# Chapter 2
# Electroencephalogram

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## 2.1 Introduction

The electroencephalogram (EEG) is a widely used non-invasive method for monitoring the brain. It is based upon placing metal electrodes on the scalp which measure the small electrical potentials that arise outside of the head due to neuronal action within the brain. Its key benefits compared to other brain imaging techniques are that it has a very high time resolution – able to track events within the brain with millisecond accuracy – and that it is in principle portable allowing real-world neuroimaging to be performed outside of clinical and lab environments. As a result it is a very widely used sensing modality for a range of health and wellbeing applications ranging from epilepsy diagnosis to emotional monitoring.

This chapter will overview the EEG: its set up, analysis and use. Section 2.2 discusses the principle of the EEG and how it is recorded and analysed, giving a practical getting started guide. Section 2.3 gives the technical details behind this set up, with significant attention given to overviewing the state of the art in the type of recorder and electrodes used. Section 2.4 then covers the typical applications where EEG is used today and discusses some of those which may become more common in the future as EEG systems become even smaller, easier to use and more robust to

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interference sources. The chapter concludes in Sect. 2.5 with a summary and potential future prospects.

## 2.2 Principle

### *2.2.1 Introduction*

To overview the EEG, it is first necessary to consider, at a high level, the origin of the signal within the brain, the set up of the recording instrumentation and the typical signals that are obtained. This section introduces these topics to give a general background to the more detailed considerations of different electrode and amplifier types that will be considered in Sect. 2.3.

### *2.2.2 EEG*

#### 2.2.2.1 Origin of EEG

The EEG was first carried out in 1929 by the German psychiatrist Hans Berger [1] and has a long history of development and use. At its core, the EEG is essentially the same as the well-known electrocardiogram (ECG) used for monitoring the heart, but applied to the head. In brief, brain activity is characterised by the passing of electrical impulses along neurones and postsynaptic responses as neurons communicate with one another. Electrodes attached to the head detect the cumulative electric fields associated with these impulses, and the potential differences produced can be amplified and stored giving characteristic representations of brain activity.

Research into the precise cerebral origin of EEG signals that manifest outside of the head is still ongoing [2–4]. It is clear that the brain has a large number of electrical sources present in it: each neuron has intrinsic electrical properties as action potentials are generated by voltage-gated ion-channels in the cellular membranes, and synapses operate based upon the flow of sodium and potassium ions. The scalp EEG is a very large-scale sum of this electrical activity from large populations of neurons and glial cells operating in synchrony and with volume conduction effects affecting the size of the brain area to be considered. For practical use, the EEG can be viewed as an emergent property of these populations and networks: a voltage waveform with its own characteristic shapes and properties appears on the scalp due to the neuronal action within the brain, and it is not necessary to consider the detailed cellular origins to make meaningful use of these EEG signals.

Nevertheless, substantial work has been carried out towards solving the *inverse problem*, that is, identifying electrical sources within the brain based upon the measured scalp signal [3]. As there are many more electrical sources than

measurements, this problem is ill-posed and has no unique solution unless additional constraints are applied. Commonly this is done by assuming a model whereby EEG activity is due to a finite number of electrical sources known as dipoles, and the inverse problem seeks to find the contribution of each dipole to the current EEG trace. Here each dipole is an electrical/mathematical construct to map the scalp EEG on to, rather than a biological construct giving precise insights into the underlying cellular level origin. When processing EEG signals (Sect. 2.2.4), many methods are based upon analysing the time-domain EEG collected on the scalp directly, while others are based upon estimating the dipoles and making use of these as the signal processing basis. Both are valid and common EEG analysis approaches.

#### 2.2.2.2 Typical Signals

The EEG signal that arises on the scalp is measured as a voltage in the time domain, with a wide number of potential signal morphologies present. Figure 2.1 shows some example waveforms, although a small number of examples could never capture the wide range of signals that are seen in practice. An atlas, giving many more examples, is available in [5]. In general, the EEG is not a *nice* looking signal. To the untrained eye, it often looks only like noise, and it takes significant experience for a human to be able to interpret anything beyond the coarse features that are present.

These features can be classified in multiple ways, with different methods being common depending on the field of application. Very common is to divide the EEG into *free-running*, *evoked* and *hybrid* components.

Free-running EEG is the brain activity that is present due to the normal operation of the brain. It is there, all of the time, as the brain is operating. This EEG is characterised by diving it into frequency bands, each given the name of a Greek letter:

- Delta: Activity at less than 4 Hz
- Theta: Activity between 4 and 8 Hz
- Alpha: Activity between 8 and 13 Hz
- Beta: Activity between 13 and 30 Hz
- Gamma: Activity over 30 Hz

An example of a single EEG trace broken down into these frequency bands is shown in Fig. 2.2, which illustrates how the different bands evolve over time.

An increase or decrease in the power present in a particular band at any point in time is then an indicator of the user's state. For example, when a user is restful and closes their eyes, a dominant alpha rhythm emerges at the back of the head over the occipital cortex. This is easily identified and is a common test used to check that the EEG is set up correctly. Alternatively, the process of falling asleep is associated with alpha activity being replaced by slower theta activity [6]. Many applications of EEG are based, at least in part, upon the tracking of these frequency bands over

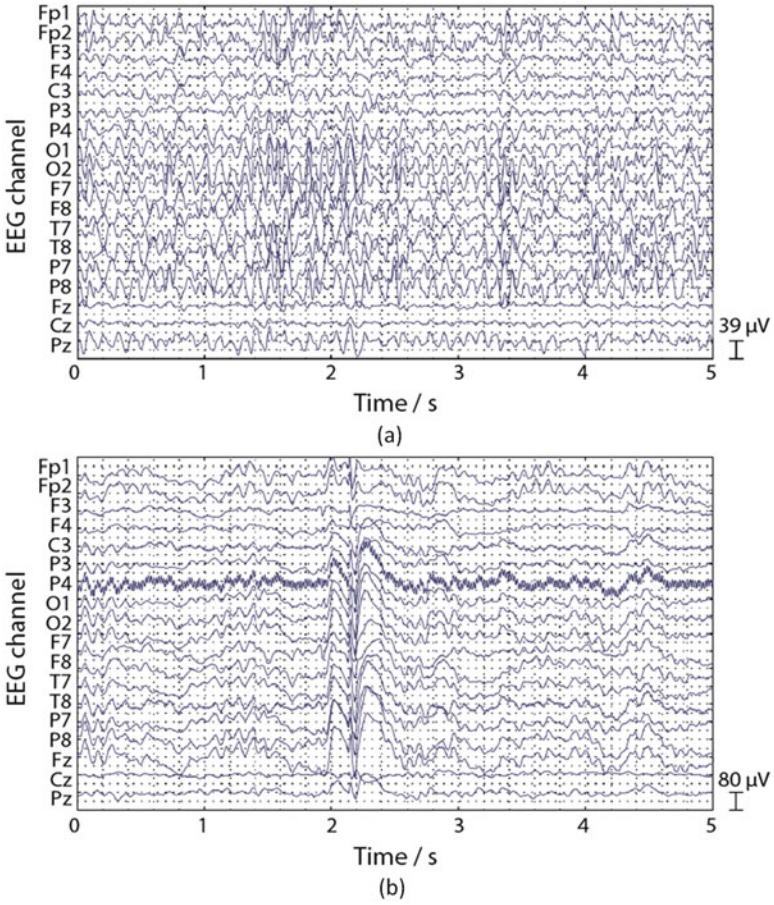


**Fig. 2.1** Examples of EEG signals. (**a**) Free-running background EEG. (**b**) An interictal spike, a feature suggestive of a person with epilepsy

time. Note that it is near universal to divide the EEG spectrum into these bands, but some EEG disciplines use slightly different frequency ranges [7] as the split points. Care should be taken to adhere to the standard practice in the precise application area.

Within free-running EEG there are then a number of features that occur due to different brain states which will be of interest for different applications. For example, Fig. 2.1b shows an *interictal spike*, which is a characteristic feature of epilepsy and can be used to help locate the epileptic foci within the brain. Focusing on epilepsy, a number of similar features can be identified:

- Spike: The spike is a classic example of epileptic activity, and its presence is useful for determining the focus of the epilepsy [8]. Spikes are defined as

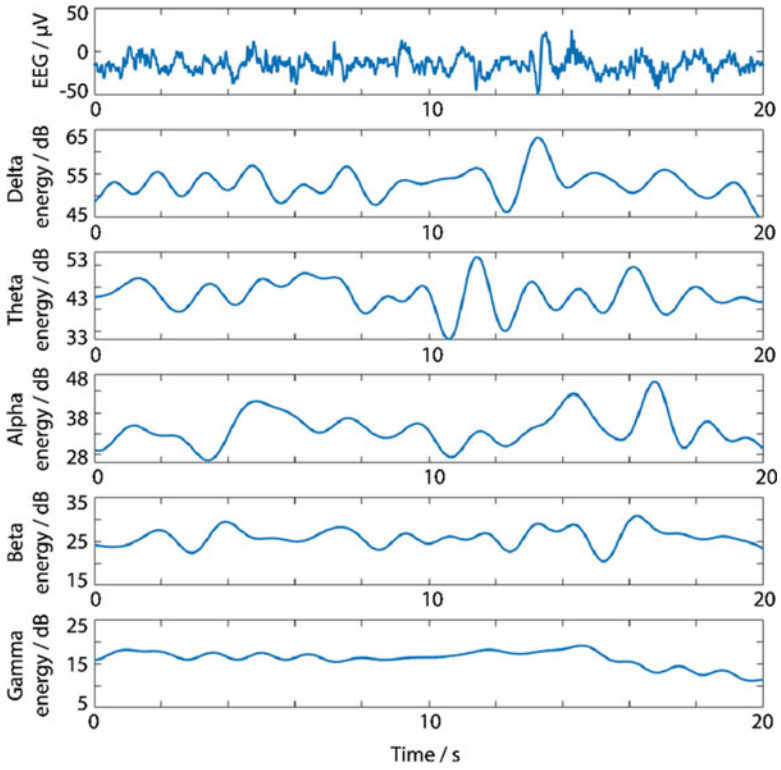


**Fig. 2.2** Example of EEG channel C4 broken down into frequency bands (using a $2^{11}$ point fast Fourier transform) and the tracking of the energy in each of these bands over time

"*transient*[s]*, clearly distinguished from background activity . . . [with] a duration from 20 to under 70 ms*" [9].

