Wearable Electroencephalography

What Is It, Why Is It Needed, and What Does It Entail?

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The electroencephalogram (EEG) is a classic noninvasive method for measuring a person's brainwaves and is used in a large number of fields: from epilepsy and sleep disorder diagnosis to brain–computer interfaces (BCIs). Electrodes are placed on the scalp to detect the microvolt-sized signals that result from synchronized neuronal activity within the brain. Current long-term EEG monitoring is generally either carried out as an inpatient in combination with video recording and long cables to an amplifier and recording unit or is ambulatory. In the latter, the EEG recorder is portable but bulky, and in principle, the subject can go about their normal daily life during the recording.

In practice, however, this is rarely the case. It is quite common for people undergoing ambulatory EEG monitoring to take time off work and stay at home rather than be seen in public with such a device. Wearable EEG is envisioned as the evolution of ambulatory EEG units from the bulky, limited lifetime devices available today to small devices present only on the head that can record EEG for days, weeks, or months at a time [see Figure 1(a) and (b)]. Such miniaturized units could enable prolonged monitoring of chronic conditions such as epilepsy and greatly improve the end-user acceptance of BCI systems.

In this article, we aim to provide a review and overview of wearable EEG technology, answering the questions: What is it, why is it needed, and what does it entail? We first investigate the requirements of portable EEG systems and then link these to the core applications of wearable EEG technology: epilepsy diagnosis, sleep disorder diagnosis, and BCIs. As a part of our review, we asked 21 neurologists (as a key user group) for their views on wearable EEG. This group highlighted that wearable EEG will be an essential future tool. Our descriptions here will focus mainly on epilepsy

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and the medical applications of wearable EEG, as this is the historical background of the EEG, our area of expertise, and a core motivating area in itself, but we will also discuss the other application areas.

We continue by considering the forthcoming research challenges, principally new electrode technology and lower power electronics, and we outline our approach for dealing with the electronic power issues. We believe that the optimal approach to realizing wearable EEG technology is not to optimize any one part but to find the best set of tradeoffs at both the system and implementation level. In this article, we discuss two of these tradeoffs in detail: investigating the online compression of EEG data to reduce the system power consumption and the optimal method for providing this data compression. Preliminary versions of parts of this article have appeared in [1]–[3].

EEG Technology

The EEG

Many excellent texts, e.g., [4], are available on EEG technology and the typical signals produced, and so, only brief mention is given here to outline the specifications required for high-quality wearable systems.

A simplified EEG setup and an example of typical background EEG signals are shown in Figure 2(a) and (b), respectively. Electrodes placed on the scalp detect small electric signals, which are then amplified and stored. A differential architecture is used to remove common-mode interference signals and recording from a pair of electrodes thus forms an EEG channel and different montages are possible depending on which electrode pairings are used.

Typical signals detected on the scalp are in the range 20–150 μV peak to peak over a 0.5–60 Hz bandwidth [4]. The signals vary both temporally and spatially, and so multiple channels are used with electrode positions usually determined using the international 10–20 standard. After amplification and bandwidth limiting, the signals are stored digitally in a suitable location. Equipment recommendations from the International Federation of Clinical Neurophysiology are given in [5] and summarized in Table 1.

Fig. 1. The evolution of ambulatory EEG to wearable EEG. Future wearable EEG systems must be unobtrusive, light, discrete, and long lasting. This can be achieved by eliminating the large ambulatory EEG recording unit and wires linking it to the electrodes. These are replaced by microchips containing the required amplifiers, quantizers, and wireless transmitter, which are mounted on top of the electrodes themselves. EEG data are then wirelessly transmitted to a mobile phone or similar suitable device, which people routinely keep within a short distance of themselves.

Present ambulatory EEG systems typically have up to 32 channels and can operate for 24 h without recharging. Wireless systems offer around eight channels and last for 12 h.

Future Trends

The trend in EEG units is undoubtedly for higher sampling frequencies and more recording channels. Although [5] proposes 200 Hz as a reasonable minimum sampling frequency, it is not uncommon for inpatient monitors to now offer sampling frequencies of 1 kHz or more (although special scalp and electrode preparations may be necessary to see such frequencies in the EEG). In addition, while recording as few as four

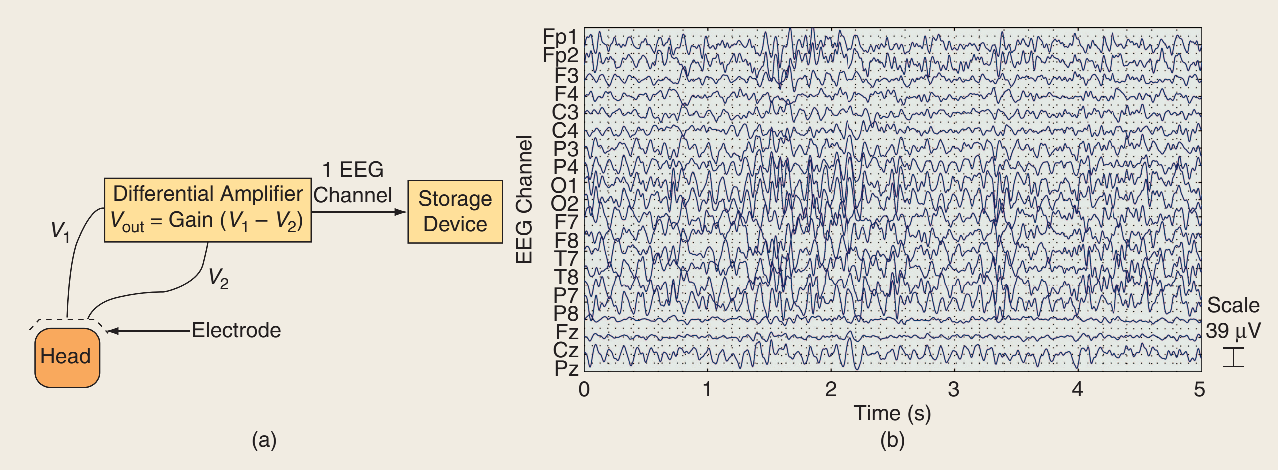


Fig. 2. Illustration of a typical EEG recording setup and the waveforms produced. (a) A simplified overview of an EEG setup: Recording electrodes are attached to a differential amplifier, which is connected to a storage medium. In traditional systems, this medium was a pen writer. In modern systems, it is an analog-to-digital converter (ADC) and a flash memory card or hard drive. (b) A set of typical of background EEG signals illustrating waveform shapes.

The electroencephalogram is a classic method for measuring a person's brainwaves.

