International Journal of Clinical Monitoring and Computing 4: 85–98, 1987

Elements of EEG signal processing

I.J. Rampil
Department of Anesthesiology, University of California, San Francisco, CA 94143, USA

Key words: signal processing, closed-loop, inhibitory post synaptic potentials, excitatory post synaptic potentials, electroencephalogram, analog to digital converter

Abstract

It is difficult to find well controlled clinical studies comparing the utility of the numerous EEG measures which have been described. A brief summary of the literature reveals a number of promising case reports, a few large series of patients, and fewer well-designed, well-controlled studies. The very abundance of algorithms makes even technical comparisons of the ability of each to transduce and reflect clinical changes useful (27, 29). Most studies are positive; but thus far (as with so many procedures in medicine), there is no definitive study demonstrating an unequivocal benefit to patients who are monitored with automated, online EEG analysis. That such a study may never be done should not detract from the possible benefits these techniques may bring to clinical practice, most particularly preparing the way for effective brain monitoring in situations in which it was impractical before.

Introduction

What is signal processing

Signal processing is the heart of modern medical instrumentation. As technology progresses, we can sense a wider variety of modalities, many of them difficult to measure without the presence of interference or noise. The goal of signal processing is to improve the *signal-to-noise* ratio. Simply expressed, the signal-to-noise ratio is a measure of the relative strength of useful information in a signal corrupted by noise versus the total strength of the signal, including noise. In the particular case of the electroencephalogram (EEG), it is sometimes difficult to distinguish signal and noise. It may take years of training to detect the subtle nuances in waveform that convey physiologic information. In the clinical setting of the operating room or intensive care unit, the clinician can not devote more than a small part of his or her attention to the EEG as a component of a larger monitoring and patient care environment. To be useful, signal processing must therefore enhance or extract clinically useful data from its random matrix. One byproduct of EEG signal processing is numerically derived parameters which quantify various aspects of the EEG signal and allow statistical manipulations of original data and correlation with other physiologic data. Future applications of such derived measures include automatic diagnosis and even automatic closed-loop control of anesthesia or other therapeutic modalities such as induced barbiturate coma. Before proceeding with a discussion of electronic signal processing in EEG, a brief review of the fundamentals of neurophysiology and the genesis of the electroencephalogram are in order.

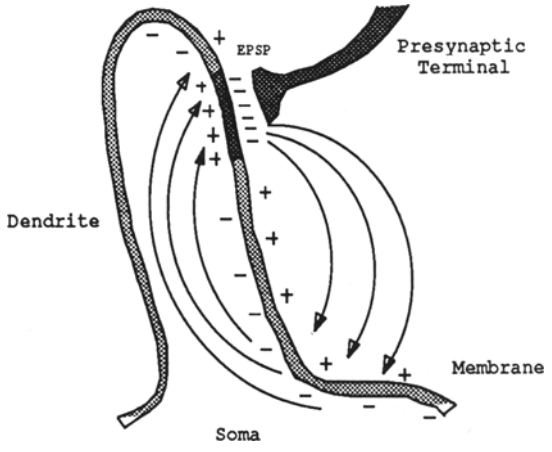

Fig. 1. Current Flow resulting from a dendritic dipole. During an EPSP current flows from a partly depolarized region of the membrane to fully polarized areas.

Neuronal sciences

Neuronal electrical activity

Neuronal membranes have a two-phased response to synaptic stimuli. If an excitatory stimulus is great enough, an action potential is generated and transmitted without decrement down the axon. At most neurons, there is a dynamic balance between inhibitory and excitatory synaptic input to a target cell's dendrites. This dynamic balance causes the dendritic (postsynaptic) membrane potential to slowly move up and down in a graded fashion between hyperpolarization and depolarization. These transitions are known as *IPSPs* (inhibitory postsynaptic potentials) and *EPSPs* (excitatory postsynaptic potentials) respectively. Postsynaptic potential activity can create a relatively stable dipole of the neuron, which is created by the separation of charged particles across the membrane. Figure 1 illustrates an excitatory postsynaptic potential created in the dendrites of a neuron. While the soma remains fully polarized, the dendrites become somewhat depolarized, and hence relatively electropositive with respect to the soma. This dipole formation, which may be stable for many milliseconds, causes an extracellular current to flow around the dipole (from soma to dendrite). This minute current creates a voltage that may be sensed

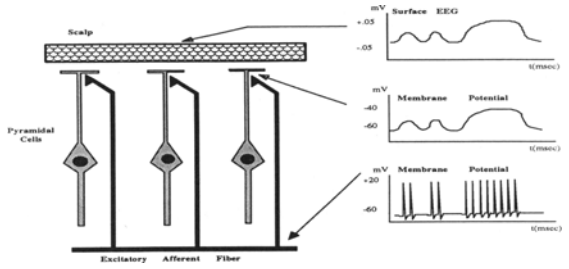

Fig. 2. Genesis of the electroencephalogram.

by an electrode in the conductive media enveloping the neuron; however, the voltage drops sharply with increasing distance between the cell and the electrode.

Cortical pyramidal cells

The neocortex is a complex six layered structure with little recognizable pattern within the neuropil. One of the few patterns identified throughout the cortex is that of pyramidal cells. These are large neurons with long dendrites arranged perpendicularly to the cortical surface. Neighboring pyramidal cells tend to have common presynaptic inputs and hence are correlated in activity (Figure 2). The geometry and common driving combine to create sheets of synchronized, parallel dipoles just beneath the cortical surface. This is thought to be the etiology of the EEG signal observed on the scalp.

