ELECTROENCEPHALOGRAPHY

An electroencephalogram (EEG) is a record of electric signals generated by the cooperative action of brain cells or, more precisely, the time course of extracellular field potentials generated by synchronous action of brain cells. The name is derived from the Greek words *enkephalos* (brain) and *graphein* (to write). An electroencephalogram can be obtained by means of electrodes placed on the scalp or directly on or in the cortex. In the latter case it is sometimes called an electrocorticogram (ECoG) or subdural EEG (SEEG). An EEG recorded in the absence of external stimuli is called a *spontaneous* EEG; an EEG generated as a response to an external stimulus is called an *event-related potential* (ERP). The amplitude of an EEG measured with scalp electrodes is 50 μV to 200 μV.

In the EEG the following rhythms have been distinguished (1): delta (0.5 Hz to 4 Hz), theta 4 Hz to 8 Hz), alpha (8 Hz to 13 Hz), and beta (above 13 Hz, usually 14 Hz to 40 Hz) (Fig. 1). The term gamma rhythm for 35 Hz to 45 Hz activity is now seldom used. The contribution of different rhythms to the EEG depends on the age and behavioral state of the subject, mainly the level of alertness. There are also considerable intersubject differences in EEG characteristics. The EEG pattern changes in different neuropathological states and is also influenced by metabolic disorders (1).

The delta rhythm is a predominant feature in EEGs recorded during deep sleep. During deep sleep, delta waves have usually large amplitudes (75 μV to 200 μV peak-to-peak) and show strong coherence with signals acquired in different locations on the scalp.

Theta rhythms rarely occur in humans and primates, except during infancy and childhood. In humans, activity in the theta band is mostly attributed to the slowing of alpha rhythms due to pathology. However, theta rhythms are predominant in rodents; in their case the frequency range is broader (4 Hz to 12 Hz) and the waves have a high amplitude and characteristic sawtooth shape. It is hypothesized that theta rhythms in rodents serve as a gating mechanism in the information transfer between the brain structures (2).

In humans, alpha rhythms occur during wakefulness and are most pronounced in the posterior regions of the head. They are best observed when the eyes are closed and the subject is in a relaxed state. They are blocked or attenuated by attention (especially visual) and by mental effort (3).

Mu rhythms have a frequency band similar to alpha, but their topography and physiological significance are different. They are related to the function of the motor cortex and are prevalent in the central part of the head. Mu rhythms are blocked by motor functions (2,3).

Beta activity is characteristic for states of increased alertness and focused attention, as was shown in several animal and human studies. It has been observed at the onset of voluntary movements and is present during the processing of sensory information (3).

In general, it can be concluded that the slowest cortical rhythms are related to an idle brain and the fastest are for information processing. The EEG is observed in all mammals, the characteristics of primates' EEGs being closest to the human. Cat, dog, and rodent EEGs also resemble human EEGs, though their spectral content is somewhat different. In lower vertebrates EEG-like activity is also observed, but it lacks the rhythmical behavior found in hgiher-vertebrate recordings.

The EEG is affected by central nervous system (CNS) disorders, including epilepsy, craniocerebral traumas, tumors, cerebral inflammatory processes, degenerative and metabolic CNS disorders, cerebral anoxia, psychiatric disorders, cerebral palsy, migraine, dementia, and pharmacological substances.

HISTORICAL REVIEW OF ELECTROENCEPHALOGRAPHY

The discovery by Luigi Galvani (1837 to 1882) of intrinsic electrical transmission in the peripheral and central nervous system and the discovery by Alexandro Volta (1745 to 1827) in generating and storing electricity were historical milestones in neurophysiology and EEG research (34). Later, the introduction of the first vacuum-tube amplifier by Alexander

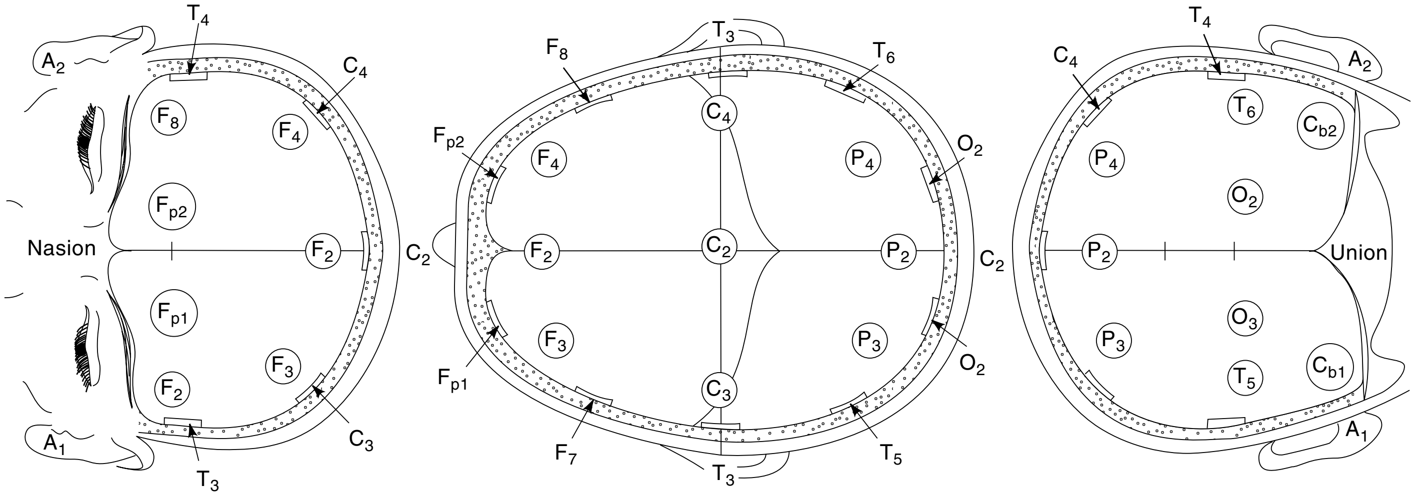

Figure 1. Electrodes (4,5).

