Chapter 2

The Electroencephalogram—A Brief Background

The human brain is the most complex organic matter known to mankind and has, not surprisingly, been the subject of extended research. Its complexity has spurred multifaceted research in which brain functionality is explored from low-level chemical and molecular properties in individual neurons to high-level aspects such as memory and learning. An early discovery established that the brain is associated with the generation of electrical activity. Richard Caton had demonstrated already in 1875 that electrical signals in the microvolt range can be recorded on the cerebral cortex of rabbits and dogs. Several years later, Hans Berger recorded for the first time electrical "brain waves" by attaching electrodes to the human scalp; these waves displayed a time-varying, oscillating behavior that differed in shape from location to location on the scalp [1]. Berger made the interesting observation that brain waves differed not only between healthy subjects and subjects with certain neurological pathologies, but that the waves were equally dependent on the general mental state of the subject, e.g., whether the subject was in a state of attention, relaxation, or sleep.

The experiments conducted by Berger became the foundation of *electroencephalography*, later to become an important noninvasive clinical tool in better understanding the human brain and for diagnosing various functional brain disturbances. The clinical interpretation of the EEG has evolved into a discipline in its own right, where the human reader is challenged to draw conclusions based on the frequency, amplitude, morphology, and spatial distribution of the brain waves. So far, no single biological or mathematical model has been put forward which fully explains the diversity of EEG patterns, and, accordingly, EEG interpretation largely remains a phenomenological clinical discipline [2].

Visual scrutiny was for many years the sole approach to EEG interpretation but has today been supplemented by the capabilities offered by modern, powerful computers. The interpretation is significantly facilitated, although not even close to being fully automated, by an array of digital signal processing methods designed for a variety of purposes, e.g., improvement of SNR, quantification of various signal characteristics, and extraction of new information not readily available by visual inspection [3–5]. Signal processing methods can be divided into two general categories: methods developed for the analysis of spontaneous brain activity (the "background EEG"[1]) and brain potentials which are evoked by various sensory and cognitive stimuli (evoked potentials, EPs). While the former category of methods certainly has helped to gain a better understanding of the EEG, the analysis of EPs is critically dependent on the availability of signal processing techniques.

In recent years, the study of brain function has been revolutionized by the introduction of various imaging modalities: positron emission tomography (PET), single photon emission computed tomography (SPECT), and magnetic resonance imaging (MRI), which can produce two- or three-dimensional images with good spatial resolution. These modalities extend the information inferred from an electrophysiological investigation by providing detailed information on, e.g., anatomy and blood flow in different regions of the brain. As a result, the EEG has today lost part of its dominance in clinical routine; however, it remains a very powerful tool in the diagnosis of many diseases such as epilepsy, sleep disorders, and dementia. Furthermore, the EEG signal is important for real-time monitoring in the operating theatre and in the intensive care unit, e.g., when monitoring the progress of patients in a coma or with encephalopathies. In monitoring applications, the fraction-of-a-second temporal resolution of the EEG is unsurpassed compared to the above-mentioned imaging modalities. Another aspect in favor of the EEG is that the total cost associated with recording instrumentation, and technicians required to manage the equipment, is dramatically lower than that associated with neuroimaging. The technical demands on equipment for recording EEGs are relatively modest and are, for a basic recording setup, restricted to a set of electrodes, a signal amplifier, and a PC for data storage, signal analysis, and graphical presentation.

The magnetoencephalogram (MEG) is yet another noninvasive technique which quantifies the weak magnetic field of mass neural activity by using an extremely sensitive magnetic field sensor—the SQUID. The main advantage of the MEG technique is that the magnetic field is less distorted by the skull than is the electrical potential. While the MEG originally was believed to

[1]The term "background EEG" is here used in a wider sense than the clinical convention and also includes abnormal brain activity such as epilepsy.

provide information which is independent of the EEG [6], it has recently been shown that the EEG and MEG signals have strong interdependence [7, 8]. Since these two types of recording technology, as well as the imaging techniques mentioned above, exhibit both strengths and weaknesses, they should ultimately be used to complement each other [9, 10].

This chapter first presents a brief description of the nervous system and the electrical activity of the brain (Section 2.1); for further details, the interested reader is referred to the multitude of textbooks which contain comprehensive descriptions of the human brain. A variety of common EEG patterns and waveforms are presented in Section 2.2 which are of special interest in the subsequent chapter on EEG signal processing methods. Section 2.3 describes the standard technique used for recording an EEG in clinical routine. Finally, Section 2.4 provides a brief overview of some important EEG applications.

2.1 The Nervous System

The nervous system gathers, communicates, and processes information from various parts of the body and assures that both internal and external changes are handled rapidly and accurately. The nervous system is commonly divided into the central nervous system (CNS), consisting of the brain and the spinal cord, and the peripheral nervous system (PNS), connecting the brain and the spinal cord to the body organs and sensory systems. The two systems are closely integrated because sensory input from the PNS is processed by the CNS, and responses are sent by the PNS to the organs of the body. The nerves transmitting signals to the CNS are called *afferent* or, alternatively, *sensory* nerves. The nerves transmitting signals from the CNS are called *efferent* or, alternatively, *motor* nerves since these signals may elicit muscle contraction.

Another important division of the nervous system is based on its functionality: the *somatic* nervous system and the *autonomic* nervous system. The somatic system includes those nerves which control muscle activity in response to conscious commands. This system also relays the physical sensations. The autonomic nervous system regulates the bodily activities which are beyond conscious control, e.g., cardiac activity and muscle activity in internal organs such as the bladder and uterus. The autonomic nervous system actually consists of two subsystems which operate against each other: the *sympathetic* nervous system, which dominates when physical activity is called for, and the *parasympathetic* nervous system, which dominates during relaxation. Both these subsystems innervate the same organs and act so as to maintain the correct balance of the internal organ environment. For example,

during physical exercise or when a subject experiences fear, the sympathetic system causes the heart rate to increase while the parasympathetic system decreases the rate. Heart rate variability as a result of the antagonistic effect between the two subsystems has been the subject of considerable research in order to better understand the relation between neurological diseases and dysfunction of the autonomic nervous system. Chapter 8 describes methods developed for quantification of heart rate variability.

2.1.1 Neurons

The basic functional unit of the nervous system is the nerve cell—the *neuron*—which communicates information to and from the brain. All nerve cells are collectively referred to as neurons although their size, shape, and functionality may differ widely. Neurons can be classified with reference to morphology or functionality. Using the latter classification scheme, three types of neurons can be defined: *sensory neurons*, connected to sensory receptors, *motor neurons*, connected to muscles, and *interneurons*, connected to other neurons.

The archetypal neuron consists of a cell body, the *soma*, from which two types of structures extend: the *dendrites* and the *axon*, see Figure 2.1(a). Dendrites can consist of as many as several thousands of branches, with each branch receiving a signal from another neuron. The axon is usually a single branch which transmits the output signal of the neuron to various parts of the nervous system. The length of an axon ranges from less than 1 mm to longer than 1 m; the longer axons are those which run from the spinal cord to the feet. Dendrites are rarely longer than 2 mm.

The transmission of information from one neuron to another takes place at the *synapse*, a junction where the terminal part of the axon contacts another neuron. The signal, initiated in the soma, propagates through the axon encoded as a short, pulse-shaped waveform, i.e., the action potential. Although this signal is initially electrical, it is converted in the presynaptic neuron to a chemical signal ("neurotransmitter") which diffuses across the synaptic gap and is subsequently reconverted to an electrical signal in the postsynaptic neuron, see Figure 2.1(b).