Distortion of fields by distance, skull, scalp

The electrical fields created by sheets of regionally synchronous pyramidal cells are modified by their passage to the scalp. First, the distance from the dipoles to the scalp is large compared with the size of the dipoles and the distance between individual dipoles. Second, the currents from many individual cells are irreversibly mixed in the extracellular fluid. Thus, the potentials of many dipoles are transduced simultaneously and averaged at the scalp. The skull also produces some distortion in signal because it forms a high resistance shell in contrast to the very conductive soft tissue of the brain and scalp. This also tends to spatially smear

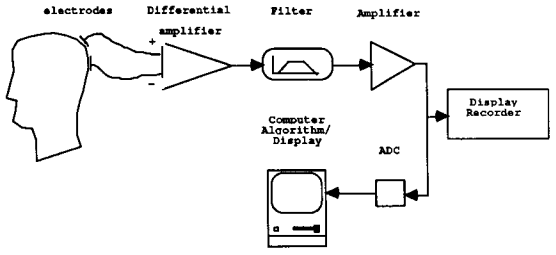

Fig. 3. An EEG system.

the potentials, although this may be partly compensated for by using closely spaced scalp electrodes.

Electronics

As an overview, a complete EEG analysis system may be divided into several component subsystems or stages. Figure 3 illustrates the relationship between the stages. In this section the various components of a functional EEG system will be described, with particular reference to aspects of signal processing.

Signals

In order to effectively process EEG data, some understanding of its nature is required. Biologically induced potentials and currents contain information about their generators. The information containing part of the measured waveform is the signal, the rest of the waveform, noise. Signals may have constant (DC) and/or time-varying (AC) components. The measurement of DC and simple AC signals is straightforward, whereas the measurement of complex, non-repetitive EEG waveforms is not. However, complex waves can be decomposed into combinations of basic sine waves using the Fourier Theorem (a cornerstone of modern signal processing). Figure 4 demonstrates the synthesis of a square wave from the summation of a particular set of sine waves. Decomposition is straightforward and yields the amplitude, frequency and phase of the component sine waves. With this approach, the actual waveforms are lost, but the energy present at differing frequencies can be quantified.

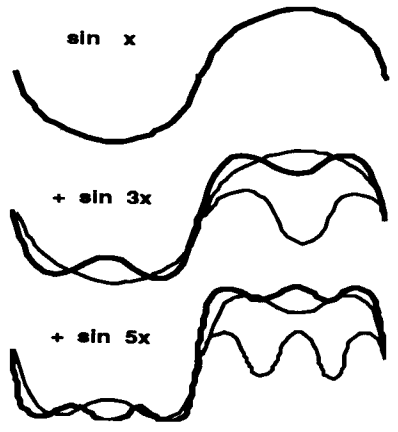

Fig. 4.

Electrodes

The attachment of electrodes to the body is the usual method for measuring bioelectric currents. Electrical contact with electrolytic solutions is complicated by the spontaneous development of voltage barriers around the metal electrodes thrust into the solution. The voltage characteristics of this barrier vary according to the specific combination of metal and electrolyte solution. Many combinations produce potentials which are unstable, resulting in noise at the electrode interface (12). The combination of silver electrodes with silver chloride solution has been empirically established as having a very stable 'electrode potential' and thus is the combination most frequently used. In contrast, stainless steel and saline form highly unstable contacts, leading to the generally poor performance of steel needle electrodes implanted in skin. The electrode potential which forms at the interface has both resistance and capacitive properties. The electrical impedance of the interface will therefore vary with the frequency of the transmitted signal. Silver-silver chloride electrodes have less impedance over the low frequency range of EEG than do many other types of electrodes. The resistive component of the contact impedance is also heavily influenced by the resistance of the stratum corneum. Another source of noise in the electrode interface is motion. Mechanical motion disrupts the electrode potential while skin deformation causes an additional, noisy biopotential.

Amplifiers

The range of scalp voltages created by the EEG is 1–100 μVolts. To display or process these signals conveniently, they should be amplified into the range of 1–10 Volts. Amplification by a factor of 10^5–10^6 is best accomplished in two or three sequential stages. Electronic circuits used to amplify can be designed to provide additional types of signal processing.

The gains or ratios of voltages are frequently expressed in a log scale known as *decibels*:

$$dB = 20 \log_{10} [v_1/v_2]$$

Bioelectric amplifiers generally have three substages. The first stage includes a set of buffer amplifiers which electrically isolate the patient while increasing the input impedance Z_i of the amplifier stage. The next stage is the differential stage. A differential input amplifier has two input terminals and its output is a function of the difference in voltage between the two inputs. This feature is important in reducing a type of noise known as the *common mode* signal. Common mode signals are those which come from generators distant to the measurement site and contribute a noise signal that is similar if not identical at both inputs. The most prevalent common mode signal in the EEG does not originate in the body – it is the 60 Hz power line hum which the body absorbs like an antenna. The differential input amplifier takes advantage of the fact that the common mode (noise) signals are essentially the same at both input terminals: the bioelectric signal of interest is (or should be) different. The amplifier substracts input A from input B and amplifies only the resulting difference. Hence a common mode signal 10,000 times the size of the bioelectric signal (80 dB) can be simply eliminated, leaving only the signal of interest for further stages of amplification. The ability of a differential amplifier to reject the common mode signal is sensitive to the relative contact impedance of the two input electrodes. At each input, the electrode impedance forms a voltage divider with the input impedance Z_i of the amplifier. The voltage seen by each amplifier input terminal is the ratio of the contact impedance over the total impedance. If only one electrode of the pair makes good contact, the common mode rejection will be poor.