Forbes (1882 to 1965) into neurophysiological research had significant impact on EEG research (34).

Richard Caton (1842 to 1926) is regarded as the first scientist to investigate brain potentials. He worked on the exposed brains of cats and rabbits, measuring electric currents by means of a galvanometer, a beam of light reflected from its mirror being projected onto a scale placed on a nearby wall (4). The results showed that "feeble currents of varying directions pass through the multiplier when the electrodes are placed at two points of the external surface, or one electrode on the gray matter, and one on the surface of skull." This first observation can be regarded as a discovery of electroencephalographic activity. The second concerns the steady dc potential.

Adolf Beck (1863 to 1939) also investigated spontaneous activity of the brains of rabbits and dogs. He was the first to observe the rhythmical oscillations of brain electrical activity (4). He also observed the disappearance of these oscillations when the eyes were stimulated with light, the first discovery of the so-called alpha blocking. Later, Napolean Cybulski (1854 to 1919) presented the electroencephalogram in a graphical form by applying a galvanometer with a photographic attachment, and was the first to observe epileptic EEG activity elicited by an electric stimulation in a dog (4).

Progress in recording techniques, namely the application of a double-coil galvanometer, made possible the recording of human EEG activity. Hans Berger (1873 to 1941) was the first to investigate human EEG activity during sleep and changes in EEG patterns that occur with different states of consciousness (5). His works on EEG of patients with localized and diffused brain disorders opened the way to clinical electroencephalography, which became a diagnostic aid in hospitals after the first World War.

THE NEUROPHYSIOLOGICAL BASIS OF THE EEG

In the brain there are two main classes of cells: nervous cells, called *neurons,* and glial cells. In both of them the resting potential is approximately -80 mV, the inside of the cells being negative. The difference of potential across a cell membrane comes from the diffeences in concentration of the cations K^+, Na^+, the anion Cl^-, and large organic anions. Ca^{++} ions are less abundant, but they have an important regulatory role. The potential difference is maintained by the active transport of K^+ to the inside of the cell and Na^+ to the outside; the energy for this transport is supplied through metabolic processes.

Neurons have the ability to generate action potentials when the electrical excitation of the membrane exceeds a threshold. The permeability for Na^+ ions increases rapidly, and influx of Na^+ ions in the cell causes a rapid increase in the potential, but subsequent increase of membrane permeability to K^+ ions leads to their outflow from the cell. Since the permeability for Na^+ ions decreases after about 2 ms, the inside of the cell again becomes negative with respect to surrounding medium. The negativity is even greater than before the neuron became hyperpolarized. By this the action potential is created. The action potentials obey the "all or nothing" firing rule, such that for subthreshold excitations action potentials are not generated, and for suprathreshold stimuli a pulse of a constant amplitude is generated.

The synapses of the neuron are in contact with the membranes of the other neurons. When the action potential arrives at the synapse, it secretes a chemical substance, called a mediator or transmitter, which causes a change in the permeability of the postsynaptic membrane to the ions. As a result, ions traverse the membrane, and a difference in potential (postsynaptic potentials, or PCPs) across the membrane is created. When the negativity inside the neuron is decreased (e.g., by the influx of $Na+$), the possibility of firing is higher—an excitatory postsynaptic potential (EPSP) is generated. An inhibitory postsynaptic potential (IPSP) is created when the negativity inside the neuron is increased (by the flux of Cl^- ions) and the neuron becomes hyperpolarized. Unlike the action potential, the PSPs are graded potentials: their amplitudes are proportional to the amount of secreted mediator, which depends on the excitation of the input neuron. Postsynaptic potentials typically have amplitudes of 5 mV to 10 mV and time spans of 10 ms to 50 ms. In order to obtain suprathreshold excitation, the amplitudes of many postsynaptic potentials have to be superimposed in the soma of a neuron. A neuron can have very abundant arborizations, making up to 10,000 synaptic junctions with other neurons.

The electrical activity of neurons generates currents along the cell membrane in the intra- and extracellular spaces, producing an electric field conforming approximately to that of a dipole. Microscopic observation of this electric field requires the synchronization of electrical activity of a large number of parallelly oriented dipoles (6). Indeed, parallelly oriented pyramidal cells of the cortex are to a large degree synchronized by virtue of common feeding by thalamocortical connections (2). The condition of synchrony is fullfilled by the PSPs, which are relatively long in duration. The contribution from action potentials to the electric field measured extracranially is negligible.

The problem of the origins of EEG rhythmical activity has been approached by electrophysiological studies on brain nerve cells and by the modeling of electrical activity of the neural populations (2,3). The question arises whether the rhythms are caused by single cells with pacemaker properties or by oscillating neural networks. It has been shown that some thalamic neurons display oscillatory behavior, even in the absence of synaptic input (7). There is evidence that the intrinsic oscillatory properties of some neurons contribute to the shaping of the rhythmic behavior of networks to which they belong. However, these properties may not be sufficient to account for the network's rhythmic behavior (2). It seems that cooperative properties of networks consisting of excitatory and inhibitory neurons connected by feedback loops play the crucial role in establishing EEG rhythms. The frequency of oscillation depends on the intrinsic membrane properties, on the membrane potential of the individual neurons, and on the strength of the synaptic interactions.

The role of EEG oscillations in information processing has not been fully recognized. However, there is strong evidence that coherent oscillations in the beta range in a population of neurons might be the basic mechanism in feature binding of the visual system (8). Indeed, it seems that this observation is not limited to the visual system and that synchronized oscillatory activity provides an efficient way to switch the system between different behavior states and to cause a qualitative transition between different modes of information processing. In this way, neuronal groups with a similar dynamic functional state can be formed, subserving perceptual processes. It has also been postulated that the role of synchronized oscillatory EEG activity in the alpha and theta range is to serve as a gating mechanism for the flow of the information through the network. Bursts of oscillatory activity may constitute a mechanism by which the brain can regulate changes of state in selected neuronal networks and change the route of information (2).