- Sharp wave: Sharp waves are similar to spikes but with a duration between 70 and 200 ms [9]. Generally, however, they are of less interest when interpreting EEGs as they provide less localising information [8].
- Spike-and-wave (spike-and-slow-wave): Here a spike is followed by a wave which has a duration of more than 125 ms [9].

These features, as is common for the EEG in general, can be highly variable. For example, based on these definitions [10] presented a detailed characterisation of 600 spikes in 120 EEG records from 100 people with epilepsy. Spike durations varied between 9 and 200 ms with a mean of 45 ms, and 98.3% of spikes had a peak-to-peak amplitude that was 30% or more above the average background amplitude from the preceding 500 ms. Further, different spike morphologies and durations were often seen in the same patient. The main component was negative in 88% of spikes, and no purely positive spikes were found.

Similar features can be identified for other medical conditions and brain states, most noticeably sleep analyses which are based upon identifying:

- Slow oscillations: A clear sub 1 Hz oscillation with negative going state, followed by an upwards going state that lasts for several hundred milliseconds [11].
- Sleep spindles: "*A burst at 11–15 Hz but mostly at 12–14 Hz generally diffuse but of high voltage over the central regions*" [9]. Generally split into fast and slow spindles depending on the peak frequency.
- K-complexes: "*A high voltage negative slow wave followed by a smaller positive slow wave frequency associated with a sleep spindle*" [9]. Noted to be variable in appearance and not due to external stimuli.

In contrast to free-running EEG, evoked EEG arises due to stimuli being presented to the user. For example, if a user concentrates on a flashing light at a particular frequency, that stimulus produces a steady-state visual-evoked potential (SSVEP) [12]. That is, an oscillation at the same frequency as the light source arises in the EEG at the back of the head. Similar steady-state responses can be found due to audio stimuli, in which case they are termed auditory steady-state responses (ASSR) [13]. These evoked responses form the fundamental basis of many brain–computer interfaces (BCIs). For example, if a screen has multiple light sources, each at a different frequency, it is possible to tell which source the user is focusing on as this will be the frequency of the resulting SSVEP. This information can then be used to control a cursor moving around the screen or to make a decision.

There are in fact a very wide number of evoked responses that are possible due to different forms of stimuli and experimental set ups. In addition to steady-state responses, also common are event-related potentials (ERPs) which arise due to the presentation of individual stimuli, with a gap present before a subsequent stimuli presentation. Below are some common ERPs:

- P100: elicited by using checkerboard (alternating black and white) stimulation
- N100: produced by the presence of an unexpected stimulus, particularly auditory, when no other task is being performed
- N170: elicited when a face is present in visual stimuli
- P300: produced by an *oddball* stimulation, that is, when looked-for uncommon stimuli are observed in a train of other stimuli
- N400: produced in response to the recognition of a face

All of these are named P, for a positive going deflection, or N, for a negative going deflection, together with a number which reflects approximately how long after the presentation of the stimuli the response is evoked (in milliseconds).

Not all of the possible ERPs will be present in every experiment, and the range of choices available gives a great deal of freedom for investigating different uses of EEG as a tool for understanding the brain (the precise shape/timing of ERPs is modulated by the current brain state) and for making BCIs. Figure 2.3 shows an example of evoked responses produced during a face detection task where the user was shown a series of pictures for 1 s, followed by 1 s pauses, with the picture randomly selected to be a recognisable face or static noise. A number of evoked responses can be seen. Here P100, N170 and P300 responses are present.

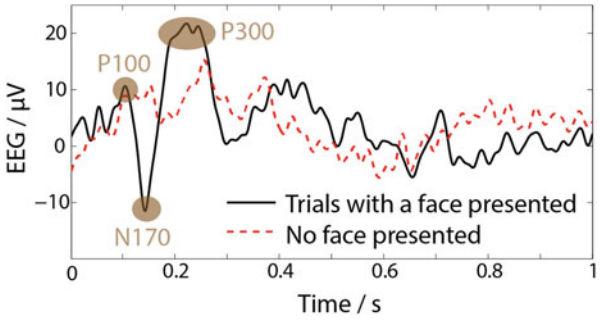


**Fig. 2.3** Averaged evoked responses at electrode position P08 in a face detection task. A number of evoked responses are seen compared to a control case where no faces are included in the visual presentations. The responses are named after their approximate timings, although these can be highly variable

For making use of such signals, it is important to note that while steady-state responses are large in amplitude (particularly in the frequency domain), other evoked responses are often very small. Indeed they can be below the noise floor of the EEG electrode and amplifier and so are not directly observable in the time domain. To extract the responses, time-locked averaging is used: in an experiment the time of each stimuli presentation is known, and this is used to cut the signal into multiple trials which can be aligned at the stimulation time and averaged together. As noise present in the system is uncorrelated between trials, it will average to zero, while the evoked response is present in all trials and will be maintained. The more trials and averages that are taken, the better the response extraction, at the cost of speed. For example, if each stimulus/trial must be separated by 1 s to allow all of the ERPs that it produces to have finished, only 1 in 3 trials randomly includes the wanted target stimuli, and 10 averages are required to robustly extract the presence of an evoked response; it takes 30 s to extract one piece of information. Lots of research effort has been invested in reliably detecting responses from a single trial and similar methods to speed up the paradigm. In addition, evoked responses are highly variable. The typical amplitudes and precise timings of evoked responses are different between different people and vary within the same person, for example, with age and a number of other factors [14]. There is also evidence that not all people reliably generate detectable evoked responses, either due to their individual variability or an incorrect use of the equipment set up [15].

The last class of data, hybrid EEG, is between the above two cases. No direct stimuli are presented to the user, but they are asked to think of something or imagine performing an action. This can then result in known signal morphologies arising in the EEG. The best known such signal is associated with motor imagery: when a user is asked to imagine performing a hand movement, EEG activity at 8–12 and 18–26 Hz decreases over the motor cortex (around electrode positions C3 and C4), and there is an *event-related desynchronization* [16]. This is illustrated in Fig. 2.4 which shows the event-related desynchronization associated with imagined

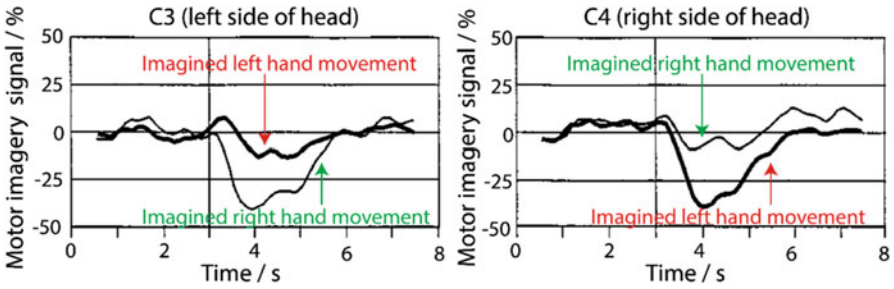


**Fig. 2.4** Imagined left and right hand movements show event-related desynchronizations (defined in [105]) on the side of the head opposite to the imagined movement. This can be used as the basis of a BCI where a user is asked to imagine different movements in order to invoke different commands from a computer (Image adapted from [105])

left and right hand movements on the different sides of the head. This and similar hybrid tasks form the basis of many BCIs.

## *2.2.3 Measurement*

### 2.2.3.1 Basic Set Up

Typical signals detected by scalp-mounted electrodes are in the range 1–150 μV over a 0.1–60 Hz bandwidth, although some higher frequency content may also be present [8, 17]. The signals vary both temporally and spatially, and so multiple electrodes are typically used. Electrode positions are determined using the 10–20 standard, so named as distances between electrodes are measured as being 10% or 20% of the skull dimensions, as illustrated in Fig. 2.5. Electrode letters correspond to their position on the skull, with odd number electrodes being on the left hemisphere and even ones on the right. A 10% system is described in [18] and can be used in situations when further electrode positions are required to get more coverage over the head. Smaller subdivisions are also possible for when a very large number of electrodes are used.

A pair of electrodes is required in order to obtain a voltage potential difference, and each pair of electrodes is thus connected to an amplifier. After suitable amplification and bandwidth limiting, the signals are stored in a suitable location. In older devices an analogue signal was stored on a magnetic tape or written out by a pen writer [8]. Modern devices digitise the signals allowing them to be stored, wirelessly transmitted or analysed in real time as desired for the particular application.