EEG channels has been shown to be clinically useful for epilepsy [6], and four channel systems may be commonly used in BCI-type applications (e.g., [7]), such low-channel systems are not in common clinical use. Instead, modern clinical inpatient EEG systems may offer up to 256 channels. Furthermore, it has been shown that, to avoid spatial aliasing (signals appearing in one location when in fact they occur in another, purely due to how the electrodes are setup), up to 600 channels may be necessary [8] (although this does not correspond to current clinical reality). For low-power, easy to use, portable systems, the channel count should be minimized without affecting diagnostic accuracy.

Parallel to the sampling frequency and channel count trends, there is also a trend for an increase in the sampling resolution. Most commercial EEG units use 16 or more bits, exceeding the 12 b recommendation from [5]. In contrast, however, traditional paper-based EEG systems only had a dynamic range of 7 b [9]. Indeed, current diagnosis from a digital EEG is performed using 16 channels on a screen with 1,024 vertical pixels giving just 6 b of resolution [9].

Thus, although it is debatable whether high-precision systems are necessary for all patients and diagnostic issues, it is clear that truly successful wearable EEG solutions should be future proof and able to contend with these developments.

Wireless transmission of the EEG data from a wearable recorder is not necessarily an intrinsic requirement of wearable EEG for medical applications such as epilepsy diagnosis, which is usually done after collecting all the signals. Wired connections between electrodes will still be required to form the EEG recording channels, but wireless transmission of the EEG signal off the body is desirable to enable miniaturization. In applications such as BCIs, the immediate collection and interpretation of data is essential, and so, to remove cumbersome wires, wireless solutions are mandatory. Furthermore, wireless data transmission will enable the integration of wearable EEG devices into body area network type applications, which allow the simultaneous long-term monitoring of many physiological parameters. Therefore, it is envisioned that wireless will be a key feature of wearable EEG.

Table 1. Summarized standards for digital EEG recording from (5).

At least 24 channels, preferably 32.	Interchannel crosstalk less than 1% (40 dB down or less).
At least 12 b analog-to-digital conversion with a minimum resolution of 0.5 μV.	70 Hz, 40 dB per decade, antialiasing low-pass filter required.
Minimum sampling rate 200 Hz, preferably higher.	Additional recording noise less than 1.5 μV peak to peak or 0.5 μV RMS.
High-pass filtering at 0.16 Hz or less.	CMRR at amplifier input at least 110 dB.
50/60 Hz notch filter (no specified Q) available but not routinely used.	Referential montage to allow later remontaging.
Electrode impedances below 5 kΩ.	Amplifier input impedance more than 100 MΩ.

Wearable EEG Application Areas

Epilepsy

Epilepsy is a common and serious neurological disorder characterized by recurrent seizures that significantly affect quality of life. For example, sufferers are typically no longer allowed to drive, limiting their freedom of movement. Epilepsy affects approximately 0.7% of the population [10], and, in 2004, the cost of the condition in Europe was more than €15 billion [11], corresponding to approximately 0.15% of the gross domestic product of the European Union for that year [12].

However, despite this large prevalence and the disorder's consequences, misdiagnosis is a significant issue. It is estimated that 13–20% of patients present diagnostic problems [13], and 25% of diagnosed epilepsy sufferers do not actually have the condition [14]. In the United Kingdom, the cost of misdiagnosis is estimated at £24 million in medical costs with a total direct cost to the economy of £140 million [15]. This figure excludes lost productivity due to factors such as morbidity, mortality, unemployment, and underemployment.

Although the EEG should never be used in isolation to avoid misdiagnosis, it is a key diagnostic tool for answering the questions: Are epileptic discharges present? What type of epilepsy is present? What is its locus within the brain?

Since its inception in 1929, many specialized types of EEG have evolved, each with its own advantages and disadvantages. A standard EEG test lasts between 20 and 30 min and so is generally restricted to recording interictal activity (activity that occurs between seizures). Synchronous video monitoring is also used often. Interictal epileptic discharges (IEDs) are found in approximately 50% of individuals with epilepsy in this short test [16], and the yield can be increased to around 80% through the use of multiple tests, sleep deprivation, and photic stimulation.

Longer-term monitoring, e.g., for 24 h, increases the chance of detecting IED, which may be confined to sleep or to the sleep–wake transition. It may also facilitate the recording of ictal (seizure) activity. Such monitoring is required in a significant number of cases that present diagnostic or management difficulty [16].

> **Wireless transmission of the EEG signal off the body is desirable to enable miniaturization.**

Fully long-term inpatient EEG monitoring may be undertaken continuously for several days, significantly increasing the likelihood of recording seizures or rare IEDs. However, the extra data produced can take a large amount of time to analyze and interpret. The method also comes with monetary and resource overheads, as well as consequences for the patient such as having to take time off work. As a result, it is not universally available [17]. In addition, it removes the patient from their natural environment in which seizure provoking factors may be more likely.

Ambulatory outpatient EEG monitoring overcomes some of the limitations of inpatient EEG monitoring with 24 h of ambulatory monitoring being more than 50% cheaper than 24 h of inpatient monitoring [17]. Overall, it is estimated that ambulatory EEG is clinically useful in 75% of patients, and abnormalities are found in 12–25% of cases for which an inpatient EEG was normal or nondiagnostic [17]. Although outpatient ambulatory EEG systems offer several benefits over long-term inpatient monitoring, several limitations are present.

1) There are issues in ensuring that the electrodes remain securely attached for the duration of the recording and also in the social acceptability of wearing head-mounted electrodes in public.
2) Systems can weigh up to 500 g, limiting their portability.
3) Each channel recorded requires a wired connection from the patient's head to the recording unit, and the compliance of these wires can limit patient movement.
4) Long-term recordings generate large amounts of data for storage or transmission, approximately 1 GB every 24 h. This storage or transmission requires a significant amount of power, limiting battery lifetime.
5) The human analysis of the EEG data is time consuming, taking approximately 2 h per 24 h recording [18].

It is these issues that wearable EEG aims to overcome, extending current ambulatory EEGs to give a longer temporal sample that includes all stages of sleep and wakefulness and increasing the likelihood of recording typical seizures.

In addition to this diagnostic aim of wearable EEG, in recent years, there has been a significant amount of interest in the use of portable EEG in closed-loop epilepsy treatment systems. The aim of such systems is to predict, within some suitable prediction horizon, when a seizure is likely to occur and then take preventative action. This action may be via electrical neural stimulation or antiepileptic drug release (see, e.g., [19]). In addition to the five obstacles mentioned earlier, closed-loop systems must have a high level of accuracy while keeping the computational complexity low for real-time operation on a portable device where the power available from small batteries is limited. Further, the treatment must be effective and rapid, and one that benefits from being automated rather than just run continuously.