Summation of the many signals received from the synaptic inputs is performed in the postsynaptic neuron. The amplitude of the summed signal depends on the total number of input signals and how closely these signals occur in time; the amplitude decreases when the signals become increasingly dispersed in time. The amplitude of the summed signal must exceed a certain threshold in order to make the neuron fire an action potential. Not all neurons contribute, however, to the excitation of the postsynaptic neuron; inhibitory effects can also take place due to a particular chemical structure

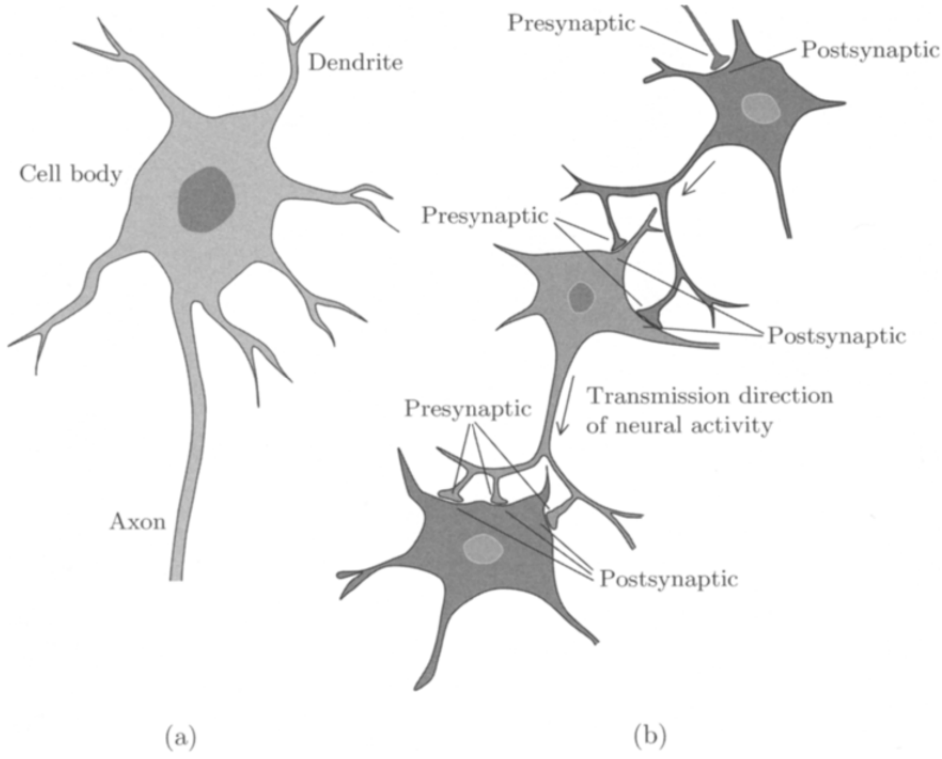

Figure 2.1: (a) An archetypal neuron and (b) three interconnected neurons. A presynaptic neuron transmits the signal toward a synapse, whereas a postsynaptic neuron transmits the signal away from the synapse.

associated with certain neurons. A postsynaptic neuron thus receives signals which are both excitatory and inhibitory, and its output depends on how the input signals are summed together. This input/output operation is said to represent one neural computation and is performed repeatedly in billions of neurons.

In contrast to the electrical activity measured on the scalp, electrical activity propagating along the axon is manifested as a series of action potentials, all waveforms having identical amplitudes. This remarkable feature is explained by the "on/off" property of the neuron which states that an action potential is either elicited with a fixed amplitude or does not occur at all. The intensity of the input signals is instead modulated by the firing rate of the action potentials. For example, this signal property implies that a high firing rate in sensory neurons is associated with considerable pain or, in motor neurons, with a powerful muscle contraction. Furthermore, it is

fascinating to realize that this modulation system is particularly well-suited for transmission of information over long distances and is tolerant to local failures. The upper bound of the firing rate is related to the refractory period of the neuron, i.e., the time interval during which the neuron is electrically insensitive.

Neurons are, of course, not working in splendid isolation, but are interconnected into different circuits ("neural networks"), and each circuit is tailored to process a specific type of information. A well-known example of a neural circuit is the knee-jerk reflex. This particular circuit is activated by muscle receptors which, by a hammer tap, initiate a signal that travels along an afferent pathway. The received sensory information stimulates motor neurons through synaptic contacts, and a new signal is generated which travels peripherally back, giving rise to muscle contraction and the associated knee-jerk response.

2.1.2 The Cerebral Cortex

The cerebral cortex is the most important part of the CNS, and the different regions of cortex are responsible for processing vital functions such as sensation, learning, voluntary movement, speech, and perception. The cortex is the outermost layer of the cerebrum and has a thickness of 2–3 mm. The cortical surface is highly convoluted by ridges and valleys of varying sizes and thus increases the neuronal area; the total area is as large as 2.5 m^2 and includes more than 10 billion neurons. The cortex consists of two symmetrical *hemispheres*—left and right—which are separated by the deep sagittal fissure (the central sulcus). Each hemisphere is divided into four different lobes: the *frontal, temporal, parietal,* and *occipital lobes*, see Figure 2.2.

Voluntary movement is primarily controlled by the area of the frontal lobe just anterior to the central sulcus—the motor cortex. Tasks requiring considerable muscle control, e.g., speech, certain facial expressions, and finger movements, are associated with the largest subarea of the motor cortex. Sensory information is processed in various parts of the lobes: the auditory cortex is located in the superior part of the temporal lobe, the visual cortex is located at the posterior part of the occipital lobes, and the somatic sensory cortex is located just posterior to the central sulcus of the parietal lobe.

The above-mentioned cortical areas are referred to as primary areas since these neurons are specialized for a particular purpose. The primary areas are relatively small in size, but are supplemented with larger, surrounding areas which are essential for the mental abilities that are characteristic of human beings. The neurons of a secondary area analyze, for example, visual information in further detail with respect to shape, color, and size of an object. These neurons also provide associative references to other senses and

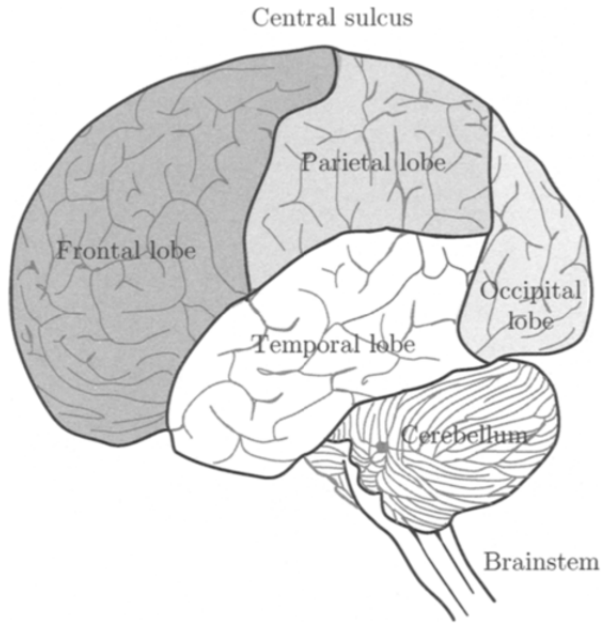

Figure 2.2: The cerebral cortex and the four lobes.

will, ultimately, integrate the present information with earlier experiences and knowledge.

2.2 The EEG—Electrical Activity Measured on the Scalp

The collective electrical activity of the cerebral cortex is usually referred to as a *rhythm* because the measured signals often exhibit oscillatory, repetitive behavior. The activity of a single cortical neuron cannot be measured on the scalp due to thick layers of tissue (fluids, bones, and skin) which attenuate the electrical signal when it propagates toward the electrode.[2] However, the joint activity of millions of cortical neurons, at a depth down to several millimeters, produces an electrical field which is sufficiently strong to be measured on the scalp; this depth depends on the "strength" of the neural source. The electrical field is mainly generated by currents that flow during synaptic excitation of the dendrites, the excitatory postsynaptic potentials.

[2]It is possible to invasively investigate the electrical behavior of only a few neurons by the use of microelectrodes. The specific properties of signals acquired by such intracerebral electrodes will, however, not be given further consideration in the present text.

