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Chapter 16

Self-health monitoring and wearable neurotechnologies

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Abstract

Brain computer interfaces (BCI) and wearable neurotechnologies are now used to measure real-time neural and physiological signals from the human body and hold immense potential for advancements in medical diagnostics, prevention, and intervention. Given the future role that wearable neurotechnologies will likely serve in the health sector, a critical state of the art assessment is necessary in order to gain a better understanding of their current strengths and limitations. In this chapter we present wearable EEG systems which reflect groundbreaking innovations and improvements in real-time data collection and health monitoring. We focus on specifications reflecting technical advantages and disadvantages, discuss their use in fundamental and clinical research, their current applications, limitations, and future directions. While many methodological and ethical challenges remain, these systems host the potential to facilitate large scale data collection far beyond the reach of traditional research laboratory settings.

INTRODUCTION

Our society faces increasing health disparities, limited access to healthcare, and rising healthcare costs. Simultaneously, the technological sector has entered an era of bio and neurotechnology producing wearable neurotechnologies providing real-time and longitudinal monitoring of physiological and neural activity, and may present viable solutions to many of these issues (Ghose et al., 2012). Consumers can now access a wide array of wearable technologies that measure, monitor and receive feedback from ongoing physiological and neural activity. The information provided by wearable technologies has numerous overlapping applications. For example, measuring patients' vital signs at-home may result in higher quality, individualized treatment protocols that incorporate continuous, detailed information about the patients' ongoing physiological status (Muse et al., 2017). A variety of prototypes and commercial products have been recently developed that provide real-time health data directly to the user or the medical center/professional physician, and can alert an individual or care provider in the event of a potentially threatening or imminent health emergency (Kumar et al., 2012). With an increasing capacity to acquire, share, process, store, retrieve, and apply big-data methods, wearable technologies may significantly improve our ability to tackle some of the major challenges of today' society (Zheng et al., 2014).

While the application of wearable technologies was previously limited to physiological measurements (e.g. heart rate, step-counter), recent advancements in wireless electroencephalography (EEG; the measurement of neural electrical activity from electrodes placed on the scalp) is now leading to the development of new applications. While wearable EEG technology faces a number of limitations and challenges in order to match state-of-the-art (SoA) research grade EEG equipment (e.g. number of electrodes and electrode locations, signal-to-noise-ratio, markers etc.), they do hold immense potential, allowing direct interfacing between an individual's brain activity and a digital recording device in other environments than clinical and research infrastructures and at affordable

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prices for a wider part of the population. These devices will eventually allow us to train and target specific cognitive skill sets (Vernon et al., 2003), reinforce specific brain rhythms (Brandmeyer and Delorme, 2013), play video games (Schoneveld et al., 2016), and create art and music based on measured real time neural activity (Grandchamp and Delorme, 2016; Levicán et al., 2017).

EEG measurement reflects the cumulative electrical activity associated with the depolarization of cortical neurons, can reflect rhythmic and transient activity (Buzsáki, 2006), and facilitates analyses of neuroimaging data with very high temporal resolution. Brain oscillations reflect the postsynaptic potentials of neuronal populations, either in response to a stimulus from the environment (i.e. evoked response potentials, ERPs), or associated with mental states (e.g. sleep, coma, cognitive activity etc.). EEG scalp electrodes measure the electrical waves as they spread across the scalp (See Chapter 19 for more information on Electroencephalography). This rhythmic activity of the brain is then analyzed in the temporal domain (i.e. frequency domain), and most often within sub-bands of specific frequencies, customarily defined based on their spectral content such as delta (<4 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (>30 Hz). Frequency bands are thought to be functionally correlated with specific cognitive processes or with specific steps of processing depending on the location of their measurement or their latency within a specific process. The high temporal accuracy of EEG also provides precise temporal information about brain processing. EEG is also used clinically to diagnose and localize which steps in the brain's information processing pathways are malfunctioning (e.g. visual, auditory, tactile processing).

The recent development of dry electrodes (Taheri et al., 1994) and wireless technologies, have led to innovative wearable EEG systems, offer quick and practical EEG data acquisition solutions (i.e. no gel, cleaning, or cables), usually include real-time data preprocessing as well as correction for head movements. Several new systems are now fully portable, where data recordings can be stored directly on the device (i.e. micro SD) or transmitted wirelessly to a smartphone (Debener et al., 2015; Stopczynski et al., 2014). As a result of these technological improvements, new possibilities in the domains of fundamental and clinical research have now emerged. With features such as the lightweight portability, the ease of dry electrodes, and relatively fast set up times, well designed wearable technologies enable access to populations that were previously harder to include in research laboratories settings.

By gaining access to wider range of populations, such as young children, the disabled, and elderly (Neale et al., 2017; Ramirez et al., 2015), neurotechnologies may enable longitudinal designs with larger sample-size studies (Hashemi et al., 2016; Kovacevic et al., 2015), and improve our ability to study the human brain in naturalistic settings (Debener et al., 2012). Many modern wearable EEG headsets are now comfortable to wear and incorporate elegant designs, and re becoming increasingly attractive for general public use (Nijboer et al., 2015). Innovative applications including practical, easy, and high-fidelity at-home recordings, have the potential to enable neurofeedback (NF) and brain-computer interface (BCI) based cognitive interventions, applications, group studies (i.e. simultaneous recording of different participants), big data analyses, and more.

At present, wearable EEG technologies remain one of the most promising candidates for the real world applications of self-health monitoring solutions (See Chapter 7 for more details on BCI principles, concepts and domains). Recent innovations in wearable headset design enables the delivery of both transcranial current stimulation (TCS), functional near-infrared spectroscopy (fNIRS; see Chapter 22 for more information on NIRS), in addition to the simultaneous combination of these methods with EEG (see Table 1). In the following chapter, we review several high-fidelity EEG wearable systems currently available (both consumer and research grade products), in addition to systems that combine EEG, TCS with fNIRS or TCS. We then explore the different applications that already exist using wearable technologies and address the limitations, prospects, and precautions associated with such technologies.

Wearable neurotechnologies

In the following section, we provide a list of both relatively low-cost (i.e. under a $1,000) and widely used (as of 2018) wearable EEG systems that are available for both fundamental and clinical research, NF, BCI and home-use based applications. We also review a non-exhaustive list of less affordable (i.e. more than a $1,000) and more advanced systems that are destined for professionals that have access to funding and are interested in the applications using these systems. Excluded from this review were several single channel EEG devices - which are relatively limited based on today's standards (Luck, 2014; Picton et al., 2000) - or EEG devices that lacks significant technical or scientific evidence or were proven to provide poor signal quality (e.g. Emotiv Insight, Foc.us EEG Dev Kit, FocusBand, Imec, Neurosky Mindwave, and the two Kickstarter products: Melon and Melomind).