Filters

Filters are electronic circuits (or computer programs) which reduce the presence of certain frequency range signals while preserving others. The rational use of electronic filters presumes that the information of interest in the signal lies in a range of frequencies different from that of the noise and artifact frequencies. This is often the case with the intraoperative EEG. Filters may be described by the following three characteristics: *Type* (shape); *Corner* (effective) *Frequency* and *Slope* (of drop off). These characteristics can be graphically summarized by a *Bode Plot* describing the relative gain (in decibels) from input to output over a wide range of input signal frequencies. A Bode plot can be calculated from the circuit design or measured empirically. In actual practice, filters do not make the sharp turn shown by the solid line in the figure, instead they follow a more gradual transition as shown by the dotted line. Since transition is gradual, the corner frequency has been arbitrarily chosen as the point at which the output signal has declined 3 dB (a ratio of 0.707) compared with the input signal.

Since no filter is perfect, there is not immediate and complete attenuation of the output signal once it has crossed the corner frequency. Rather, the attenuation by the filter increases as the signal frequency moves further from the corner frequency. If drawn on a log-log scale, like the Bode plot, the rate of attenuation is constant. Most one-stage filters have a drop off slope of 20 dB/decade or a factor of 10 voltage attenuation per factor of 10 change in frequency. Adding more stages of filtration is simply additive to the slope; e.g., a two stage filter will drop off at 40 dB/decade.

The common types of filters and their typical Bode plots are shown in Figure 5.

In addition to attenuating the presence of certain frequencies in the output signal, filters also cause phase shift distortion. This means that different frequencies will have different transit times through the filter. The numerous frequencies

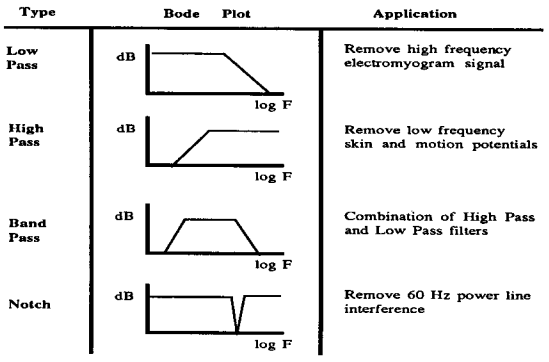

Fig. 5. Filter types by Bode plot.

which make up a complex waveform will be delayed by differing amounts and thus the output waveform will be somewhat distorted.

Careful thought should be applied to the filter settings in an EEG system. Most EEG systems will have a bandpass filter which allows separate adjustment of the high pass and low pass corner frequencies. If the corner frequencies are set too close together, then relevant EEG information will be lost. If the pass band is too wide, the extraneous noise will contaminate the filter's output. In routine (neurology-clinic) EEG recordings, a bandpass of 0.5–70 Hz is reasonable (17). However, the increased noise and artifact which are present in the operating room and intensive care unit dictate a reduction in the bandwidth to perhaps 0.5–30 Hz in order to improve the signal-to-noise ratio (18).

Analog to Digital Conversion

Following amplification, the EEG signal may be translated into digital format so that it may be manipulated by a digital computer to yield additional data. The EEG signal up to this point has of course been in analog format. This implies that it is a continuous waveform which may be measured at any point in time to any arbitrary degree of resolution or accuracy. A digital representation of the same data would be a stream of fixed length (resolution) numbers representing the instantaneous value of the analog voltage at a set of regular intervals known as the sampling rate. Thus an *Analog-to-Digital Converter* (ADC) in use creates the possibility of two types of distortion which must be considered in the initial design of the signal processing system. The first type of distortion comes from the limited amplitude resolution of the converter. Many of the current, commercially available computer assisted EEG machines have an 8–10 bit resolution ADC. An 8 bit ADC has 256 (2^8) possible levels at which to *quantize* the incoming signal. As an example, if the full scale input voltage range to an 8 bit ADC were 0.0–2.56 Volts, then the resolution of the ADC would be 10 mV, and signals which were different by less than 10 mV (or 0.4% of the full scale voltage) could not be distinguished in the output of the ADC. It is possible to use higher resolution (e.g., 12 bit) ADCs, but they are more expensive, slower, and produce digital data, which requires more computer memory to store and process. On machines with limited ADC amplitude resolution, it is beneficial to adjust the preceding amplifier gain so that the EEG signal occupies as much of the ADC input range as possible.

The second type of distortion inherent in the ADC process is that due to discrete sampling intervals. It is easy to envision that voltage excursions of the EEG in between digital samples will be ignored. More insidious than missed voltage fluctuations is a condition known as *aliasing*. Aliasing is the erroneous sensing of high frequency input data as low frequency data. This occurs when the ADC is presented with input signal which contains energy in frequencies higher than one half the sampling frequency of the ADC. Figure 6 illustrates the principle. The only way to prevent this distortion is to low pass filter the analog signal so that it contains *no* energy in the frequencies at or above one half the sampling rate. This mandate includes not only the signal of interest but any possible noise as well. The customary sampling rate for EEG is 128 Hz. This rate is more than double the 50/60 Hz power line noise and thus simplifies the prefiltering requirement by reducing the need to completely eliminate the power noise. There is actually a circumstance in which aliasing can be profitably utilized and it will be discussed later.