The diversity of EEG rhythms is enormous and depends, among many other things, on the mental state of the subject, such as the degree of attentiveness, waking, and sleeping. Figure 2.3 illustrates a number of EEG rhythms observed during different states. The rhythms are conventionally characterized by their frequency range and relative amplitude.

The amplitude of the EEG signal is related to the degree of synchrony with which the cortical neurons interact. Synchronous excitation of a group of neurons produces a large-amplitude signal on the scalp because the signals originating from individual neurons will add up in a time-coherent fashion. Repetition of the synchronous excitation results in a rhythmic EEG signal, consisting of large-amplitude waveforms occurring at a certain repetition rate. On the other hand, asynchronous excitation of the neurons results in an irregular-looking EEG with low-amplitude waveforms. In both cases, the excitation may very well involve an identical number of neurons, but, depending on the time dispersion of the neuronal input, different amplitudes of the EEG result.

The frequency, or the oscillatory rate, of an EEG rhythm is partially sustained by input activity from the thalamus. This part of the brain consists of neurons which possess pacemaker properties, i.e., they have the intrinsic ability to generate a self-sustained, rhythmic firing pattern. Another reason to the rhythmic behavior is coordinated interactions arising between cortical neurons themselves in a specific region of the cortex. In the latter case, no pacemaker function is involved, but the rhythm is rather an expression of a feedback mechanism that may occur in a neuronal circuit [11].

High-frequency/low-amplitude rhythms reflect an active brain associated with alertness or dream sleep, while low-frequency/large-amplitude rhythms are associated with drowsiness and nondreaming sleep states. "This relationship is logical because when the cortex is most actively engaged in processing information, whether generated by sensory input or by some internal process, the activity level of cortical neurons is relatively high but also relatively unsynchronized. In other words, each neuron, or very small group of neurons, is vigorously involved in a slightly different aspect of a complex cognitive task; it fires rapidly, but not quite simultaneously with most of its neighbors. This leads to low synchrony, so the EEG amplitude is low. By contrast, during deep sleep, cortical neurons are not engaged in information processing, and large numbers of them are phasically excited by a common, rhythmic input. In this case synchrony is high, so the EEG amplitude is large" [11].

The meaning of different brain rhythms largely remains unexplained, although several hypotheses have been put forward. Despite this gap in understanding, quantification of EEG rhythm characteristics has nevertheless

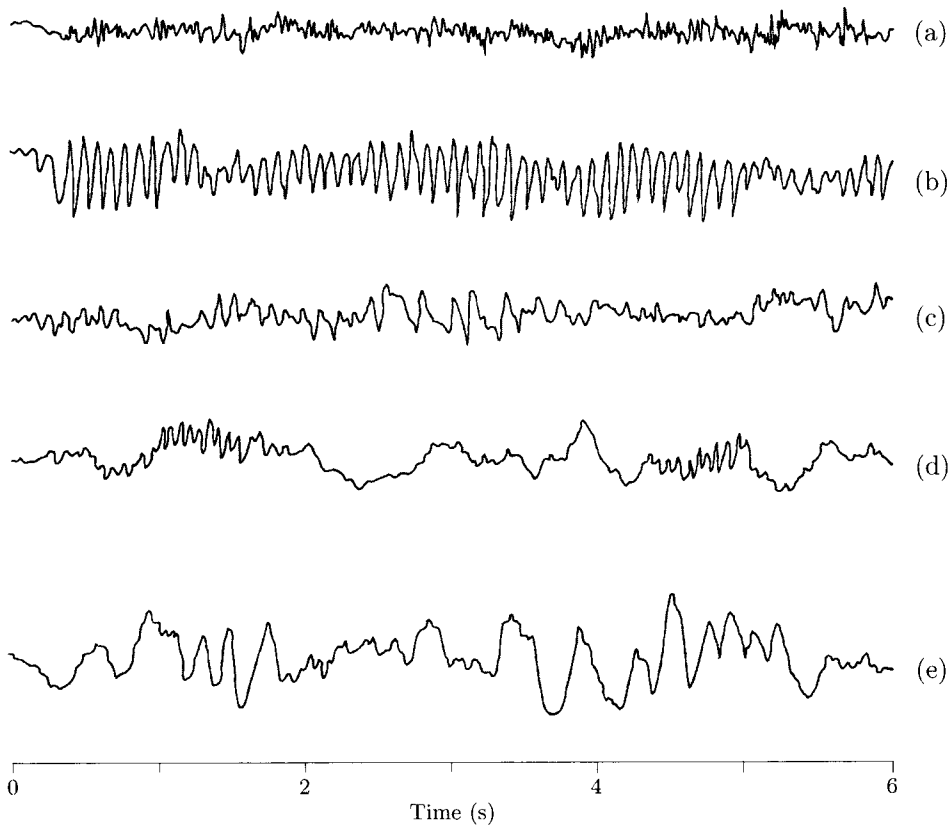

Figure 2.3: Electroencephalographic rhythms observed during various states from wakefulness to sleep: (a) excited, (b) relaxed, (c) drowsy, (d) asleep, and (e) deeply asleep. This example is classical and was originally presented by the famous EEG pioneer H.H. Jasper [12].

proved to be an extremely useful clinical approach in studying functional states of the brain.

2.2.1 EEG Rhythms and Waveforms

The characteristics of the most frequently occurring rhythms and waveforms will now be briefly summarized. Signals recorded from the scalp have, in general, amplitudes ranging from a few microvolts to approximately 100 μV and a frequency content ranging from 0.5 to 30–40 Hz. Electroencephalographic rhythms, also referred to as background rhythms, are conventionally classified into five different frequency bands. The interpretation of these

bands in terms of "normal" or "abnormal" is relative and depends on the age and mental state of the subject. For example, the EEG of a newborn is drastically different from that of an adult and has, in general, a considerably higher frequency content. The frequency bands indicated below are somewhat coarse, but nevertheless provide a clinically useful categorization of different rhythms (the band definitions below follow those presented in [13]).

Delta rhythm, <4 Hz. The delta rhythm is typically encountered during deep sleep and has a large amplitude. It is usually not observed in the awake, normal adult, but is indicative of, e.g., cerebral damage or brain disease (encephalopathy).

Theta rhythm, 4–7 Hz. The theta rhythm occurs during drowsiness and in certain stages of sleep.

Alpha rhythm, 8–13 Hz. This rhythm is most prominent in normal subjects who are relaxed and awake with eyes closed; the activity is suppressed when the eyes are open. The amplitude of the alpha rhythm is largest in the occipital regions.

Beta rhythm, 14–30 Hz. This is a fast rhythm with low amplitude, associated with an activated cortex and which can be observed, e.g., during certain sleep stages. The beta rhythm is mainly observed in the frontal and central regions of the scalp.

Gamma rhythm, >30 Hz. The gamma rhythm is related to a state of active information processing of the cortex. Using an electrode located over the sensorimotor area and connected to a high-sensitivity recording technique, the gamma rhythm can be observed during finger movements [14].

Most of the above rhythms may persist up to several minutes, while others occur only for a few seconds, such as the gamma rhythm. It is important to realize that one rhythm is not present at all times, but an irregular, "arrhythmic"-looking signal may prevail during long time intervals.

Spikes and sharp waves. Spikes and sharp waves (SSWs) are transient waveforms that stand out from the background EEG with an irregular, unpredictable temporal pattern (paroxysmal activity). Their presence indicates a deviant neuronal behavior often found in patients suffering from epileptic seizures [15]. Because of their relation to seizures, SSWs are often referred to as interictal since they occur between ictal events, i.e., epileptic seizures.

The clinical definition of SSWs is somewhat ambiguous, but both types of waveforms are generally characterized by a steep initial upstroke. A spike is differentiated from a sharp wave by its duration: a spike has a duration in the range 20–70 ms, while a sharp wave is 70–200 ms long. Although the waveform morphology is essentially monophasic, it is not uncommon to observe both bi- and triphasic waveforms. The waveform morphology is naturally dependent on where the electrode is located on the scalp.