At this point, it is important to note that a wide number of variants on this core set up are available, and sometimes also referred to as the EEG. For example, semi-invasive electrodes placed not on the scalp, but under it, above the bones of the skull, have been proposed as an approach for very long-term recordings performed

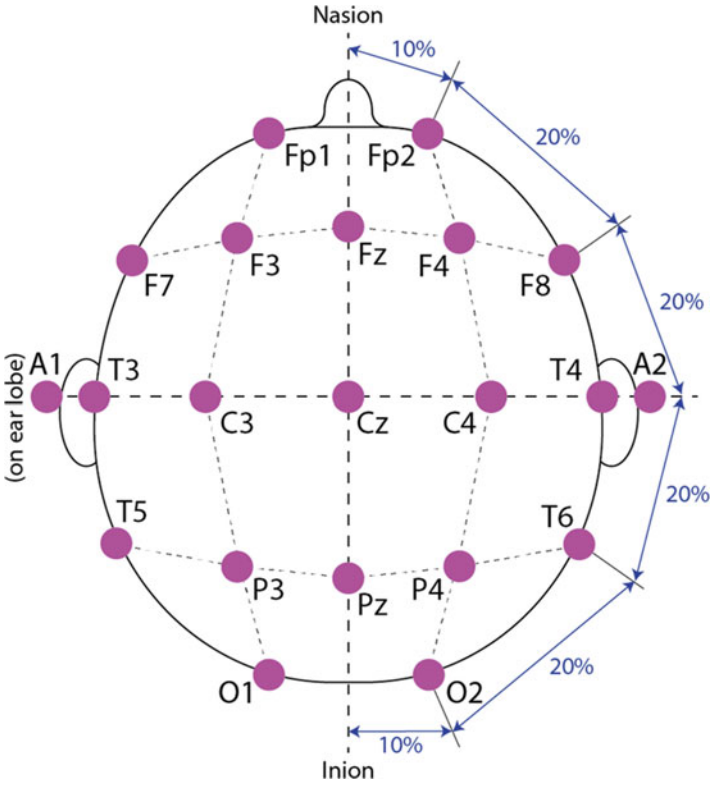


**Fig. 2.5** The standard 10–20 electrode system for electrode placement and names

in intensive care units [19]. Similarly, the Electrocorticogram (ECoG) [2] is sometimes referred to as depth EEG (DEEG) or incorrectly as simply EEG [9]. The ECoG uses similar recording principles to the EEG but with electrodes placed invasively inside the head typically directly on the surface of the brain. Depth recordings, where microneedle electrodes penetrate the brain, are also possible. The skull tends to act as a low-pass filter, and ECoG and depth recordings show much higher frequency and higher amplitude content along with different artefacts and a higher level of source localisation compared to scalp EEG [8]. As a result the instrumentation and signal processing requirements for the two situations are very different, and techniques cannot necessarily be used in both domains. Due to its invasive nature, the ECoG is not suitable for use in most situations, except in the most severe of cases. In this chapter we focus on technologies for non-invasive scalp-based EEG recording.

#### 2.2.3.2 Practical Set Up

Although a wide range of choices are available when performing a modern EEG recording, the conventional set up that first comes to mind when discussing the EEG is shown in Fig. 2.6a. This illustrates a user with a head cap on which has holes to hold a number electrodes next to the scalp. Each electrode has a long wire which allows it to be connected to recording instrumentation. On each electrode a conductive gel is placed in order to ensure that a good contact is made between the metal of the electrode and the scalp, and a close-up view of this is shown in Fig. 2.6b. In conventional EEG this gel is critical to getting a good electrical contact with the head, and it can act as a mechanical buffer to ensure that the connection is maintained even during and after head movements.

Figure 2.7 then illustrates a conceptual set up of EEG recording instrumentation. Electrodes placed on the scalp detect a small electric signal which is amplified and stored. A differential architecture is used to remove common-mode interference signals which may couple to the (potentially) long wires coming from the head, and an explicit ground or driven right leg electrode (as with the ECG, see [20]) is used to further suppress common-mode interference. A recording from a pair of electrodes forms one EEG *channel*, and different *montages* are possible depending on which electrodes are used. For example, in a referential montage, the second input to the differential amplifier is the same for all of the channels, whereas in a bipolar montage, electrodes are connected in chains (so channels are formed as electrode 1–electrode 2, electrode 2–electrode 3 and so on).

Modern set ups favour referential recordings as this allows any desired other montage to be derived offline by software [21]. For clinical-grade recordings, equipment recommendations from the International Federation of Clinical Neurophysiology for digital EEG recording are given in [21] and summarised in Table 2.1.

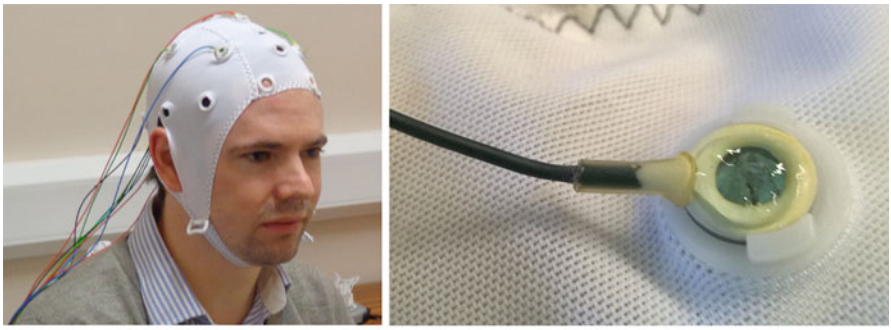


**Fig. 2.6** (**a**) A conventional EEG set up with metal electrodes on the scalp held in place by a cap. Long wires connect them to recording instrumentation. (**b**) Close-up of an electrode making contact with skin via a conductive gel

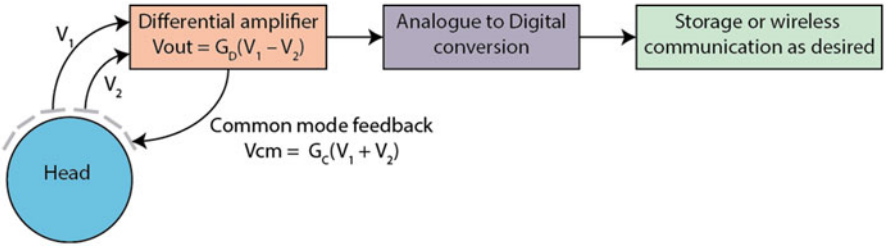


**Fig. 2.7** A simplified overview of an EEG set up: recording electrodes are attached to a differential amplifier which is connected to a storage medium. In traditional systems this medium was a pen writer. In modern systems it is an analogue-to-digital converter and on-board memory or wireless transmitter

**Table 2.1** Summarised standards for clinical-grade digital EEG recording from [21]

| | |
|---|---|
| At least 24 channels, preferably 32 | Interchannel crosstalk less than 1% (40 dB down or better) |
| At least 12 bit analogue-to-digital conversion with a minimum resolution of 0.5 μV | 70 Hz, 40 dB per decade, anti-aliasing filter required |
| Minimum sampling rate 200 Hz, preferably higher | Recording noise not more than 1.5 μVpp or 0.5 μVrms |
| High pass filtering at 0.16 Hz or less | Common-mode rejection ratio 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 re-montaging |
| Electrode impedances below 5 kΩ | Amplifier impedances over 100 MΩ |

## *2.2.4 Signal Processing and Data Analysis*

### 2.2.4.1 Overview

Analyses of EEG for medical applications are very much based upon a human scrolling through the collected data to identify and differentiate points that are of interest. However, the EEG is a very small signal which can be hard to collect, is often subject to substantial interference (particularly artefacts due to motion) and can be difficult to interpret reliably even by a human. For example, in EEG-based epilepsy diagnosis, when experts are asked to mark candidate epileptic events in the same EEG recording, they will often mark noticeably different sections, with agreement ranging from 0% to 90% of the time [22]. As a result there has been very substantial interest in applying signal processing to automate the many different analyses of EEG data that are possible. It is an ongoing task with much research activity in this area today. The aims and benefits are generally:

- To speed up analysis compared to needing a human to look at all of the data
- To increase accuracy compared to human interpreters who may overlook features of interest

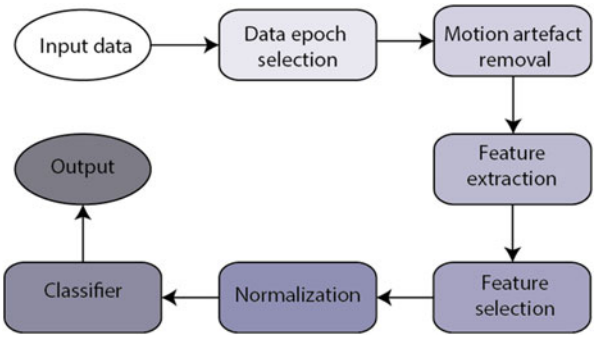


**Fig. 2.8** Basic EEG signal processing begins by selecting the data section of interest and cleaning the EEG to remove interference and artefacts, followed by feature extraction, normalisation and classification to make a decision based upon the data

- To disambiguate analysis, giving a single justifiable interpretation of an EEG trace and removing scope for debate
- To enable new applications, such as BCIs which do not require a human to interpret data, and would be infeasible to have responsive systems, or ones based on difficult to calculate measures, if human analyses were required
- To give novice users access to EEG technology without having to spend several years becoming familiar with the wide range of signal morphologies that are present

The short summary of EEG signal processing is thus that: if you name a signal processing approach, it has almost certainly been applied to the analysis of EEG signals at some point. As a result it is very difficult to concisely summarise the wide state of the art available in this area. Nevertheless, although many variants are possible for different application set ups, Fig. 2.8 gives a brief overview of the standard signal processing flow that is applied. Below we give a general overview of these steps, without going into large numbers of variations or into mathematical details which are very well summarised in [23] for the interested reader.