	Sensors	Price ($)	Battery autonomy (h)	Connectivity / storage	Signal resolution (bits)	Sampling rate (Hz)	Weight (g)	Additional features	Auxiliary measures (EXG)	EEG	NF/BCI (included)	fNIRS	Neuromodulation	Audience and applications
Muse (Interaxon)	- 4 dry active electrodes (TP9, TP10, AF7, AF8): 2 silver and 2 conductive silicone rubber. - Reference on Fpz (DRL/DMS) - Adjustable headband (52 to 60 cm)	180	5	BLE	12	256	60	- Allows recording of raw EEG data directly on iPod, smartphone, or tablet - NF App - Allows to record data from multiple devices simultaneously on computer - Real-time impedance check - Triggers	- 6-axis motion-sensor - 1 input for custom physiological sensor - HR (Muse 2) - respiration (Muse 2)	X	X			For researchers and the public: home use, real-world recordings, attention/meditaiton training, relaxation, raw EEG recording, big data analyses, sleep research, BCI.
EPOC+ (Emotiv)	- 14 saline soaked felt pads (AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2) - CMS/DRL references (P3/P4) - Adjustable by pressure control	800	6	BLE	14/ 16	128/ 256	120	- Raw EEG data - Available detections of mental commands (neutral + up to 4 pretrained items per training profile), performance metrics (excitement, engagement, relaxation, interest, stress, focus), facial expressions (blink, wink L/R, surprise, frown, smile, clench, laugh, smirk). - Real-time impedance check	- 9-axis motion sensors	X	X			For researchers and the public: home use, real-world recordings, raw EEG recording, enhancing brain performance, 3D brain visualization, BCI.
Dreem (Rythm)	- 6 channels (4 frontal and 2 occipital) -1 micro-amplifier - Adjustable headband - Reference electrodes on O1 and O2 (but flexible)	500	12	WIFI & BLE	24	250	120	- Sound is discretly diffused to the inner ear via your forehead (using bone conduction technology). - Can connect to smartphone and iPod directly. - Sleep monitoring App that works without BLE and WIFI during sleep (data transferred later for report).	- 3-axis motion sensor - 2 pulse oximeters (respiration and HR)	X	X			Sleep monitoring, managing and improvement
Sleep headband (Cognionics)	- 2-8 active dry and semi dry electrodes (can be placed in any of 14 positions along the band).	4,5k	4	BLE/ micro SD	24	250/ 1000	110	- Real-time impedance monitoring - Optional wireless triggers - Raw EEG - Recording via microSD card possible	- Optional add-on module for EXG	X	X			Sleep monitoring, managing and improvement
Quick 20/30 (Cognionics)	- 20/30 active dry and semi dry electrodes (10/20 system + 10 additionnal from 10/5 system) - Adjustable by pressure control	24k	8	BLE/ micro SD	24	500/ 1000	610		- 3-axis motion sensor - 2 optional EXG	X	X			Designed for real-world applications, BCIs.
Ultracortex Mark IV (OpenBCI)	- 8 (cyton board) or 16 (cyton + daisy boards) channels, with 35 possible different locations. - Passive gold cup electrodes using gel paste; or any standard electrode using adapter cables. - DRL, positive voltage supply (Vdd), and a negative voltage supply (Vss) - 3 different head sizes, and flexible structure	~ 850/ 1,4k	?	BLE and WIFI	24	250/500		- Compatible with active and passive electrodes (adapters). - 3D printable - 30 sec to set up - Micro SD input for local storage - The prices correspond to the printable EEG headset with the OpenBCI boards. The headset can also be purchased printed but unassembled, or fully assembled for higher prices. Batteries are not included but represent a cost of around $10.	- 3-axis motion sensor - optional EXG (EMG, ECG)	X	X			Raw EEG recording, BCI, NF, first 3D printable device.
B-Alert X10/X20 (ABM)	- 9 or 20 channels (frontal, central, parietal lobes), using a conductive cream - Fixed gain referenced to mastoids - 3 sensor strip sizes (S, M, L)	11,5 k	12-24	BLE	16	256	11	- Ultra-low profile and comfortable fit allows for 8+ hour recording sessions - Patented real-time artifact decontamination - Software with classifications of cognitive states (for $16,5k in total price) - setup: 10/20 min	- 3-axis motion sensor - 1 EXG with the B-Alert X10; and 4 EXG for the B-alert X20 (EOG, ECG, EMG)	X	X			Raw EEG recording, BCI, cognitive assessment or training, performance enhancement, group studies, sleep studies, military studies
DSI 10/20 (Quasar)	- Up to 21 dry EEG electrodes (flat-ended finger electrodes) - Ground at Fpz and references on mastoids.	7k	24	BLE	16	300/ 600	500	- Patented shielding and circuit design reduce environmental noise - Mechanical design carefully controls contact pressure allowing comfortable wear all day - Internal storage (1 GB) - Impedance monitoring for each sensor - Cognitive states classification software	- Wireless belt that measures EKG, skin temperature, and 3D body acceleration and position - trigger inputs	X				Raw EEG recording, BCI and NF, cognitive states classification, real-world recordings.
Enobio (Neuroelectrics)	- 8/16/32 channels, using innovative solid-gel electrodes or dry electrodes - A disposable pregelled electrode or a earclip can be used for CMS/DRL reference - Six different neoprene, flexible, head cap sizes	~ 4k/ 14k/ 20k	16/ 15/ 14	BLE	24	500	65	- 3D visualization real-time - Specific headcaps for children - microSD card for internal storage - compatible with TES and TMS - "Mickey Mouse" Headcap Cover for kids	- EOG/ECG	X				Researchers and clinicians: high quality raw EEG, high mobility, real-world studies, BCI and NF applications.
OctaMon (Artinis)	- 8-channels fNIRS headband	~ 17k	6	BLE		10	230	- 8x2 wavelengths: 760/850 (standard) - optode distance: 35 mm - no interference with EEG, EOG, ECG, EMG - TMSI packages: Octamon + EMG (2 channels or more), and Octamon + EEG(16 channels or more) - Real-ime processing of fNIRS data in 3D	- Can be combined with external EEG and EXGs		X			Researchers and clinicians only: study of hemodynamic response with very high mobility, real-world studies, can be combined with other neuroimaging techniques, BCI, educational applications
g.Nautilus (g. tec)	- 8, 16, 32, 64 active, dry or gel-based EEG electrodes - GND and REF - flexible positioning of electrodes, 3 head sizes for both adults and children	from 5k	6-10	2.4 GHz ISM	24	250/500	<140	- Contactless charging of the battery - Waterproof - Allows simultaneous tDCS and TMS - Internal impedance check - 8 digital triggers - microSD (up to 2GB) - BCI software applications available	- 3-axis motion-sensor - 4 possible exg (ECG, EMG, EOG, GSR, limb movement, oxygen saturation, respiration effort and flow)	X		X		For researchers and clinicians only: high quality raw EEG, possible simultaneous EEG-fNIRS, and compatible with EEG-tDCS and EEG-TMS (with external equipment). Recording during physical activity, easy access to children and elderly, rehabilitation, real-world recordings, BCI.
	- 8 fNIRS channels, combined with EEG - Works with both dry and gel-based electrodes (8/16/32 channels) - flexible positioning of electrodes, 3 head sizes (including for kids)	from 25k	1.5-6	BLE		10	<140	- 4x 2 wavelengths: 760/850 nm - Optode distance: 35 mm - Control box weight: 230 g including battery - LED-based						
Starstim 8, R20, R32, (Neuroelectrics)	For EEG specifications, see the Enobio above								- 3-axis motion-sensor - ECG, EOG	X	X	X	X	For researchers and clinicians only: EEG recording, NF, simultaneous EEG and TES/fNIRS (all in one headset), BCIs, telemedicine, home-use, real-world recordings.
	- up to 20 or 32 electrodes with 39 possible locations - the Pistim hybrid electrodes allow for both EEG recording and TES (includes tDCS, tACS, tRNS) at the same site but not simultaneously. The geltrodes and sponstim electrodes allow for simultaneous EEG/TES, but at different sites - Multiple head cap sizes	~ 11k/ 29k/ 43k	4	Wifi	1 µA	1000	65	- Frequency stimulation: 0-250 Hz for tACS, and 0-500 Hz for tRNS. - ±15 V per electrode (30 V potential difference) - 2mA max current, 1 hour max duration of stimulation - Abortion possible at anytime - MRI compatible stimulation electrodes - Nube cloud platform allows scheduled stimulation from distance -can be combined with the OctaMon fNIRS						

Sensors: EEG activity is typically recorded from the scalp using gel-based electrodes to achieve a high signal-to-noise ratio (SNR) between the source (the brain activity) and the measurement device (the electrode). Active electrodes contain individual microamplifiers which significantly improve the SNR and reduce application time. When passive electrodes are used, the skin must be properly prepared and abraded in order to achieve a high SNR. The main advantage of gel-based active electrodes is their high SNR. Disadvantages include high cost and relatively lengthy preparation and cleaning time. The recent development of dry electrodes (Taheri et al., 1994) along with wireless technologies have led to the development of innovative wearable EEG systems. While dry electrodes have an increased sensitivity to motion artifact, movement of cables, and electrostatic charges, they do not require extensive cap mounting time, skin abrasion, or hair washing.
Sensor locations: The international 10–20 system is an internationally recognized method to describe and apply the location of scalp electrodes for EEG (Klem et al., 1999). The 10–20 system is necessary for the comparison of brain data collected from different laboratories, which entails the comparison across subjects and populations, variations in equipment, and variations in the electrode montage. In the 10–20 system, each electrode placement site is labeled according to the corresponding topographical location on the scalp prefrontal (Pf), frontal (F), temporal (T), parietal (P), occipital (O), and central (C).
Motion sensors: To prevent the loss in signal quality, a majority of high-end wearables using dry electrode technology generally include motion sensors. The gyroscope indicates the orientation of an object in space (i.e., Along the 3-axis: X, Y, Z), and the accelerometer measures the acceleration (along the 3-axis as well). Their sampling rates are similar to those of EEG. This information can be used to reject artifacts in the data. However, motion sensors—especially gyroscopes—generally present a significant drain on battery power and may decrease battery life.
Sampling rate: Sampling rates generally vary from 128 Hz to 2048 kHz. Low cost EEG usually use multiplexing of a single analog to digital (AD) converter which scan each channels sequentially. So a 2048 kHz AD converter can convert 8 channels at 256 Hz sampling rate. Note that research systems usually have one AD converter per channel which not only allows for higher sampling rate but also ensures simultaneous acquisition of all channels (with the sequential solution, the acquisition time of each channel is slightly delayed for each channel which could potentially affect subsequent processing—although resampling techniques may be used to realign data collection time of each channel).
Connectivity: Bluetooth and Wi-Fi use the same band at 2.4 GHz (Wi-Fi may also use the 5.0 GHz frequency). Wi-Fi direct promises device-to-device transfer speeds of up to 250 MBPS, while Bluetooth 4.0 promises speeds similar to Bluetooth 3.0 of up to 25 MBPS. Bluetooth technology cannot transmit as much data as Wi-Fi.
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Data resolution (in bits): It is generally accepted that EEG signal resolution does not go beyond 24 bits (due to environment and electric noise). However, this means that all systems acquiring less than 24 bits may lose important data, unless a dynamical gain mechanism is implemented to increase the range of possible values. Most low-cost wearable EEG system use 16-bit A/D (analog/digital) conversion resulting in some loss of data.