Sleep Studies

Sleep disorders affect more than 70 million people in the United States. The impact of this is huge: 20% of road accidents involving serious injury are sleep related and the annual cost of sleep disorders in the United States is hundreds of billions of dollars [20]. Despite this, diagnosis of sleep disorders is difficult and resources limited. In the United Kingdom, the overall waiting time from referral to sleep study can be up to three years [21].

According to a market report by Frost & Sullivan in November 2006, "Sleep diagnostics is a relatively new market in the European patient monitoring industry. Clinicians and healthcare delivery personnel are becoming increasingly aware of the co-morbidities and consequences of unattended sleep disorders" [22]. They conclude that "innovative product development [is necessary] to create inexpensive, ambulatory systems that are reliable and extensively validated to be comparable to the 'gold standard' of polysomnography" [22].

Diagnosis typically uses polysomnography (PSG) that monitors multiple body functions such brain activity (EEG), heart rhythm [electrocardiogram (ECG)], and reparatory function during sleep. The requirements for wearable EEG for sleep studies are slightly different to those for epilepsy studies. Principally, the duration of operation will be shorter: 24 h at a time is usually sufficient to cover all night and daytime sleep. However, if anything, the devices have to be even less cumbersome so that the subject's sleep is not disturbed. Thus, the device and its interconnections should be even smaller, and the use of wearable EEG devices is essential.

BCIs and Augmented Cognition

Although the EEG has its roots in medical instrumentation EEG signals are not only indicative of abnormal health states. This fact is used in BCIs (see, e.g., [23]).

The basic mode of operation is that a person's brain exhibits measurable changes in electrical activity when responding to stimuli or preparing for physical exertion. These changes can be detected and used to direct a cursor or control a robot arm. As a result, these applications could revolutionize the way in which people use computers.

The logical evolution of BCIs, where a human influences the operation of a computer based on their thoughts, is to close the loop: a computer monitors a person via an EEG and uses this to provide feedback, affecting the user's environment. This is a research concept known as augmented cognition, which has arisen at the intersection of cognitive science, neuroscience, and engineering and envisions the closed-loop optimization of the human–computer interface based on the cogitative state of the user [24].

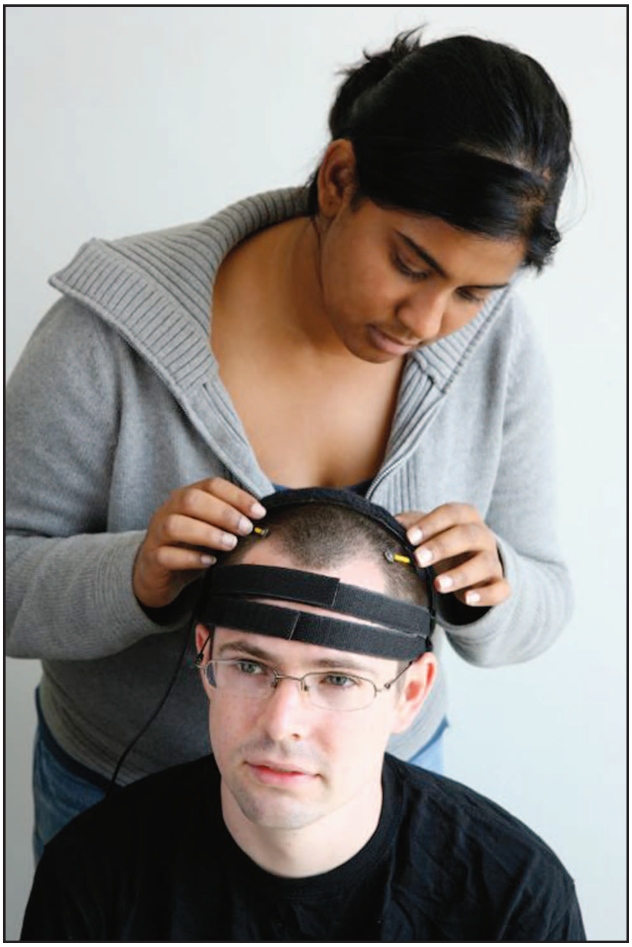
For example, it is possible to attempt to determine whether a person is drowsy, asleep, awake, or very alert. This

information could be used to help prevent people from falling asleep while driving or in computer-assistance technologies that will help pilots and others who face high stress situations. Here, it would be possible to detect when a user is stressed, or has a high workload, and deny any incoming communications until the user is in a more receptive state. The EEG is a key tool for this, as it can provide a millisecond accuracy in the measurements that are taken.

Many of these BCI and augmented cognition methods are still at the research stage, but in addition to the success of the signal processing algorithms, the success of the entire field and end-user acceptance will strongly depend on the physical unit: the EEG system itself. It is ideally free of cumbersome wires and must be small, discrete, and comfortable while also offering good battery performance. All of this puts future BCIs into the realm of wearable EEGs.

Current Technology Limitations

It can thus be seen that small, discrete, and long-lasting wearable EEG units have potential applications in a range of fields. Given this, we now review some of the research that is still necessary to make wearable EEG systems feasible. Two core research areas are present: new electrode technologies and lower power consumption electronics.



NEVILLE MILES

Fig. 3. EEG electrodes are connected to the scalp and record microvolt-sized signals that result from synchronized neuronal activity within the brain. Comfortable, long lasting and discrete electrodes are a current research topic.

Electrode Technology

Traditional EEG electrodes connecting the recording equipment to the scalp (Figure 3) are made from silver/silver chloride (Ag/AgCl) and are wet: a conductive gel is used to make the connection between the electrode and the scalp. This lowers the electrode impedance and allows recording of EEG through a high input impedance input amplifier. Over time, however, the conductive gel dries out and reduces the quality of the electrode contact and the EEG recording produced.

Furthermore, regardless of the connection method used in an uncontrolled environment, such as ambulatory monitoring, it is possible for an electrode to become loose, preventing the EEG from being recorded. Methods are needed to overcome these significant limitations to make long-term systems practical. The authors envisage three possible solutions to this problem, and key to realizing them is further electrode research.

First, one of the advantages of a wireless system is that it provides real-time access to the EEG being recorded. It would thus be possible to monitor the EEG recording remotely for a few minutes a day to check the quality of the signals. If electrode connection issues are found the patient could arrange to be seen at a clinic to have them reattached promptly. Alternatively, the patient or a carer could be tutored to reattach the electrode. Although this method is resource intensive, it is a simple solution that can be implemented immediately.

