysis. Ideally, a real-time automatic artifact reduction is preferred.

Artifact reduction (removal) is a process of identifying artifact components in the EEG signal and separating them from the neuronal sources. Most artifact reduction techniques assume that the recorded signal is a combination of the signal of interest and the artifact signal such that their combination is additive in nature. Furthermore, these techniques assume that the number of recorded signals is larger than the number of signal sources, as most of EEG recordings are done with more than eight electrodes. With such assumptions, the removal of artifact is simplified to minimizing the error between the output signal and the signal of interest. Artifact reduction approaches might use only EEG signals in artifact reduction, but might also include auxiliary information sources that capture physiological signals (EOG, ECG, and EMG) or movement (accelerometers and gyroscopes). In most cases, techniques that are applied when solely EEG signals are used in most cases include linear combination and regression, blind source separation (BSS) methods (such as ICA and PCA), wavelet transforms, and empirical mode decomposition (or a combination of these methods). When a referential signal that depicts the artifact component is available, adaptive filtering, Wiener filtering, and Bayesian filtering are used. For a recent overview, we refer to [5], [68].

Numerous approaches exist for the removal of EOG artifacts and they are mostly based on regression and (semi-) automatic BSS [70], [71]. Although there are several approaches for the reduction of EMG artifacts, handling EMG artifacts is not extensively explored [69]. Finally, reducing ECG and motion artifacts during daily life activity is still in its infancy, given that only few approaches are available in the literature. At this point in time, we lack suitable and comprehensive physiological and motion artifact handling methods. This is also the case for the EEG recordings with gel electrodes and becomes a larger hurdle when EEG solutions with dry electrodes in an uncontrolled lifestyle environments are used.

Due to the complexity and detrimental nature, motion artifacts are by far the biggest hurdle that intelligent, wireless, and wearable EEG systems have to overcome. Due to the complexity of these artifacts, contextual information has to be used. Such information can be provided by either gyroscope [72], [73] or accelerometers [74]. The work by O'Regan *et al.* [72], [73] demonstrates that such contextual information can be used to detect and categorize motion artifacts. However, the outcome of the motion artifact reduction presented by Sweeney *et al.* [74] shows limited usefulness of accelerometers. A two-step method, that first identifies the type and the extent of motion artifact and then tries to reduce it based on the approach tailored toward that specific artifact would result in better motion artifact reduction [67]. Furthermore, additional contextual information, such as ETI might be a more useful reference source for motion artifact reduction [75], given also their origin discussed in Section IV. Furthermore, to what degree can combination of ETI with other contextual information modalities (such as gyroscopes and accelerometers) help in motion artifact reduction is yet to be determined.

### C. *Feature Extraction and Interpretation*

Algorithms for extracting EEG features and EEG feature interpretation are very diverse and involve different techniques and tools [76], [77]. These algorithms are based on spatiotemporal linear or nonlinear signal processing methods, the usage of averaging methods (e.g., for ERPs) and supervised or nonsupervised classification algorithms. More recently, graph theory algorithms are introduced for studying brain networks (e.g., resting state networks). Wireless, wearable EEG applications are (and will be) using the available solutions already exploited and tested in various EEG application domains. The only differences might be in 1) the need for real-time processing of signals, which would be the most dominant case and 2) in the number of electrodes that might need to be reduced due to design. More stringent boundaries have to be considered in terms of algorithm complexity, the number of features simultaneously extracted, limitations on using supervised learning approaches and graph theory algorithms.

A number of toolboxes exist that provide a vast amount of implementations of algorithms used for EEG feature extraction and interpretation. EGLAB [78] and OpenViBe [79] are the most frequently used ones. We believe that these toolboxes will provide a sound base for developing application-specific implementations. The optimal EEG feature extraction and interpretation algorithms will heavily depend on the aim of the application. For example, alpha–theta neurofeedback application would require the implementation of essential EEG spectral feature extraction, while monitoring the progress of Alzheimer disease would require complex coherence and network analysis, as well as more advanced classification algorithms. In summary, the pool of required feature extraction and interpretation approaches is varied and the important question is how to translate these into particular solutions. One potential option is the inclusion of the algorithm implementations in the hardware (e.g., microprocessor) to facilitate more convenient EEG solutions.

