A user-interactive graphics-based computer system for analysis of the EEG

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Computer technology provides a powerful high-resolution tool for the analysis and understanding of the electroencephalogram (EEG). A system of user-interactive graphics-based computer programs analyzing the power spectral density (PSD), coherence, and phase-angle relationships of the EEG is described, along with the mathematical algorithms used. The analytic variables inherent in coherence analysis are reviewed. These variables include choices of sampling parameters, auto- and cross-spectral algorithms, smoothing techniques, and use of the $\gamma^2(f)$ or $\gamma(f)$ value for coherence. These variables in the analysis itself have a net interactive effect on the calculated results that often makes comparability of data across studies impossible. Thus, it is proposed that studies include a graph showing the authors' derived coherence values for a set of standard test signals to enhance scientific communication.

The electroencephalogram (EEG) is a record of electrical potentials generated by the brain as measured between two electrodes on the intact scalp and recorded as a function of time. EEG potentials are dynamic oscillatory phenomena, usually sinusoidal in nature, that represent changes in the excitability of cortical neurons (Brazier, 1977). They are usually recorded simultaneously from multiple loci on the scalp and are used as an important diagnostic and screening procedure in medicine.

The pattern of EEG activity is complex and subject to modification by a variety of conditions, only some of which are pathologic. Biochemical, metabolic, infectious, degenerative, neoplastic, circulatory, hormonal, neuroelectric, and behavioral factors are all variables that affect the pattern of EEG activity (Kiloh, McComas, & Osselton, 1972). In addition, the differences in normative EEG activity between individuals can be quite large (Kooi, 1971). This multitude of variables has limited the analysis of the EEG to visual inspection and interpretation by skilled neurologists looking for distinctive manifestations of central nervous system (CNS) abnormality, and its clinical use has been confined to the detection of certain gross organic pathologies and the epilepsies, in spite of the fact that it "provides the best and most direct measure currently available for assessing the functional state of the central nervous system" (Begleiter & Platz, 1979, p. 294).

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Increasing attention has turned toward expanding the scope of the procedure through the application of quantitative approaches to EEG analysis (Kunkel, 1977). For example, some central nervous system lesions can be localized through the computation of power spectral ratios (Gotman, Gloor, & Ray, 1975; Steadman & Morgan, 1974). EEG frequency content as determined by percent-time determinations has been shown to predict pharmacotherapy outcome in schizophrenics (Itil, Marasa, Saletu, Davis, & Mucciardi, 1975). The monitoring of patients under anesthesia using the compressed spectral array technique of Bickford (1977) has decreased neurologic morbidity during surgery. Coherence analysis has been useful in discriminating dyslexic children from controls (Hanley & Sklar, 1976), hyperkinetic children from controls (Shaw, O'Connor, & Ongley, 1977), organic brain syndrome elderly patients from normal elderly subjects (John, 1977), and alcoholic patients from controls (Scammon, 1980). This expansion of EEG research has been divergent in nature, exponential in growth (Kunkel, 1977), and heavily dependent upon evolving computer technology.

The purpose of this paper is to describe a comprehensive package of computer programs called EEG GRAPHICS, developed for the more extensive and meaningful collection, manipulation, and analysis of EEG data. Currently, the package includes power spectral analysis, coherence analysis, and averaged evoked response calculations. Three important design features have been incorporated into the system. First, the system is highly user interactive, allowing the investigator to quickly develop a "feel" for the data and to easily change the analytic parameters. Second, the package provides both a soft/interactive display via a CRT and a hard-copy display of the data. Finally, the overall design of the package allows the easy incorpora-

tion of additional analytic programs that may be developed in the future.

The hardware includes a Digital Equipment Corporation (DEC) PDP-15 computer equipped with a VT15 graphics processor, a VT07 graphics display terminal with 21-in.-diagonal CRT, and two RP02 disk drives. The programs are written in FORTRAN IV and run under control of the RSX-III operating system.