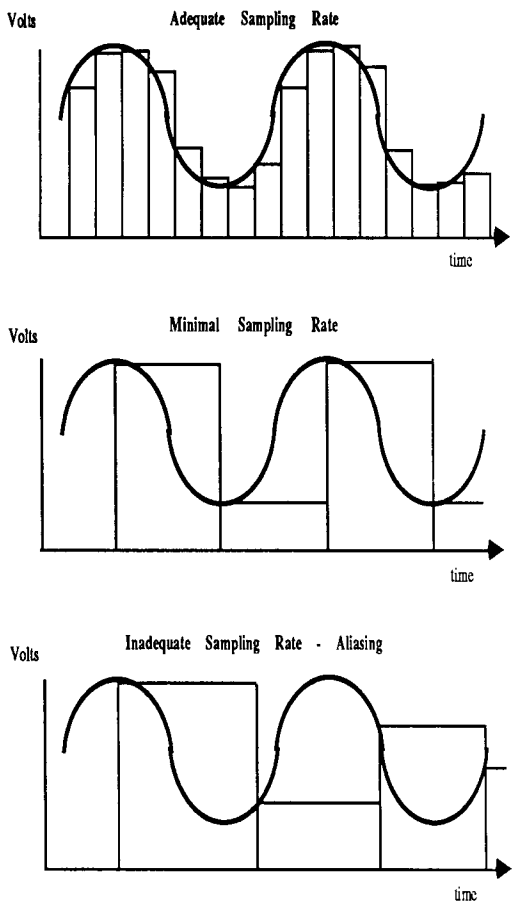

Fig. 6. Aliasing and its effect on the reconstructed waveform.

Algorithms

Once digitized, the computer can be quite flexible in how it displays the EEG signal. When doing automated analysis, it is still useful to examine the raw or original signal. A computer can emulate a paper strip chart recorder presentation on a video screen. More significantly, the computer provides the ability to process, enhance and compress EEG information and display it in ways hitherto impossible. This next section discusses some of the algorithms which have been used to extract useful quantitative information from the EEG.

Digital filtering

Once a signal is digitized, a set of very powerful tools becomes available to process the data. The primary tool is digital filtering, with which a designer can either replicate any given type of analog (hardware) filter or create filter functions which would be difficult to engineer in the analog domain. Digital filters for EEG processing are usually implemented as software programs or subroutines which take bytes of data as they become available from the analog to digital converter, perform a predefined arithmetic operation on it, and provide an output which represents the filtered input. There are basically two types of digital filters, the distinction between them based on the response of each to a single-impulse input. An impulse input is a sample stream of all zeros, save a single reading of a full-scale voltage, somewhat analogous to a bolus input. If the filter algorithm, by design, has an output which settles back to zero within a finite amount of time (usually a few sample times), then the filter is classified as a *Finite Impulse Response* (FIR) filter. An example of an FIR filter is a moving average filter of length = 4:

$$Y_t = (X_t + X_{t-1} + X_{t-2} + X_{t-3})/4$$

where Y_t is the current output of the filter, X_t is the current input, and X_{t-i} are previous inputs. At four samples past the impulse input, the output returns to zero as illustrated in Figure 7. In contrast, an *Infinite Impulse Response* (IIR) filter has (theoretically) an infinitely long response to a single-impulse input. In practice, the IIR response is usually truncated because most computers use finite precision arithmetic. An example of an IIR is:

$$Y_t = (Y_{t-1} + X_t)/2$$

where the variables are the same as before. As shown in Figure 7, the response to an impulse declines by one half with each succeeding sample time until it is no longer measurable.

FIR filters are easier to customize to arbitrary specifications but they require more arithmetic for a given degree of filtering than IIR filters. The decision as to which filter stages should be implemented in analog and which in digital is difficult to make. Analog filters are expensive, difficult to adjust, and physically large compared with digital filters. Digital filters, however, require computer

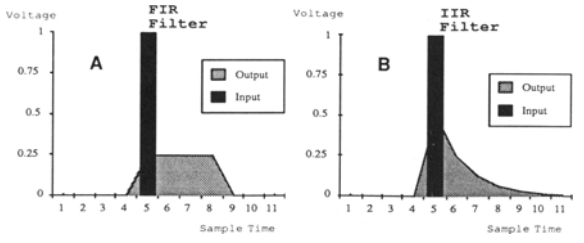

Fig. 7. (A) FIR Filter; (B) IIR Filter.

power, and if the system computer is busy, there may not be time to perform the filter calculations.

Once filtered to the degree desired to reduce certain types of artifact, the resulting EEG waveform can be displayed. In some cases, this form of signal processing may suffice. In other cases, additional processing is desirable to simplify analysis. This may be added by displaying the results of a frequency analysis, or by extracting quantitative data.