Spikes may occur as isolated events or in various types of runs. Such runs are collectively referred to as *spike-wave complexes*, and each complex consists of a spike followed by a slow wave [15]. Spike-wave complexes occur at repetition rates which range from less than 3 to 6 Hz; the repetition rate may correlate with different clinical interpretations. An example of spike-wave complexes is presented in Figure 2.4.

Certain artifacts in a normal EEG can occasionally be mistaken for SSWs. For example, cardiac activity may interfere with the EEG to such a degree that a heartbeat (particularly the waves of the QRS complex) masquerades as a spike.

Sleep rhythms. The brain has three essential functional states: awake, sleep without *rapid eye movement* (REM), and sleep with REM. The two sleep states, commonly referred to as non-REM and REM sleep, are passed through several times during one night. Non-REM sleep is an "idle" state associated with resting of the brain and the bodily functions. Slow, large-amplitude EEG rhythms during non-REM sleep indicate a high degree of synchrony of the underlying cortical neurons. This sleep state can be further subdivided into four distinct stages related to the degree of sleep depth, see Table 2.1.

A number of transient waveforms usually occur which are characteristic of the different sleep stages: *vertex waves*, *sleep spindles*, and *K complexes*, see Table 2.1 and Figure 2.5. Vertex waves occur during the earlier sleep stages and constitute responses to external stimuli such as sounds. Sleep spindles are bursts of alpha-like activity with a duration of 0.5–1 s. The K complexes can be viewed as the fusion of sleeps spindles and vertex waves.

Rapid eye movement sleep corresponds to an active brain, probably occupied with dreaming. It is therefore not surprising that the EEG closely resembles that of the waking brain and that beta rhythms are present. A prominent feature of the REM sleep state is that the eyes, with the lids closed, move rapidly back and forth in an irregular pattern. These eye movements produce a sawtooth pattern in the EEG when the electrodes are attached close to the eyes.

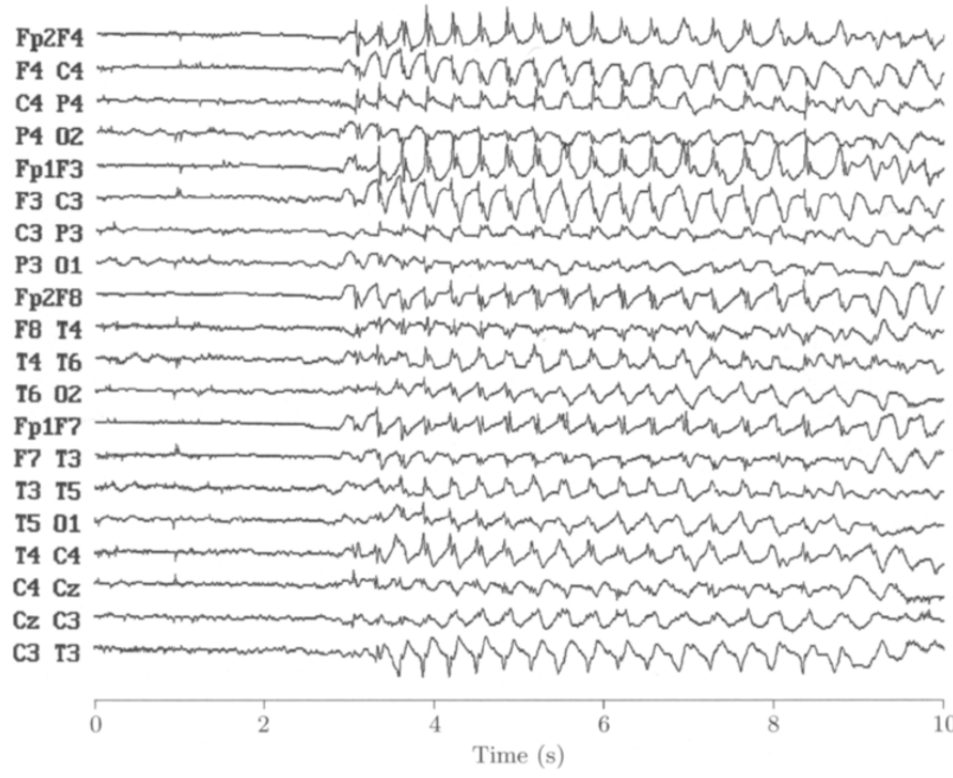

Figure 2.4: A multichannel EEG with spike-wave complexes occurring at a 3-Hz repetition rate. Each channel results from two electrodes placed at locations defined by the codes displayed next to the signal; the definitions of electrode placements are given in Figure 2.7. (Reprinted from Wong [16] with permission.)

Ictal EEG. During an epileptic seizure the EEG is referred to as an ictal EEG, manifested by an abnormal rhythm with a sudden increase in amplitude, as illustrated in Figure 2.6. The onset of a seizure is also associated with a sudden change in frequency content which often evolves into a rhythm with a spiky wave pattern. The ictal EEG may exhibit considerable variability from seizure to seizure, making its detection, whether approached manually or automatically, difficult.

2.2.2 Categorization of EEG Activity

The above-mentioned activities can be roughly categorized into the following four groups with respect to their degree of nonstationarity. The categoriza-

Table 2.1: Essential characteristics of the four non-REM sleep stages and REM sleep [17].

Sleep stage	Sleep depth	Waveforms
1	Drowsiness	From alpha dropouts to vertex waves
2	Light sleep	Vertex waves, spindles, K complexes
3	Deep sleep	Much slowing, K complexes, some spindles
4	Very deep sleep	Much slowing, some K complexes
REM	REM sleep	Desynchronization with faster frequencies

tion was originally presented in [18], and the categories were defined with special reference to their suitability for spectral analysis.

Activity without major temporal changes. Normal, spontaneous waking activity at rest, e.g., with open or closed eyes; various kinds of alpha, beta, and theta rhythms.

Slowly time-varying activity. Sleep background activity, postictal background activity, lengthy seizure discharges.

Intermittent activity. Intermittent, slow rhythm, sleep spindles, i.e., activity with stable patterns over intervals of several seconds.

Paroxysmal activity. Spikes, sharp waves, spike-wave complexes, 3-Hz spike-wave formations, K complexes, and vertex waves observed during sleep, i.e., different types of transient activity.

2.3 Recording Techniques

The clinical EEG is commonly recorded using the International 10/20 system, which is a standardized system for electrode placement [19]. This particular recording system (electrode montage) employs 21 electrodes attached to the surface of the scalp at locations defined by certain anatomical reference points; the numbers 10 and 20 are percentages signifying relative distances between different electrode locations on the skull perimeter, see Figure 2.7. Bipolar as well as so-called unipolar electrodes are used in clinical routine, with the latter type requiring a reference electrode either positioned distantly or taken as the average of all electrodes.