The software currently contains analyses of power spectral density (PSD), coherence, phase angle determination, and the averaged evoked response. Individual programs require 32K of memory.

SOFTWARE DESCRIPTION

Data Collection

At present, eight channels of EEG are recorded on a Grass Model 78B polygraph. Surface electrodes are attached to the scalp according to the International Numeric System. These EEG signals are digitized on-line by a PDP-12 computer. The analog-to-digital conversion of these signals is performed by the program ADMAG, a variation developed in our laboratory of the standard DEC program ADTAPE (DEC-12-UW2A-D). ADMAG digitizes 128 samples/sec for each of eight channels and stores this data on nine-track magnetic tape. The data may be sampled continuously or partitioned into sections corresponding to various experimental conditions. A header block is written on tape for each data file for future identification.

Processing Format

The EEG GRAPHICS package, under the control of the graphics display terminal, currently contains a series of 14 programs. A logical order to the running of these programs is summarized in Figure 1. A brief description of each of these programs follows. Note that any data displayed on the CRT by these programs can be saved in a special file on disk for conversion to hard-copy plots.

The program EEGFIL allows the user to choose one or more files to be read from a magtape and written on disk. At this time, a code name is given to the file and each EEG channel is identified with a label. After the file has been written on disk, a summary of the magtape input is displayed on the CRT. All subsequent GRAPHICS operations utilize the disk for input and output.

EEGCAL allows the user to synthesize a file of composite data in which all the components are user defined, in order to test the output of the programs with signals whose parameters are already known. For each channel, the user may define up to 10 different frequency components, each having its own initial frequency, amplitude, rate of change of frequency, and initial phase angle. Thus, signals can be constructed that closely mimic EEG signals so as to provide a conclusive evaluation of system performance.

Figure 1. Diagram displaying the various programs that constitute the EEG GRAPHICS package in their logical processing order.

EEGLOK allows the user to display a 1-sec epoch of digitized EEG data reconverted to analog form. The user may opt to examine each second, epoch by epoch, or to go into a scan mode that displays consecutive epochs automatically. While in the scan mode, the user may freeze the display whenever desired.

For any epoch of data currently displayed, the user may choose to have the corresponding PSD (from 0 to 63 Hz) of the eight channels also displayed.

Both the raw data and the power spectra may be reduced for visual clarity at any time by a scale factor, n , where $0 \leq n \leq 99$ and the scaled signal is $1/n$ times the original size.

EEGEDI allows the user to edit data contained in an EEG file. The user may delete, split, combine, or resequence sections, delete epochs containing artifacts, and edit any labels.

EEGPLT takes any displays that the user requested to be saved and writes them on magnetic tape. This tape can then be read by our PDP-12 computer and con-

verted to hard-copy plots via a Calcomp 565 incremental plotter.

EEGDEL deletes all files (raw EEG, FFTs, and plots) for a given file name from the disk to make room for new data.

Spectral Analysis Programs

The program EEGFFT calculates fast Fourier transforms (FFTs) of the EEG data and stores them in a companion file. Establishment of this companion file is necessary before proceeding to subsequent analyses of coherence and phase angle.

EEGISO takes the data derived in the frequency domain by EEGFFT and organizes it in a time sequence, producing vertical isometric displays of power as it varies over frequency and time. Three-axis isometric displays for each of two user-selected channels are juxtaposed on the CRT (see Figure 2). The x-axis shows frequency from 0 to 31 Hz, the y-axis shows absolute power, and the z-axis shows time (58 smoothed 1-sec epochs). Included in this display are graphs of the phase angle and coherence relationships for a user-selected frequency from 1 to 31 Hz.