#### 2.2.4.2 Motion Artefact Removal

The first step is in ensuring that high-quality EEG data, as far as possible, is the input to the signal processing chain. Figure 2.9 shows a *worse case example* set of traces in the presence of bad electrode connections and motion artefacts. Essentially no information of physiological origin is present in the signal, and so it is not meaningful to process this directly. In the worst cases, such sections of data are simply discarded from the analysis. A key aim of longitudinal EEG analysis is to collect sufficient data to allow the required insights into the brain to be obtained, even if large sections of data must be removed due to such artefacts. Motion artefacts can be minimised at the data collection stage by ensuring that the electrodes are correctly and well connected to the head and that any wires are kept short in length and not allowed to move freely.

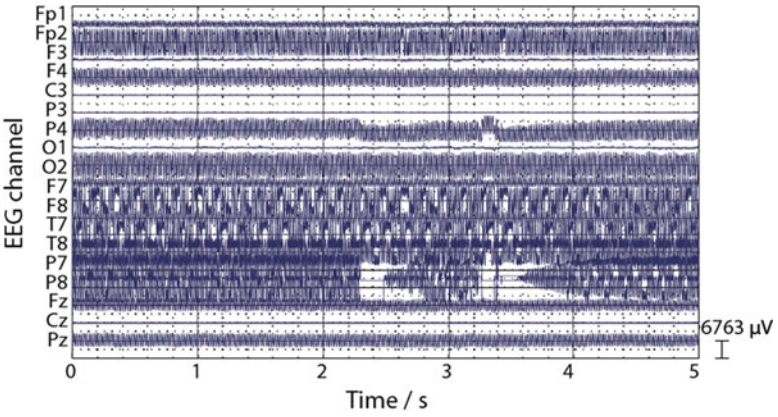


**Fig. 2.9** Examples of EEG signal artefacts caused by bad electrode contacts which mean large amounts of mains (50/60 Hz) and motion interference are collected. Note the change in scale compared to Fig. 2.1

For other sections of data, it is possible to remove motion interference algorithmically. Most approaches for removing such interference, and recovering *clean* EEG underneath artefacts, are based upon signal decomposition techniques such as independent component analysis (ICA) and principal component analysis (PCA) [23]. ICA is particularly popular and implemented in the widely used EEGlab toolbox for Matlab [24] which allows artefact removal to be performed without having to be involved with the full mathematical details. ICA assumes that the EEG signals are made up of a number of non-Gaussian signal components which are also statistically independent of one another. ICA finds these signal components, and it is then the case that artefacts, which are statistically very dissimilar to true EEG components, dominate only one or two of the components. The contaminated components can thus be discarded, and analysis continued with the remaining components or a time domain *cleaned* EEG trace reconstructed by performing an inverse procedure with the reduced number of components.

Such ICA-based cleaning can be very successful, and a number of groups have now demonstrated the recording of evoked potentials, below the free-running EEG noise floor, while subjects are walking on a treadmill [25, 26]. The walking speeds used in such experiments tend to be slower than real-world walking but demonstrate substantial potential for use in rehabilitation applications. EEG during cycling has also been demonstrated [27, 28].

The limitation of ICA- and PCA-based approaches is that their mathematical conditioning is dependent on the number of EEG channels present. Generally, around 20 channels are regarded as the minimum required in order to get good decomposition performance. (Note that there are only 18 channels in Fig. 2.9.) Many computational neuroscience studies use 64 or more channels as a standard. For lower channel count measurements, of interest in wearable and quick to set up situations, the use of empirical mode decomposition has been proposed [29] to

artificially increase the number of inputs that can be passed to ICA. However such efforts are still very much at the research stage.

#### 2.2.4.3 Data-Driven Machine Learning

Given the EEG input, the remaining steps in Fig. 2.8 are the same as those used in many data-driven machine learning approaches. The end aim is to use a classifier, whether a support vector machine, artificial neural network, k-means-clustering or other method (potentially a simple threshold) to make an end decision about the current window of data being analysed. This might be to indicate the presence of an evoked response or to classify a section of data as being associated with a high workload or a low workload or reporting the current sleep stage. To do this a number of features are calculated from the data. That is, signal processing is applied to emphasise the points of interest in the signal to increase the discrimination between these points and other *uninteresting* data sections. The list of potential features and feature extraction methods is essentially limited only by the algorithm designer's imagination and will be very particular to the precise application being pursued. A list of 65 such features is given in [30], and it is also recognised that non-linear mathematics can provide many methods for discriminating points of interest from background EEG and residual artefacts [31].

Within this wide array of choices, for completeness it is important to briefly mention here the three common groupings. Firstly, time–frequency features remain a very common basis. This allows the extraction of EEG frequency bands (Sect. 2.2.2.2), which are directly used in many applications. The standard fast Fourier transform (discrete Fourier transform) is commonly applied for this, although it is recognised that the EEG is nonstationary: the frequencies present in the signal evolve other time rather than always being present as is assumed with the Fourier transform. Approaches such as the wavelet transform [32] which overcome this have thus been explored extensively. Secondly, ICA can be used to calculate the EEG dipoles used as source models for the EEG voltages [33] (Sect. 2.2.2.2) and this domain used as the signal processing basis rather than the time or time–frequency domain. Thirdly, methods based upon common spatial patterns (CSP) are becoming very common for motor imagery brain–computer interface applications. The common spatial pattern approach weights different electrodes such that the variances of the resulting time series are optimal for discriminating between patterns, with each electrode contributing depending on its importance to the end classification task [16, 34]. It is one of the key methodologies behind recent advances in robust motor imagery-based control, particularly of drones [35, 36].

#### 2.2.4.4 Performance Assessment

Finally, attention must be given to the performance assessment methodologies for EEG signal processing. Applying signal processing to the EEG is straight forwards.

Proving that the signal processing operates as expected and that the reported level of performance is accurate and repeatable is much more challenging. This is most keenly seen in epilepsy feature detection applications, which due to their substantial personal and economic burden were some of the first clinical EEG interpretation areas to have signal processing applied, going back to the 1970s [37]. However, despite over 40 years of substantial work, and thousands of academic papers investigating all manner of different signal processing bases, many with *performances* in excess of 90%, it is widely recognised that few clinical groups routinely use such algorithms as part of their care procedures. Similar statements can be made for automatic sleep staging and other clinical applications of EEG signal processing.

Robustly, repeatably and believably reporting the performance of different algorithms is extremely challenging due to the wide number of factors that affect EEG traces. Age significantly affects the EEG amplitude [38]; EEG changes with tiredness and with alcohol consumption and with different medications, amongst other factors [39]. As a result the EEG is autocorrelated with itself in time, and signal processing features can have very different statistical distributions depending on which recording session they are collected from [40]. Controlling for all possible factors that affect the EEG is not possible in small-scale developmental studies, and this can lead to an overestimation of the performance when the developed signal processing is applied to new *unseen* data sets. Robust methodologies are application specific, and best practices have been reported elsewhere [39]. Here, it is sufficient to note that equal attention must be given to both the signal processing development and to the performance verification strategy used. Works which overlook the importance of performance assessment methodology are unlikely to produce results which are generalizable to EEG data beyond that used in the current specific study.

### 2.2.5 Summary

This section has given a brief introduction to EEG technology, the typical waveforms that are encountered and how they are processed. A wide number of choices are available. The next section investigates some of these choices in more detail, particularly with regard to the advances in wearability of the EEG sensing equipment.

## 2.3 Modality of Measurement

### *2.3.1 Introduction*

Section 2.2 demonstrated that EEG hardware has a long history – nearly 100 years of technological development. The result is that a wide number of choices are available for EEG experiments today in terms of both the electrodes, which are critical for signal quality and user comfort, and the recording hardware. In general there is no one *perfect* EEG system that gives the optimal set up for all situations and applications. Rather, there is always a trade-off required between the number of channels, wearability, ease of set up, data quality and similar. This section introduces the state of the art in seamless EEG monitoring informing such trade-off decisions, focusing particularly on the EEG electrodes, how they attach to the scalp and the EEG instrumentation.

### *2.3.2 Electrodes*

The choice of EEG electrode is critical for obtaining good-quality EEG signals. The EEG is very low amplitude, easily corrupted by noise, and without good-quality electrodes and set up to connect them well to the head, it is very difficult to obtain high-quality data. Today, there are three main types of electrode available: passive wet, active and dry.

Figure 2.10 shows a classical, passive wet, EEG electrode in disposable (Fig. 2.10a) and reusable (Fig. 2.10b) forms. Both are very commonly used, with the choice determined by whether it is economically worthwhile to spend time cleaning and sterilising the electrodes after use. Figure 2.10c gives the equivalent electrical circuit. In many ways these electrodes are unchanged from the early days of EEG recording: they are a piece of metal attached to a long wire. There is a hole in the centre of the electrode (or a cup) to allow a conductive gel to be added which ensures a conductive path is made between the electrode metal and the scalp. Passive electrodes such as these are very commonly used today and remain the gold standard in clinical use and in many research labs.