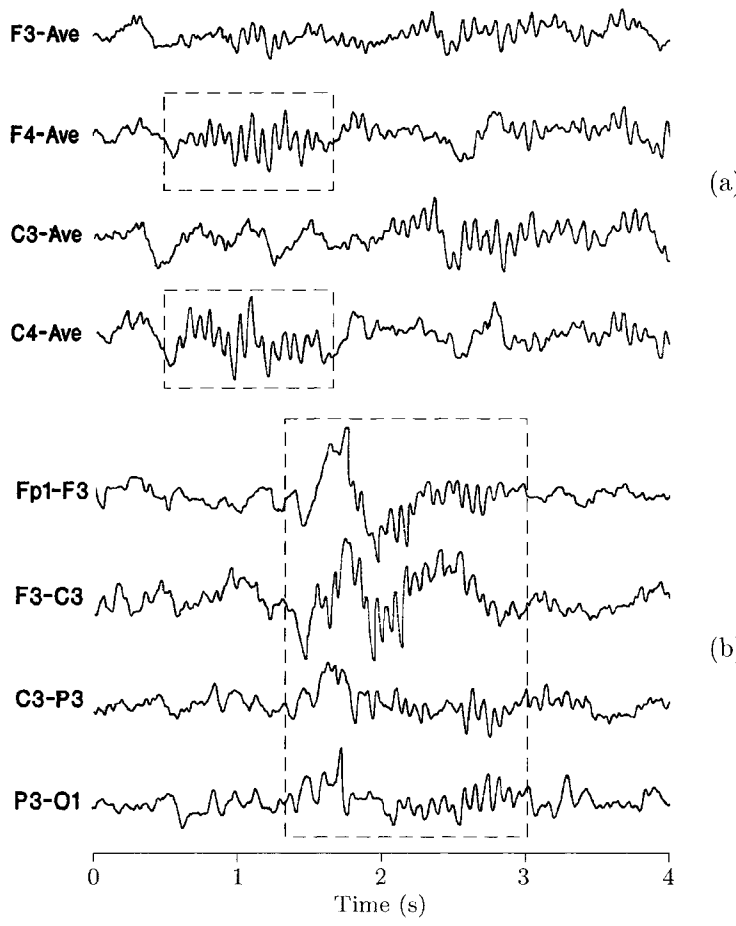

Figure 2.5: Electroencephalographic signals recorded during sleep with (a) sleep spindles and (b) K complexes; note that each K complex is the fusion of a vertex wave and a sleep spindle. (Reprinted from Wong [16] with permission.)

The spacing of electrodes with the 10/20 system is relatively sparse: the interelectrode distance is approximately 4.5 cm on a typical adult head. Improved spatial resolution may be required when brain mapping is of interest. Mapping constitutes a spatial analysis technique in which the EEG activity is represented as a topographic map projected onto the scalp [20]. Using too few electrodes may result in aliasing in the spatial domain, and, consequently, the electrical activity will be inaccurately represented. Studies have indicated that the total number of electrodes used in brain mapping applications should be 64 or higher in order to provide sufficient detail [21].

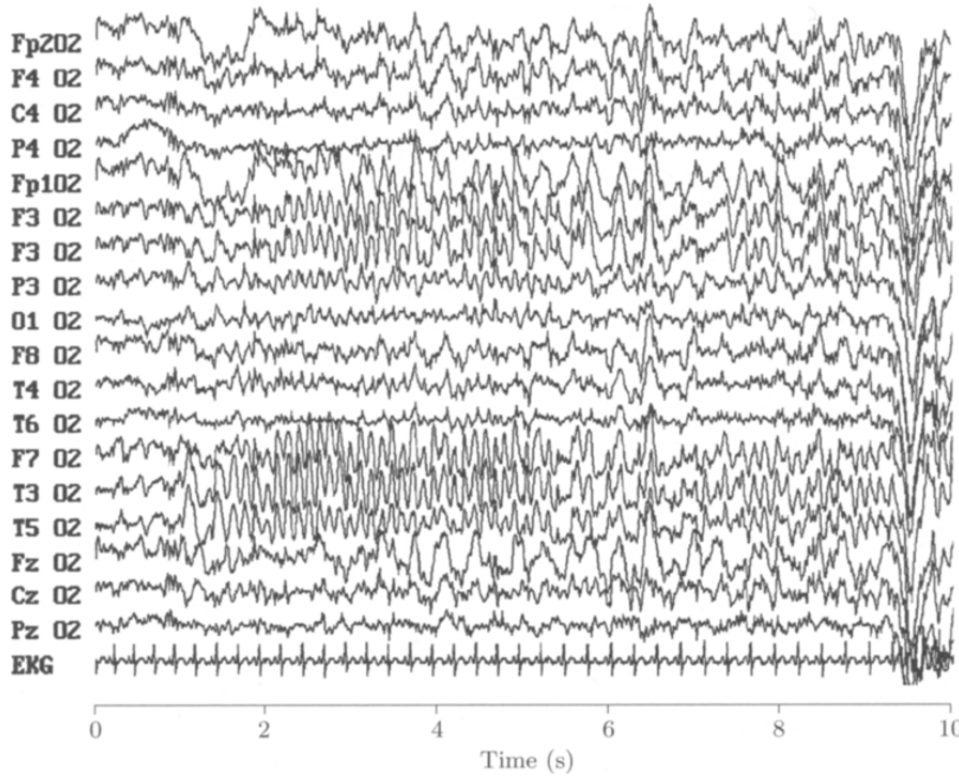

Figure 2.6: A multichannel EEG showing the onset of an epileptic seizure, occurring after the first second. The onset is characterized by an increase in amplitude and a change in spectral content. The seizure is particularly pronounced in certain channels. Note that the ECG is displayed at the bottom (the abbreviations EKG and ECG are synonymous). (Reprinted from Wong [16] with permission.)

The sampling rate for EEG signal acquisition is usually selected to be at least 200 Hz, when taking the frequency ranges of the rhythmic activities previously given into account. A more detailed analysis of transient, evoked waveforms may, however, necessitate a considerably higher sampling rate; see Chapter 4 which describes the analysis of EPs.

2.4 EEG Applications

This section considers two of the most important clinical applications of the EEG, namely, the study of epilepsy and sleep disorders. The design of a brain–computer interface is another EEG application which is considered; so far, this has primarily been studied from a research-oriented perspective.

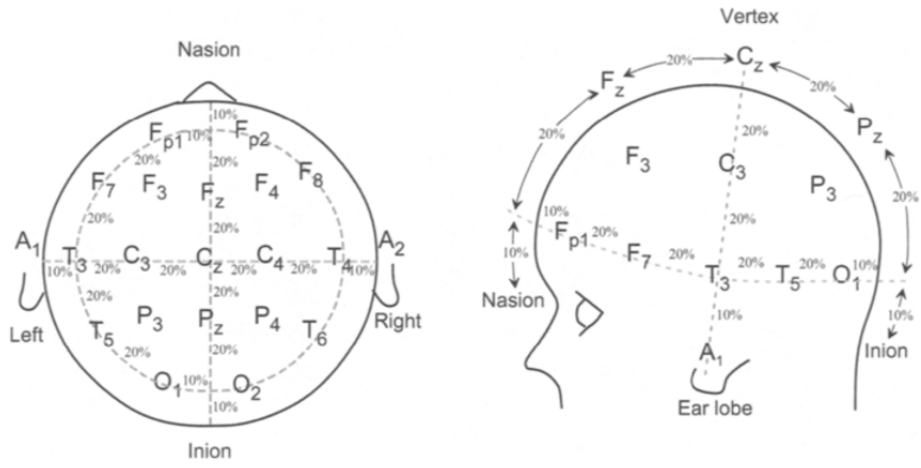

Figure 2.7: The International 10/20 system for recording of clinical EEGs. The anatomical reference points are defined as the top of the nose (nasion) and the back of the skull (inion). The letters F, P, C, T, O, and A denote frontal, parietal, central, temporal, occipital, and auricle, respectively. Note that odd-numbered electrodes are on the left side, even-numbered electrodes are on the right side, and z (zero) is along the midline.

While the descriptions by necessity are kept brief, it is nevertheless hoped that they will help illustrate the importance of signal processing in various EEG applications. The interested reader is referred to the specialist literature for more information on these topics.

2.4.1 Epilepsy

A person with epilepsy suffers from seizures during which sudden bursts of uncontrolled electrical activity occur in a group of neurons of the cerebral cortex. Epileptic seizures are manifested in many different ways depending on where the origin (focus) of the electrical activity is located and how different areas of the brain become successively recruited during a seizure. For example, a seizure which begins in the sensory areas of the cortex is usually manifested by some visual or auditive sensation. The epileptic focus is defined by a group of neurons whose functionality is impaired, whereas the other areas involved in a seizure are often normal.

The interplay between excitatory signals, which increase the electrical activity of the brain by causing nerve cells to fire, and inhibitory signals, which decrease the activity by preventing nerve cells from firing, is well-balanced during normal conditions. However, an imbalance between the two

activities is believed to be an important cause of epilepsy. In particular, the neurotransmitters that chemically convey the signals in the synapse are central to causing such an imbalance; if the excitatory neurotransmitters are too active or the inhibitory ones are not active enough, the likelihood of a seizure increases. As a result, bursts of uncontrolled electrical activity will occur. Recently developed antiepileptic drugs are aimed at changing this impaired balance of the neurotransmitters by either decreasing the excitatory activity or increasing the inhibitory activity.