## V. Output Interface

### A. *Information Fusion*

EEG applications require sophisticated software tools for signal processing (including artifact handling, feature extraction and feature interpretation discussed in previous sections) and for information feedback generation. Currently available software tools and systems range from open source, general purpose ones, such as EEGLAB [78] and OpenViBe [79], to proprietary ones designed to work with specific acquisition equipment and for specific applications, such as Applied Neuroscience NeuroGuide [80] and ANT Neuro software tools [81]. The applications can record or read EEG data only in a proprietary data format or some of the formats which are designed for EEG data interchange, such as European Data Format—EDF. Although EDF is designed to be the 'standard' for EEG recordings, it comes in different flavors and different versions, making storage and exchange of EEG recordings, as well as creation of shareable EEG databases, extremely difficult. The lack of support for capturing contextual information (including other physiological signals), makes comprehensive EEG data recording and exchange virtually impossible.

Most existing software tools support a number of signal and artifact processing algorithms and different ways of visualizing the output. The algorithms typically include a subset of general purpose temporal and spatial signal analysis, coherence and phase analysis, blind source separation, and optionally application specific methods such as spike sorting (for epilepsy applications) and source localization (for neuroimaging studies) [6], [77]. These tools neither support sophisticated signal analysis methods nor provide sophisticated algorithms for handling motion artifact. Except for few of them (such as OpenVibe [79] and BCI2000 [82]), they do not support real-time signal analysis algorithm implementation, which makes the information fusion from EEG signal analysis algorithms difficult.

Wearable and wireless EEG applications would require instantaneous processing and information fusion. Hence, time and memory efficient implementations of algorithms on a portable device or within a microprocessor are required. The proper implementation choice would be driven by the application for which the EEG system is designed. The two extreme examples that illustrate the need for application tailoring are 1) alpha activity monitoring and 2) source localization while performing locomotion. The former can be based on a single channel estimation of the spectral power of alpha activity and a simple artifact rejection algorithm based on standard deviation of the EEG signal. The latter must at least include substantial preprocessing, including motion artifact reduction and spatio-temporal filtering techniques on a number of EEG channels, as well as application of a source localization method in real-time. Therefore, the success of the EEG information fusion modules depend on the proper treatment of available EEG information before the feedback generation step [83], [84].

### B. Feedback Generation

Today's EEG solutions are designed either for clinicians who monitor brain activity (e.g., ANT Neuro and NeuroGuide), or for gaming and communication applications of BCI (e.g., OpenViBe [79] and BCI2000 [82]). The former include cluttered presentations of raw EEG data for each EEG channel (which might be in the order of 128 or 256), EEG spectra for each channel and additional information specific to a certain application for which the software is designed. The latter are typically much simpler and may include only a cursor with a few letters displayed on the screen. It is debatable whether the former provides more comprehensive information over the current brain activity. However, the latter might actually provide the information that the user is required to see (e.g., navigation status and which steps are performed). This illustrates the challenge in the feedback generation for the future wireless and wearable EEG solutions.

The way how feedback is tailored toward a specific application and how it addresses the current user needs through feedback, might make a difference in whether a particular EEG system would penetrate the market or not. Unlike the current EEG feedback generation options, which are mostly designed to be displayed on a large screen, the very nature of the wearable


Fig. 5. Artistic feedback visualizing the concentration of two persons engaged in interaction. The level of concentration is associated with the number of flowers present on the display.