Many conductive materials can be used for the electrodes in order to fundamentally carry out a recording [41], although these all have different properties in terms of contact noise, long-term drift and similar. The passive electrode is a transducer which converts ionic currents coming from the human body into electron currents that can be measured by conventional electronics. In Fig. 2.10c, $V_{hc}$ represents the half-cell potential of the electrode, which is a function of the material used and which occurs in the presence of charge carriers (ions) concentrated at the electrode–electrolyte interface and which introduces noise and a long-term drift in the recorded potentials [42]. In Fig. 2.10c, $R_i$ and $C_i$ are parameters which determine

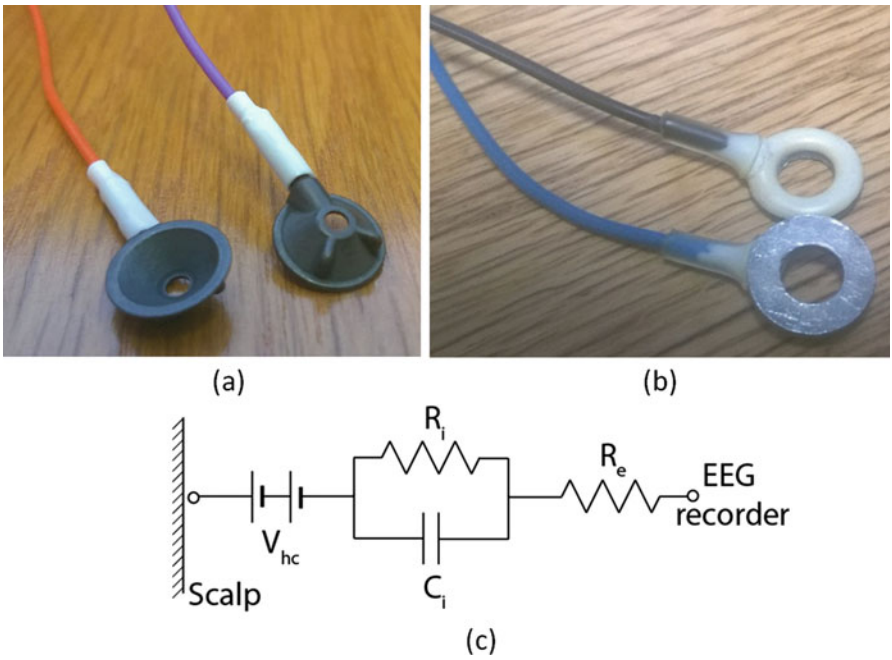


**Fig. 2.10** Silver/silver chloride (Ag/AgCl) passive wet EEG electrodes. (**a**) Disposable. (**b**) Reusable. (**c**) Equivalent electrical circuit

the impedance of the electrode–electrolyte interface, and $R_e$ is the material resistance of the electrode.

Although other materials are used, silver/silver chloride (Ag/AgCl) electrodes are the most common due to their excellent performance in practice. They have a very low half-cell potential resulting in better drift and noise performance at DC and low frequency measurements and are nonpolarisable. Polarisation is an undesired effect which occurs when there is a build-up of charge carriers at the electrode–electrolyte interface which acts as an insulating barrier such that current is no longer able to pass and reduces the long-term stability of the electrode interface. Typical electrodes are about 1 cm in diameter, with the electrode contact noise being inversely proportional to the electrode diameter [43].

Key to good operation of passive electrodes is to ensure that the contact impedance between the electrode and the scalp is low, always below 10 kΩ and ideally below 5 kΩ. Electrode set up is always done while monitoring the connection quality via an impedance metre, and different levels of hair parting, skin cleaning, top layer skin abrasion, adding gel and compacting gel to make good contact can be carried out to bring the impedance to an acceptable level. (See also Sect. 2.3.3.) Typically impedance measurements would be done at the start and end of an EEG recording to help confirm the electrodes have been attached throughout the data collection, noting that impedances typically fall after initial connection

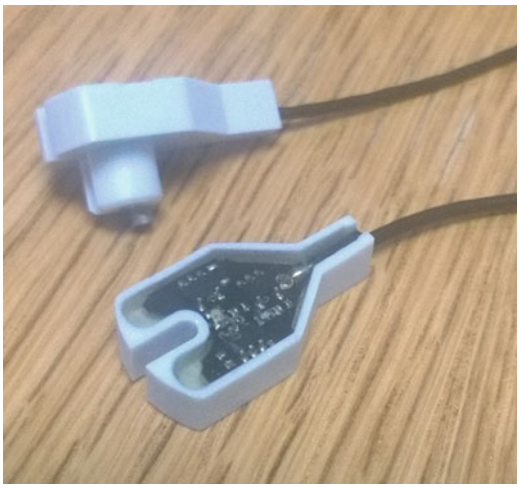

**Fig. 2.11** Active EEG electrodes where a buffer amplifier is placed immediately on top of the Ag/AgCl sensing contact

(as the half-cell chemical reaction stabilises) and then increase over time as the gel dries out and the electrode contact quality reduces.

Figure 2.11 shows the second electrode type: active electrodes. Here part of the instrumentation electronics, principally a buffer amplifier, is placed on top of the electrode itself. The obvious drawback is that it increases the electrode size and weight. However, it has the advantage of reducing mains interference and artefacts due to the movement of the recording wires. With the passive electrodes from Fig. 2.10, the entire cable is connected to the high input impedance amplifier input. These cables are long and can pick up a large amount of interference from the electrical mains. As the impedance is high, small amounts of picked-up current, essentially due to a loop area and the Biot Savart law, result in a large interference voltage as the cables move through the electrical field due to the mains. In contrast, if a buffer amplifier is included, the cable is connected to the low-output impedance buffer and the same amount of induced current produces a much smaller interfering voltage. The high impedance node between the amplifier and the electrode is made to be much shorter (just the height of the electrode) minimising the path for interference to be introduced.

A number of variants on this basic arrangement, varying the gain provided at the electrode in order to get the best trade-off between noise and power consumption, have been proposed [44]. These electrodes generally still require a gel to be added but much less than in the classical passive case as high-quality recordings can be obtained with such a set up even with impedances up to 40 kΩ present [45].

Figure 2.12 shows a selection of examples from the final electrode type: dry electrodes. These attempt to overcome the need to have a conductive gel present. Although very important for getting the best signal quality, this gel takes a long time to apply, leaves a mess, dries out over time and is highly unpopular with both users and researchers. There have been many attempts to make electrodes that do not require it, with academic papers dating back to at least 1994 [47]. Taheri et al.

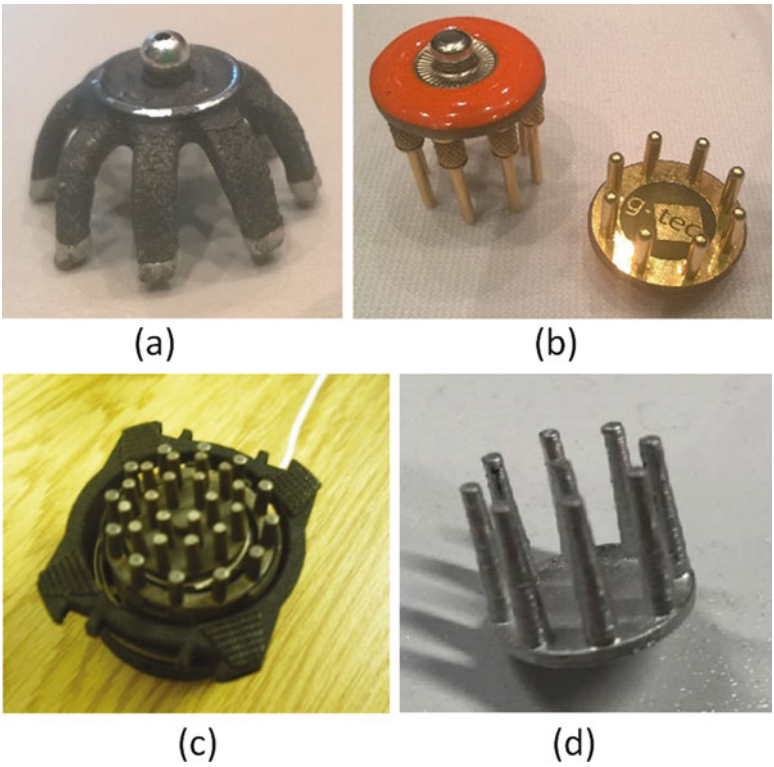


**Fig. 2.12** A selection of dry EEG electrodes which do not require a conductive gel to be present. (**a**) Cognionics (http://www.cognionics.com/). (**b**) g.tec (http://www.gtec.at/). (**c**) Wearable sensing (http://www.wearablesensing.com/). (**d**) 3D printed [46]

[47] presented a dry active electrode for EEG recordings based on a 3 mm steel disc coated with nitride on one side and an impedance-converting amplifier on the other.

The key challenge in designing dry EEG electrodes, without the gel bridge present, is that it is much more difficult to keep the electrodes in place and next to the scalp for long-term recordings. Most dry electrodes focus on having *fingers* as shown in Fig. 2.12 in order to better penetrate the hair and are attached to springs to help keep them in place. In addition, the electrode contact impedance is much higher, and this necessitates careful design of the EEG amplifier and PCB in order to avoid introducing contact noise and motion artefacts. Research into these factors is still ongoing [48]. Nevertheless, today in 2017, dry electrodes are available commercially from a number of suppliers and can also be 3D printed to allow easy access and personalisation for each individual [46]. Current designs can certainly be used to record EEG signals without requiring a gel but are unlikely to be the electrode of choice for when the highest-quality recordings are required. Part of the challenge is that there is little standardisation on how to characterise dry electrode properties [49], and direct comparisons between designs presented in

different papers are difficult to do accurately. A recent review comparing different types of dry EEG electrode is given in [50].

### 2.3.3 *Electrode Attachments to the Scalp*

Most overviews of EEG electrodes focus on the choices given in Sect. 2.3.2, that is, the choice of gel [41], the electrode material, whether a buffer amplifier is included and the physical arrangement of fingers in dry electrodes. Equally important however is to give attention to the scalp preparation and how the electrode is physically held in place. Many poorer electrodes can get better performance simply by pressing them against the body more forcefully, at the obvious cost of comfort. It is not a large area of investigation, and it is more that each lab has its own internal style which works for them. Nevertheless, several choices exist.