Several parameter options are available to the user. For the FFTs, the scale factor and two smoothing factors are user defined. For the coherence display, a minimum power threshold may be imposed that sets the displayed coherence to zero if either channel fails to surpass the selected power threshold. For the phase angle display, a minimum coherence threshold may be defined

Figure 2. Sample display from the program EEGISO. The PSDs for two channels may be displayed as a function of time, accompanied by frequency-specific graphs of coherence and phase angle as a function of the same time epoch. In the above display, a highly coherent 14-Hz component is prominent in the EEG of the left and right temporal areas.

Figure 3. Sample display from the program EEGCOH. The coherence is displayed as a function of time and frequency. Temporal continuity filtering (Levine, Herbert, Haynes, & Stroebel, 1975) is utilized to suppress isolated high-coherence peaks.

that suppresses the display of phase angles for epochs in which the coherence threshold is not exceeded.

EEGCOH produces an isometric display of the coherence of two channels as it varies over frequency (0-31 Hz) and time (120 sec) (see Figure 3). User-defined parameters include a time-smoothing factor, minimum power and coherence thresholds, and temporal continuity filtering (Levine, Herbert, Haynes, & Stroebel, 1975). Temporal continuity filtering will display a coherence peak if, and only if, there was an acceptable coherence peak in the previous 1-sec interval.

The EEGSYN program calculates the percent time that two EEG signals surpass a minimum coherence threshold and have a phase angle less than a user-defined value. The output from this program is a tabular print-out of these percent-time figures for each 1 min of data for two channels, plus the average power, maximum power, percent power, and average coherence. These values are tabulated for each frequency from 1 to 31 Hz, and averages are tabulated for frequency bands (delta, 1-4 Hz; theta, 5-8 Hz; alpha, 9-12 Hz; beta, 13-31 Hz).

EEGPOW displays normalized power spectral graphs (percent power vs. frequency) for up to eight channels by individual frequencies or by frequency bands. Multiple graphs representing different sections may be displayed simultaneously for each of the eight channels (see Figure 4).

MULPOW displays data from different files in the same manner as EEGPOW displays data from different sections. This allows comparison of different people with

Figure 4. Sample display from the program EEGPOW, showing normalized PSDs (percent power vs. frequency) for various channels and various experimental conditions.

each other in the same display or the comparison of the same individual's data from sessions recorded at different points in time.

Average Evoked Potential Programs

The program EEGEPS is used to segregate and time lock segments of digitized EEG data to the occurrence of a logic level. This level is usually a trigger representing a stimulus presentation, but it could also be, for example, a stimulus response such as a recording of skin conductance. In this case, EEG activity time locked to and preceding the occurrence of a physiological response could be extracted from background activity.

These time-locked segments, or "windows," around the trigger may be up to eight epochs long, with any number of these epochs defined to occur before or after the trigger. Up to four different trigger levels may be defined so that data may be segregated for experiments employing multiple stimuli.

A second logic-level channel may be defined whose levels represent the behavioral response of the subject to the previous stimulus. This allows EEG data to be segregated according to different combinations of stimulus and response. Thus, an evoked response can be generated based on both the subject's perception of the stimulus and the stimulus itself.

EEGAVG takes the trigger-synchronized data generated by EEGEPS and calculates the average evoked potential, the standard deviations, and the first, second, and third quartiles. These calculations may be done not only for data representing the actual EEG channels recorded, but also for data representing the difference between any two channels.

EEGAPP displays the data generated by EEGAVG on the graphics terminal, along with PSD graphs for each epoch displayed (see Figure 5). Optional scaling and smoothing operations are available.

COMPUTATIONAL TECHNIQUES

There are several mathematical techniques available for PSD analysis. These techniques produce similar but not identical results. Comparisons of data derived by these various techniques, however, are possible, the data comparability breaking down only for "pathological cases" seldom encountered with real data (Otnes & Enochson, 1972). The issues involved in choosing one technique over another lie not so much in any qualitative differences in techniques as in the consideration of computational time. An overview of the computational flow is presented in Figure 6.