Some seizures are difficult to observe and only result in minor mental confusion, while others cause loss of consciousness, although rarely leading to permanent injury or death. Seizures are typically recurrent events at a highly variable rate, ranging from a few seizures during a lifetime to a few dozen during a single day. The duration of each seizure ranges from a few seconds to a few minutes. Since the manifestations of epileptic seizures differ widely, a scheme for classifying seizures into different groups has been established based on the characteristics of the EEG [22]. The two main groups are defined by the location at which the seizure starts: *partial seizures* start in a restricted (focal) area of the brain, while *primary generalized seizures* involve the entire brain from their onset (Figure 2.8). The seizures belonging to the former group are related to a single epileptic focus, while this does not apply to the latter group. As a result, certain partial seizures may be cured by a surgical procedure in which a small part of the cortex is removed. The procedure must be preceded by a series of extremely thorough investigations in order to assure that the location of the epileptic focus is accurately delimited. In some cases, a partial seizure may evolve to other parts of the brain and is then referred to as a partial seizure with secondary generalization. Figure 2.9 displays an EEG which was recorded during the onset of a primary generalized seizure.

Epilepsy is caused by several pathological conditions such as brain injury, stroke, brain tumors, infections, and genetic factors. The largest group of epileptic patients has, however, an unknown etiology.

The EEG is the principal test for diagnosing epilepsy and gathering information about the type and location of seizures. For subjects with suspected epilepsy, an EEG is recorded in clinical routine for half an hour in a relatively dark and quiet room. During this period, the subject is asked to open and close his/her eyes to study changes in the EEG related to light (recall the presence or absence of alpha activity mentioned on page 34). At the end of the investigation, two "activation" methods are commonly used to provoke waveforms which are associated with epilepsy. In one activation method, the subject is instructed to breath rapidly and deeply (hyperventilation), and in the other method to face a strobe light flashing at a rate of 1–25 Hz

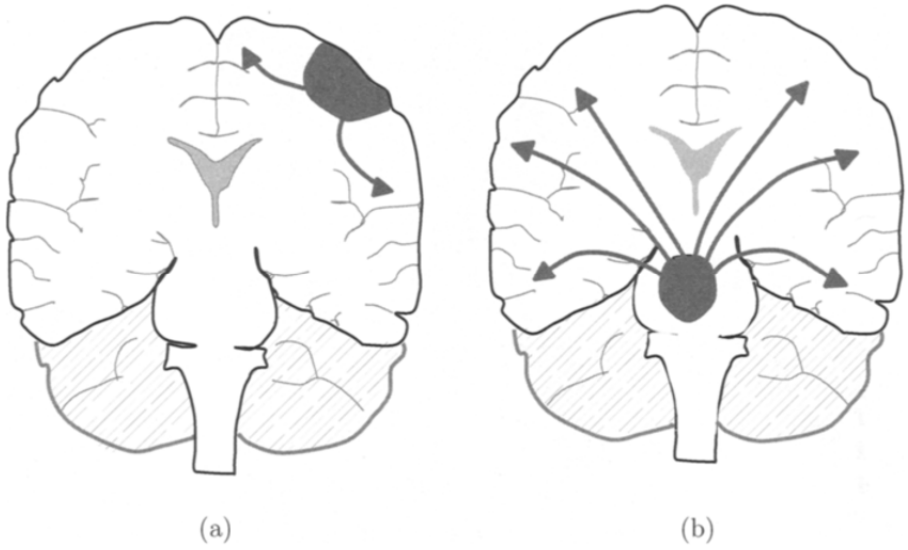

Figure 2.8: (a) A partial epileptic seizure with focus in the motor cortex. Related symptoms are muscle twitches in one of the arms, but the subject is fully conscious. (b) A primary generalized seizure which spreads across the entire brain. Symptoms are spasms and unconsciousness. In both figures, a vertical cross-section of the brain is viewed from the front.

(photic stimulation). Sleep deprivation represents another type of activation method which may also be considered.

Although the EEG obtained in clinical routine is often recorded between seizures, i.e., the interictal EEG, the signal waveforms may nevertheless indicate a tendency toward seizures. Examples of interictal waveforms have already been presented in Figure 2.4. The occurrence of SSWs in a local area of the brain, such as in the left temporal lobe, suggests that partial seizures are initiated in that particular area. Spike-wave complexes which are widespread over both hemispheres of the brain suggest, on the other hand, the occurrence of primary generalized seizures. Unfortunately, the absence of interictal waveforms does not rule out the possibility of a seizure.

In order to record an EEG during a seizure, it is often necessary to record the EEG during prolonged periods. Such recordings are often done while video filming the patient, allowing the neurologist to correlate EEG findings to visual findings in order to improve seizure assessment. This type of recording is referred to as "video EEG" and is usually done in the hospital over a period of several days. Another, more convenient, less expensive method is to record the EEG during normal, everyday conditions by a small-sized, digital recording device attached to a belt around the patient's waist [23]. This

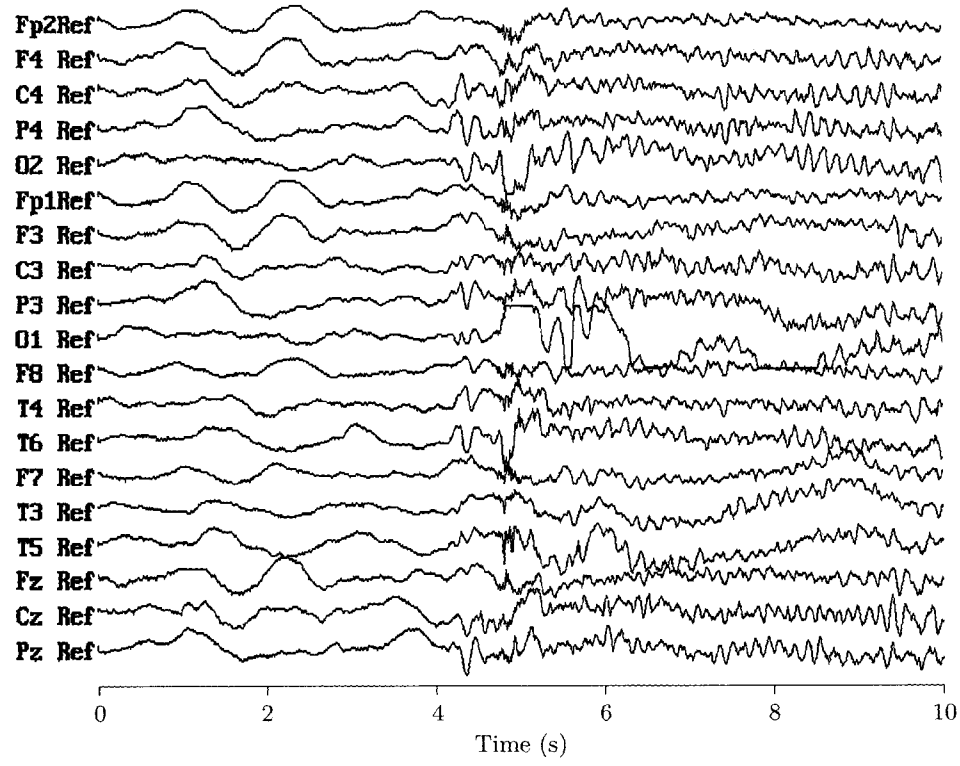

Figure 2.9: A multichannel EEG showing the onset of a primary generalized seizure about halfway into the recording. (Reprinted from Wong [16] with permission.)

type of recording, referred to as "ambulatory EEG", is done in the home for a period of 24 hours or more and therefore includes both waking and sleeping cycles. Similar to video EEG recordings, several electrodes must be attached to the scalp for long periods of time which sometimes cause itching. Scratching the head introduces noise into the EEG recording which may occasionally resemble waveforms of physiological origin. A variety of other noise types, such as those caused by blinking and frowning, can also appear, which may make the interpretation of an ambulatory recording difficult.