For long-term clinical-grade recordings, typically up to 24 h in a single session, electrodes can be glued in place using collodion. This gives a very high-quality electrode contact, which is relatively inconspicuous for portable use, but one which is very difficult and uncomfortable to remove. A tape measure and head crayon are used to work out the 10% and 20% positions on the head (see Fig. 2.5), a mark is placed on the scalp and the electrode placed over this before applying the gel and glue.

More commonly in research set ups, as shown in Fig. 2.6, an electrode cap is used. Such caps are quick and easy to use and have predefined holes to place each electrode accurately. Many different sizes and cuts of cap are available to account for different people/head sizes, head shapes and ethnicities. However, in many cases the cap will not be fully flush with the head in every place, instead having an area that *bags* away from the scalp due to excess material or hair being present. Electrodes in these areas are not held against the scalp, and it can be very difficult to get the electrodes to connect in these regions. The caps also tend to be limited to a few hours of recording time as the tight chin strap becomes uncomfortable, and the caps are prone to slight movements that disconnect the electrodes.

An alternative to these approaches is to use a conductive gel which is also adhesive, such as Grass Technologies EC2 [51]. Typically a cap is used to mark the electrode locations on the head, and then removed, and the EC2 doubles up as the conductive recording gel and adhesive. This takes more skill to administer than a plain cap, but can give very good results, and in our lab is the preferred choice unless there is a particular reason to use a cap.

As will be seen in Sect. 2.3.4, EEG units are also becoming increasingly available as headsets (see Fig. 2.13) as predefined sizes with plastic arms extending to different parts of the head from a central electronics housing. These headsets have the advantage of being more aesthetically pleasing, not covering the entire head, and being more comfortable than caps as no chin strap is required. Nearly all modern wearable units take this approach. The downside is that, while the arms are designed to be flexible in order to accommodate different head sizes and shapes, on

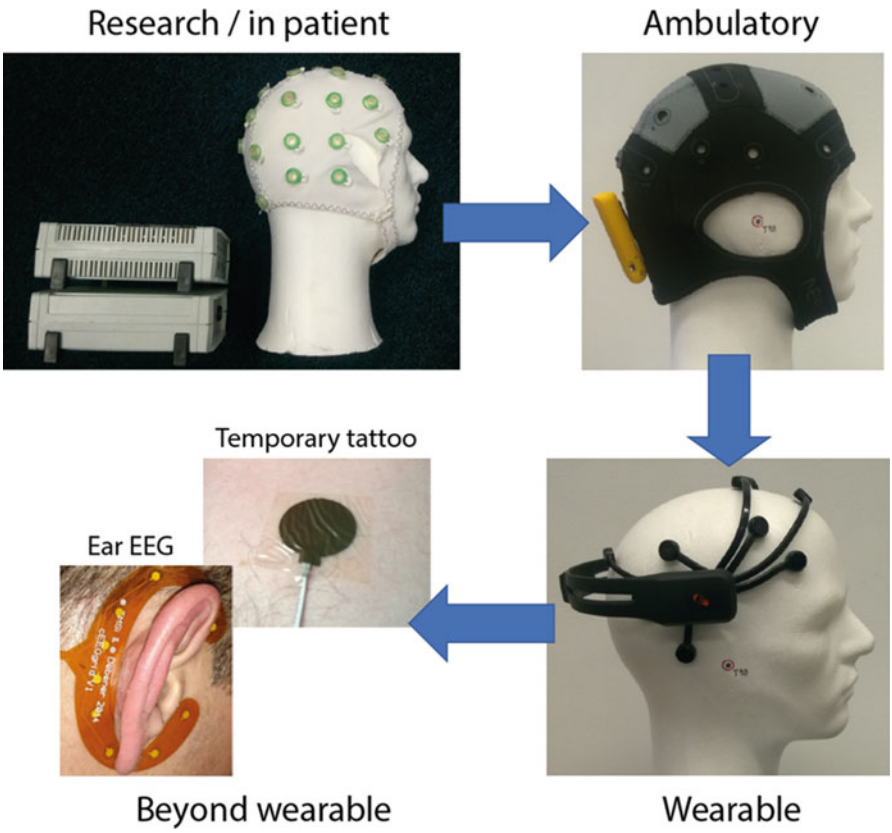


**Fig. 2.13** An overview of EEG modalities, with reducing size and increased portability (Ear-EEG picture originally from [52])

any one person it can be very difficult to get all of the arms to actually contact all of the parts of the head at the same time. In some cases it can be extremely difficult to get all of the electrodes to connect with the scalp.

For all of the above, for good-quality recordings scalp preparation is key. It is possible to put a unit on and then adjust and adjust the electrodes to eventually get a good contact. However, this takes a significant amount of time, experimenter skill and cooperation from the user. It is much better to prepare the scalp first. A simple cleaning of the scalp under each electrode location with a q-tip and mild alcoholic rub will drastically improve the connection quality, reduce impedance and reduce the set up time. The same can be said for parting the hair in advance. For most hair types, this is easily achieved using a q-tip, and the aim should be for electrodes to make contact with the scalp directly, rather than for them to sit on top of the hair with a large layer of gel going through to the scalp.

## 2.3.4 Instrumentation

### 2.3.4.1 Overview

Figure 2.13 shows the evolution of EEG instrumentation hardware from large research lab/inpatient units to highly miniaturised wearable units and research based units that go beyond current wearables in order to increase the invisibleness of EEG devices. Each of the steps in this evolution is discussed in detail below.

### 2.3.4.2 Research Lab/Inpatient

Inpatient units are large, and non-portable, but very high quality and flexible in their use. They can be used for anything from a standard short EEG test for clinical use which lasts between 20 and 30 min [53], up to a few hours for experiments in a research laboratory, to overnight in the case of sleep study recordings and potentially up to several days for long-term inpatient monitoring [54]. However, this latter option requires considerable resources in a clinical setting and is not universally available [54].

These durations are dictated by the needs of the study and the willingness of participants to take part over the required duration. For example, in a 20–30 min EEG test for epilepsy, assessment indicative activity is shown by approximately 50% of people with epilepsy [55]. The yield can be increased to around 80% through the use of multiple tests. In sleep testing, daytime sleep tests are used, but generally diagnosis relies on a complete night of recording allowing the number and duration of sleep cycles and awakenings to be investigated.

The electrode set up is typically that given in Fig. 2.10, with long wires connecting the electrodes to an amplifier box, which is generally physically large. Modern systems commonly include video monitoring which allows the subject's behaviour and any clinical manifestations to be compared to the underlying EEG, very useful for interpreting the collected data. The key disadvantage of this approach is that the subject is essentially tethered to the amplifier and can only move within a very small distance of it. While the electrodes might be temporarily disconnected from the amplifier to allow the user to use the toilet and similar, the room/location of the recordings is essentially fixed.

### 2.3.4.3 Ambulatory

Since the 1980s the miniaturisation of electronics has allowed all of the EEG instrumentation to be put into a portable unit, allowing subjects to move about while being recorded and so not being required to stay immediately next to an amplifier box. This method is known as ambulatory EEG (AEEG). A typical modern unit is shown in Fig. 2.13, and this might be worn on the back of the

head or on a belt lower down the body. Originally, only a few EEG channels (3–4) would be recorded on to a cassette tape [56]. Today's units use solid state memory, potentially with real-time wireless transmission of the data. They are readily available with high channel counts, with some compromises to maintain battery life, but negligible reduction in data quality compared to using an inpatient system. The main limitation is that they have fewer auxiliary ports for trigger inputs for synchronisation, simultaneous video and similar simultaneous sensing of other modalities (e.g. heart rate) compared to inpatient units.

Clinically, the key advantage of AEEG is that it can be used as an outpatient monitoring arrangement, which is cheaper than inpatient monitoring. It is estimated that 24 h of ambulatory monitoring is more than 50% cheaper than 24 h of inpatient monitoring [54]. It also allows the patient to be monitored in their natural environment, of use for research studies where the subject might be biased by being in a lab environment that they are not familiar with. Overall in epilepsy it is estimated that AEEG is clinically useful in 75% of the patients it is used with, and abnormalities are found in 12–25% of AEEGs for which an inpatient EEG was normal or non-diagnostic [54]. This is despite the fact that AEEG recordings are likely to have more artefacts present, for example, due to motion, as the subject is in an uncontrolled environment. For most research studies which use an AEEG monitor, the subject would still be asked to be generally stationary. In addition, size, weight, portability and social acceptability remain as limiting factors.

#### 2.3.4.4 Wearable

Wearable EEG attempts to overcome the above limitations of AEEG and creates ever smaller and more discrete EEG units that are quick and easy to set up by non-trained users. There is no concrete line for when an ambulatory unit becomes a wearable one, [57] puts it as "*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*." A number of such units are now available commercially, as shown in Fig. 2.13 normally based upon using headsets with arms that wrap around the head, rather than needing a full head cap.

Generally the focus of wearable devices is on enabling real-world neuroimaging in places and situations where conventional EEG is just not possible. The focus is not to perform identical monitoring to that used for inpatient studies which need, and get, the very best data quality. Rather, often there is a requirement for the equipment to be set up by a non-specialist user or to be used in environments where lots of motion is present. Thus a focus might be given to low channel counts allowing quicker set ups and the collection of information at key points around the head, rather than a full head montage. There is also significant emphasis on ease of use, and a number of EEG units targeted at consumers are now available, for example, the Emotiv [58], Muse [59] and Neurosky [60] units, for performing general purpose EEG. For non-trained users working in specific applications, there

are also specialist units optimised for those applications, such as the Rythm headset [61] and Kokoon headphones [62] for consumer sleep monitoring. Many questions have been raised about the data quality from consumer-grade headsets such as these [63], but there is no doubt they have been very successful at giving easier, and lower cost, access to EEG monitoring. There is even a widely recognised open source initiative – OpenBCI [64] – to help make EEG technology widely and freely available.