RECORDING STANDARDS

The EEG is usually registered by means of electrodes placed on the scalp. They can be secured by an adhesive such as collodion or embedded in a special snug cap. The resistance of the connection should be less than 5 kΩ, so the recording site is first cleaned and diluted alcohol, and conductive electrode paste applied to the electrode cup.

Knowledge of the exact positions of electrodes is very important for both interpretation of a single recording and comparison of results; hence the need for standardization. The traditional 10–20 electrode system (9) fixes the positions of 19 EEG electrodes (and two electrodes placed on earlobes: A_1, A_2) in relation to specific anatomic landmarks, such that 10% to 20% of the distance between them is used as the electrode interval [Fig. 1(a–c)]. The first part of derivation's name indexes the array's row from the front of the head: F_p, F, C, P, and O. The second part is formed from numbers, even on the left and odd on the right side, or z or 0 for the center. Progress in topographic representation of EEG recordings demands a larger number of electrodes. Electrode sites halfway between those defined by standard 10–20 system have been introduced in the extended 10–20 system (10).

The EEG is a measure of potential difference; in a referential (or unipolar) setup it is measured relative to the same electrode for all derivations. This reference electrode is usually placed on an earlobe, nose, mastoid, chin, neck, or scalp center. There is no universal consensus regarding its best location. In the bipolar setup (mortgage) each channel registers the potential difference between two particular scalp electrodes. Data recorded in a referential setup can be transformed into any bipolar montage, for the sake of display or futher processing. The *average reference* montage can be obtained by subtracting from each channel the average activity from all the remaining derivations. The Hjorth transform references each electrode to the four closest neighbors, which is an approximation of the Laplace transform (LT). The LT, calculated as a second spatial derivative of the signal, represents the scalp current density (11).

In contrast with the open question of the reference, the necessity of artifact rejection is universally acknowledged. The main problem lies in the lack of a working definition for an EEG artifact—it can stem from muscle or heart activity (EMG, ECG), eye movement (EOG), external electromagnetic fields, poor electrode contact, the subject's movement an so on. Corresponding signals (EMG, EOG, ECG, and body movements) registered simultaneously with EEG are helpful in the visual rejection of artifact-contaminated epochs.

An EEG is usually digitized by a 12 bit analog-to-digital converter (ADC) with the sampling frequency ranging from 100 Hz for spontaneous EEGs to several hundred hertz for ERPs to several kilohertz for recording short-latency far-field ERPs. Prior to sampling, low-pass antialiasing filters are used; high-pass filters are applied in order to eliminate artifacts of the lowest frequencies.

SLEEP EEG

A sleep EEG displays a characteristic alternating pattern.

The classical description of sleep involves division into stages (12): stage 1 (drowsiness), stage 2 (light sleep), stage 3 (deep sleep), stage 4 (very deep sleep), and REM (dreaming period accompanied by rapid eye movements.). A polysomnogram includes not only an EEG, but also an electrooculogram (EOG), electromyogram (muscular activity), and respiration. It may also include measurement of blood flow, an electrocardiogram (ECG), and the oxygen level in the blood. The EOG is recorded by means of electrodes placed at the canthi of the eyes. As a result of the corneoretinal standing potential (the cornea is positive relative to the fundus), the eye movements produce changes in the potential between electrodes.

The EOG and EMG help to differentiate REM from the awake state: while these sleep states have similar spectral characteristics, in REM eye movements are more pronounced, and there is a loss of muscular activity. The sequence of sleep stages is usually illustrated in the form of a *hypnogram* (Fig. 2). The recognition of states is based on the contribution of the different rhythms and the occurrence of characteristic signal structures absent in the waking EEG, namely, sleep spindles, vertex waves, and K complexes. Sleep spindles are rhythmic waves of frequency 11 Hz to 15 Hz characterized by progressively increasing and then gradually decreasing amplitude. A vertex wave is a compound potential: a small spike discharge of positive polarity preceding a large spike, which is followed by a negative wave of latency around 100 ms and often another small positive spike. Vertex waves are a kind of auditory evoked response (AER), as can be judged from their shape and place of occurrence. The K complex consists of an initial sharp component, followed by a slow component that fuses with a superimposed fast component. The sharp component may be biphasic or multiphasic. Sometimes the K complex is described only as having slow and fast components; the initiating sharp component is equated with a vertex wave (1).

Sleep stages can be briefly characterized as follows:

Stage 1. Decrease of alpha rhythm, appearance of mixed frequencies in the 2 Hz to 7 Hz band of low amplitude, occasional vertex waves and slow rolling eye movements

Stage 2. Spindles, vertex waves, K complexes

Stage 3. Preponderant slow rhythm, K complexes, some spindles

Stage 4. Very slow rhythm of high amplitude, some K complexes

REM. Decrease of amplitude, faster rhythms, rapid eye movements, and decrease of muscular activity

The evolution of slow wave activity and characteristic spindles during overnight sleep is shown in Fig. 2.

It has been found recently that when the sleep becomes deeper the sources that drive EEG activity move from the posterior regions of the head (prevalent in the waking state with eyes closed) to the centrofrontal regions (13). There is a