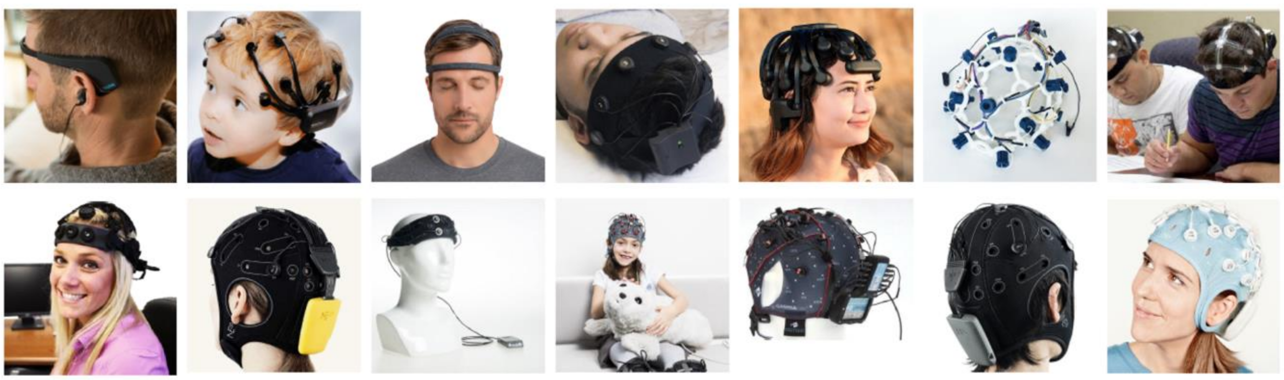

Figure 1: Illustration of the wearable EEG headsets reviewed in Table 1

Top row (from left to right): *Muse (Interaxon), Epoc (Emotiv), Dreem (Rythm), Sleep headband (Cognionics), Quick 30 (Cognionics), Ultracortex Mark IV (OpenBCI), B-Alert X10 (ABM).*
Bottom row (from left to right): *DSI 10/20 (Quasar), Enobio (Neuroelectrics), Octamon (Artinis), g.Nautilus (g.tec), g.Nautilus EEG-fNIRS (g.tec), Starstim 8 and 32 (Neuroelectrics).*

APPLICATIONS

Fundamental research

Over the past century, EEG studies have served as a key methodological tool for the scientific study of human cognition, sleep, neurodegenerative diseases, and brain disorders (Luck and Kappenman, 2011; Regan, 1989). While traditional EEG laboratory recordings require lengthy application and recording procedures, several of these technical factors can be overcome by increasingly sophisticated lightweight, easy to setup wearable EEG headsets and headbands that implement wireless and dry electrode technologies and allow scientists to gain access to large volumes of raw data for research purposes.

However, it is important to note that several technical specifications are required to obtain good data quality when conducting both continuous EEG and event-related brain potential (ERP) research (Luck, 2014; Picton et al., 2000). Electrode type, the minimum number of electrodes needed for meaningful interpretation, the importance of the scalp electrode locations (i.e. standard nomenclature of the 10/20 and 10/10 systems), inter-electrodes impedance, reference-electrode selection, and amplifier capabilities (e.g. number of bits available, the common-mode rejection ratio, or the amplifier gain). An obvious concern with low-cost EEG systems is whether the actual hardware meets the standards necessary to achieve sufficient EEG signal quality. As described in Table 1, not all, but some wearable neurotechnological systems currently record the data at high fidelity sampling rates (i.e. > 256 Hz) and with high signal resolution (i.e. superior to 8 bits). Regarding the argument for increased number of electrodes, as highlighted by Picton et al. (2000), “the optimal number of recording channels is not yet known. This number will depend on the spatial frequencies that are present in the scalp recordings (Srinivasan et al., 1998), provided that such frequencies are determined by the geometry of the intracerebral generators and not by errors in positioning the electrodes or modeling the impedances of the head." (Picton et al., 2000). In order to determine if wearable neurotechnologies meet such signal quality requirements, several studies have directly tested the signal quality of some advanced EEG wearable headsets (see Table 1) to directly determine whether they can provide data that reliably results in visible and statistically quantifiable ERP components.

Krigolson et al. (2017b) were able to reliably identify the N200, P300, and reward positivity ERP components with the Muse EEG headband in two 5-minute experimental paradigms. De Vos et al. (2014) conducted a single-trial P300 classification with linear discriminant analysis and revealed high classification accuracies for both indoor (77%) and outdoor (69%) recording conditions. Barham et al. (2017) showed that while significantly more trials are rejected from data acquired by systems such as the Emotiv Epoc, the raw EEG waveforms captured were found to have a high degree of highly similarity to the corresponding waveforms measured with a state-of-the-art system (e.g. SynAmps). Similarly, Mayaud et al. (2013) compared the performance of six traditional EEG disc electrodes (i.e. electrodes made from silver metal and lead wires) with the electrodes provided by the Emotiv Epoc wearable headset, and found no significant difference in performance between the two. They did find, however, that performance and 'level of comfort' decreased after long periods of recording using the wearable headset (i.e. between 2 and 3 hours of use). Pinegger et al. (2016) evaluated three different commercially available EEG acquisition systems that differ in the type of electrode (gel-, water-, and dry-based), the amplifier technique, and the data transmission method. Every system was tested regarding three different aspects, namely technical, BCI effectiveness and efficiency (i.e. P300 detection, communication, and control), and user satisfaction (comfort). They found that the water-based system had the lowest short circuit noise level, the hydrogel-based system had the highest P300 spelling accuracies, and the dry electrode system caused the least inconveniences. They concluded that building a reliable BCI was possible with all evaluated systems and it is on the user to decide which system meets the given requirements best (Pinegger et al., 2016).

While these findings suggest that the hardware specifications of these wearable EEG systems are sufficient to conduct successfully ERP studies, some studies found that such low-cost wearable EEGs (e.g. Emotiv Epoc) showed poor performance compared to clinical-grade equipment (Duvinage et al., 2013). This brings the importance of the methods employed by the experimenter. When thorough methods are employed, such as specific methods to increase the signal quality (i.e. clean hair, clean skin, a shielded environment, comfortable recording conditions), accurate results can be obtained. In fact, a fair amount of studies have now used several different sophisticated low-cost wearable EEG headsets to study a wide array of fundamental topics such as visual and auditory attention and perception (Abujelala et al., 2016; Badcock et al., 2015; Barham et al., 2017; Boutani and Ohsuga, 2013; Debener et al., 2012; Krigolson et al., 2017a, 2017b; Kuziek et al., 2017; Maskeliunas et al., 2016; Poythress et al., 2008; Wascher et al., 2014), emotions (Bashivan et al., 2016; Brouwer et al., 2017; Brown et al., 2011; Jiang et al., 2016, 2017; Peter et al., 2005), learning and memory (Berka et al., 2007b, 2005a).