The second solution, and one in which significant progress has been made in recent years, is in the use of dry electrodes. These electrodes require no special preparation of the subject, are simply placed on the scalp, and can be easily held in place by a hat, readily accepted in social situations. Multiple potential methods have been investigated, e.g.,

- stainless steel with various coatings for capacitive coupling of the EEG [25], [26]
- hybrid resistive-capacitive coupling of the EEG [27]
- carbon nanotube and micro electro mechanical systems electrodes based on piercing the outer layers of skin for better electrical conductivity [28], [29].

Undoubtedly, these electrodes have a big future, but there would still be the issue of keeping the electrodes in place over a long period of time: a hat cannot be worn 24 hours a day, seven days a week.

Instead, the third solution may be a semi-implanted approach, similar to that investigated in [30]. This would not involve invasive electrodes within the skull, but instead, electrodes placed below the scalp (subcutaneously or subdermally) essentially not externally visible and intrinsically held in place. A recent study has shown the use of subdermal electrodes in the intensive care unit continuously for 60 days [31].

Such a semi-implanted system may provide a true EEG analog of the Reveal Heart Monitor [32]. This is an implantable monitor that records 42 min of ECG in response to an automated detection algorithm. The device is implanted in an outpatient procedure and allows monitoring for 18 months. Of course, the ECG situation is significantly simpler: the ECG signals are larger, fewer channels are involved, the features of interest are better defined, and the ECG surgery is less complex. However, the fundamental principle is the same.

Power Consumption

The power constraints for wearable EEG systems are summarized well in [33]. If the overall device is assumed to have a volume of 1 cm^3 (a common aim for body area network

applications) and half of this space is reserved for a custom-made battery of energy density of 200 Wh/L, 100 mWh of energy is stored. For 30 days operation, the average power consumption must be less than 140 μW.

A front-end system with a measured 25 μW power consumption per channel is presented in [34], representing the current state-of-the-art performance. Taking typical figures from Table 1, at 200 Hz and 12 b sampling, 300 B/s per channel of data are produced. For a typical transmitter that consumes 50 nJ/b transmitted, transmitting each channel consumes approximately 120 μW. With these figures, only a one-channel system is feasible. To realize high-quality wearable EEG systems, significantly better performance is required on all fronts, and this represents a major challenge.

Historically, the capacity of off-the-shelf batteries has doubled only every 5–20 years [35], and so, capacities are unlikely to reach satisfactory values in the near future. In some circumstances, battery recharging or changing is feasible and can extend battery life indefinitely. However, ensuring user compliance to reliably and regularly charge batteries is a major issue. This also goes against the concept of wearable EEG systems being easy to use: it is no longer enough simply to wear the EEG unit, battery maintenance now has to be performed. Idealized systems must simply work. This is particularly illustrated when working with people with learning difficulties or with military personnel who may be out of contact for large periods of time. Here user recharging of batteries is by no means a trivial operation and is unlikely to be feasible.

Power-scavenging techniques in which power is harvested from the ambient environment of the user, e.g., from body heat or movement [36], is a potentially useful technique for overcoming the power issues. It is believed that such techniques may harvest up to 100 μW, significantly relaxing the power constraints, and [37] describes a two-channel EEG system powered by body heat alone. The drawback of this is that the power source will not scale to a large number of channels and is nonconstant, which may present regulatory issues. Nevertheless, work is progressing to make such systems feasible for when these issues are overcome.

The alternative to improving the amount of energy available from batteries or energy harvesting is to improve the electronic design, decreasing the required power consumption from the 145 μW per channel identified earlier. We believe that this can be done via the use of online signal processing applied to optimize both the system power consumption and the EEG data collection.

Mitigating These Limitations

Our research focuses on identifying these system-level optimizations and tradeoffs as well as developing electronic design techniques to mitigate them. We assume that long-lasting electrode technologies will become readily available in the future, and we are not tackling this problem at present. Given this assumption, we begin by considering the detailed requirements of wearable EEG systems.

Neurologist Opinions

To illustrate the medical needs and requirements for wearable EEG, we have carried out a survey of 21 neurologists who are a key user group particularly for the epilepsy and sleep disorder usage situations. The survey participants are six consultant neurologists from the National Hospital for Neurology and Neurosurgery in London, four neurologists from Humanitas in Italy responding via e-mail, and 11 being from the National Society for Epilepsy in the United Kingdom, who filled in the questionnaire after a presentation about wearable EEG. The results are summarized in Table 2.

The vast majority of respondents thought that current ambulatory EEG recordings are useful and that there is a need for wearable EEG devices. In addition, similar numbers thought that wearable EEG would be a major improvement in EEG practice both for them and their patients. This clearly illustrates the desire for wearable EEG systems. Linked to this, all but three respondents thought that ambulatory recordings will be more common in the future, and so this desire is likely only to increase with time.

Opinion, however, was more divided over the amount of data produced and the ability of signal processing algorithms to automatically reduce it, and this is key to the tradeoffs to be discussed here. Despite many years of software availability, further work is still required on, or at least on the perception of, automated detection methods.

Most respondents thought that wearable EEG would be of use for sleep studies, but opinion was divided on the other application areas. The medical usage of wearable EEG was thought to be more significant than the nonmedical usage. This said, our study population being doctors is not necessarily representative of the users of augmented cognition and BCI systems and so may underestimate its utility. It is known that the U.S. Defense Advanced Research Projects Agency has shown a large amount of interest in augmented cognition and its potential applications [24].

Overall, our results clearly illustrate the medical desire for wearable EEG systems, and it is likely that, if they can be satisfactorily developed, they will play a large part in future medical care.

Tradeoffs

Given this motivation and insight from neurologists, we now need to consider how to optimize the electronic aspects of the system to reduce the power consumption. In general, this optimization takes the form of investigating the tradeoffs between a set of system parameters. For example, a typical tradeoff encountered is: the energy storage capacity of a battery is directly related to its physical size; larger batteries store more energy. Given a set amount of energy storage, there is then a direct tradeoff between deliverable power (power draw) and the operating lifetime of the battery. The larger the battery the more energy it can store; the higher the power draw the quicker this energy is expended.

Table 3 illustrates the energy storage capacity and physical size of a range of current commercial batteries, and the power draw tradeoff is illustrated in Figure 4. Figure 4 also highlights where typical state-of-the-art EEG systems operate, e.g., Advanced Brain Monitoring's B-Alert at 200 mW for a six-channel system [38] and the Interuniversity Microelectronics Center's (IMEC) system operating at 800 μW with two channels [37].