From the methods available, we have chosen to use the direct Fourier transform (DFT) method for calculation of both the autospectra and cross-spectra because of the savings in computational time using this method. Given our sampling parameters, the DFT method is

Figure 5. Sample display from the program EEGAPP. An averaged evoked response with 1-sec prestimulus and 1-sec post-stimulus is displayed. The top graph shows the evoked response mean with its associated standard deviations. The lower graph shows the evoked response median with its associated quartiles. A PSD of the evoked response is displayed in the lower left corner.

Figure 6. Diagram of the computational steps involved in the spectral analysis calculations.

9.1 times faster than the Blackman-Tukey method in calculating cross-spectra (Otnes & Enochson, 1972). In the analysis of entire EEG recording sessions, computer time is the critical factor in determining whether or not the type of applications we describe in this paper are feasible. For more complete discussions of the concepts underlying spectral density analysis, the reader is referred to Bloomfield (1976) and Jenkins and Watts (1968). Coherence analysis is discussed by Orr and Naitoh (1976). The implementation of these techniques is thoroughly discussed by Otnes and Enochson (1972, 1978).

The temporal and frequency characteristics of the EEG activity of interest dictate the data collection parameters, the sampling epoch, and the sampling rate. Our interests include clinically important EEG activity of a transient nature (often only 1 or 2 sec in duration) and of low frequency (less than 30 Hz). From pilot studies, we felt that a frequency resolution of 1 Hz

was optimal. Having defined these characteristics of the EEG activity, we were then able to determine our data collection parameters.

For spectral analysis, the interaction between the length of the sampling epoch (L) and the frequency bandwidth (f) is described by the equation $f = 1/L$. Thus, a 1-sec sampling epoch produces a frequency resolution of 1 Hz. By increasing the sampling epoch, a finer frequency resolution can be achieved; however, short transient events would then start to become obscured in the longer epoch.

The relationship between the highest discernible frequency (the Nyquist frequency) and the sampling rate (N points/sec) is described by the equation Nyquist frequency = $N/2$. While our primary interest is in EEG activity of less than 30 Hz, we are also concerned with the degree of signal contamination from spurious electrical noise. We chose, therefore, to look at frequencies up to 64 Hz in the power spectra generated by EEGLOK in order to verify our signal clarity and to be able to reject data contaminated by 60-Hz noise. Thereafter, analyses focus on the activity of major interest, 0-31 Hz. Accordingly, a sampling rate of 128 data points/sec was chosen, providing a Nyquist frequency of 64 Hz. Nyquist foldover, or aliasing (Blackman & Tukey, 1958), is minimized by the use of 30-Hz 12-dB roll-off high-pass filters on each EEG channel.

Calculation of Power Spectra

First, the Fourier transform (X_f) is calculated directly from the raw data, where

$$X_f = \sum_{i=0}^{N-1} X_i e^{-j[(2\pi if)/N]}, f = 0, \dots, N-1,$$

where j = square root (-1). This calculation produces a real and an imaginary component.

Next, the PSD $G_x(f)$ is computed, where $G_x(f) = (2\Delta t/N)|X_f|^2$, $f = 0, \dots, (N+1)/2$, where $\Delta t = L/N$ and $|X_f|$ is vector notation for the magnitude of the vector X_f .

Calculation of Cross-Spectra

The cross-spectra $G_{xy}(f)$ for two time series X_n and Y_n is then calculated, where $G_{xy}(f) = [(2\Delta t)/N](X_k^* Y_k)$ and where X_k^* is the complex conjugate of X_k .

Smoothing the Data

At this point, the power and cross-spectra are smoothed (averaged). A mandatory smoothing is done in the time domain (ensemble smoothing). This procedure is mandatory because coherence calculations for unsmoothed data always produce values of 1 (Orr & Naitoh, 1976).