Laboratory studies in psychology and cognition conducting research using artificial stimuli and fixed response options inevitably result in findings that are less ecologically valid in relation to real-world behavior. Advanced wearable EEG systems may facilitate a more accurate understanding of the human brain and its highly complex mechanisms occurring in the natural settings. Data from wearable EEGs have now been collected on participants walking outdoors on university campus (Debener et al., 2012) and in urban and green space environments (Aspinall et al., 2015; Neale et al., 2017; Tilley et al., 2017). Wearable EEG systems also facilitate an improved access to populations that were previously harder to include in studies due to lengthy uncomfortable experimental conditions, such as in studies with children (Badcock et al., 2015), in classrooms (Bozkurt and Coskun, 2014; Stevens et al., 2007), and with elderly populations (Abbate et al., 2014; Dimitriadis et al., 2016; Neale et al., 2017; Ramirez et al., 2015; Tilley et al., 2017).

Critiques have been made regarding the viability of wearable EEG headsets for conducting EEG research in non-laboratory or non-clinical settings (Cester et al., 2008; Przegalinska et al., 2018). EEG wearables systems will always face the challenges (that can exist in almost any data collection environment) of successfully collecting high fidelity EEG data acquisition. While EEG wearables allow for more mobility, they remain highly sensitive to movement artifacts. High fidelity EEG data requires individuals to limit all body and face movements as much as possible, and will always present a challenge in signal analysis. More advanced machine-learning algorithms must be developed to increase the variety of artifacts that can be corrected in real-time while not losing the signal of interest. Another considerable challenge involves the inability to directly control events occurring in the environment. While under laboratory settings, stimulus timing is the highly accurate marking of the occurrence of experimental event. To our knowledge, no simple solutions have been found to mark the occurrence of natural events, except for the use of a synchronized video recordings and then a manual synchronization offline. It is important to note that while some of these devices may offer a high signal-to-noise ratio (SNR) and waveform quality when thorough methods are applied, other technical aspects are equally as important when recording EEG such as a the number of electrodes, and accurate electrode placement. Wearable EEG headset often implement the use of dry electrodes which are practical, however they often reported to be less comfortable over long periods of time. Wearable headsets are equally as sensitive to movement artifacts as SoA systems, do not allow marker information and events to be directly embedded into the raw data, are often mishandled by users, and significantly vary in their advantages and disadvantages across device (see **Table 1**). While these limits are important to keep in mind, some promising applications of advanced, low-cost wearable EEG systems have already emerged.

FROM VIRTUAL REALITY TO REAL-WORLD APPLICATIONS

The accelerating development of increasingly sophisticated virtual reality (VR) platforms is now advancing our ability to study real-world environment simulations in laboratory settings. VR is now being applied in neuroscience research as well as expanding the development of clinical interventions (Bohil et al., 2011) through the creation of immersive and highly controlled environments wherein the ecological conditions of natural environments can be simulated. Wearable EEGs have been combined with VR in a range of studies investigating the cognitive processes underlying (simulated) driving conditions such as alertness, vigilance, reaction time, fatigue, and drowsiness of automobile drivers in simulations (Armanfard et al., 2016; Brown et al., 2013; Foong et al., 2017; Johnson et al., 2011; Lin et al., 2014; Wang and Phyo Wai, 2017; Wascher et al., 2014). This combination allows for the development of new closed-loop systems that may be integrated into the technology of newly manufactured vehicles in the near future. This technology holds the potential to ensure safer driving performances through the incorporation of features such as feedback alarms (Berka et al., 2005b), emergency braking predictions based on EEG/ERP signatures (Haufe et al., 2011), red and yellow stop lights distinctions (Bayliss and Ballard, 2000), in addition to the control of a virtual car based on EEG activity (Zhao et al., 2009). While the continued use of standard research grade equipment is more appropriate when studying specific neural mechanisms and processes implicated in VR environments, these findings can later be used to inform models applied to real-world investigations implementing wearable EEG technologies.

Wearable EEG devices offers advantages such as increased freedom of movement for research participants, increased accessibility (i.e. lower-cost equipment), and research that studies properties of locomotion (REF). However, often these technologies have yet to bring about a better understanding of brain processes than what has been shown by studies using the conventional golden standard (i.e. 64-channel research grade EEG equipment) that contain >32 electrodes and provide higher signal quality and SNR (e.g. gel-based systems). The application of wearable systems can be highlighted by new research which may lead to the first 'prevention system' which uses real-time data recorded from a pilot or driver's brain that would enable the detection of mind wandering, the loss of attention, and/or drowsiness and could provide an auditory, tactile, or visual feedback cue to the driver in order to avoid an accident (Akbar et al., 2017; Healey and Picard, 2005; Wei et al., 2018). Recently, new research (Chavarriaga et al., 2018; Martínez et al., 2018; Zhang et al., 2015) developed innovations in the EEG paradigms designed to study real-life driving situations which aimed to identify an EEG marker of an individual's intention to brake or to turn at an intersection. While these findings are groundbreaking, the machine learning methods used by these BCI systems still need to be improved to bring to 0 the margin of error. One way of compensating for changes in SNR while driving as suggested by Chavarriaga et al. (2018) is the inclusion of additional physiological measures such as the eye movements, the heart rate or the electromyography (EMG) of the driver, as well as contextual information gathered by in-car sensors will allow intelligent cars to provide timely and tailored assistance.

SCIENCE AND EDUCATION

Cultivating and enhancing creativity within the domains of science and education are another potential avenue whereby these technologies may help to facilitate improved and engaged educational opportunities, while educating the next generation of future neuroscientists in more engaged and interactive way. Grandchamp and Delorme (2016) developed the 'Brainarium', a portable planetarium dome on which the real-time EEG data is recorded from a subject and directly transformed to visually represent the real-time activity as vibrant and colorful multimedia content. Projects such as these demonstrate the growing importance of the art and its contribution towards the sciences in ways that have been overlooked for the last several decades (Andujar et al., 2015). BCIs have now been developed to create music using devices such as the Emotiv Epoc (Levicán et al., 2017) and the 'Encephalophone' system (Deuel et al., 2017), as well as visualize music performance (Mullen et al., 2015).

GROUP STUDIES AND BIG DATA

Wearable technologies also enable the simultaneous recording of multiple individuals, opening up new applications of EEG research for the study of group dynamics, team cohesion, or social synchronicity (Stevens et al., 2013, 2010, 2012). Big-data research studies have the potential to revolutionize the way we investigate individual differences and differentiate commonalities in brain activity across subjects due to the power that large participant sample size provides in distinguishing nuanced individual characteristics. A majority of neuroimaging studies is conducted on small samples due to the cost and time-consuming nature of measuring EEG on large groups of participants. With larger samples come more robust statistical inferences about the general population, as well as a better representation of the sociodemographic differences. For instance, Hashemi and colleagues (2016) used the Interaxon wireless 4-channel EEG headband to analyze the brain data (i.e. the participants were doing a neurofeedback mindfulness task such as a breath-focus exercise) of 6029 subjects ranging from 18 to 88 years in age and were able to identify subtle but robust age-related shifts in EEG activity (i.e. EEG power, peak frequencies, asymmetry measures between frontal and temporoparietal sites) on a year-by-year scale, as well as how these changes differed between males and females in a representative population of individuals completing the tasks in uncontrolled natural environments. In another study, Kovacevic et al. (2015) recorded 523 subjects with the same wearable EEG system for 12 hours in a collective and immersive NF multimedia science-art installation. They found that the participants' EEG baseline activity predicted subsequent NF training, indicating the existence of a state-dependence effect in learning ability during NF.

The brain data recorded by NF Applications available on smartphones/tablets is currently aggregating some of the largest EEG databases in history (Hashemi et al., 2016). These big-data archives will allow for the development of new types of statistical analyses implemented via machine learning, and may highlight patterns and trends in brain activity that have not been previously possible with smaller data sets. The validity and value of such databases will depend on the signal quality being measured by users. Given that these users lack advanced training and experience in EEG recording movement artifacts and inaccurate electrode position (even though some Apps provide clear instructions and visual feedback about electrodes impedance) is inevitable. As a consequence, a large portion of data is usually lost due to these low quality recordings. Furthermore, these devices measure the EEG from only a few electrodes and therefore lack the accuracy and value of a brain signal that is normally recorded from multiple sites on the scalp. As a consequence, the use of these databases is limited to small regions of the brain related to electrode placement (e.g. frontal and temporal for the Muse headband). Additionally, neurofeedback results provided by these smartphone Apps as the algorithms used to generate these values are company trade-secret. It is therefore unknown what type of EEG activity they are targeting for the NF they provide, and often these algorithm have not been validated.