In the past, significant research interest has been concentrated on reducing the system power consumption by optimizing the design of each constituent part. The electronics in a wireless EEG consists of at least an amplifier, an analog-to-digital converter (ADC) and a radio transmitter as illustrated in Figure 5(a). Yazicioglu et al. [34] presents a 200-μW eight-channel amplifier and ADC in a system that meets the standards

Table 2. Results from the wearable EEG survey carried out.

Question	Yes	No	Don't Know	Not Answered
Are current ambulatory recordings diagnostically useful over traditional inpatient recordings?	16	0	3	2
Do you think that there is a need for wearable EEG devices?	18	1	1	1
Would you consider it a major improvement in your EEG practice if wearable EEG devices were available?	16	2	2	1
Do you think that your patients would consider it a major improvement their EEG experience if wearable EEG devices were available?	18	2	1	0
In the future, do you anticipate ambulatory recordings being:	More common? 18 Used about the same? 2 Less common? 0			1
Is the amount of EEG information produced by monitoring for weeks or months to capture rare events too much to be useful in practice?	7	6	8	0
Would you trust automated detection or data reduction software to reduce the amount of data presented to you?	8	4	9	0
Would you trust the automated diagnosis of disorders based upon detection software?	2	11	6	2
Do you think wearable EEGs would be useful for sleep studies in allowing more natural, unrestricted sleep than current sleep EEG units do?	16	2	2	1
Are you interested in the other potential applications of wearable EEGs, such as controlling computer games or receiving feedback based upon your current awareness level?	10	5	5	1
Do you think that wearable EEGs will be of more use to this sort of application area rather than in medical applications?	4	9	7	1

from Table 1. More speculative systems have also been reported, which do not necessarily meet all of these specifications, and may only have simulated, as opposed to measured, results. For example, [39] and [40] present front-end amplifier circuits that require only around 1 μW per channel, and a suitable submicrowatt ADC is presented in [41]. Taking these more speculative figures and assuming that there are between 24 and 32 channels, the total power consumed by these two circuit blocks in future systems will be no more than about 60 μW.

Table 4 shows the power consumption and data rates of various state-of-the-art low-power transceivers. When the required data rate is significantly less than the achievable data rate, the transmitter can be operated at a low duty cycle, considerably reducing the average power dissipation. The energy used per bit transmitted, also given in Table 4, is therefore a useful metric. From the performance of the nRF2401 [42] and the BRF6150 [43], 50 nJ/b is taken as a conservative value, definitely achievable in most environments for short-range communications, whereas 5 nJ/b is taken as a more speculative but still realistic figure, based on the reported performance of ultrawideband devices such as the XS110 [44] or on cutting edge narrowband devices such as Zarlink's ZL70100 [45].

Based on 32 channels, a sampling rate of 200 Hz, and a resolution of 12 b from Table 1, the required data rate is approximately 76.8 kb/s. This corresponds to a transmitter power consumption of 3.8 mW with the conservative case transmitter and 380 μW in the speculative case. It can thus be clearly seen that the transmitter will dominate the system power consumption in both cases,

Table 3. Specifications for off-the-shelf batteries of variable sizes and capacities.

		Examples				
Group	Approximate Energy Stored (mWh)	Make	Type	Voltage (V)	Capacity (mAh)	Size ($d \times h$) (mm)
AA	3,500	Sanyo HR-3U-4BP	NiMH	1.2	2,500	15×51
		Duracell Ultra MX1,500	Alkaline MnO_2	1.5	2,500	15×51
Large coin cell	400	VARTA	NiMH	1.2	250	25.1×6.7
		Panasonic	$LiMnO_2$	3	165	20×2.5
Small coin cell	30	RS RX364-2C5	AgO_2	1.5	23	6.8×2.15
		Power Paper STD-1	$ZnMnO_2$	1.5	15	39×0.6

and this is not accounting for the power needed to control the transmitter or to store the data to be transmitted.

The overall system power is thus optimally reduced by focusing on the transceiver stage, and the design of robust transceivers for short-range low-power applications has seen extensive research and development from various academic and commercial groups around the world in recent years [46]–[48]. Instead of continuing this trend, we propose to reduce the overall power consumption by including some local signal processing, which will reduce or compress the data to be transmitted, presenting a lower data rate to the transceiver. In this way, the transceiver can be operated at a much lower duty cycle, enabling a significant power saving, provided that the data reduction or compression can be carried out using very little power.

Key here is that the optimal solution to the low-power problem comes from finding the best set of tradeoffs for the given system aim rather than optimizing the power consumption of any one component. To this end, here we consider in detail two sets of tradeoffs: the power tradeoff determining the amount of compression required and the power budget available for this compression; and the tradeoff between the compression methodology, the computational complexity required, and the implications on the data produced and any interpretation of it.

Power Tradeoffs

To reduce the system power consumption, the idea is thus to introduce a new compression block into the system [Figure 5(b)] where it is noted that this compression block could be implemented in either the analog or digital domain (before or after the ADC). If the system of Figure 5(a) is taken as the reference, the power consumption of a single channel EEG (excluding necessary control overheads) is given by

$$P_{sys} = P_{amp} + P_{ADC} + P_t,$$

where P_{amp} and P_{ADC} are the power consumptions of the input amplifier and ADC, respectively, and P_t is the transmitter power consumption. In turn, if the transmitter has a net power consumption of J J/b, P_t is given by

$$P_t = J f_s R,$$

where f_s is the sampling frequency and R is the resolution in bits of the ADC.

Incorporating the compression block from Figure 5(b), if the block has power consumption P_{comp}, the system power consumption becomes

$$P_{sys} = P_{amp} + P_{ADC} + P_{comp} + C \cdot P_t,$$

where C is the compression ratio giving the fraction of the full number of bits that are transmitted (the compressed bit rate

Table 4. Performance summary of low-power off-the-shelf transceivers.

Model	nRF2401 (42)	BRF6150 (43)	XS110 (44)	ZL70100 (45)
Type	GFSK[a]	Bluetooth	UWB[b]	MICS[c]
Data rate (b/s)	1M	1M	110M	800k
Transmission power (mW)	21	75	750	5
Energy per bit transmitted (nJ/b)	21	75	6.8	6.25

[a]Gaussian frequency-shift keying.
[b]Ultrawideband.
[c]Medical implant communication system.