Whether performed in the hospital or under ambulatory conditions, long-term EEG monitoring produces large amounts of data which would be very time-consuming to scrutinize. Automatic spike and seizure detection is therefore an important means of reducing the amount of data and improving the efficiency of EEG interpretation. The design of such detection algorithms involves several signal processing considerations regarding the mathematical characterization of interictal waves and epileptic seizures [24–26]. Algorithms

for noise and artifact rejection are another important part of such programs. An algorithm for seizure prediction/warning may help a patient wearing an ambulatory recording device take appropriate safety measures prior to a seizure.

A number of therapeutic devices have been developed for epileptic patients which trigger an action that prevents a seizure before it begins. Of these devices, the vagus nerve stimulator is the most well-known and is programmed to regularly stimulate the vagus nerve[3] with a series of intermittent electrical pulses [27]. As the pulses reach the brain, an antiepileptic effect has been observed in some patients, although the mechanisms behind this effect so far remain poorly understood. The vagal nerve stimulator is surgically implanted, similar to a cardiac pacemaker. The stimulating electrode is wrapped around the vagus nerve in the neck, see Figure 2.10. Current stimulators operate blindly by eliciting a preset pattern of stimulation pulses; no attempt is made to predict seizures and modify the therapy accordingly. However, the development of more intelligent vagal stimulators is underway and will involve signal processing algorithms for the prediction of seizures [28, 29].

2.4.2 Sleep Disorders

Sleep disorders, which are frequent in our society, may be caused by several conditions of medical and/or psychological origin. A commonly used scheme for classification of sleep disorders defines the following four groups [30].

Insomnia. Disorders in initiating or maintaining sleep. Most people have at some point in their lives suffered from insomnia due to an agonizing event or approaching examination; this condition is normally transient and is not treated. Depression is associated with poor sleep and causes a substantial reduction in deep sleep, i.e., stages 3 and 4, which makes the patient tired during the daytime. Alcohol and drug abuse are other factors that cause insomnia.

Hypersomnia. Disorders causing excessive sleep and somnolence. Narcolepsy is one example of hypersomnia characterized by uncontrollable daytime sleep attacks while night-time sleep is still fairly normal. Sleep apnea is another condition which indirectly causes hypersomnia. During night-time sleep, the patient suffers from frequent, prolonged suspensions of breathing (>10 s) which cause the patient to wake due to

[3]The vagus nerve is one of the 12 pairs of cranial nerves which emanate from the brain; it branches out into the chest and abdomen. The name "vagus" means "wandering" since this nerve is found in many different places. The vagus nerve is also of central importance for controlling heart rate, see Section 8.

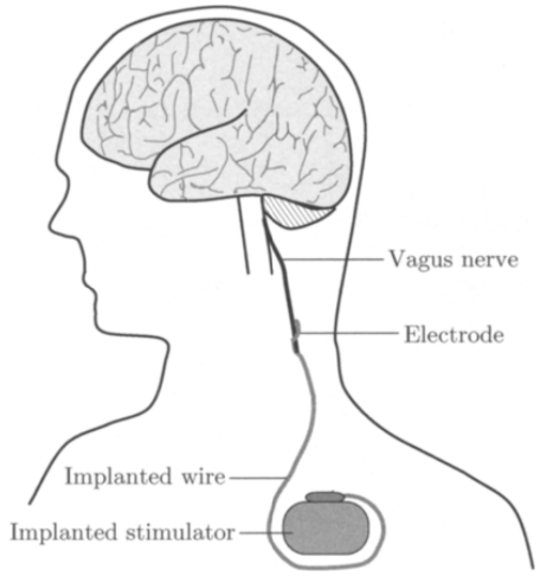

Figure 2.10: The vagus nerve stimulator can prevent epileptic seizures by electrical excitation.

snoring. As a result, a patient with sleep apnea has interrupted deep sleep and is very tired during the daytime (sleep apnea may also be classified as insomnia).

Circadian rhythm disorders. Disorders in the sleep–wake schedule. The most well-known example of such disorders results from flying across several time zones ("jet lag"). Fortunately, the difficulties related with adapting to the new sleep–wake schedule are typically temporary and disappear within a week. A more serious condition arises in subjects whose diurnal rhythm is slightly longer than 24 hours. These subjects sleep later by up to half an hour every day and progressively move into daytime sleep and then back into night-time sleep. As a result, it is difficult to maintain a normal work–rest schedule.

Parasomnia. Deviations in the normal sleep pattern. These sleep disorders are related to deviations from the normal well-being during sleep, although not necessarily leading to awakening. The nightmare is the most common type of parasomnia, being a dream which contains a threatening situation; the nightmare is related to increased autonomic activity as reflected by a drastic increase in heart rate. Sleep terror is a more serious condition, unrelated to dreams, which is characterized by piercing screams or cries; this condition is mostly seen in children

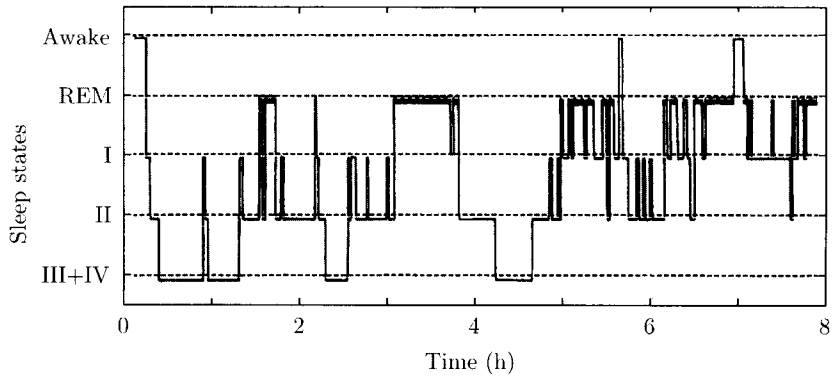

Figure 2.11: Variations in sleep stages observed during one night's sleep. Sleep stages III and IV have been combined. Dream sleep occurs during the REM stage.

and disappears with age. Sleepwalking is another condition, similar to sleep terror, which occurs during the deep stages of sleep.

Each of the different types of sleep disorder exhibits certain manifestations in the EEG. To properly diagnose each disorder, it is therefore important to quantitatively determine how the pattern of sleep stages changes over time, see Figure 2.11. This information is commonly acquired by having the patient stay overnight in a sleep laboratory with electrodes attached to the scalp. Since the manual effort associated with sleep staging is enormous, it is highly desirable to develop and implement a system that automatically performs the sleep staging described in Table 2.1. A fundamental task of such a system is obviously to detect the individual waves that characterize the different stages (i.e., vertex waves, sleep spindles, and the K complexes) and the different rhythms such as delta, theta, alpha, and beta. In order to mimic the method by which a neurologist interprets an EEG, it is important to develop a system that considers contextual information on how individual waves are distributed spatially across channels as well as temporally within each channel [31, 32].