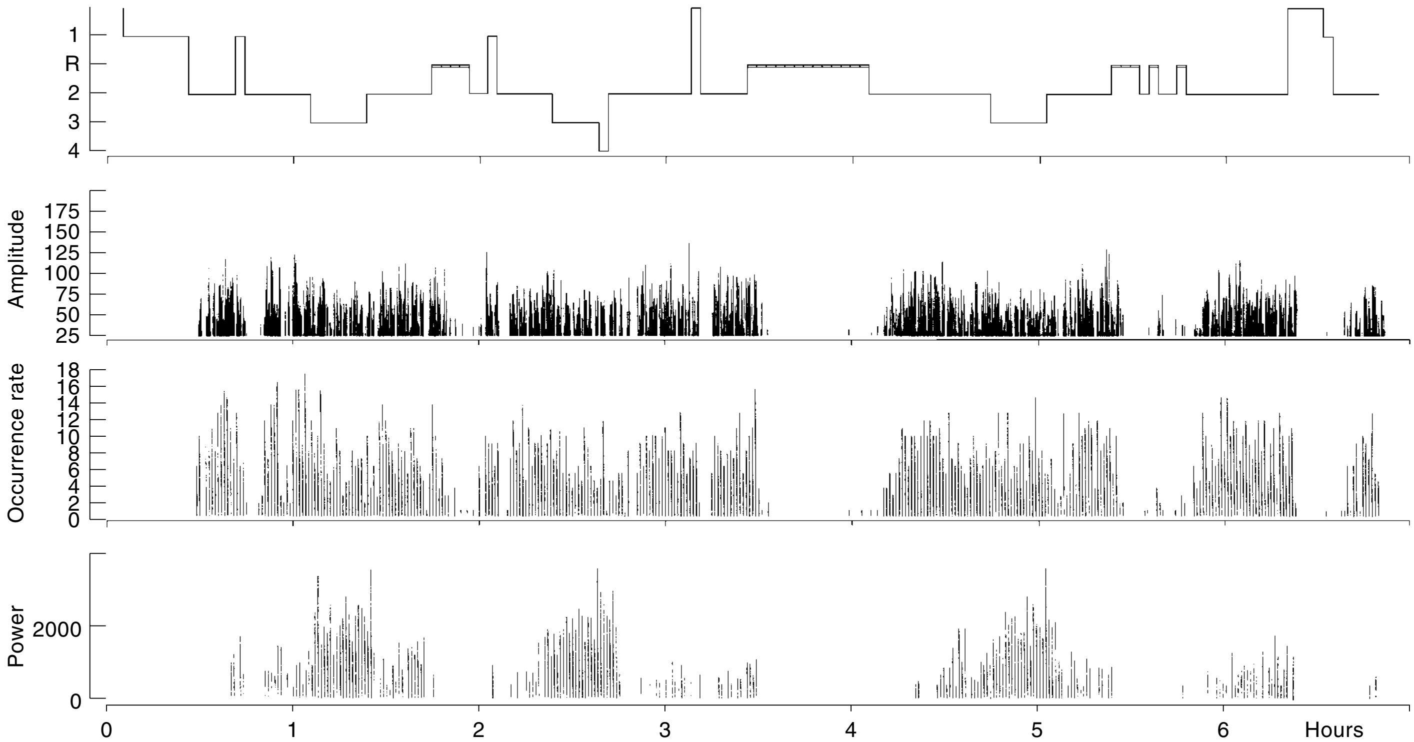

Figure 2. Hypnogram, sleep spindles, vertex waves, and K complex.

tendency to perceive sleep as a continuous process, revealing a microstructure which may be described in terms of "cyclic alternating patterns." They consist of a phase A of enhancement of electric activity and a subsequent phase B characterized by attenuation of EEG activity. Each phase lasts only between 2 s and 60 s.

The sleep pattern changes greatly during childhood and adolescence. In old age the contribution of stages 3 and 4 decreases markedly. The changes of the sleep pattern may be caused not only by a normal aging, but also by degenerative diseases. An abnormal polysomnogram is often present in sleep disorders and in some psychiatric disorders (e.g., depression). Therefore, investigation of the sleep pattern is an important clinical tool.

MATURATION OF THE EEG

The maturation of the brain as evidenced by the EEG has its peak at 30 years; then it stabilizes, forming a plateau, and starts to decay. The rate of decay is correlated with mental health.

The first continuous signal resembling an EEG can be seen in premature babies of conceptual age 32 weeks to 35 weeks. EEG development in infancy and adolescence is characterized by a shift of the EEG rhythm toward higher frequencies. In newborns, slow delta rhythms predominate; then the basic frequency shifts toward theta at the age of 12 months. The posterior slow activity characteristic of young children constantly diminishes during adolescence. Alpha rhythm appears at the age of 10 years (1). In young adults (21 years to 30 years) the EEG still shows mild signs of immaturity, including contributions of 1.5 Hz to 3 Hz and 4 Hz to 7 Hz waves during the waking state, normally not seen past the age of 30.

The sleep pattern changes dramatically during maturation. For newborn babies REM takes most of the sleep time, and in young children only REM and non-REM stages can be distinguished.

Maturation changes in electrocortical activity of fetal animals also involve an increase of power in the higher frequency bands, as was shown for fetal lambs by means of wavelet transform (14). Increased correlation between EEG, respiratory activity, and blood pressure was also found with increasing age (15). However, morphine destroys these correlations. These observations indicate that maturation is connected with increased CNS integration.

Physiologically, the maturation process is connected with the development of dendritic trees and myelination. Myelin layers produced by glial cells cover the axons of neurons and act as an insulator of the electrically conductive cells. The propagation of electrical activity is faster and less energy-consuming in myelinated fibers.

EVENT-RELATED POTENTIALS

ERPs are the stimulus-induced synchronization and enhancement of spontaneous EEG activity (16). Among them, the most clinically used are the evoked potentials (EPs), usually defined as changes of EEG triggered by particular stimuli: visual (VEP), auditory (AEP), somatosensory (SEP). The basic problem in the analysis of EPs is detecting them within the usually larger EEG activity. EPs' amplitudes are one order of magnitude smaller than that of the ongoing EEG (or even less). Averaging is a common technique in EP analysis; it makes possible the reduction of background EEG noise on the assumption that the background noise is a random process but the EP is deterministic.

The EP pattern depends on the nature of the stimulation, the placement of the recording electrode, and the actual state of the brain. Visual EPs are best seen in the posterior regions of the head, auditory potentials at the vertex, and somatosensory EPs at the brain hemisphere contralateral to the stimulus (e.g., stimulation of the right hand will give rise to an EP in the left hemisphere).