In conclusion of this section, sophisticated wearable neurotechnologies should be used by experienced EEG practitioners and reserved to real-world applications as they do not yet replace SoA systems (e.g. gel-based electrodes) in controlled conditions for testing fundamental questions. Each device offer advantages and disadvantages compared to others, therefore researchers should determine which is best suited to their needs, taking into account all the features of the devices (i.e. sampling rate, electrode locations, SNR, expected length of use, the availability of skilled labor for system setup and patient comfort). We recommend the collection of raw data and the development of customized neurofeedback code instead of using the non-transparent programs provided by companies designing these devices

Clinical Applications

One of the more significant clinical applications of wearable EEG involves the use of event-related potentials (ERPs; also named evoked potentials), which reflect stereotypical changes in EEG activity evoked by environmental events. They have played a pivotal role in our understanding of the relationships between physical stimuli and brain activity (Luck and Kappenman, 2011), and have been widely used in the study of cognitive disorders such as developmental dyslexia (Hämäläinen et al., 2013), specific language impairment (McArthur and Bishop, 2004), psychiatric disorders (Park et al., 2010), and autism (Čeponienė et al., 2003), among others. The four main EEG patterns used in BCI systems include the P300 (i.e. positive brain oscillation occurring at 300 milliseconds), used generally for bi-directional communication BCIs, the mu (i.e. 8-12 Hz) and beta (i.e. 18-26 Hz) rhythms, usually used for sensorimotor BCIs, and the steady-state visual evoked potentials (SSVEP) which corresponds to the measured active visual focus (see Chapters 7-11 and 14 for more details).

As described in Section “A. Fundamental research”, some wearable EEGs were shown to accurately measure certain types of ERPs such as the P1/P100, N1/N100, P2/P200 (assessed by their peak amplitude, latency and mismatch negativity; Badcock et al., 2015), the N2/N200 and P3/P300 (assessed by latency and peak amplitude during an auditory oddball task by Barham et al., 2017 and Mayaud et al., 2013; assessed by classification accuracy by Jijun et al., 2015; and assessed by a visual oddball task and a reward-learning task by Krigolson et al., 2017b).

As BCIs integrate the real-time analysis of ERPs (Sullivan et al., 2012), new potential applications emerge with the continuous improvement of wearable EEGs. If this type of brainwave discrimination is maintained in real-world settings while the individuals are moving, if the events occurring in the environment are monitored, and if these neurotechnologies keep improving in terms of discreteness and design. For instance, early diagnosis of brain disorders by detecting specific EEG components and markers associated with a given disorder may be possible in the patient's home (e.g. unclear paroxysms in epileptic patients; Askamp and van Putten, 2014; Nunes et al., 2014). Hofmeijer and colleagues (2018) were able to detect the cortical spreading depolarization (CSD; producing detrimental effects) in patients with traumatic brain injury and ischemic stroke. Abbate and colleagues (2014) tested the usability of wearable technologies (both physiological and EEG activities) with an elderly population victim of advanced Alzheimer's disease (AD) in a nursing home. Nieuwhof and colleagues (2016) tested the feasibility of using a new portable and wireless fNIRS device to measure prefrontal cortex (PFC) activity during different dual task walking protocols in Parkinson's disease (PD). Billeci and colleagues (2016) evidenced changes in neurophysiological and autonomic response from the state of disengagement to the state of engagement of autistic children. Maddox and colleagues (2015) measured brain activity for assessing concentration and stress levels during surgical simulator performance of laparoscopic tasks to determine if expert surgeons have different brain activity patterns compared with intermediate and novice surgeons.

PHYSICAL ACTIVITY

While sedentarity is considered a high-risk factor for health, the benefits of physical activity have been extensively documented in the scientific literature (de Rezende et al., 2014; Tremblay et al., 2010). Several studies have shown that regular sport-based activities produced neuro-angiogenesis (i.e. creation of new blood vessels) and neurogenesis (i.e. creation of new neurons) in the brain (Fabel et al., 2003; Olson et al., 2006; Pereira et al., 2007). While most of the studies on exercise assess pre/post measures, a lack of research studying the neural mechanisms taking place during the practice of exercise is due to the reduced mobility imposed by cables and the signal artifacts produced by the movements of the subjects. However, with the development of wearable technologies, researchers have now been able to study the electrical activity of the brain during exercise, during performance on attentional tasks while walking outdoors (Armanfard et al., 2016; Aspinall et al., 2015; Debener et al., 2012), walking on a treadmill (Lin et al., 2014), or riding a stationary bike (Scanlon et al., 2017). Some expert athletes train their whole life to develop relaxation techniques in order to keep a steady performance under stress and muscular fatigue. Some researchers were able to record EEG data from elite archers in order to study their relaxation capacities under stress and muscular activity (Lee, 2009), while others have accelerated the training of archers, golf players, and rifle marksman using NF strategies (Berka et al., 2010). Studying the brain of individuals while they are doing a physical activity will bring precious information on the effects and mechanisms of physical activity on the brain, which may have an important impact on both sports science (e.g. training strategies) and medical applications. Additionally, longer recordings using wearable neurotechnologies would allow to assess long-term (i.e. from several days to several months or years) of a regular physical activity on the brain, as opposed to measure only the pre and post session differences. Such studies could compare the long-term effects of different types of physical activity (e.g. weekly frequency of training sessions, interruptions, intensity and nature of the exercise) on different types of populations. This would apply to clinical therapies as well.

NEUROFEEDBACK

Stress has strong repercussions on both psychological and physical systems. As a consequence, chronic stress was shown to trigger unhealthy behaviors that contribute to morbidity and mortality (Jackson et al., 2010), such as depression, obesity, sleep deprivation, attention deficit, mood disorders, grey matter atrophy in the brain, or substance abuse, to name a few (Dallman et al., 2003; Duman and Monteggia, 2006; Miller et al., 2011; Sapolsky, 1996). However, meditation has been found to improve stress-related outcomes (Goyal et al., 2014). Meditation techniques include focused breathing exercises that help to directly regulate the cardiovascular system (Steinhubl et al., 2015), negative mood, stress, pain, anxiety, and mind wandering (Bhasin et al., 2013; Brandmeyer and Delorme, 2016; Prinsloo et al., 2013; Zeidan et al., 2010). Moreover, meditation practices were found to increase regional brain gray matter density (Hölzel et al., 2011). Neurofeedback (NF) provides the possibility of endogenously manipulating brain activity as an independent variable, making it a powerful neuroscientific tool. NF training results in specific neural changes relevant to the trained brain circuit and the associated behavioral changes. These changes have been shown to last anywhere from hours to months after training and to correlate with changes in grey and white matter structure (Sitaram et al., 2017). Thus, by implementing meditation techniques, NF can help users become aware of their emotions or negative mind wandering (Brandmeyer and Delorme, 2013; Mooneyham and Schooler, 2013) that are associated with stress, and develop strategies to overcome them (Brandmeyer and Delorme, 2016), as well as slowing down the neurodegenerative process of neuronal structures (Hölzel et al., 2011). The demonstration of robust clinical effects remains a major hurdle in neurofeedback research. The results of randomized controlled trials in attention deficit and hyperactivity disorder and stroke rehabilitation have been mixed, and have been affected by differences in study design, difficulty of identifying responders and the scarcity of homogenous patient populations (Sitaram et al., 2017).

These benefits apply to cognition as well, as findings showed that NF increased memory, attention, and cognitive performance (Mishra and Gazzaley, 2015; Nan et al., 2012; Wang and Hsieh, 2013; Zoefel et al., 2011). Brainwave training provided by NF induces neuroplastic changes (Ros et al., 2010), suggesting important implications for therapies of brain disorders associated with abnormal cortical rhythms, and support the use of NF as a non-invasive tool for establishing a causal link between rhythmic cortical activities and their functions. NF has been well investigated in the treatment of attention-deficit/hyperactivity disorder (ADHD) and has shown clinical efficacy (Arns et al., 2014; Gevensleben et al., 2009).

The sharp rise of computer processing capacity has solved many of the difficulties faced by the NF and BCI pioneers of the 70's (Dewan, 1967) and 80's (Vidal, 1977). Some of the sophisticated software and hardware are now designed to process EEG data in real-time (Hu et al., 2015; Sullivan et al., 2007), facilitating reliable NF and BCIs to consumers. Video games have been shown to be powerful NF companions. Research suggests that the combination of NF methods and video game interfaces significantly improves symptoms associated with conditions such as ADHD and anxiety (deBeus and Kaiser, 2011; Muñoz et al., 2015; Perales and Amengual, 2017; Schoneveld et al., 2016). Additionally, some studies are combining NF, video games and VR to obtain more immersive results (Lécuyer et al., 2008). Musical NF paradigms are being developed as well, presenting an interesting alternative to other treatments by offering to users the ability to manipulate expressive parameters in music performances using their emotional state (Ramirez et al., 2015). However, these systems are now marketed to consumers as forms of cognitive enhancement and entertainment (Sandford, 2009) and may present potential dangers, as they do not involve professional supervision. Not only appropriate methods need to be employed, but more transparency on the algorithms that are being used by these private software companies must be enforced so researchers can validate their use.