Sleep analysis is commonly based on a polygraphic recording, i.e., a recording that involves several types of physiological signals, not only an EEG; the resulting recording is therefore referred to as *polysomnographic.* Such a recording was exemplified in Figure 1.8 in the Introduction where a number of signals such as the EEG, ECG, EMG, EOG, blood pressure, and nasal and abdominal respiration were included. Polysomnography may also include video filming as a record of the patient's behavior during sleep as expressed by sounds and body movements, see Figure 2.12. Since a polysomnographic recording contains many signals of different origins, its analysis may

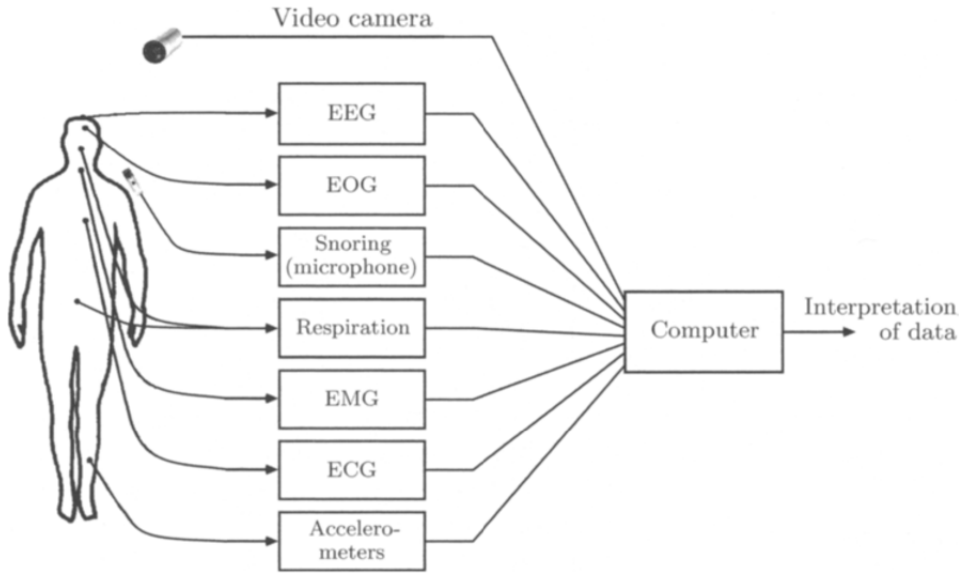

Figure 2.12: Setup for acquisition of a polysomnographic recording in the sleep laboratory. Some of the acquired signals are often multichannel. Additional physiological measures such as blood pressure and blood oxygen level may also be monitored.

be quite complicated. Computer-based analysis of such recordings makes it possible to quantify correlations that may exist between different types of signals. Similar to systems for automated recognition of epileptic seizures, noise and artifact rejection are important parts of a system for automated sleep analysis [33, 34].

2.4.3 Brain–Computer Interface

A brain–computer interface (BCI) enables a subject to communicate with and control the external world without using the brain's normal output through peripheral nerves and muscles [35–37]. Messages are conveyed by spontaneous or evoked EEG activity rather than by muscle contractions which are otherwise used for communication through speech and writing. Subjects with severe neuromuscular disorders, or sometimes those who are completely paralyzed (the "locked-in" syndrome), benefit greatly from a BCI which offers them basic communication capabilities through which they can express themselves, for example, by controlling a spelling program or operating a neuroprosthesis. Although the BCI was first conceived in the early 1970s [38], it was not until the 1990s that its development took a great

leap forward [39, 40], owing to more detailed knowledge of the EEG signal and the rapid progress in computer technology.

The following two closely interrelated steps are fundamental to the design and use of a BCI:

- The mental process of the user which encodes commands in the EEG signal; and
- the BCI which, by employing sophisticated signal processing techniques, translates the EEG signal characteristics into commands which control a device.

The imagination of different simple hand and feet movements is associated with different EEG signal characteristics which can be used to encode a set of commands [35, 40, 41]. The related mental process, usually referred to as *motor imagery*, is identical to the process that results in an actual physical movement, except that the motor (muscle) activity is blocked. In order for the BCI to learn the meaning of different EEG signal characteristics, the subject is instructed to imagine one of several actions. For each imagined action, a set of descriptive parameters ("features") is extracted from the EEG signal and submitted to a classifier. By repeating the imagined actions several times, the classifier can be trained to determine which action the subject is imagining. Subsequent to the learning phase, the BCI relies on the classifier to translate the subject's motor imagery into device commands, such as the selection of a letter in a spelling program. The block diagram in Figure 2.13 presents the basic components of a BCI. Since BCIs must operate in real time, it is important that the signal processing does not introduce unacceptable time delays.

The learning phase of a BCI is unfortunately not a one-off procedure resulting in a fixed-parameter classifier, but must be repeated on a regular basis. Since the EEG exhibits considerable variability due to factors such as time of day, hormonal level, and fatigue, it is necessary to adjust the classifier in order to maintain an acceptable performance. In addition, the overall success of the BCI depends on how well the two adaptive "controllers"—the user's brain and the BCI system—are able to interact with each other. The user must develop and maintain good correlation between his/her intent and the signal features used in the BCI. The BCI system must extract signal features that the user can control and translate those features into commands correctly [36].

The most common technique for extracting features from an EEG signal is to analyze spectral power in different frequency bands [42–46]. Spectral analysis of a single channel may be useful although multichannel analysis is preferable since it accounts for spatial variations associated with different

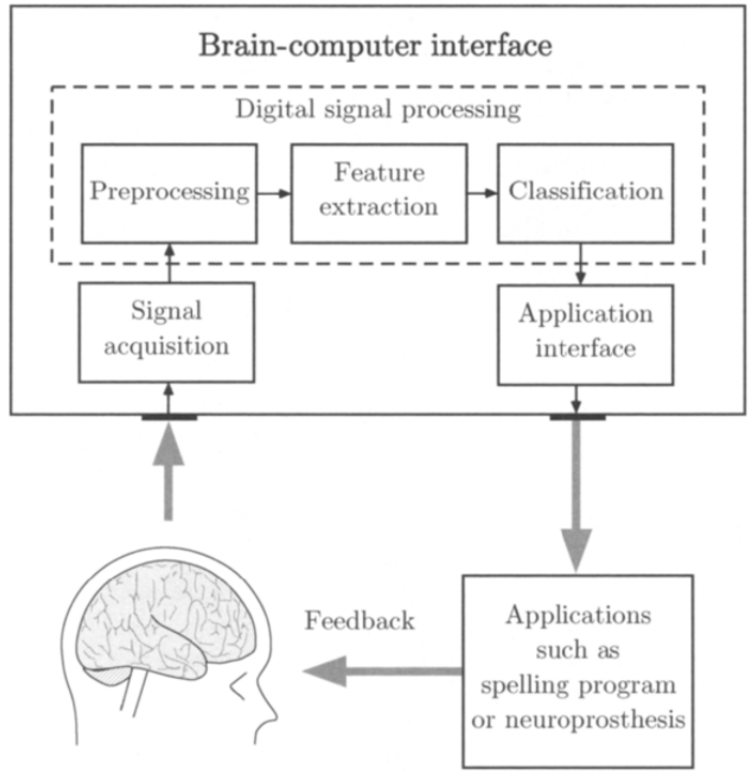

Figure 2.13: Block diagram of a brain–computer interface.

types of motor imagery; for example, differences between the hemispheres can be exploited by multichannel analysis [47]. The frequency bands are selected so that they reflect the EEG rhythms of interest: the mu rhythm[4] and the beta rhythm have been found particularly useful in a BCI. These two rhythms originate from the sensorimotor cortex, i.e., the area which is primarily responsible for the control of hand and foot movements. The extraction of spectral features is further considered in Chapter 3 where a number of spectral estimation techniques that have been implemented in BCIs are presented.

The performance of a BCI may be measured in terms of information transfer rate and is defined in bits per minute. The performance depends on the accuracy with which the different imaginative states are classified. At present, a sophisticated BCI is not able to decipher more than 10–25

[4]The mu rhythm has a spectral content similar to the alpha rhythm. While the alpha rhythm is related to idling activity in the visual cortex, the mu rhythm is related to idling activity in the motor cortex.

bits/minute—an information transfer rate which would enable a completely paralyzed subject to write approximately two words per minute. However, these rates are much too slow for the control of complex movements or the interaction with a neuroprosthesis. The information rate can be increased through surgical implantation of microelectrodes which record the activity of more localized populations of neurons.

The above-mentioned approach to BCI design is based on analysis of the spontaneous EEG. However, a BCI can also be based on the use of EPs which result from sensory stimulation [36, 38, 48–50].

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