#### 2.3.4.5 Beyond Wearables

Inevitably the wearable EEG devices available today still have a number of limitations [65], and research is ongoing to produce units that are even easier to put on, give better data quality with robustness to motion artefacts, have better battery life and more functionality and enable new applications for clinicians and lay users of EEG technology. There are two key directions in this continuing drive beyond current wearables.

Firstly, an emerging research direction is in making better use of EEG collected from non-haired regions on the head. As discussed in Sect. 2.3.3, getting electrodes attached through the hair is a challenging task. It is the key factor that slows down putting an EEG unit on and means that it can only be done by a trained person. In recent years it has been demonstrated that EEG components can be recorded from the forehead [66], behind the ear in locations covered by standard hearing aids [52] and from inside the ear canal [67]. Historically, many of these locations have been considered to be purely artefactual, and, for example, the mastoid behind the ear has been a common location for ground/reference electrodes as it is electrically very quiet compared to the rest of the head. Nevertheless, advances in signal processing have allowed information to be extracted from these locations. For example, [68] demonstrated ASSR measurements from in-ear electrodes. Locations such as around the ear are particularly promising as many people are already used to wearing hearing aids in these places, overcoming some of the social acceptability issues of placing electrodes in clearly visible locations on the head.

Secondly, the instrumentation electronics are becoming increasing miniaturised. A particularly promising research direction is that of temporary tattoos, as pioneered by the Rogers group at Northwestern University [69]. Unlike wearable devices, *conformal* temporary tattoo-based devices use very flexible, non-permanent, substrates similar to those given to children as rub on tattoos. These have in-built adhesive to connect directly to the skin without requiring a gel, cap or similar. The result is that the tattoos maintain a high-quality connection to the body for many days at a time, and because they are highly flexible, they can follow the contours of the skin and get a much larger contact area compared to a bulk metal electrode. This gives better quality signals and maintains signal-to-noise ratios even at very small sensor sizes. As such they intrinsically overcome the limitations of wearable devices, giving better signal quality, longer-term connections to the body and a more discrete profile for better social acceptability. The

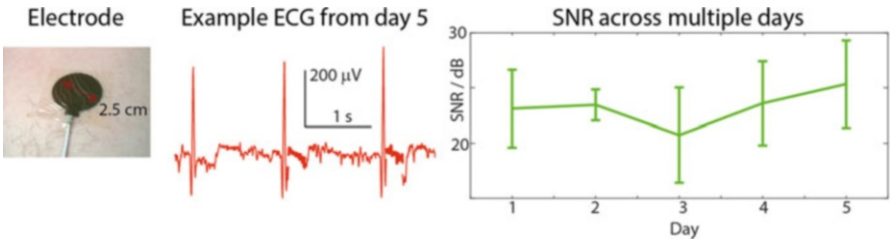


**Fig. 2.14** Example of a temporary tattoo electrode, in this case sized for heart monitoring via the ECG. In principle if placed on the head, it would record EEG. It shows that high signal-to-noise ratio (SNR) recordings can be performed over long periods (5 days here), unthinkable with other electrode techniques (Results originally reported in [71])

Rogers group has demonstrated EEG recordings from the forehead using this technology [69] and from the ear auricle [70]. In this latter case recordings were recorded for 2-week periods.

An example of our own work towards such long-term sensing is summarised in Fig. 2.14 which shows an example of a tattoo-based electrode. These are currently designed and applied for ECG monitoring of the heart but in principal can be used interchangeably on the chest for ECG and on the head for EEG. They were manufactured using an in-house process with three layers of electrically conductive silver nanoparticle paint, using similar procedures to [72] previously used for printing antennas [73]. The printing is done on temporary transfer tattoo paper which is commonly given to children, with excellent biocompatibility and longevity. After the paper backing material is removed, the printed metal electrode is left behind, stuck to the body by a very thin, approximately 10 µm, layer of plastic, which provides adhesion under the entire electrode surface, key to maintaining a good body contact. To date, for heart monitoring as shown in Fig. 2.14, these have been used for up to 5 days of recordings with high signal-to-noise ratios (SNRs) maintained throughout. They have yet to be applied for monitoring the EEG, but if the technology can be successfully mapped from heart monitoring (ECG), these electrodes offer the potential to make a step change in monitoring durations compared to current EEG methods.

However, at present, as with the forehead- and ear-EEG approaches, temporary tattoos are restricted to recording in hair-free parts of the head. While it is now clear that a lot of information can be extracted from these locations, it is unlikely that they could be suitable for all EEG applications, as many EEG applications are reliant on recordings from haired regions. For example, epilepsy diagnosis relies on recording a full head montage with electrodes in all locations in order to help localise the epileptic foci. Sleep staging analyses ask for at a minimum C3 and C4 [74], over the centre of the head. Brain–computer interfaces based upon visual stimuli rely on electrodes placed on the back of the head over the occipital (O) and parietal (P) electrode locations (see Fig. 2.5), while BCIs based on motor imagery place electrodes over the motor cortex (around electrode positions C3 and C4). For most people all of these locations are characterised by large amounts of hair being

present. Devising *beyond wearable* technologies for haired regions remains an open research challenge.

### 2.3.5 Summary

EEG systems have changed radically in recent years, from large non-portable systems to highly miniaturised ones that can be placed on or in the ear to give very inconspicuous EEG monitoring, with the aims of being more socially acceptable, quicker to set up and easier to use by non-specialists. This development enables a wide number of established and emerging EEG applications, which will be explored in Sect. 2.4.

## 2.4 Applications

### 2.4.1 Introduction

The EEG has a long history, predominately originating with clinical applications in epilepsy and sleep disorder diagnosis. Recent developments in cheap and portable EEG units have allowed the creation of *consumer neuroscience* applications for the first time where real-time insights into the current state of the brain can be used to enable a number of novel applications. This final section overviews the main current applications of EEG technology in and out of the lab.

### 2.4.2 Medical, Clinical and Neuroscience Research Applications

The EEG has its roots in medical instrumentation, and this is still the widest application domain for the technology today. This is based upon its potential for multi-hour recordings with high time resolutions. Sampling rates are typically between 200 and 1000 Hz which allows rare transient events such as epileptic seizures or sleep abnormalities to be captured in a way not possible with other brain imaging techniques such as MRI which may take several seconds per measurement.

Epilepsy is frequently described as the most common serious neurological condition [53, 75], although incidence (cases per year) and prevalence (total number of cases) figures vary considerably between different studies [75] (the discrepancies being attributed to inclusion criteria and the difficulty of diagnosis). In developed societies the overall incidence is around 50 cases per 100,000 people per year, and the prevalence rate is around 10 people per 1000 [75]. In the UK this

corresponds to approximately 96,000 people who require hospital-based treatment, of which 15,000 will have more than one major seizure a month, and 12,000 who may require institutional care [75]. In the USA, approximately 10% of the population experience a single seizure during their lifetime [54], and approximately two million people have the disorder with 100,000 new cases each year [76].

The commonly known aspects of epilepsy are undoubtedly the most dramatic ones: generalised seizures where the sufferer falls to the ground and has rhythmic, uncontrolled limb movements. This is often thought to be brought on by exposure to flashing lights (photosensitivity) which may arise from a disco or a standard TV or a computer game. This symptom is undoubtedly a part of epilepsy, but epilepsy is in fact a very broad area with many different aetiologies and manifestations. At a broad level epilepsy is defined as: "*A chronic condition characterised by a tendency to develop recurrent unprovoked seizures*" [53]. The most serious consequence of any disease is death, and epilepsy shows a mortality rate (the ratio of people with the disorder who die compared to the standard for the age group) of 5.1 in the first year following diagnosis [53]. This then falls to 3.1 after 5 years [53].

Overall, epilepsy can be very difficult to diagnose correctly, and the EEG is a key tool in the diagnosis process as seizures manifest with identifiable waveforms in the EEG, Fig. 2.15. A trained interpreter can assess these and use the information provided to inform the type of epilepsy that is present, and its origin within the brain. As noted in Sect. 2.2.4, although lots of effort has been invested in automating the detection of seizures, the sheer range of seizure morphologies and EEG variances that are possible mean that such automation remains an unresolved challenge. This is despite large disagreements between EEG interpreters when asked to analyse the same EEG section [22]. Importantly, it must always be remembered that the EEG will only be one part of the diagnostic picture, which will also include seizure diaries, family histories, blood tests and others [77]. As [78] recommends, care must be taken to not overweigh the contribution of any one

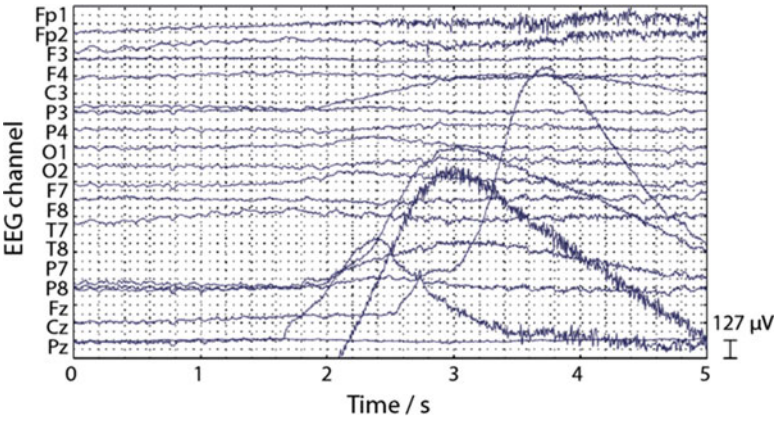


**Fig. 2.15** An example EEG morphology showing epileptic seizure onset as time 2 s

piece of evidence, and if diagnostic doubt remains, it is perhaps best to allow the passage of time [53]. The EEG is highly useful but not a panacea.