Neurofeedback may also be coupled with other technologies to enhance its efficacy. The Neuroscape[a] center for translational neuroscience at the University of California, San Francisco has developed multiple games that implement NF, neuromodulation, and VR/AR such as the NeuroRacer, Meditrain, the Ace, or the Beep seeker to name a few. Neuroelectrics developed the Neurosurfer[b] software for advanced NF applications, offering for the first time the possibility of combining NF with brain stimulation (if combined with the Starstim device; Aguilar Domingo, 2015). They also provide NF games that are ready for use with a regular monitor or in a VR environment (3D; Desai et al., 2014). Combined with VR, NF training may be used to enhance attention (Cho et al., 2002) and learning (Hubbard et al., 2017). In another experiment, a multimodal embodied interface was designed for 3D navigation as a modular wearable, with the user suspended in a harness that was directly controlled by the EEG activity of the user. This allows both physical and virtual displacement within an immersive virtual environment, allowing to simulate a flying experience (Perusquía-Hernández et al., 2016). A team is also developing a socially assistive robot that provides a personalized NF training session to maximize user engagement and performance (Tsiakas et al., 2017).

Heart rate variability (HRV) is the change in the time intervals between adjacent heartbeats that may be used to predict future health outcomes (Dekker et al., 1997; Shaffer et al., 2014; Tsuji et al., 1994). Reduced HRV has been shown to correlate with disease onset and mortality as it reflects reduced regulatory capacity of the body to adaptively respond to challenges like exercise or stressors (Beauchaine, 2001; Dekker et al., 1997). Self-regulation techniques (Alabdulgader, 2012) were found to improve the cognitive function, the parasympathetic system, as well as a wide range of clinical outcomes (Lehrer et al., 2003; McCraty and Zayas, 2014). It can be enhanced by HRV feedback (McCraty et al., 2003), representing a therapeutic tool with a considerably reduced health care cost (Bedell, 2010). Several wearable headsets offer features that allow for the simultaneous recording of the heart rate, the heart pressure, the respiration, and the EEG (see **Table 1**). By combining neural and physiological measures such as EEG and HRV (Billeci et al., 2016; Riera et al., 2008; Steinhubl et al., 2015) it is possible to develop NF paradigms aimed at improving measures related to anxiety, stress, emotions, cognition, and performance (Gruzelier et al., 2014; Shaw et al., 2012; Thompson et al., 2013). Given that some NF protocols are already considered a first line of treatment for children with ADHD (Arns et al., 2014; Gevensleben et al., 2009), new NF protocols may soon be available as treatment options for stress management and the associated physical outcomes.

[a] https://neuroscape.ucsf.edu/technology/

[b] https://www.neuroelectrics.com/products/software/neurosurfer/

SLEEP

Poor sleep quality concerns one-third of the adult population (Roth et al., 2007), has been linked to many clinical and medical conditions such as depression and pain (Giron et al., 2002), and has proven costly (i.e. lost productivity, health etc.) for the societies and the individuals. The deleterious effects of chronic sleep deprivation and the associated outcomes have potentially dangerous and expensive consequences as a result of impaired neuropsychological functions for individuals at work, at home, and on the roads (Dongen et al., 2003; Pilcher and Huffcutt, 1996). In addition, long-term health-related concerns include increased risk for metabolic and cardiovascular diseases (Cappuccio et al., 2011), as well as an overall decrease in immune (Bryant et al., 2004). Research shows that 90% of the American population is using a technological device (e.g. television, laptop or smartphone) in the hour preceding sleep (Gradisar et al., 2013). Some wearable technologies developed in the last decades (e.g. wristbands, mobile apps, smart pillows) target sleep quality monitoring, but don't focus on interventions supporting a healthier sleep or making use of sleep cognition (Bianchi, 2018; Ravichandran et al., 2017). While only a limited number of sleep studies have been conducted using wearable EEG systems (Berka et al., 2007a; Debellemaniere et al., 2018), recent advancements in neuroimaging research offer new ideas. These include the use of transcranial direct current stimulation (tDCS) in the gamma frequency band during rapid eye movement (REM) sleep to increase self-reflective awareness in dreams (Voss et al., 2014), the use of transcranial magnetic stimulation (TMS), and the use of pink noise to effectively manipulate sleep depth increasing sleep efficiency (Massimini et al., 2009; Suzuki et al., 1991). Those findings could be implemented in BCI or NF applications with the help of wearable headsets such as the Starstim that allows simultaneous EEG and TCS (see **Table 1**). Some wearable EEG headbands that don't have electrodes behind the head and focus and frontal and temporoparietal brain activity offer the possibility to record EEG during sleep in the user's home environment (Debellemaniere et al., 2018; Onton et al., 2016; respectively). Although these studies are easy to perform with healthy individuals that are aware of the situation and make a conscious effort to limit their movements, it might prove more difficult for patients suffering from pathological conditions such as Alzheimer's disease (AD; Abbate et al., 2014). Furthermore, some of these wearable neurotechnologies may allow for closed-loop auditory stimulation to modulate brain oscillations at the right moment by using a classification of sleep cycles (Chambon et al., 2018; Debellemaniere et al., 2018), enhancing sleep quality at night (Arnal et al., 2017). To go further, a team from MIT media labs developed the first sleep BCI, an interactive interface named 'Dormio' (Haar Horowitz et al., 2018). When the user enters the hypnagogic sleep stage (associated with high creativity), EEG and motor signals detect it and trigger an auditory feedback response provided by a robot located next to the sleeping user. The sound makes the user more aware of being in that state and extends the duration of the semi-lucid hypnagogic period, enhancing his/her creativity. Semantics can be used instead of a sound to influence the dreams of the users. The most sophisticated wearable EEG systems, therefore, present a promising future for sleep research, management, and monitoring.

BIOMEDICAL BCI

Modern BCI present a number of solutions for individuals with disabilities. Under certain circumstances, patients can regain partial if not all of the lost motor control if provided effective rehabilitation. Motor-imagery based BCI (Curran and Stokes, 2003) have been used as a means of providing patients real-time visual feedback of limb movement (corresponding to the injured limb) through a representative simulation on a computer screen. BCI protocols host the potential to accelerate rehabilitation through repeated reactivation of the underlying neural pathways (Güneysu and Akin, 2013; Pfurtscheller et al., 2006; see Chapter 10). A difficult and frequent obstacle present in patient rehabilitation involves maintaining the necessary levels of motivation to remain persistent during repetitive and demanding physical tasks. NF and BCI rehabilitation paradigms may improve patients' sense of well-being and motivation by providing more entertaining and engaging interfaces (e.g. video games) as opposed to more traditional clinical/medical settings.

When rehabilitation is not possible, prosthetic control can still provide improved mobility assistance, while promising research on BCI controlled wheelchair movements may soon be an option for patients with paralysis (Carlson and Millan, 2013; see Chapter 9). The complex control commands required for robotic prosthetic limbs or exoskeletons have evaded BCI scientists for the last few decades, recent systems have overcome several key limitations (McFarland et al., 2010). BCI patients are now capable of moving prostheses with increasing accuracy, flexibility (Clement et al., 2011), and affordability (using 3D printing technology; Sullivan et al., 2017). An exciting new study developed a way to allow locked-in ALS patients (see Chapter 3) to remote control a humanoid robot using their EEG activity (Spataro et al., 2017). Their findings show that three out of four subjects were able to control the robot so that he could speak, move and act for them. These technologies have tremendous potential for patients who are unable to engage with single-switch systems operated by movements such as eye-blinks, or the breath (e.g. late-stage ALS, high-level spinal cord injury, stroke/aphasia, autism, severe cerebral palsy; see Chapters 2-5). BCIs can also be used to facilitate linguistic communication, with the most renowned BCI paradigm being the P300 speller designed by Farwell and Donchin in 1988 (Cipresso et al., 2012; Farwell and Donchin, 1988; Mellinger et al., 2004). Other BCIs allow the patients to navigate text, to control a cursor on a computer screen, browse forward and backward or use bookmarks (Fruitet et al., 2010; Krusienski et al., 2007; Kübler et al., 2005; Mugler et al., 2010). While only a limited number of studies have integrated fNIRS for BCI applications (Aranyi et al., 2015; Coyle et al., 2007) an increasing number of researchers are developing hybrid P300-based BCI interfaces via simultaneous fNIRS and EEG (Blokland et al., 2014; Buccino et al., 2016; Coyle et al., 2007; Fazli et al., 2012; Kaiser et al., 2014; Khan et al., 2014; Liu et al., 2013; Pfurtscheller et al., 2010; Tomita et al., 2014; Yin et al., 2015). These studies show that simultaneous measurements of fNIRS and EEG can significantly improve classification accuracy of brain signals, improve user performance, and may serve to be a viable multimodal imaging technique suitable for future BCI applications.