Our smoothing technique in the time domain involves averaging successive data epochs at a given frequency. For a given data point, $X_f(t)$, a smoothed data point,

$\hat{X}_f(t)$, is derived, where $\hat{X}_f(t) = [X_f(t-1) + X_f(t) + X_f(t+1)]/3$. For a 60-epoch set, the first smoothed point is $\hat{X}_f(2)$ and the last smoothed point is $\hat{X}_f(59)$.

One smoothing of 60 epochs in the time domain generates 58 smoothed epochs. This approach avoids a feature of some smoothing methods in use in which data points toward the middle of the epoch set become averaged more times than data points at each end of the epoch set, producing a center-weighted smoothed epoch set. (For example, when the EEG activity of interest may be of a transient nature, center-weighted techniques would tend to suppress transient events occurring in the middle of the epoch set.)

An option for utilizing the same smoothing techniques in the frequency domain is also available to the user.

Calculation of Coherence

The coherence $\gamma_{xy}^2(f)$ is then calculated on the smoothed data, where $\gamma_{xy}^2(f) = |G_{xy}(f)|^2 / [G_x(f)G_y(f)]$ and $0 \leq \gamma_{xy}^2(f) \leq 1$.

Some authors use the positive square root of $\gamma_{xy}^2(f)$ as the coherence value. We have chosen not to use the positive square root because this extra step simply inflates the coherence value and, in effect, decreases the resolution of the coherence analysis.

This point is important in comparison of results. For example, an author reporting a coherence value of .50 using the $\gamma_{xy}^2(f)$ value would have reported a coherence value of .71 using the positive square root value. This point assumes further importance when one determines at what coherence value one can confidently discuss the phase angle relationship of two signals, since the phase angle is only meaningful if the waveforms have high coherence. The phase angle relationship $\phi(f)$ is then calculated, where $\phi(f) = \arctan [\text{Im } G_{xy}(f) / \text{Re } G_{xy}(f)]$.

DISCUSSION

Coherence analysis based on autospectral and cross-spectral calculations is a frequency-specific, phase-independent, linear index of the degree of coupling of two periodic phenomena. Specifically, coherence is the measurement of the degree of variability of the phase difference between two signals during a given segment of time. The less the variability of the phase difference, the more time dependent or "coherent" the two signals are. The implication of consistently high coherence values derived for two electrically active brain sites is that either both sites are being driven by a common generator or one site is driving the other.

The value of coherence analysis in electrophysiology relates to the fact that the computation is frequency specific. In the typical electrophysiological recording, the complex waveforms being measured are the end result of many different processes. The electrical activity recorded at a given brain site is the net result of both the

Figure 7. Sample display from the program EEGCAL. Waveforms A and B were synthesized from 3-, 7.1-, 9-, 13.1-, 23.2-, and 35.1-Hz sine waves. Each sine-wave component in A has the same constant amplitude as its counterpart in B and differs only in its initial phase. While visually the waveforms appear dissimilar and would have a low correlation coefficient if subjected to a cross-correlation, they are, in fact, time locked and have perfect coherence at each component frequency.

Figure 8. Derived coherence values for sinusoid test signals of unequal frequencies.

inherent electrical activity of the site itself and the electrical impulses impinging upon the site from other areas of the nervous system. Thus, the activity that manifests the coupling of two brain sites represents only a part of the net electrical activity being recorded. Coherence analysis provides the capability to extract time-dependent information from background activity.

Consider the two waveforms in Figure 7 synthesized by the program EEGCAL. Both waveforms have the same frequency components (3, 7.1, 9, 13.1, 23.2, 35.1 Hz), all of the same amplitude. The two waveforms differ only in the initial phases of their component frequencies. Visually, the two signals appear quite unlike. Correlation analysis would produce a low correlation between the two. Yet coherence analysis produces a coherence value of 1 for each of the component frequencies, showing that at each frequency the two signals are time locked.