EEG would require completely different feedback generation approaches. These can include visual display on tablets, smartphones, or watches and will not focus on displaying raw EEG in all channels but on the intelligent depiction of a semantic concepts derived from, e.g., EEG spectral power, coherence, or brain region activation. Fig. 5 illustrates one way of visualizing the level of concentration of a user, by depicting a garden flowers growing when concentration level is high. Also, EEG activity can potentially be integrated with other contextual or physiological concepts [85]. Other sensor modalities might be used for communicating the information on EEG, such as audio [86] or textile feedback [87], which might be more suitable for a specific application. It is open for discussion whether such modalities, or the ones that include artistic components, are more appealing to end users.

## VI. Discussion

In the previous sections, we have illustrated the state-of-the-art on different aspects of wireless and wearable EEG solutions for daily life applications. This overview is by far not exhaustive, but we have illustrated current problems and pitfalls in the design of such systems and suggested direction for future progress. This section summarizes the presented overview and emphasizes what in our view are the most important aspects that will determine the future prospects of intelligent, wearable, wireless EEG solutions. We argued that the main reason for the absence of EEG solutions in daily life is in the lack of integration of knowledge that comes from a number of different disciplines. The proper design and development of an intelligent wireless and wearable EEG solution has to be driven by the application at hand, tailored toward the end user and must handle artifacts that can be encountered during daily life usage. The design and development of such intelligent EEG solution has to encompass all or most of the relevant aspects of the EEG signal path illustrated in Fig. 1:

1) personal traits, previous and current environmental stimuli, and knowledge on how EEG signals are generated and transmitted through biological tissue;

2) capturing EEG signals from electrodes and low-power, miniaturized technology used for acquiring, amplifying, processing, and transmitting EEG signals;
3) algorithms and methods used for EEG signal preprocessing, artifact handling, feature extraction, and feature interpretation;
4) methods to process and present fusion of context-related brain activity.

### A. Application-Based Design and Development

Although monitoring EEG activity is quite useful in itself for clinical applications, in the lifestyle arena, wireless EEG systems have to provide clear benefits for users. Due to the inherent difficulty in designing a complete EEG solution, most nonclinical EEG solutions are designed for general purpose EEG applications with a lack of support for sophisticated signal processing and effective feedback generation. They suffer from a number of forced tradeoffs that severely limit the usefulness of such systems. For example, Emotiv Epoch [14] has a suboptimal design for a number of applications, given the fixed electrode position, which is not according to the 10–20 system and has suboptimal headset design. Lower quality of acquired signals is observed by many research groups. This is partially compensated by offering software development kits for implementing signal processing algorithms. The solution offered by Neurosky [13] is oversimplified in the design such that it can only be used for toy applications in a niche market (i.e., a small set of serious games). To avoid the signal quality evaluation issues, it can only be used in specific set of games for which signal processing and interface design is provided.

Currently, no EEG solutions available on the market are designed with a specific EEG application in mind, as discussed in Section III. The typical applications of brain activity monitoring in real-life, currently based on gel-electrodes and usually not on wearable and wireless technology, include the ones focused on communication and control. They fall into a category of BCI applications [22]. Apart from such applications, brain activity monitoring is applied in several areas of neurofeedback, which can be considered both as healthcare and as lifestyle solutions. Examples include treating ADHD [26], PTSD [88], and peak performance training [25]. A few areas where wireless EEG solutions are starting to be used are drowsiness detection [23], emotion recognition [89], and mental fatigue estimation [90]. Such applications require different number of electrodes located over different cortical regions. For example, alpha peak neurofeedback training requires one or more electrodes over the central or parietal sites. Basic signal processing methods could be used to extract spectral power (or spectral peaks) and simple visual or auditory feedback mechanisms can be employed. However, emotion recognition applications might require electrodes positioned over the frontal areas of the brain, extraction of spectral content, network features and potential source localization. Signaling the emotional state of a user in a desired format is also required.