REMOTE MONITORING AT HOME

BCI based applications have now been effectively delivered in home-based settings (Askamp and van Putten, 2014; Käthner et al., 2017; Wolpaw et al., 2018), and have shed light on the potential for future clinical-based interventions. The 'home-based' setting is key here as it can facilitate accessible and high-quality treatment options, reduce commute times, reduce the volume of consultations at clinics, increase the quality and quantity of patient information collected by healthcare professionals, and improve longitudinal measures of care quality. With increasing availability and integration of wearable EEG headsets, phone-based BCI applications have been developed to enable practical and affordable everyday use.

Neuro-phones are brain-mobile phone interfaces, which allow neural signals to drive mobile phone applications on the iPhone using wireless EEG headsets (Campbell et al., 2010; Kumar et al., 2012; Wang et al., 2011). Applications of NF devices in home-based settings could provide significant aid to patients with traumatic brain injuries, ADHD, and more, by improving motivation for engaging in treatment, as well as directly improving secondary symptoms through access to applications that train mindfulness and stress-reduction techniques (Gray, 2017). Advanced wearable EEG systems may help support the autonomy and independence of people with disabilities living at home, improve early detection of certain medical conditions, monitor sleep quality, and ultimately, provide large-scale longitudinal data on the effects of aging in the brain and body (Light et al., 2011). Companies specialized in mobile neurology diagnostic devices are developing potential solutions for epilepsy using mobile and continuous EEG recording, smart clothing, a smartphone application and cloud platforms (Valenza et al., 2015). In the Netherlands, this type of home-based EEG applications are currently used in ~30% of hospitals for the treatment and monitoring of epileptic patients (Askamp and van Putten, 2014).

In a study by Valenza et al. (2015), they used wearable textile technology to characterize depressive states in bipolar patients during their normal daily activity. Some very advanced wearable neurotechnologies such as those developed by Neuroelectrics could also be very valuable for home-based use as they enable simultaneous EEG recording and brain stimulation (Dutta and Nitsche, 2013; Helfrich et al., 2016), which was found to improve neurorehabilitation effects by training motor function and learning processes (Gandiga et al., 2006). These technological advancements present valuable applications for many clinical conditions such as epilepsy, depression, or Parkinson's disease (PD). The NUBE Cloud Service[3] from Neuroelectrics provides a telemedicine platform, wherein clinicians and researchers can prepare general stimulation protocols, schedule the stimulation sessions for patients, confirm whether the sessions have been executed or not, and create pre/post stimulation questionnaires. Clinicians can also remotely guide the stimulation sessions that patients can conduct by themselves from home. While Starstim is currently classified as an investigational device under US federal law, it is approved in Canada for medical use and complies with the European legislation for clinical research (e.g. depression, pain, addiction, stroke).

Another growing field is the development of Smart houses (Stefanov et al., 2004; Yin et al., 2015). Numerous intelligent devices, embedded into the home environment, can provide the resident with both movement assistance (e.g. intelligent bed, intelligent wheelchair, and robotic hoist for effortless transfer of the user between bed and wheelchair), and 24-h health monitoring. They are therefore particularly relevant for elderly and disabled populations, as it helps restore independence and autonomy. However, these devices lack methods for decoding the intentions of disabled residents, which in the future may be solved through the integration of BCI and wearable headsets (Lee et al., 2013; Miralles et al., 2015b, 2015a; Vaughan et al., 2006).

DISCUSSION

Limits and possible solutions

While a majority of NF and BCI systems require a minimal level of experience and knowledge to effectively acquire quality data, misrepresentative findings and applications are always potential confounds to be taken into consideration when assessing the validity of scientific findings, respectively. Ensuring the proper application of wearable technologies is essential. Manuals and tutorials provided in the documentation are generally not sufficient to cover the complexities of measuring, analyzing, and interpreting physiological data, let alone factoring in potential confounds and placebo effects that can interfere with the proper use of the technology. Furthermore, both structural (i.e. anatomical) and functional (i.e. brain activity) differences in brain activity have been observed across different categories of the population (e.g. children, elderly, mental disorders, etc. (Bjork et al., 2004; Paus, 2005; Reiss et al., 1996; Schlaggar et al., 2002). Moreover, no gold standard has been established regarding the choice of reference electrode(s), with the region of interest playing a key role when selecting the appropriate measures for obtaining good signal quality. Consequently, comparing different EEG systems remains a challenge. Future studies should aim to identify reference systems that could be standardized across protocols and headsets. Additionally, the correct positioning of electrodes across the scalp is critical for applications involving neuromodulation, wherein cortical regions are selectively targeted and exert neuromodulatory effects (Villamar et al., 2013). Variability in electrode types, location, software, file formats, or interfaces constitute a barrier in attempting to combine big databases across a range of sources. The newly developed Research Resource Identifiers (RRID), such as SciCrunch[4], may help resolve these issues, as they offer a platform which enables straightforward searches of information pertaining to research studies implemented with specific types of technology and contain user information about the device, signal quality, and the literature. Unlike more general search engines, they provide extensive access to a focused set of resources relevant to its communities, and provides access to content that is traditionally "hidden" from web search engines. Users can also add their own data to the platform. Novel tools are actively being developed to help facilitate the recording and streaming of EEG data from consumer headsets that can be interfaced with a variety of programming languages and software packages, allowing for interchangeability across devices. The MuSAE lab is developing the MuSAE Lab EEG Server (MuLES[6]), an EEG acquisition and streaming server that aims to create a standard interface for portable EEG headsets in order to accelerate the development of BCI and of general EEG applications in novel contexts. Similarly, the Lab Streaming Layer (LSL[7]) from OpenBCI allows to synchronize streaming data for live analysis or recording via applications such as Matlab. Successful, large studies could be conducted using these servers, with the open source data then available for future studies, limiting costs and time spent collecting new data.

Another limitation regarding wearable devices pertains to the identification of event-related signal onset. In laboratory settings, these triggers are produced by a controlled system or by the experimental paradigm whereas in real-life conditions these events can originate from the environment upon which the experimenter or developer has no control. While some companies provide features for markers and triggers which indicate the beginning and end of epochs in the data, several companies do not incorporate such features, making the analyses of data time-consuming a challenge when attempting to identify event-related activity. For studies comparing conditions across trials, it is crucial that these features are implemented in all wearable EEG devices. One solution (although not ideal) is the instruction for the subject to perform a small series of eye blinks at the beginning and end of each trial, as it is very easy to identify in the EEG signal. While this alternative is not sufficient for ERP type studies that require high temporal accuracy of the markers (i.e. milliseconds), it highlights simple and novel methods that can be implemented for advancing wearable methodologies. While it is likely that significant challenges pertaining to the proper annotation of events that occur in real-life conditions will persist (i.e. the generators of such triggers), new and novel solutions are needed to address this critical shortcoming.

The future of wearable neurotechnologies

A major limitation to the daily integration of wearables remains the feasibility of people feeling comfortable wearing such devices in public spaces. Abbate et al. (2014) showed that in a study with AD patients, a few simple modifications to the placement of the wearable EEG system, its color, and how it is integrated with clothing significantly improved its usability and acceptance, especially in the elderly population. While great improvements in design, weight, and comfort are under active development, wearable neurotechnologies will eventually need to diversify their designs to satisfy cultural differences, characteristics, and sensitivities. Furthermore, populations such as the elderly often prefer simple, loose, and comfortable clothing, making the necessary placement of tight fitting wearable devices close to the body difficult (Abbate et al., 2014). New technologies developed by companies that offer innovative solutions such as the production of smart clothing that incorporates biometric sensors embedded into the material (see 'Remote monitoring at home' section; Valenza et al., 2015) are promising, however more research will be necessary in order to establish and ensure high SNR as well as comfort to users.