EEG Signal Analysis

Unless specifically noted, the following discussion concerns only background EEG activity and not spike phenomena or evoked responses. At our elementary level of understanding, the EEG appears to be a random, or *stochastic* voltage signal (10, 21). Random appearing signals may be conveniently described by their statistical properties, such as their mean, variance, and frequency distribution. Certain statistical measures of the EEG are empirically relatively stable measures over time and may reflect ongoing physiological processes. Under ordinary circumstances of rest or anesthesia, background activity can be safely assumed to be statistically stable or *stationary* for periods of up to 20 seconds. Many analysis techniques examine sequential segments of EEG called epochs, which usually range from 2–16 seconds. Some algorithms have been designed to sense and adapt to nonstationarity (2).

Literally dozens of algorithms which attempt to refine the information content of the EEG have been described. An organized approach to this multitude invites division of these algorithms into classes. At least three systems of classification are possible: *Semantic* vs *Statistical, Time* vs *Frequency Domain* (3), and *Parametric* vs *Non-Parametric* (21) analysis. Semantic or syntactic processing attempts to directly analyze patterns of waveshapes and thus emulate the trained human observer. Statistical approaches use more numerically oriented algorithms. Frequency domain analysis proceeds from the spectral content of an EEG epoch, whereas time domain analysis uses the original voltage versus time waveform. Parametric analysis makes a-priori assumptions about the statistical nature of the 'underlying generator' of the EEG in order to build statistical models whereas the nonparametric algorithms have no such constraint. Parametric modeling is only a statistical contrivance useful for predicting future activity and for producing a sparse description of the EEG state (13, 36). These models are essentially digital filters which

Table 1.

Non-Parametric	*Parametric*	*Semantic*	*Statistical*	*Time*	*Frequency*
Amplitude	*ARMA Models*	*Aperiodic*	*Amplitude*	*Amplitude*	*Correlation*
Aperiodic	*Kalman Filter*	*Waveform*	*ARMA Models*	*Aperiodic*	*FFT*
CFM	*Waveform*		*CFM*	*ARMA*	*Spectral Parameters*
Correlation			*Correlation*	*CFM*	
Hjorth descriptors			*FFT*	*Hjorth*	
Power Spectra (FFT)			*Hjorth*	*Kalman*	
Spectral Parameters			*Kalman Filters*	*Waveform*	
ZXF			*Spectral Parameters*	*ZXF*	
			ZXF		

are tuned to take truely random noise input and produce an output signal which has the same statistical descriptors (ie variance, frequency content) as the current observed EEG. They should not be construed as a model of the physiology. *Parameters* refer to the coefficients of model filters which make it fit the EEG data. A model may have 3–30 parameters depending on its complexity. Parametric algorithms have not been frequently employed in the past in real-time applications such as the operating room and intensive care unit for a number of reasons, including their relative complexity as well as their non-intuitive approach for clinicians without mathematical or engineering backgrounds. Algorithms which do not use models are called *non-parametric.* Non-parametric statistical techniques are the most often reported in the literature encompassing operating room and intensive care applications with about equal division between the time versus frequency algorithms. The table enumerates some of the more popular algorithms, sorted by classification system.

Waveform analysis approaches

Two of the earliest automated approaches to EEG signal processing involved calculation of the 'average' frequency and amplitude of epochs of EEG. The individual amplitude of each wavelet may be determined by using the derivative of the signal as a guide to finding the local minima and maxima, then establishing the absolute value of the peak-to-peak voltage difference between them. Or an average amplitude can be obtained by rectifying the raw EEG and low pass filtering (5, 8, 20) (Figure 8). The frequency of a wave is usually calculated by locating the points at which the EEG voltage crosses the zero voltage axis and changes polarity (15, 31). The reciprocal of twice the time interval between sequential crossing points is the 'instantaneous' frequency (Zero Crossing Frequency or ZXF) of that wave (Figure 9). Some authors have suggested refinements of this algorithm which include the following: using hysteresis about the zero axis (35), concomitant zero crossing analysis of the first and second derivatives of the signal (4), prefiltering the signal into distinct pass bands (6),

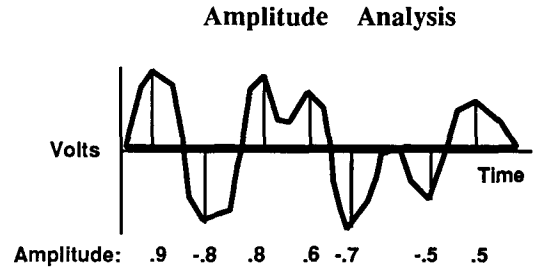

Fig. 8. Peak by peak amplitude analysis.

and combining amplitude information with the zero crossing information ref (7, 26). Many investigators have computed the mean of these values for an epoch and reported the 'average' frequency and amplitude. Unfortunately, the distribution of amplitudes and frequencies in an epoch is seldom *Normal,* or in the form of a sharp Gaussian bell-shaped curve; in fact it is often multi-modal (11). The mean will tend to describe the dominant activity and exclude other less prominent activity. Under these circumstances, the mean value may inadequately describe these distributions. Furthermore, as demonstrated by Figure 9, the zero-crossing approach tends to be insensitive to low-amplitude wave (they do not necessarily cross the axis). These two approaches are most accurate with an input signal containing a narrow range of frequencies and amplitudes. Nevertheless, these algorithms have been applied with some success in the operating room. They form the basis of a number of commercial instruments (ABM^{tm}, CFM II^{TM}, Lifescan^{tm}, and PSA−1^{tm}). The Lifescan, using a variant of combined prefiltered, amplitude/zero crossing analysis known as aperiodic analysis (7), does not average the instantaneous values as do the other instruments but does 'thin' or delete data prior to display.