By careful selection of the desired application and design and development of the intelligent lifestyle EEG solution toward this application will provide the necessary edge required for wider penetration on the marker. Tailored headset design and specific (dry) electrode integration over the selected scalp area has to be addressed. Knowledge on conductivity of the tissue and the skin–tissue interface, as well as signal acquisition and transmission properties of the system have to be available, as discussed in Sections II and III. The correct signal analysis methods have to be selected and implemented to handle artifacts and noise and to extract the right information, as discussed in Section IV. Finally, as presented in Section V, the outcome of the signal processing has to be visualized to serve the purpose of a particular application and to make sense to the end user of the EEG solution.

### B. User-Driven Design and Development

Proper design of EEG systems including the end-user needs is an essential factor in wider adoption of such systems in ambulatory as well as home monitoring applications. Particularly, if we would like to attract users to use brain activity monitoring as a tool in their personal health management. Convenience and comfort of a user are aspects that could differentiate between the technology that will be used by niche user groups and the one that will be a mainstream solution. Currently available wearable and wireless EEG solutions have several features that are not convenient and comfortable (as discussed in Section III). Most systems use rigid or spring-loaded pins which are mounted in a headset, either through an elastic or spring-loaded handle or directly within it. As these headsets are not lightweight, the result is a solution which is not appreciated by end users. In intelligent wearable and wireless EEG solutions, electrodes used to obtain EEG signal have to be designed to make direct contact to the skin without the use of any adhesives. More advance concepts have to evolve to minimize obtrusiveness and stigmatization of users. Electrodes should be able to penetrate the hair, independent of the hair length, type, and density and at the same time be comfortable to wear. One option is to develop electrodes and headsets with different design parameters to accommodate different hair lengths and densities, as well as different head shapes and sizes. For example, if dry electrodes with pins are used, they might be designed with different pin lengths, pin diameters, or pin density, to accommodate for comfort and improve signal quality.

Furthermore, an average user is not familiar with the ways of how to apply and use EEG equipment. The intelligent EEG solution has to educate and help the user to obtain EEG signals of desired quality. It should be designed such that the user positions the electrodes at the required location simply by placing the headgear solution, or by providing (audio or visual) guidance to the user that will help in positioning the headgear. Furthermore, it has to indicate to the user whether the electrode–skin contact is satisfactory in each electrode and guide the user to readjust the positioning of some of the electrodes or the whole headgear. If the contact becomes poor or unstable during the recording, the system has to notify the user and to help achieve the stable contact. These are some of the requirements that need to be addressed in the design and development of feedback generation and visualization discussed in Section V. Also, the user should not be required to take any actions after the usage of the headset and to just remove the headset and continue with regular activities, i.e., no need for hair washing or cleaning the scalp. Currently, none of the commercially available systems supports such requirements.

Finally, EEG solutions should enable a certain degree of personalization, both in terms of the performance of the system, as well as ergonomics and feedback. A user needs be able to, e.g., tune neurofeedback 'power' to his/her speed of learning or change the visual feedback provided from a simple bar to a more appealing visual feedback (such as the one presented in Fig. 5). The user needs to be able to adjust the headset and pressure exerted by electrodes according to his/her preference. Furthermore, an EEG system should be configurable to accommodate for personal traits and states, as well as various sensory inputs discussed in Section II. Overall, the requirements extend throughout all aspects of the EEG signal path depicted in Fig. 1. Addressing personalization with those aspects might not only result in less aversion toward the use of such devices but also to more frequent and more effective usage of the device itself [91].

### C. Importance of Standardization and Sharing

As stated in the introduction, in the future, we can expect empowered users taking control of their health. The scientific community has to strive in giving the right tools and knowledge into the hands of users. This requires abundance of available data and systems for EEG measurement, as well as agreed monitoring and measurement protocols and data formats. To prevent problems in exchanging EEG data as well as analysis methods, more effort is required in standardizing the recording formats and especially on the recording protocol and the context capturing during the recording or monitoring sessions (including environmental or physiological cues other than EEG). This is discussed in Section II where personal traits and sensory inputs are presented, as well as in other sections that discuss the acquisition and data processing.