In sleep disorder diagnosis, the gold standard is to use polysomnography which records the EEG, heart rate, breathing rate, blood oxygenation and eye/leg movements during a full night of sleep. (Wearing all of these equipment does not make for a very comfortable night of sleep!) For analysis well-defined standards have been in place for many years [74, 79] for classifying the EEG data into different stages:

- Wake
- Stage one (sleep onset)
- Stage two
- Stage three/four (slow wave/deep sleep)
- REM (rapid eye movement) sleep
- Movement time

The EEG data is split into 30 s epochs, and the interpreter identifies features according to the scoring manual, and those defined in Sect. 2.2.2.2, to classify each epoch into one of the above stages. In healthy sleep a person cycles through the stages 3–4 times in one night, with cycles shortening in duration over the night. Deviations from this general pattern allow underlying pathologies to be investigated [80].

Closely linked to this is the automatic detection of sleep onset/drowsiness from the EEG. Reliable and robust detection and prediction of human drowsiness are of huge importance for reducing operator error and improving performance. For example, 20% of road accidents involving serious injury are sleep related [81], and these can potentially be avoided by detecting drowsiness and lapses of concentration and alerting the driver to these. Such drowsiness detection devices could also be of significant use in other safety critical situations, such as for pilots, power plant monitoring personnel and military personnel.

With the increasing availability and ease of use of EEG equipment discussed in Sect. 2.3, in recent years a wide number of other medical applications of EEG have begun to emerge. Particular examples are in brain–computer interfaces for prosthetic control [82] and stroke rehabilitation [83]. There is also increasing evidence that EEG biomarkers could indicate the development of mild cognitive impairment and dementia [84]. There are many brain-related disorders to which EEG neuroimaging could provide insights, although these have yet to become established clinical practice, and such wider use of EEG is expected to increase significantly in the medium-term future.

### *2.4.3 Brain–Computer Interfaces (BCIs)*

The most widely developed non-directly medical applications of EEG technology are in brain–computer interfaces, which allow the operation of a computer to be changed or adapted without having to use standard interfacing methods such as

mice, keyboards or voice. Works on such interfaces have been ongoing for over 25 years [85], and a wide number of different paradigms are available [86] making use of the different free-running, hybrid and evoked EEG features described in Sect. 2.2.2.2. Common methods include P300 spellers where the user is presented with a flashing grid of letters allowing them to enter words, SSVEP-based buttons where a number of images (e.g. arrows for directing a cursor) are presented flashing at different frequencies, and motor imagery where the user imagines a left arm movement to move a device to the left (and vice versa) [36]. This latter paradigm has obtained particularly good accuracy in recent years.

There are many applications of such BCI technology, particularly for assisting subjects who are paralysed and who might not be able to control a computer or a powered wheelchair using conventional interfaces [87]. The challenge in doing this is in ensuring that the developed systems are accurate, fit for purpose and actually codesigned with the targeted end users. It is now widely recognised that many BCIs are not developed in consultation with users and as such may not be representative of the needs and typical signals from the target user groups [88]. Instead systems are commonly designed with users who are young, healthy and easily available on University campuses. The potential benefits of BCIs for this user group are much more debatable. While there is undoubtedly a certain novelty in allowing devices, drones and similar to be controlled using only *thought*, as discussed in Sect. 2.2.2.2, many evoked responses are very slow which results in a slow information transfer rate. Although some high rates have been reported [89] in BCI keyboard applications, the typing rate is typically only a few characters per minute [90], and this is after having to take time to set up the EEG equipment, to train the signal processing classifiers for the current user/session and to deal with user complaints of discomfort/fatigue after long sessions [91]. It is difficult to imagine a heathy user with a range of computer input options available to them going to the effort of making current BCIs their preferred input choice.

Nevertheless, it is widely recognised that there is substantial potential in BCIs, and work is ongoing to identify "killer apps" which add meaningful value to the user by providing information which is not available through other routes. Real-time workload monitoring and classification are quickly emerging as one potential area, as it can be based upon free-running EEG allowing frequent update rates compared to using evoked responses, and it is difficult to estimate using other sensing methods. At the extreme fatigue end, sleep onset is characterised by a reduction in alpha activity, which is replaced by theta activity (Sect. 2.2.2.2). There are numerous papers (e.g. [40, 92, 93].) demonstrating that frequency band changes can be used to identify less extreme changes in vigilance level. This can then be used to detect when an operator is in a high or a low workload state to potentially change the speed at which information is presented. This allows the workflow and operating environment to be optimised in a real-time and time-varying manner [94]. It can also be used to enhance human training: the mental load of a new task can be objectively measured and training times increased or decreased to end the training only when the task involves a low level of effort [95].

### 2.4.4 Consumer Neuroscience

Finally, a wide number of out of the lab applications of EEG technology are currently in development as part of the trend towards personalised and preventative healthcare. Although to date the most successful wearable monitors have been "fitbit type" ones for activity monitoring and "Apple Watch type" ones for heart rate monitoring, these are only a very small subset of all the physiological parameters that may be of interest. The wearable EEG units discussed in Sect. 2.3.3 have enabled and encouraged a wide number of consumer driven applications, and the market for such neurotechnology is estimated to be worth over $13B by 2019 [96].

Such neurotechnology ranges from drowsiness detectors for car drivers mentioned in Sect. 2.4.2, to at home sleep monitors as mentioned in Sect. 2.3.4.3, to assisting with meditation [97]. In addition, considerable attention has been given to neuromarketing applications of the EEG as it potentially allows subconscious decision-making processes to be extracted [98], and this can be done in a portable way as a user moves around a shop. Many academic papers have shown that it is possible to extract correlates of emotion from the EEG band powers [99].

Most of these highly novel applications of EEG technology are still at the research stage. Critical to their wider take up is the believability of their results and outputs. Being based upon highly portable instrumentation and dry electrodes, while a subject is nonstationary for significant parts of the experiment, the EEG data quality is not the same as that obtained from traditional highly controlled inpatient recording set ups. This has to be compensated for with good testing methodologies (Sect. 2.2.4.4) or else it is easy to overstate results early on and lose credibility. As a nascent field, it is inevitable that some false starts will be present, and it is important that these do not undermine the creation of true "killer apps" which really exploit the latent impact that real-world neuroimaging would allow.

### 2.4.5 Summary

The EEG has its core applications in medical diagnoses of epilepsy and sleep disorders and in fundamental neuroscience experiments. Using new portable hardware, many different brain–computer interface and consumer neuroscience applications, for example, drowsiness detectors and neuromarketing, are now being investigated. The key challenge is in devising "killer apps" which are only possible because of the use of EEG, rather than applications where the EEG could be used, but does not add any real benefit compared to more easily available and useable approaches.

## 2.5 Conclusions and Future Prospects

The EEG is a very widely used technology for neuroimaging. It is unique amongst sensing methods in that it can monitor the brain portably, over a long period of time, and with a high time resolution for capturing rare and transient events. As a result it has seen substantial use in medical diagnoses and increasingly in out-of-the-lab brain monitoring. In recent years this has been driven by the creation of wearable EEG devices which are small, discrete and socially acceptable, and work is ongoing to create even more miniaturised devices which can record EEG signals from the ear, ear canal and forehead. Combined with advances in temporary tattoo structures for conformal electronics, there are now demonstrations of EEG recordings lasting up to 2 weeks at a time, a timeframe unthinkable a few years ago. Nevertheless, much work remains to demonstrate the ease of use, to quantify the sensing performance/noise of new electrode structures and to optimise such new approaches to EEG instrumentation. There are many emerging consumer neuroscience applications which will benefit from these technology developments. Drowsiness detection, emotion tracking and workload monitoring are just the start, and there is significant scope present for much innovation in the coming years.

Within medical environments the key future prospect is to move beyond simply monitoring the EEG and to making more use of it to enable real-time actuation and interventions. As with many current wearable sensors, the EEG measurement is presently a *one-way street* for data generation only. Next-generation EEG will focus on enabling *two-way streets* that both sense and actuate. These will provide data-driven feedback that leads to the right treatment at the right time and could minimise the amount of treatment required and make it timelier and more effective. Such *closed-loop data responsive treatments* are beginning to emerge, with adaptive deep brain stimulation systems for Parkinson's disease [100], closed-loop electrical stimulators for epilepsy [101] and GlaxoSmithKline recently making substantial investments in closed-loop non-pharmacological electroceuticals [102]. However, these current approaches are focused on implanted sensors, which have very different signal properties (larger, higher bandwidth, less noise) and interference sources (less motion, less 50 Hz pick-up, fewer nearby devices) compared to the scalp EEG.

Although effective, the costs and practicalities of surgery mean that implanted devices will inevitably be limited to a subset of the most serious cases, and there are many opportunities for similar, non-invasive devices to act as an intermediate between current pharmacological approaches and highly invasive surgery. Designing closed-loop interventions is incredibly challenging and presents regulatory hurdles but is a key future direction for EEG electrode and instrumentation research. For the EEG this most likely takes the form of transcranial electrical stimulation [103], which is based upon injecting currents into the head. It thus naturally complements the EEG which measures electrical voltages reflecting temporal changes in the electrical state of neurons and current flows, which are directly modulated when applying transcranial electrical stimulation. However,

present transcranial stimulation introduces significant artefacts into simultaneous EEG recordings, preventing neuroimaging at the same time as stimulation [104]. Work is ongoing to overcome these issues and move towards future closed-loop EEG systems.

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