Another measure of the amplitude of the EEG can be obtained by squaring the input data and then computing the mean. This yields (assuming the epoch has a mean amplitude of zero) the mean square amplitude or amplitude variance of an epoch.

$$\sigma_a = \frac{\sum X_i^2}{N}$$

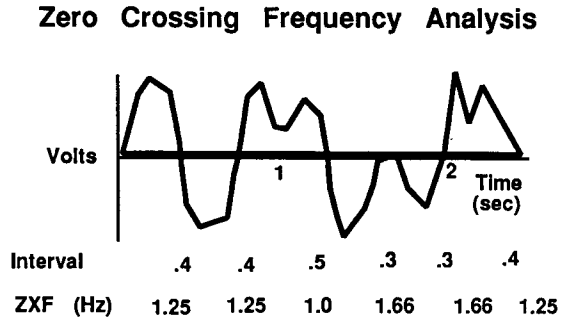

Fig. 9. Simple zero crossing analysis.

where: X_i is the input at time i
N is the number of samples in the epoch
σ_a is the amplitude variance

Summing the variance for all the waves in an epoch provides a measure of the power (e.g., μWatts) present in that epoch. EEG power measurement should not be interpreted as measurement of the 'energy output' or 'metabolic rate' of the brain. One must recall that the size of the EEG signal is related to many things, including the degree of synchrony of the pyramidal cells. There are many pathological states in which hypersynchrony (large delta waves) and poor brain function coincide.

Taking algorithms a step further, Hjorth (16) introduced measures known as activity, mobility, and complexity which are in fact functions of the variance of the signal. The activity is the variance of the amplitude. Mobility is the ratio of the variance of the derivative of the EEG divided by the amplitude variance. The complexity estimates the bandwidth of the EEG as a function of the variance of the signal and its first and second derivatives.

$$\text{Activity} = \sigma_a^2$$

$$\text{Mobility} = \sigma_d/\sigma_a$$

$$\text{Complexity} = [\sigma^2_{dd}/\sigma^2_d - \sigma^2_d/\sigma^2_a]^{0.5}$$

where: σ_d is the variance of the 1st derivative
σ_{dd} is the variance of the 2nd derivative

Saltzberg and Burch (32) have demonstrated that when the EEG has a normal distribution about a mean of zero, then the mobility and complexity may be simply estimated from the zero crossing rate of the EEG and its first derivative. The Hjorth

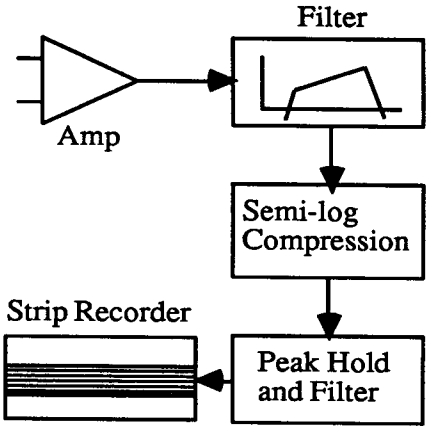

Fig. 10. The cerebral function monitor.

descriptors, like the average amplitude and frequency, work best when the EEG signal is relatively simple.

The original Cerebral Function Monitor (CFM) designed in 1969 by Maynard, Prior and Scott (24) sought to integrate frequency and amplitude information into a single variable. Following amplification, the EEG signal passed through a combination bandpass filter-differentiator. This had the effect of accentuating the frequencies at the high end of the 2–15 Hz pass band (Figure 10). The filtered signal was then logarithmically compressed and rectified to provide a signal which approximated the product of the power and the mean frequency in the pass band. The CFM actually did all of its signal processing in analog circuitry. The CFM was most useful in detecting major depression of the EEG (loss of most activity); it was not very sensitive to small changes due to anesthetics. Because its algorithm multiplied frequency and amplitude, it could not differentiate between large slow waves and small fast waves if they gave the same product. A later development by Maynard (25) (CFAM or CFM II) produced separate output of the amplitude and frequency information.

Correlation analysis

Prior to the discovery of the *Fast Fourier Transform* (FFT) algorithm the mathematical techniques of autocorrelation and crosscorrelation provided a means of deriving frequency spectra and also the

relationships between multiple channels of EEG. A correlation is performed by summing the result of a point by point multiplication of one waveform against another. The process is repeated as one waveform is incrementally offset by a lag τ, against the other.

$$R_{xx}(n, \tau) \simeq \sum x(n) \cdot x(n + \tau)$$

The autocorrelation function R_{xx} performs this operation on one waveform against itself. The autocorrelation technique detects and emphasizes periodicity or regularity in appearance of a waveform and can be used in lieu of direct Fourier transformation. Since the introduction of the FFT algorithm, however, correlation techniques are no longer as popular in EEG research as they once were.