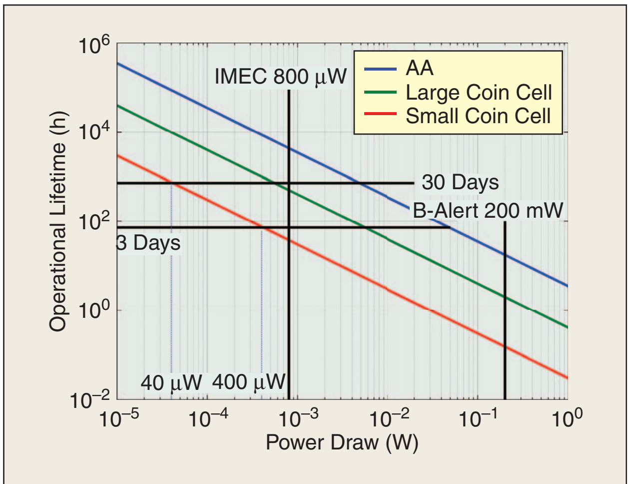


Fig. 4. The lifetime–power consumption–battery size tradeoff, illustrating how the device operating lifetime depends on the battery size and power draw. Figures for state-of-the-art ambulatory EEG systems are also illustrated, along with the maximum power draw from a small coin cell battery for set operational lifetimes.

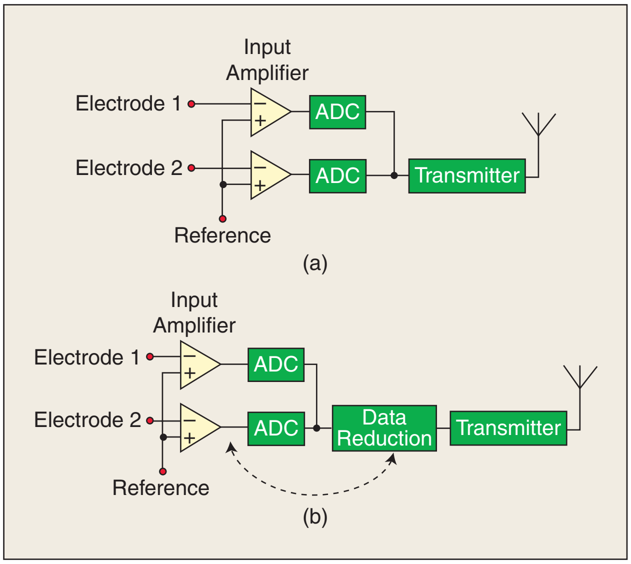


Fig. 5. A simplified two-channel wireless EEG recording system consisting of: an input amplifier; an ADC, and a transmitter. (a) A typical current system. (b) A system incorporating a data compression block to reduce the number of bits to be transmitted and hence the system power consumption. This compression block could be implemented in either the analog or digital domain.

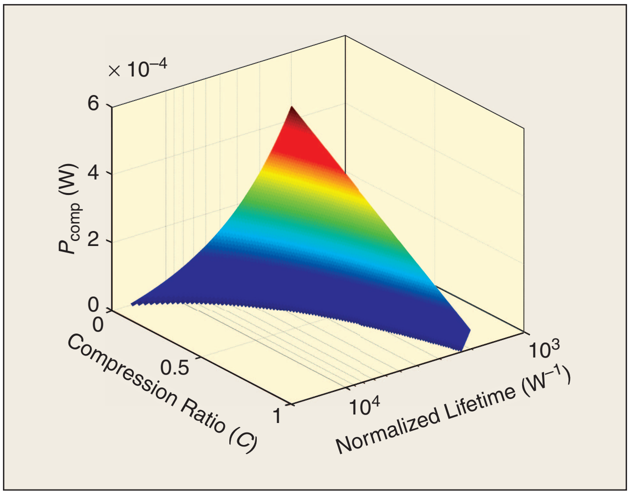


Fig. 6. Maximum power for compression (P_{comp}) against compression ratio (C) and normalized lifetime for a transmitter that consumes 5 nJ/b. For a given compression performance, this graph can be used to set the power budget for the implementation of the compression algorithm.

divided by the uncompressed bit rate). A lower figure is better. To reduce the system power consumption, the inequality

$$P_{comp} + C \cdot P_t < P_t,$$

must be satisfied. In general, a better (lower) compression ratio (C) can be achieved at the cost of a more computationally complex data compression algorithm, which implies higher P_{comp}.

In addition to this inequality, for wearable systems, the lifetime and physical size of the battery and its implications on P_{sys} must also be taken into account: the C and P_{comp} achieved must improve the lifetime to battery size ratio. For a wearable EEG system powered from a battery, the total system power available will be determined by the battery volume V_{cell} and

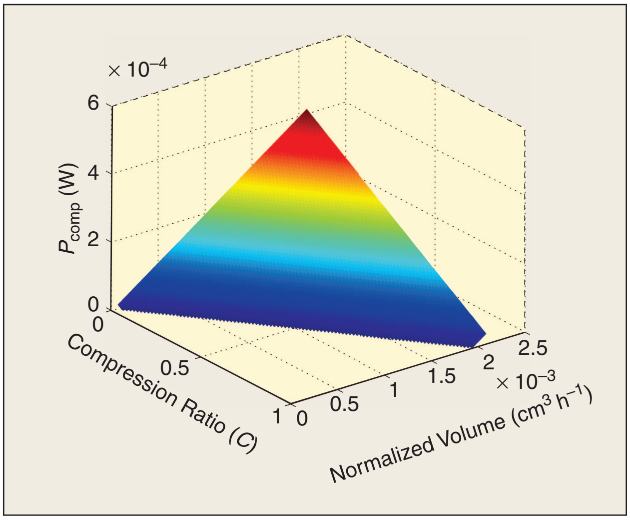


Fig. 7. Maximum power for compression (P_{comp}) against compression ratio (C) and battery volume normalized to lifetime for a battery with energy density equal to 1,100 J/cc and a transmitter that consumes 5 nJ/b. This graph can be used to find the power budget for a compression algorithm, given a fixed battery volume.

capacity C_{cell}. For the device to operate over a lifetime T, the maximum possible system power draw is thus

$$P_{sys} = \frac{C_{cell} \times V_{cell}}{T}.$$

Combining these equations gives a three-way tradeoff between the compression achieved (C), the compression block power consumption (P_{comp}), and the device operating lifetime (T). This tradeoff is illustrated in Figure 6 for the 5 nJ/b transmitter, where the total amplifier and ADC power consumption is assumed to be 60 μW and the uncompressed data rate 76.8 kb/s. To make the curve battery independent, the lifetime is normalized with respect to the available energy of the battery given by $C_{cell} \times V_{cell}$.

Given an existing data compression algorithm for which C is known and targeting a specific device lifetime, Figure 6 can thus be used to find the maximum power budget available to implement the compression block. For example, if compression ratios of around 0.25 can be achieved using no more than 200 μW, then the small coin cell battery class could be used to operate a wearable EEG unit for 24 h, which would be the same as many current ambulatory EEG systems. The large coin cell battery class could operate a device for two weeks, which is much longer than current ambulatory EEG devices.