EPs are usually described in terms of the amplitudes and latencies of their characteristic waves. The components occurring at different times are different in nature; they are called *early* and *late* EPs. The early EPs of latency < 10 ms to 12 ms (sometimes called "far fields") are connected with the response of the receptors and peripheral nervous system; late EPs ("near field" potentials) are generated in the brain. In late EPs, exogenous components (primarily dependent upon characteristics of the external stimulus and endogenous components) and endogenous components (dependent upon internal cognitive processes) can be distinguished. Endogenous components of latencies above 100 ms to 200 ms are influenced by attention to the stimulus. The later components, around 300 ms, reflect recognition and discrimination between stimuli.

EPs are widely used in clinical practice as a tests of the integrity of the sensory pathways of their different dysfunctions. They are also helpful in the diagnosis of diffused brain diseases (e.g., multiple sclerosis or psychiatric disorders). Particularly in the diagnosis of psychiatric disorders, identification of *contingent negative variation* (CNV) is helpful (1).

CNV is a potential consisting of a slow surface negativity that depends upon the association or contingency of two successive stimuli. A first stimulus serves as a preparatory signal for the *imperative* stimulus, to which a response is made. *Early CNV* is considered an indicator of arousal, whereas *late CNV* is associated with attention to the experimental task. CNV is a sensitive test of weakness in higher mental functions (e.g., schizophrenia, Alzheimer's disease, migraine, and anxiety) (18).

ERP potentials, also known as *Bereitschaft* (readiness) potentials, precede voluntary actions such as speech or movements. Usually they involve event-related desynchronization (decrease of power in the alpha band) and an increase of high frequencies (17).

EPILEPTIC SEIZURE DISORDERS

Epilepsy is caused by the massive synchronization of neuronal electrical activity. During an epileptic seizure, groups of neurons discharge synchronously, creating a large-amplitude signal and leading to uncontrollable oscillations. Tumors, infections, trauma, or metabolic and toxic disorders may be responsible for the synchronized discharges. Epilepsy is the second most common neurological disease (18). Its clinical symptoms may involve the loss of awareness, drop attacks, facial muscle and eye movements, aggressive outbursts, prolonged confusional states, and flexor spasms of the whole body.

Seizure types can be divided into three main categories as follows (18):

1. Local: the synchronized electrical activity starts in a well-localized part of the brain. The seizure, lasting a few seconds, is accompanied by jerking or spasms, as well as by a loss of consciousness.
2. Generalized: the EEG patterns are bilaterally symmetrical and roughly synchronous; the epileptic activity is spread over wide areas of both hemispheres simultaneously from the onset of attack.
3. Unclassifiable: different from types 1 and 2.

In epileptic discharges the membrane potential of cortical and deeper neurons changes in a dramatic way, which leads to the massive bursts of action potentials and large fluctuations of intra- and extracellular fields. The seizure initiation is probably connected with the breakdown of the local inhibitory mechanisms. The crucial factor in the generation of epileptic activity is the synchronization of neural pools. The mechanisms of this synchronization are probably connected with recurrent excitation operating through positive feedback loops. An important problem for diagnosis is the localization of the epileptic focus, which in severe cases can sometimes be removed by surgical intervention. Usually intracranial electrodes are placed in the suspected region, found from the scalp EEG, in order to better localize the focus. The tests involving measurement of ERPs are performed in order to check if the removal of that part of brain will impair vital brain functions. The epileptic focus will not necessarily be detected by imaging techniques such as tomography, so the information contained in the EEG, and possibly also a magnetoencephalogram (MEG), is essential for localization of epileptic foci.

EEG ANALYSIS

The original method of EEG analysis is visual scoring of the signals plotted on paper. Modern computer analysis can extend electroencephalographic capabilities by supplying information not directly available from the raw data. However, visual analysis is still a widespread technique, especially for detection of transient features of signals. In most cases the agreement of an automatic method with visual analysis is a basic criterion for its acceptance.

Due to its complexity, the EEG time series can be treated as a realization of a stochastic process, and its statistical properties can be evaluated by typical methods based on the theory of stochastic signals. These methods include probability distributions and their moments (means, variances, higher-order moments), correlation functions, and spectra. Estimation of these observables is usually based on the assumption of stationarity, which means that the statistical properties of the signal do not change during the observation time. While the EEG signals are ever changing, they can be subdivided into quasistationary epochs when recorded under constant behavioral conditions.

EEG signal can be analyzed in the time or the frequency domain, and one or several channels can be analyzed at a time. The applied methods involve spectral analysis by the fast Fourier transform (FFT), autoregressive (AR) or autoregressive moving-average (ARMA) parametric models, time–frequency and time-scale methods (wavelets), nonlinear analysis (including the formalism for chaotic series), and artificial neural networks.

The estimation of power spectra is one of the most frequently used methods of EEG analysis (Fig. 3). It provides information about the basic rhythms present in the signal and can be calculated by means of the FFT. Spectral estimators with better statistical properties can be obtained by application of parametric models such as AR and ARMA models or, for time-varying signals, the Kalman filter. For quasistationary EEGs, and AR model is sufficient. The AR model represents a filter with a white noise at the input and the EEG series at the output; it is compatible with a physiological model of alpha rhythm generation (19). The AR model also provides a parametric description of the signal, and makes possible its segmentation into stationary epochs. It also offers the possibility of detecting nonstationarities by means of inverse filtering (1).

Interdependence between two EEG signals can be found by a cross-correlation function or its analog in the frequency domain—coherence. Cross-correlation can be used for comparison of EEGs from homologous derivations on the scalp. A certain degree of difference between these EEGs may be connected with functional differences between brain hemispheres, but a low value of cross-correlation may also indicate pathology. Cross-covariance functions have been extensively used in the analysis of ERPs for the study of the electrophysiological correlates of cognitive functions (20). Coherences are useful in determining the topographic relations of EEG rhythms. Usually, ordinary coherence calculated pairwise between two signals is used. However, for the ensemble of channels taken from different derivations the relationship between the signals may come from common driving by another site. In order to find intrinsic relationships between signals from different locations, partial coherences should be calculated: EEG signals recorded from the ensemble of electrodes are realizations of one EEG process and are usually correlated (21).