Within the BCI domain, transparent EEG systems such as the "Ear-EEG" include both microelectrodes located in the ear canal (i.e. "in-ear EEG"; Goverdovsky et al., 2016; Nakamura et al., 2017) as well as cEEGrids, a flex-printed C-shaped 10-channel grid that can be placed around the outer ear (Bleichner et al., 2015; Bleichner and Debener, 2017). The Ear-EEG is capable of extracting relevant focal temporal neural features such as the P300 ERP, presenting potential innovative solutions and applications for augmenting hearing technology (Christensen et al., 2018; Fiedler et al., 2016). Sensors are also being integrated into accessories such as smart glasses (Vahabzadeh et al., 2018), smart EEG-glasses (e.g. Jiang et al., 2017), stick-on electronic tattoos (Zheng et al., 2014), and chemical wearable sensors (Matzeu et al., 2015). Another feature necessary for the future of wearable neurotechnologies is the development of advanced machine learning algorithms that monitor and correct artifacts in real-time so that movement and muscular activities no longer interfere with the performance of BCI systems. In order to accomplish this, techniques must be developed that would allow for markers in the data that would reflect the occurrence of uncontrolled events taking place in real-world environments in order to build a better understanding of their impact on the brain and body activity. Given the rapid advancements in machine learning techniques and analyses (see Chapter 25), in the not-so-far future we will most likely acquire a far more extensive knowledge and understanding of unknown EEG artifacts and the methods to necessary to correct them (in real-time) without losing the brain activity of interest (i.e. non-artifactual).

Ethical and safety questions

The rapid advancements in the biomedical-tech sector present clear ethical questions such as consent, data protection, and identity (Trimper et al., 2014; See Chapter 26). At present, there is no legislation regulating informed consent and protecting personal data extracted via BCI, either therapeutically or outside clinical and research contexts. While the research and clinical use of BCIs across the world is regulated by national laws and Institutional Review Boards (IRBs), the private and commercial use falls out of these legislations, allowing the potential for non-ethical practices and applications of the technology. Furthermore, the non-invasive nature of these technologies, the ease of engineering the relevant hardware, and the enthusiastic 'Do It Yourself' (DIY) culture interested in cognitive enhancement make exploring these ethical issues especially pressing. Having observed the public outrage and opposition to previous scientific and technological advancements, such as was seen with the cloning of Dolly the sheep, ethicists and scientists must work together to ensure that the technology is developed with the highest ethical standards and that the public is informed accordingly (Wolpe, 2006).

While it is safe to say that a majority of wearable technologies are designed under the premise of improving health monitoring and outcomes, and or enhancing or regulating cognitive and emotional processing, these technologies also host tremendous power and potential to drastically influence the choices and actions of the users (i.e. how to breath, to eat, drink, exercise, work, sleep etc.). The short-term reality is that the user is often in the illusion that the feedback provided is highly accurate, which can heavily influence the way of life of that user. This is seen heavily with companies claiming their device can "read the mind, thoughts or intentions" of the users. By offering consumers a way to simultaneously embrace and outsource the task of lifestyle management, one could imagine that such products exemplify and short-circuit cultural ideals for individual responsibility and self-regulation (Schüll, 2016). This concern is even greater regarding the potential for electrical simulation technologies (e.g. tDCS) becoming widely available to the public. Following the advice of commercial applications wherein participants are instructed to actively modulate their brain with technologies such as tDCS without any validation or control, present a major concern (Walsh, 2013). Ultimately, the companies depend on the engagement and participation of their customers, thus it is the role of consumers to educate themselves and to exert the 'consumer influence' over the quality and trajectory of future technologies.

As lifestyle, health, and technology become increasingly integrated and interfaced, it is crucial that these devices remain as tools to support and assist human needs. With an increasing rate of reliance on our technology, human beings are increasingly vulnerable to the potential dangers and pitfalls of this reliance. Furthermore, when something is used to enhance or assist a function, this function no longer needs to be accomplished by the body, further directing one's attention towards additive systems (e.g. atrophied muscle after injury). This could potentially apply to the brain itself, given that too many cognitive functions were to become supported or replaced by technologies. On the other hand, it is also possible that the technological support could participate in training natural abilities beyond their initial potential (e.g. a system detecting cues that are imperceptible to the awareness to warn from a danger, could train the brain to detect these stimuli). Additionally, one can argue that the brain resources no longer necessary because they are supplemented by technology could be recruited for new abilities (e.g. the invention of writing offered many new possibilities for human cognition). If this is possible, future studies should focus on how to develop technologies that aim to produce long-term benefits. For example, NF systems are used to help users train cognitive regulation (e.g. increased attention and improved emotion regulation).

Along with the development of new wearable technologies surfaces concerns surrounding the potentially deleterious effects of radio frequencies (RF), cell phones (Cassani et al., 2015; Croft et al., 2010; Hung et al., 2007; Krause et al., 2006; Laudisi et al., 2012; Mohan et al., 2016; Pyrpasopoulou et al., 2004; Vecchio et al., 2010), bluetooth, and Wifi frequencies (Balachandran et al., 2012; Banaceur et al., 2013; Mandalà et al., 2014; Othman et al., 2017; Saili et al., 2015) on the biological systems. Detrimental effects are generally considered to be dependent on the distance and relative size of a given object, but also on the environmental parameters, and there may be additional interindividual differences in sensitivities to exposure, making the assessment of these risks difficult. However, research suggests that regular and long-term use of RF emitting devices (especially at close distance to the body) can have a negative impact on biological systems, most notably in the brain (Atasoy et al., 2013; Avendaño et al., 2012; Ishak et al., 2011; Kesari et al., 2013; Megha et al., 2012, 2015; Shahin et al., 2013; Volkow et al., 2011). Wearable neurotechnologies concentrate RF energy from Bluetooth and Wifi in and around the area of the brain in larger amplitudes then has been studied previously. The potential for chronic exposure to RF frequencies resulting from daily BCI use demands that future studies explore solutions for RF protection or alternatives deliverance modalities.

CONCLUSION

Advancements in EEG wireless technology allow researchers and clinicians to study the brain easily, in natural environments, and with greater access to a wide range of the population (i.e. children, elderly). While several new wireless devices enable the collection of data with both high temporal and spatial resolution (i.e. combined EEG and fNIRS respectively), they also facilitate the simultaneous modulation of brain activity through the addition of stimulation sensors which administer TCS. At home-use of wireless and wearable technologies has the potential to significantly reduce medical costs for both patients and medical centers in terms of both diagnosis and long-term treatment options. Online platforms now enable clinicians to arrange medical assessments and treatment interventions, such as EEG recordings or TCS therapeutic sessions for patients (e.g. epileptic, disabled patients) without ever having to leave the comforts of their home. Advanced wearable neurotechnologies such the ones listed in Table 1 show recent improvements in terms of signal quality, sampling rate capacity, battery life, affordability, setup speed, implementation of manual triggers in the signal, data storage, comfort, and design. However, caution must be taken when using these devices as they still encounter limits such as their sensitivity to movements, limited electrode number and locations (i.e. limiting the variety of cognitive processes that can be studied), the lack of control regarding events occurring in the environment (when used in real-life settings), and the validity and reliability of the software and phone based applications that claim to train certain neural features but fail to provide transparency as to how they are designed (which are namely due to proprietary reasons). We therefore suggest that these technologies are used in priority by informed and educated users for raw data acquisitions in non-ordinary situations (e.g. real-life environments), and in a controlled manner. These technologies hold great potential for the home-use of BCI and NF therapies by using simple and robust EEG features such as ERPs, frontal theta, sensorimotor mu, and occipital alpha that have been found to be accurately measured by advanced wearable EEG systems. With time, widely accessible wearable EEG technology and large scale data collection will inevitably lead to an increased understanding of the brain and our abilities to interface with technology. By allowing patients to move, communicate, and create, these technologies aid not only in rehabilitation but hold promise in aiding an individual's ability to regain a sense of well-being, autonomy, and independence. These technologies also present applications to the healthy population such as entertainment, art, education, and cognitive enhancement.

Major advancements in the technological sector combined with advanced data processing are bound to lead to an exciting and unpredictable future for wearable technologies. While these technological advancements host the potential for significantly improving the monitoring of one's health and in rehabilitation, mindful measures need to be taken to direct the evolution of wearable neurotechnologies towards positive applications serving the general interests and ethics of the public.

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