The status at this moment is far from desirable. A large number of different storage formats exist, including the various versions of the EDF intended to ensure standardization [92]. There are no clear specifications on the use of protocols. Finally, there is no consensus on the method used to acquire contextual information. All these aspects have to be considered to make large public databases of EEG recordings and exhaustive analysis toolboxes to extract the precious knowledge from our brain activity and make it available for a wide audience of users interested in maintaining and improving their health. An European Union BNCI Horizon project [93] and the US Government initiative called The Brain Research through Advancing Innovative Neurotechnologies (BRAIN) [94] are two frameworks that have the opportunity to address these issues on a global scale. It is up to the members of these frameworks to realize the importance of the issue of standardization and sharing and address it urgently.

### D. Handling Artifacts

Due to the detrimental impact of various artifacts, artifact handling becomes the crucial aspect of lifestyle EEG monitoring in uncontrolled environments, when the user is able to freely move. While a) environmental artifacts, b) recording equipment artifacts, and c) artifacts due to improper usage can be handled by proper signal filtering, system design, and correct usage, physiological and motion artifacts are much more difficult to handle (see Section IV). Obviously, it is not suitable to have manual handling of such artifacts due to the cost and the amount of recorded data in case of offline analysis applications and due to the real-time applications which we expect will be the most dominant use case. Avoiding artifacts by refraining from head and body movements would oppose the very purpose of lifestyle monitoring. Therefore, approaches that can identify the presence of physiological and motion artifacts and reduce the impact of these artifacts are a great challenge for intelligent wireless lifestyle EEG solutions.

Handling motion artifacts is a perfect example that also illustrates the importance of application design, user-driven development, standardization and sharing, as well as the know-how on all the aspects on the EEG path discussed in Sections II to V. For example, if an application does not require constant continuous monitoring of EEG, having simple standard deviation thresholding based artifact rejection methods might be sufficient for the required data analysis. Generation of motion artifact databases, with correct capturing of contextual information (including, e.g., acceleration and ETI) can offer irreplaceable platform for testing different motion artifact handling algorithms and exchanging experience within the research community. Having a well-established ETI model and head conductivity model helps in translating continuous ETI information into the artifact component of the captured electrical activity during motion artifacts. Efforts into designing headsets and dry electrodes to minimize motion artifact impact and provide comfort to the user lead to greater user acceptance and higher signal quality. System design optimization using active sensor chips with local signal processing to reduce the artifact at the input of the system can also help. Finally, fine-tuning signal processing to reduce the contribution of such artifacts and proper communication to a user about the quality of the obtained EEG-based information would introduce completely new functionality to the intelligent EEG solution.

## VII. Conclusion

This paper presented guidelines toward developing intelligent wearable, wireless, convenient, and comfortable lifestyle EEG solutions that provide high signal quality. We discussed a number of aspects where existing solutions require improvements to facilitate further progress. These aspects include personal traits and sensory inputs, brain signal generation and acquisition, brain signal analysis, and feedback generation. Where appropriate, we provided suggestions on how to overcome current pitfalls. We argued that the most critical areas, which progress will to a large extent determine the evolution and deployment of wireless, wearable, lifestyle EEG systems, are the following ones:

1) application driven design of EEG solutions;
2) user driven development of EEG systems;
3) standardizing and sharing of EEG data and contextual information;
4) handling artifacts in daily life EEG.

Addressing these challenges in future research, design, and development endeavors would help in bringing EEG solutions to a more advanced level. With such devices at hand, users interested in promoting their quality of life and mental health, as well as the ones in need of cognitive monitoring solutions, would be able to enjoy the full potential of EEG monitoring.

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