The representation of EEG activity in a spatial domain is usually performed by mapping. However, it is more effective for a human observer to look at the map than at the table of numbers. A map may help to make a direct comparison between the topographic distribution of EEG features and an anatomic image (given, e.g., by a tomographic brain scan). Three types of features are most commonly mapped for clinical applications: (1) direct variables such as amplitude, (2) transformed variables such as the total spectral power or the relative spectral power in a frequency band, (3) the results of statistical test applied to given EEG feature.

The appearance of a map depends very much on the electrode reference system. Therefore, especially in many cases it is recommended to use the spline-generated surface Laplacians, which are reference-independent. This approach approximates the source current density and cancels a common component due to volume conduction (6,11). The maps can be superimposed on 3-D images obtained by means of CT or MRI scans. This approach was used to map chosen temporal segments with epileptic events, extracted by means of wavelet analysis (22).

The problem of automatic computer-assisted EEG diagnosis is approached by means of pattern recognition techniques that involve choosing a number of characteristic features, and clustering and classification of these features.

One of the first automatic diagnostic methods (23) was based on the observation that an increased amount of slow EEG activity might be analogous to the slow activity seen in the immature EEG. For each electrode, the maturity calculated on the basis of spectral features was compared with the actual maturity. A significant discrepancy was considered an abnormality. In another diagnostic system (1), the ratio of slow to fast EEG activity and the degree of asymmetry between homologous derivations were taken into account. The most extended system, called neurometrics (24), is based on standardized data acquisition techniques and EEG and ERP feature extraction. Statistical tranformations are performed in order to achieve Gaussian distributions before application of multivariate statistical methods such as factor analysis, cluster analysis, and discriminant analysis. Profiles of neurometric features that deviate from age-matched normals have been obtained for patients suffering from cognitive disorders, psychiatric illnesses, and neurological dysfunctions.

Recently, pattern recognition and classification problems in EEG research have been modeled in the form of *artificial neural networks* (ANNs). The multilayer perceptron with backpropagation of errors is the most common such technique and has been used for spike detection (25). Self-organizing ANNs have been used for recognition of topographic EEG patterns (26,27).

The methods of analysis described so far are based on the assumption of the quasistationarity of the EEG time series. However, the understanding of brain processes involves analysis of dynamic features of brain activity offered by time–frequency methods operating on a short time scale. The first method aiming at dynamic analysis is the windowed Fourier transform with a sliding window. Substantial progress has also been achieved with wavelet analysis. The wavelet transform (WT) describes signals in terms of coefficients representing their energy content in specified time–frequency regions. This representation is constructed by means of decomposition of the signal over a set of functions generated by translating and scaling one function called a wavelet. WTs have been successfully used for reconstruction of a single AEP, for parametric description of SEPs, and for other biomedical applications reviewed elsewhere (28).

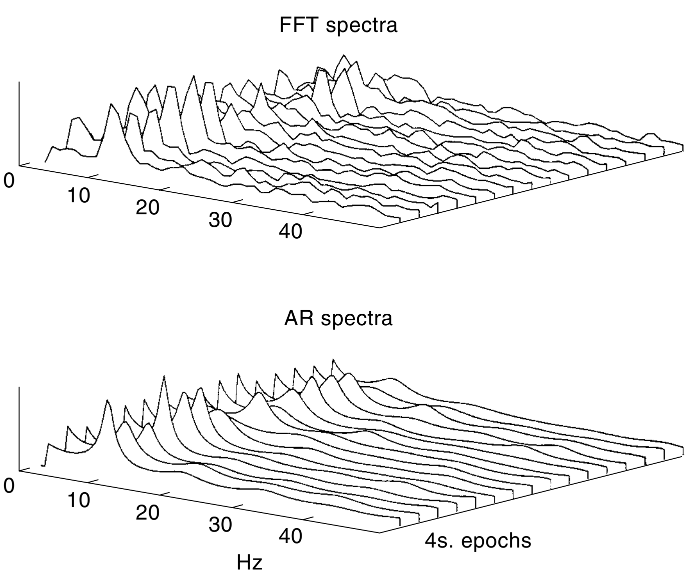

Figure 3. FFT and AR power spectra.

However, the time and frequency resolution in WTs are subject to certain restrictions that lead to poor frequency resolution at high frequencies, as shown in Fig. 4. The representation also depends on the setting of the time window, which makes WT suitable mainly for the evaluation of time-locked signals such as EP, and less appropriate for detecting structures appearing more or less randomly in the signal. This problem has been approached by application of time-shift- and frequency-shift-invariant time–frequency distributions of the Cohen class. However, in the resulting Wigner plots the cross terms are present and sophisticated mathematics has to be applied to diminish their contribution. Also, the Wigner plots obtained by these methods, being continuous functions, do not provide the parametrization of signal structures.

These problems can be solved by a *matching pursuit* (MP) algorithm introduced by Mallat and Zhang (29), which decomposes the signal into waveforms of well-defined frequency, time of occurrence, time span, and amplitude. A Wigner plot of the EEG obtained by means of MP parameterization is shown in Fig. 5. It is easy to perceive the absence of the cross terms observed in Wigner distributions obtained by other methods. The parametrization makes possible the statistical evaluation of EEG features and automatic detection of desired signal structures (30). The application of MP to the detection of EEG structures is shown in Fig. 5. See Ref. 28 for the details of modern time–frequency methods.

The determination of the geometry and orientation of cortical sources of electrical activity is a complex problem. Electrical activity propagates along neuronal tracts and by volume conduction. The potentials measured by scalp electrodes are attenuated by media by different conductivity (cerebrospinal fluid, skull, skin), which results in the decrease of their amplitude by a factor 10 to 20. The determination of source localization from the field distribution involves solution of the inverse problem and is nonunique. In solving the inverse problem, usually one or several dipole sources are assumed and their positions and orientation are estimated by an iterative fit to the measured field (e.g., Ref. 31). A possibility of approaching the inverse problem without assuming dipole sources is offered by low-resolution tomography (32).