FFT

Much of modern signal processing was made possible by the discovery of an efficient numerical algorithm known as the Fast Fourier Transform by Cooley and Tukey in 1965. Much of this efficiency is achieved by systematically removing redundant calculation so that in a 256 point transform only 1/16 the arithmetic is done and in a 1024 point transform the ratio is 1/51 when compared with the old method. As alluded to earlier, this algorithm functions much like an optical prism, breaking up a complex input signal (like white light) into its component parts (Figure 11). The actual FFT algorithm still requires a great deal of 'number crunching' and many modern microcomputers would have trouble performing an FFT on more than four simultaneous channels of EEG in real time. Special purpose chips have been designed to perform the actual FFT calculation with a considerable increase in speed and capacity.

The FFT algorithm typically takes N points (where N is a power of 2, e.g. 128, 256, 512, 1024) of digitally sampled signal data. The output is an array of N/2 frequency 'bins'. The frequency resolution and the highest calculated frequency bin represented by the array are functions of sampling rate and N:

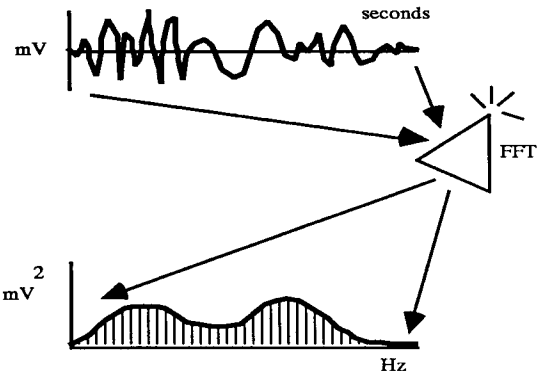

Fig. 11. The FFT as a mathematical prism.

Sampling interval (seconds) = 1/Sampling rate (Hz)
Resolution (Hz) = Sampling Rate/N
Highest frequency (Hz) = Sampling Rate/2

The expression for the highest frequency is a corollary of Shannon's Sampling Theorem. This is relevant, because the aliasing phenomena described earlier will distort the FFT output in the manner described if excessively high frequencies are present.

Once the output array of frequency bins is obtained from the FFT calculation, there are several schemes for displaying an otherwise intimidating mass of data. The most commonly used at present, is the *Compressed Spectral Array* (CSA) display technique which was popularized by Bickford (1) in the early 1970s. The CSA is the now familiar 'hill and valley' pseudo-three-dimensional plot of frequency versus amplitude (power (amplitude (2)) actually is plotted) versus time. Another display technique is the *Density Spectral Array* (DSA) introduced by Fleming and Smith (9). This display is similar to the CSA except that the power at any specific frequency and time is represented by the density of a dark spot on the display rather than by the height of a plotted line.

Quantitation of spectral patterns

Calculation of the contribution of various frequencies has always been a central part of EEG analysis, from past description of the classical bands (delta, theta, alpha, beta) to current frequency spectral

analysis. High resolution examination of the frequency distribution of energy in the EEG provides a strong argument against the use of the classic but crude representation of the EEG as delta, theta, alpha and beta bands. This is particularly true in the operating room where changes in anesthetic dose cause smooth transitions of EEG activity through the classically defined boundaries. Nevertheless, some authors have successfully utilized either the relative power in a specific band (e.g., alpha) (23) or a band ratio (e.g., (delta + theta/alpha) to correlate with various physiologic processes such as sleep activity. These ratios are preferable to absolute measurements because there is generally a high degree of correlation in activity among all the bands and therefore less spontaneous variability in the quotients than in individual bands. This method is useful when the numerator can be expected to move in the same direction as the denominator but may not be useful when they change in the same direction.

Yet another approach to condensing the information present in a frequency spectrum is to treat it as a statistical distribution (which it is) and apply some descriptive statistics to it. Three such measures (34) which have been applied in the acute care setting are the median power frequency (MPF), the peak power frequency (PPF), and the spectral edge frequency (SEF) (Figure 12). The MPF, as the name implies, is the frequency at which half the power is above and half below in the spectrum. The PPF is the frequency with the greatest power in the spectrum, i.e., the mode of the spectrum. Most implementations of the PPF and MPF exclude the very low frequency end of the spectrum (as much as the entire delta band) because of the strong possibility of high amplitude artifact that would unduly influence the calculations. In principal, the SEF (33) is the upper frequency limit of the distribution, i.e., the + 2 S.D. point. In practice, however, random variation of the EEG spectrum requires a more intuitive approach to obtain a stable measure. The standard algorithm used by the author incorporates a search downward from the 97th percentile point in the spectrum to a pattern of contiguous EEG activity at least 2 Hz wide, in which each frequency bin

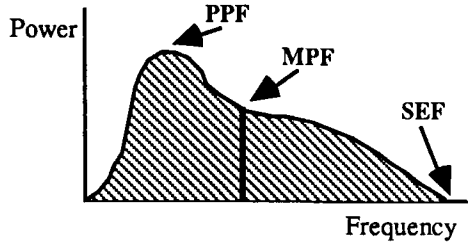

Fig. 12. Spectral derived parameters.

(0.5 Hz wide) contains more than some preset threshold (usually the Total Power/256) power. This approach disregards small random outliers in the highest frequencies and is an functional attempt to emulate the visual inspection algorithm for spectral edge. Some authors have used simple percentile algorithms (e.g., 97th percentile) with reasonable success when other noise suppression techniques are used.