In addition to these calculations, it is also possible to visualize this tradeoff in a different way: instead of aiming for a set lifetime, it is possible to aim for a set battery volume, limiting the size of the overall device. This tradeoff is illustrated in Figure 7, which is based on the energy density of a lithium secondary cell, which is 1,100 J/cc [49]. Battery volume has been normalized to lifetime measured in hours.

These figures set the power budget for the compression stage, although it is not necessarily easy to meet this budget. Few EEG data compression papers provide both a data reduction figure and a power consumption figure. Avila et al. [50] presents a direct cosine transform-based EEG compression algorithm but with a minimum power consumption for a hardware/software codesign implementation of 71 mW: orders of magnitude over the microwatt power budget. The question now is what compression techniques are available that can operate within this power budget, and what is their impact on the overall EEG system design?

Data Compression Tradeoffs

In this article, we do not attempt to implement different algorithms in ultralow power to assess the differences in performance. In principle, this is achievable, but the electronic design of each algorithm is a nontrivial task. Instead, we investigate the optimal data reduction method to employ as a basis for this future implementation, given the fixed power budget from the above calculations. Three principle options for carrying out the compression are available:

- reduce the quality of the recording
- use data compression algorithms on the raw signal
- do not transmit a continuous data set (discontinuous recording).

The relative compression performances of these techniques are shown at a high level in Table 5. From this, it is seen that by simply recording fewer channels or using a lower sampling rate or resolution a significant reduction in the amount of data to transmit can be made. Adaptive sampling rates [56] may

By recording only the ictal and interesting interictal activity, significant data reductions can be achieved.

also be used to achieve the same effect. As noted earlier, however, the overwhelming trend over time has been for channel counts and effective sampling rates to increase and wearable EEG solutions should not ignore this. Thus, while simple, this approach may not be clinically acceptable.

The use of online compression algorithms takes a different approach: the idea is to take the same information that is in an EEG trace and represent it in fewer binary bits giving fewer bits to transmit. Offline implementations of this technique have shown good results with approximately a 50% reduction of the raw data being achievable using lossless compression techniques [51]. Approximately 15% compression ratio is achievable when mildly lossy compression, where the original and end EEG signals do not match exactly, is deemed acceptable [52]. These levels are impressive, and the schemes should certainly be used where possible. However, given the results from [50] discussed previously, it is clear that the implementation of suitable algorithms at the low-power levels required will not be a trivial task.

In addition to the issues mentioned previously, none of the techniques considered so far help with decision support: in the case of epilepsy, e.g., identifying the presence of epileptic EEG activity. In contrast, the third method, discontinuous recording, allows the amount of data to be transmitted and the amount of data to be analyzed to be reduced simultaneously. This allows longer duration recordings to be analyzed during the same amount of observer's time.

We illustrate the operation of the discontinuous monitoring technique in Figure 8 using epilepsy as an example, although analogs in the other application areas can be found. The method is based on the fact that epileptic EEG traces can be broken down into two phases: ictal (seizure activity) and interictal (spikes and spike and waves that occur between seizures). Interictal activity usually contains isolated events along with normal background signals. By recording only the ictal and interesting interictal activity, significant data reductions can be achieved.

The concept, therefore, is to detect and eliminate most of the background EEG that is not diagnostically useful. This principle is not new and is employed in the Reveal Heart Monitor for ECG, and discontinuous EEG recording systems have long been implemented for inpatient epilepsy monitoring in the EEG unit at the Montreal Neurological Institute [57]. This shows that such discontinuous schemes can be practical for

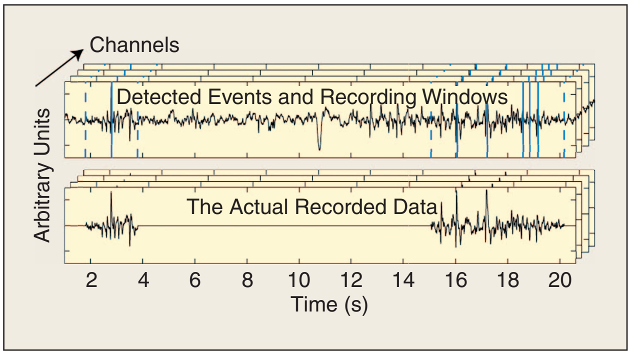


Fig. 8. The discontinuous recording procedure only saves data for a brief period (dashed blue lines) on either side of an automated detection (solid blue lines). This can significantly reduce the amount of data to be transmitted from the wireless EEG unit. Simultaneously, the amount of data to be analyzed by a neurologist is reduced.

Table 5. Performance comparison of EEG data reduction schemes.

Method	Notes	Approximate Amount of EEG Tested	Lossy?	Reduces Analysis Time?	Sensitivity[a] (%)	Compression Ratio (%)
Full recording (baseline)	32 channels, 12 b, 200 Hz	N/A	No	No	100	0
Reduced quality	32 channels, 8 b, 120 Hz	N/A	Yes[b]	No	100	40
Reduced quality	Four channels, 8 b, 120 Hz	N/A	Yes[b]	No	100	5
Lossless compression	See (51)	154 data sets	No	No	100	38–61
Lossy compression	See (52)	Eight data sets	Yes	No	100[c]	11–19
Discontinuous (Gotman)	See (18), (53), and (54)	200 h	Yes	Yes	Unknown	5–10
Discontinuous (Casson)	See (55)	96 h (982 events)	Yes	Yes	90	50

[a]Sensitivity is the ratio of events correctly recorded compared with the total number present (usually determined by an expert marker).
[b]Lossy as intrinsically contains less information than the baseline.
[c]Assuming that reconstruction accuracy is sufficient to not affect the EEG interpretation.

> **Epilepsy is a common and serious neurological disorder characterized by recurrent seizures that significantly affect quality of life.**

standard EEG measurements; the challenge now lies in the low-power implementation.

Given its ability to simultaneously reduce the EEG data for both transmission and analysis, the authors believe that the discontinuous monitoring method deserves further investigation and implementation for use in long-term wearable EEG systems in epilepsy. This implementation lies beyond the scope of this article, although our initial work in this area is reported in [55]. Before pursuing the method in detail, however, it is essential to assess the impact of the data reduction method on the overall EEG system and its use. For example, the results in Table 2 illustrate that the perception of automated diagnostic systems by health-care professionals is poor, and care must be taken to differentiate the proposed approach from classical event quantification or automatic diagnosis systems.