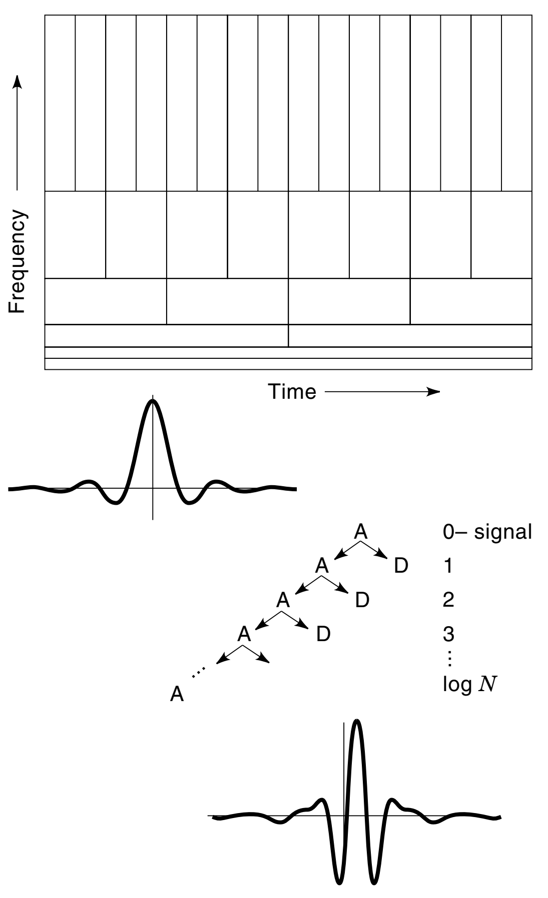

Figure 4. Wavelets.

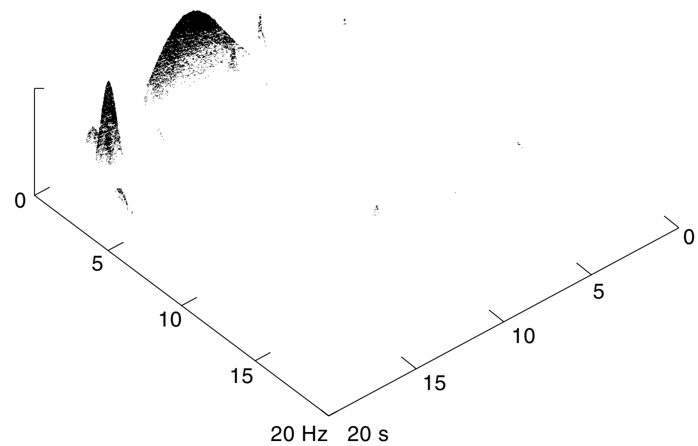

Figure 5. MP: 3-D map.

Recently, MEG—recording of the magnetic field of the brain—has proven to be helpful in solving the inverse problem. The magnetic field is perpendicular to the electric field that produces it. Therefore, in a MEG the sources tangential to the brain surface will be more visible, contrary to the EEG, where the contribution of radial sources is larger. The combination of EEG and MEG is an optimal solution. Unfortunately, magnetoencephalographs are still very expensive.

Methods of brain activity localization such as positron emission tomography (PET) and nuclear magnetic resonance (NMR) give a measure of metabolic rate or glucose consumption, not the brain electrical activity itself. Although their spatial localization properties are good, their time resolution is much lower than that of EEG and MEG. Therefore, they are not likely to replace EEG, which is a totally noninvasive and low-cost technique capable of providing information about relationships between cortical sites.

MODELS OF EEG GENERATION AND CHAOTIC PHENOMENA IN EEG

The most successful models of EEG developed so far are based on the consideration of neural populations characterized by pulse density and slow electrical activity amplitude due to postsynaptic potentials. The dynamic behavior is described in terms of differential equations (3,18). It has been shown that populations of excitatory and inhibitory cells connected by a feedback loop produce rhythmic activity of frequency and bandwidth depending on the coupling strength determined by synaptic interactions (18).

A model of the olfactory system was considered in a linear and a nonlinear regime (3). Nonlinear characteristics of the transition between slow activity and pulses produced chaotic behavior of neural populations. A chaotic system may be described by its trajectory in the phase space, which usually becomes confined to a limited region of the phase space called a basin of attraction. It was postulated that the complexity of dynamics depended on the behavioral state; the recognition of the stimulus was connected with a dynamics described by strange attractor of lower dimension than the attractor describing the state of alertness (3). The physiological observation of chaotic attractors is difficult; the multitude of processes running in parallel in the brain and their changing dynamic pattern make the resulting EEG process apparently stochastic (except for the special situations when large pools of neurons are synchronized, e.g., in epileptic seizure). In the search for chaotic behavior of EEGs, it is important to check the results by comparison with surrogate data (signals where the phase relations were destroyed), since the procedures of calculation of attactor dimensions and Lyapunov coefficients are subject to large systematic and statistical errors. The most striking chaotic dynamics is observed in the vicinity of an epileptic focus, which paves the way for diagnostic applications (33).

The EEG historically has been an important diagnostic tool, and more recent investigations have proven its significance for understanding information processing by the brain.