Since the EEG is random in its moment-to-moment variation, there is a relatively high short-term variance in the computed measures, regardless of type. It is reasonable to low-pass filter or average the calculated measures over the course of time and present the smoothed data to the clinician. Smoothed readouts are easier to read but there is a trade-off in that if a sudden event such as ischemia occurs, smoothing may significantly delay its recognition. A balanced approach is to provide a single-stage filter with a time constant of 10–20 seconds. Digital filters can be made *adaptive* so that they strongly filter small upward frequency transients most commonly associated with noise, and weakly filter the downward frequency transients which may be associated with ischemia.

Special purpose algorithms

Algorithms have been developed for relatively special purposes. Some examples include the automatic detection of epileptiform spike waves, quantification of burst suppression, and a measure of co-existing electromyographic (EMG) activity (14). Algorithms which detect seizure activity can be fairly simple or extremely complex, depending on the degree of sensitivity and specificity required. Algorithms used in clinical neurology for

the diagnosis of epilepsy in ambulatory EEG recordings have complex pattern-matching criteria (22, 37), whereas an algorithm designed by the author to detect enflurane-induced spikes was successful with only a simple test of amplitude and slope of the waveform (28). An algorithm which might be useful in the management of barbiturate coma would compare periods of bursts with relative electrical silence, and compute the percentage suppression per minute, averaged over a five-minute interval. By providing additional band pass during amplification and a higher sampling rate, the frequency spectrum can be calculated to include the range where EMG can be measured if it exists. A clever signal processing trick can use the aliasing phenomena to translate EMG to a region of the calculated spectra unoccupied by the EEG. There the EMG activity can be simultaneously, separately quantified. The spontaneous EMG has been posited by some investigators as a useful index not only of relaxation but of depth of anesthesia as well (14).

Artifacts

Artifacts and interference are omnipresent in clinical EEG work. There are many maneuvers to decrease the amount of artifact entrained into the measuring system (30). Nonetheless, a significant quantity of artifact does leak in. Although many of the newer EEG systems have some artifact recognition capability, it is far less than that of the most naive human observer. Unrecognized artifact when processed by any of the previously discussed algorithms will lead to unpredictable, erroneous outputs. It is worth remembering that one observer's artifact may be another's signal. Several biologically generated 'artifacts' are present in EEG recordings, for example ECG, and EMG. Optimal signal processing would cleanly separate these signals and extract information from each. Even the presence of 60 Hz noise can be used to assess the adequacy of electrode contact impedance. Clinicians who rely exclusively on the outputs of computerized EEG analyzers may unexpected fall victim to one of the oldest laws of computer science.

Garbage In – Garbage Out!

The best insurance is to manually inspect the raw signal from time to time, especially when the derived measures have dramatically changed. An enumerated list of all possible artifacts would be endless, but included in Figure 13 are some of the most common. Automatic artifact detection algorithms are a poorly explored branch of signal processing. The simplest algorithms (and those which may be implemented in portable analyzers) tend to rely on a combination of simple tests on the waveform. For example, an epoch which is flat-line for longer than a few hundred milliseconds, contains a derivative greater than some threshold, or contains greater than a threshold energy at 60 Hz (implying inadequate common mode rejection) would be classified as containing an artifact. Since most analyzers also calculate the frequency spectra, simple tests may be applied to the signal at that level.

Future developments

The field of EEG signal processing is quite active. A number of interesting new algorithms have recently become available for clinical application. One such technique involves mapping EEG spectral data on to a topographic display in real time, allowing detection of regional patterns and other spatial information. This technique involves the simultaneous amplification, digitizing and fast Fourier transform of 16 or more EEG channels. This is accomplished with special computer hardware consisting of multiple microprocessors and special FFT integrated circuits, each handling a few channels and being coordinated by yet another microprocessor which also computes the interelectrode interpolation and drives a graphic display.

Another development involves heuristic or syntactic analysis of the EEG waveforms, the output of which then drives a *production rule-based, expert* artificial intelligence program. The AI program emulates in a limited way, the diagnostic algorithms of a neurologist (19).

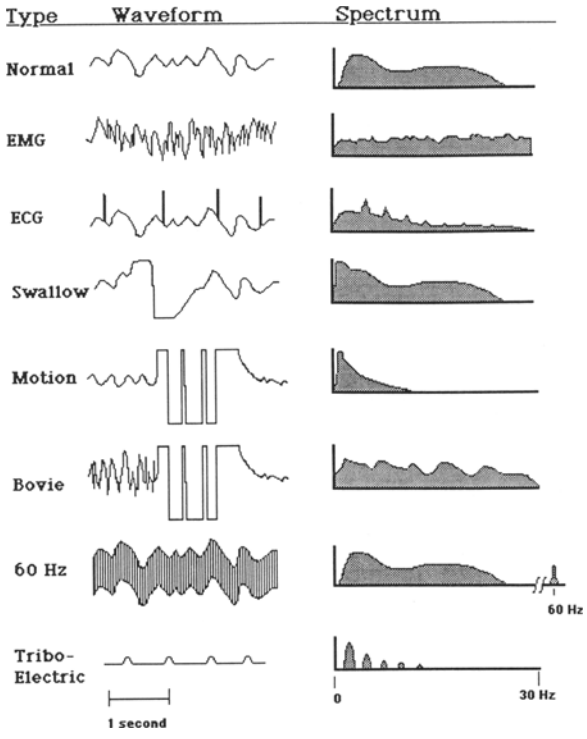

Fig. 13. A partial catalog of intraoperative EEG artifacts.

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