The key point must be that the method will reduce the amount of raw data that is presented to the neurologist but does not replace them or their role in diagnosis. There is no hard definition of a significant epileptic EEG feature. As a result, a discontinuous recording system can only present the neurologist with candidate events, and they must analyze these to determine their significance in the same way as they would for a continuous EEG signal in which essentially each section of the record can be regarded as a candidate event. As any system will not be perfect and will have some false detections, the fact that a data section has been recorded should not be taken as proof that epileptic activity is present, only that it is likely to be, and so should be reviewed by a human expert.

Of course, to aid diagnosis, it is important that the system records all epileptic activity. Ordinarily, the performance of a detection algorithm is measured via two factors: the sensitivity and the specificity [58]. The wanted features must be correctly identified with few missed detections (few false negatives), leading to a high sensitivity. Simultaneously, unwanted features or artifacts must not be incorrectly detected. Having few wrong detections (false positives) leads to a high specificity. However, in a discontinuous recorder for which the EEG data are analyzed following the method described earlier, high sensitivity is required, but recording unwanted features or artifacts does not carry the same negative cost, as it is the neurologist, not the data selection algorithm, that performs the specificity stage of rejecting any incorrect features.

Recording of false detections will result in more data being recorded, but this does not affect the EEG analysis, and power savings can still be made, even with limited data reduction. Overall, the recorder can thus be thought of as performing data selection (selecting sections with a high sensitivity for epileptic features) as opposed to event detection (having high sensitivity and specificity). This is unlike event quantification or automated diagnosis methods where any false detection causes the overall result to be fundamentally wrong.

Linked to the issue of being tolerant of false detections, is the question of determining when a relevant event is actually present. When EEG experts are asked to mark interictal events

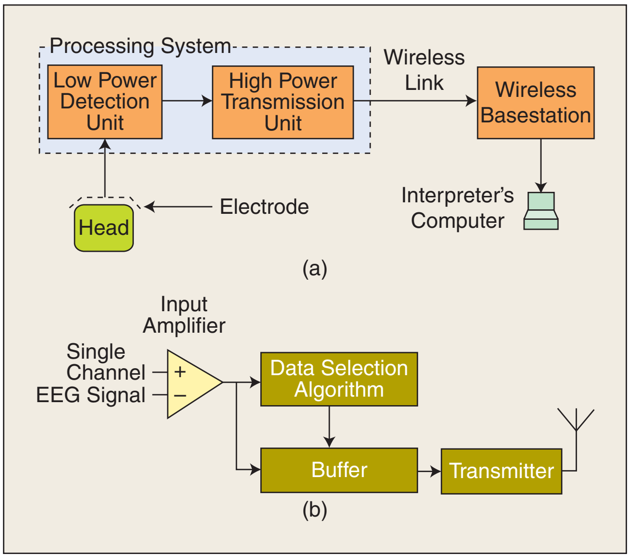


Fig. 9. An overview of the proposed discontinuous, wearable EEG incorporating the needed signal processing blocks. (a) Addition of a low-power detection unit allows the high-power transmission unit to be turned off, reducing system power. (b) Each EEG channel is processed with data temporarily stored in a buffer to allow sections from before and after a detection to be transmitted.

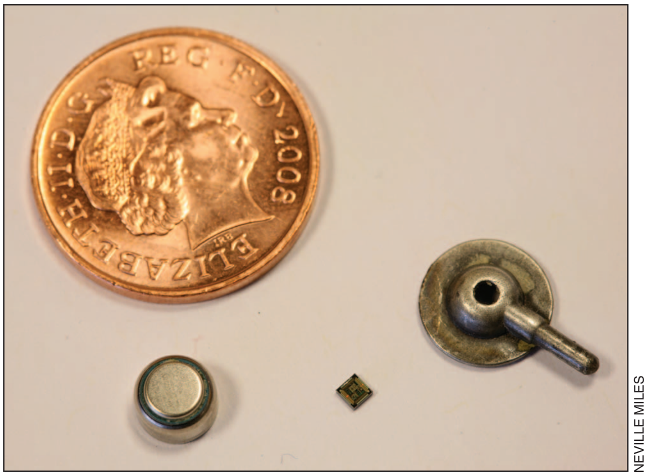


Fig. 10. The scale of the end wearable EEG solution: a standard recording electrode, a large coin cell battery, and unpackaged electronics. A British 1 pence piece is included for scale.

in the same EEG recording, they will often mark noticeably different sections, with agreement ranging from 0 to 90% of the time [53]. This can affect the reported sensitivity of the monitoring scheme as any two experts will disagree over its performance. As noted earlier, however, a monitoring system does not need to reject nonfeatures. The fact that one expert has marked an event shows that it is worth recording, even if a second expert then discounts it. This, of course, affects the reported sensitivity of the scheme, which can now only be taken as an approximation. The true performance must be measured by assessing the results of analysis of the full and the discontinuous records, and the time taken to analyze each tracing, although this can only be done once systems are in place.

Future Directions

In addition to electrode research, the development of online, low-power discontinuous event recorders represents the state of the art for wearable EEG solutions. These can be used to improve the battery performance, reduce battery size, and decrease the analysis time required. It is beyond the scope of this article to investigate different algorithm methodologies and performances, and these will form the subject of many future articles. We begin the process in [55], but there is much more work to be done.

Even when such systems are realized, in the first instance, they open more research questions than they close. For example, what is the diagnostic impact of the discontinuous recording technique? For epilepsy diagnosis, what value for the sensitivity can be tolerated while still achieving acceptable diagnostic accuracy? With prolonged ambulatory monitoring will new signal patterns be observed? Alternatively, for BCI systems to control a computer game, how many electrodes are people really willing to wear? This links to the amount of setup time that people will tolerate and the likelihood of having one electrode fail, both of which will increase with the number of electrodes present.

These questions can only be answered in controlled experiments once wearable EEG systems are in place. The results will depend on the end electrode design used and the specifications of the EEG electronics. With such results, iterations on electrode design, electronic design, and algorithm design will all be likely possible. This will enable further miniaturization of the EEG unit.

In conclusion, Figure 9 illustrates the system that is required to implement wearable EEG, incorporating the signal processing block. By incorporating a low-power data selection unit, it is possible to turn off the high-power transmission unit, significantly reducing the system power. Any implemented algorithm will have to operate in real time and to allow a section of data from before and after any detection to be transmitted a memory buffer [Figure 9(b)] will be required. This is contrasted with Figure 10 that shows a standard recording electrode, a large coin cell battery, and the size of a typical unpackaged microchip, which would contain the input amplifier, signal processing, ADC, and transmission circuitry. A British 1 pence piece is included for scale, and it clearly illustrates what is achievable with wearable EEG.

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