BIBLIOGRAPHY

1. E. Niedermayer and F. Lopes da Silva (eds.), *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields,* 3rd ed., Baltimore: Williams & Wilkins, 1993.
2. F. H. Lopes da Silva, The generation of electric and magnetic signals of the brain by local networks, in R. Greger and U. Windhorst (eds.), *Comprehensive Human Physiology,* Heidelberg: Springer-Verlag, 1996.
3. W. J. Freeman, The physiology of perception, *Sci. Amer.,* **264**: 78–85, 1991; C. A. Skarda and W. J. Freeman, How brain makes chaos in order to make sense of the world, *Behav. Brain Sci.,* **10**: 161–195, 1987.
4. M. A. B. Brazier, *A History of the Electrical Activity of the Brain. The First Half-Century,* London: Pitman, 1961.
5. P. Gloor, *Hans Berger on the Electroencephalogram of Man,* Amsterdam: Elsevier, 1969.
6. P. L. Nunez, *Electric Fields of the Brain,* New York: Oxford Univ. Press, 1981.
7. H. Jahnsen and R. Linas, Electrophysiological properties of guinea-pig thalamic neurones: An in vitro study, *J. Physiol. (Lond.),* **349**: 205–226, 1984.
8. C. M. Gray et al., Mechanisms underlying the generation of neuronal oscillations in cat visual cortex, in E. Basar and T. H. Bullock (eds.), *Induced Rhythms in the Brain,* Birkhäuser, Boston, 1992, pp. 29–45.
9. H. Jasper, Report of the Committee on Methods of Clinical Examination in Electroencephalography, *Electroenceph. Clin. Neurophysiol.,* **10**: 370–375, 1958.
10. R. T. Pivik et al., Committee report: Guidelines for the recording and quantitative analysis of electroencephalographic activity in research context, *Psychophysiology,* **30**: 547–558, 1993.
11. S. L. Law, P. L. Nunez, and R. S. Wijesinghe, High resolution EEG using spline generated surface Laplacians on spherical and ellipsoidal surfaces, *IEEE Trans. Biomed. Eng.,* **40**: 145–153, 1993.
12. A. Rechtschaffen and A. Kales, *A Manual: Standardized Terminology, Technique and Scoring System for Sleep Stages of Human Subjects,* Los Angeles: Brain Information Service/Brain Res. Inst., Univ. California, 1968.
13. K. J. Blinowska et al., Methods of topographical time–frequency analysis of EEG in coarse and fine time scale, in F. L. Silva, J. C. Principe, and L. B. Almeida (eds.), *Spatiotemporal Models in Biological and Artificial Systems,* Amsterdam: IOS Press, 1996.
14. M. Akay et al., Time–frequency analysis of the electrocortical activity during maturation, *Biol. Cybernet.,* **71**: 169–176, 1994.
15. M. Akay and H. Szeto, Investigating the effects of drugs on the fetal EEG using wavelet transform, *Biol. Cybernet.,* **72**: 431–437, 1995.
16. E. Basar, *EEG Brain Dynamics: Relation between EEG and Brain Evoked Potentials,* Amsterdam: Elsevier, 1980.
17. G. Pfurtscheller, A. Stancak, and C. Neuper, Post-movement beta synchronization. A correlate of an idling motor area? *Electroenceph. Clin. Neurophys.,* **98**: 281–293, 1996.
18. J. S. Dunkan, S. D. Shorvon, and D. R. Fish, *Clinical Epilepsy,* New York: Churchill Livingstone, 1995.
19. A. van Rotterdam et al., A model of the spatial–temporal characteristics of the alpha rhythm, *Bull. Math. Biol.,* **44**: 283–305, 1982.
20. A. S. Gevins, Dynamic functional topography of cognitive tasks, *Brain Topography,* **2**: 37–56, 1987.
21. M. Kamipski, K. J. Blinowska, and W. Szelenberger, Topographic analysis of coherence and propagation of EEG activity during sleep and wakefulness, *Electroenceph. Clin. Neurophysiol.,* **102**: 216–227, 1997.
22. L. Senhadij et al., Wavelet analysis of EEG for three-dimensional mapping of epileptic events, *Ann. Biomed. Endo.,* **23**: 522–543, 1995.
23. M. Matousek, P. Petersen, and S. Freeberg, Automatic assessment of randomly selected routine EEG records, in G. Dolce and H. Kunkel (eds.), *CEAN—Computerized EEG Analysis,* Stuttgart: Fisher, 1975, pp. 421–428.
24. E. R. John et al., Neurometrics: Computer assisted diagnosis of brain dysfunctions, *Science,* **29**: 162–169, 1988.
25. T. Kalayci and O. Ozdamar, Wavelet preprocessing for automated neural network detection of EEG spikes, *IEEE Eng. Med. Biol. Mag.,* **14** (2): 160–166, 1995.
26. S.-L. Jountsdiniemi, S. Kaski, and T. A. Larsen, Self-organizing map in recognition of topographic patterns in EEG spectra, *IEEE Trans. Biomed. Eng.,* **42**: 1062–1067, 1995.
27. A. J. Gabor, R. R. Leach, and F. U. Dowla, Automated seizure detection using a self-organizing neural network, *Electroenceph. Clin. Neurophysiol.,* **99**: 257–266, 1996.
28. M. Akay (ed.), *Time–Frequency and Wavelets in Biomedical Signal Processing,* Piscataway, NJ: IEEE Press, 1997.
29. S. G. Mallat and Z. Zhang, Matching pursuit with time-frequency dictionaries, *IEEE Trans. Signal Process.,* **41**: 3397–3415, 1993.
30. P. J. Durka and K. J. Blinowska, Analysis of EEG transients by means of matching pursuit, *Ann. Biomed. Eng.,* **23**: 608–611, 1995.
31. C. Bumgartner et al., Investigation of multiple simultaneously active brain sources in the electroencephalogram, *J. Neurosci. Methods,* **30**: 175–184, 1989.
32. R. D. Pascual-Marqui, C. M. Michel, and D. Lehmann, Low resolution electromagnetic tomography: A new method for localizing electrical activity in the brain, *Int. J. Psychophysiol.,* **18**: 49–65, 1994.

33. F. H. Lopes da Silva, J. P. Pijn, and D. Velis, Signal processing of EEG: Evidence for chaos or noise. An application to seizure activity in epilepsy, in I. Gath and G. F. Inbar (eds.), *Advances in Processing and Pattern Analysis of Biological Signals.* New York: Plenum, 1996.
34. E. S. Goldensohn, Animal electricity from Bologna to Boston, *Electroenceph. Clin. Neurophys.,* **106**: 94–100, 1998.

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ELECTROFILTER. See ELECTROSTATIC PRECIPITATOR.