In applying coherence analysis to real data (such as the EEG), coherence almost never equals 1. In the interpretation of reported coherence values for real data, authors utilizing different sampling parameters and analysis techniques will not be deriving coherence values that are exactly comparable. Several variables must be considered that affect the value of coherence derived for a given set of data. The use of the positive square root value and its effect on the resolution of the coherence analysis have already been discussed.

Another factor that will have a significant effect on the derived coherence value is the length of the sampling epoch. The longer the sampling epoch, the more pronounced slight differences in two signals will become, and, thus, the lower the derived coherence values will be.

Yet another factor influencing the derived coherence value for a given set of data is the method of data smoothing employed. Different smoothing techniques may or may not effectively lengthen the sampling epoch. Our particular smoothing technique produces a smoothed data point representing the averaged activity of three 1-sec epochs. This effectively produces a coherence value that represents a 3-sec epoch, lowering derived coherence values.

The point is clear that, for the same set of data, various calculation, sampling, and smoothing techniques interact to make the derived coherence value a relative and dependent phenomenon. Thus, it is important when reporting results that a clear explanation be made of the analysis techniques utilized.

In order to extend the usefulness of this analysis technique, we have approached coherence from a statistical viewpoint. Since coherence is a measurement of the linear dependence of two signals, we derived a distribution of coherence scores for independent signals. This was done by computing the coherence between the identical EEG sites of subjects matched by age, sex, handedness, time of recording, and EEG type (i.e., frequency, amplitude, and response characteristics). From this data, we have derived probabilities for coherence scores calculated with one smoothing in the time domain. We found that the probability of a coherence score greater than .78 was .05, and greater than .89 was .025 if the signals were independent. Coherence averages were calculated for 1-min sections of independent EEG data. The probability of a coherence average being greater than .39 was .05, being greater than .42 was .01, and being greater than .48 was .001. Individual

coherence scores exhibit a highly skewed distribution, requiring the use of Fisher's z transformation (Bartlett, 1947; Otnes & Enochson, 1972) to impose a normal distribution on the data: $z = \tanh^{-1} \gamma = \frac{1}{2} \ln [(1+\gamma)/(1-\gamma)]$, γ = positive square root γ^2 . Our coherence averages, representing 60 individual coherence scores, exhibit a normal distribution, thus allowing the use of parametric statistics without the use of a transformation.

A convenient way to summarize the effect of the analysis variables on derived coherence values is through the use of a graph that plots derived coherence values for sinusoid test signals of unequal frequencies (see Figure 8). A base signal of 10 cycles/sec was paired with test signals of 10.1 cycles/sec, 10.2 cycles/sec, and so on, and coherence values for these pairs were calculated. These coherence values were then plotted against the difference in frequency for each pair. Thus, for a frequency difference of .05 cycles/sec, the graph shows that our analysis techniques will derive a coherence value of .93.

It is proposed here that authors include a graph of this type when reporting their results so that readers may compare data. As coherence analysis assumes a greater role in research investigations, this issue of comparability will become increasingly more important.

REFERENCES

- BARTLETT, M. S. The use of transformations. *Biometrics*, 1947, 3, 39-51.
- BEGLEITER, H., & PLATZ, A. The effects of alcohol on the CNS in humans. In B. Kissen & H. Begleiter (Eds.), *The biology of alcoholism* (Vol. 2). New York: Plenum, 1979.
- BICKFORD, R. G. Computer analysis of background activity. In A. Remond (Ed.), *EEG informatics. A didactic review of methods and applications of EEG data processing*. New York: Elsevier, 1979.
- BLACKMAN, R. B., & TUKEY, J. W. *The measurement of power spectra*. New York: Dover, 1958.
- BLOOMFIELD, P. *Fourier analysis of time series: An introduction*. New York: Wiley, 1976.
- BRAZIER, M. A. B. *Electrical activity of the nervous system*. Baltimore, Md: Williams & Wilkins, 1977.
- GOTMAN, J., GLOOR, P., & RAY, W. F. A quantitative comparison of traditional reading of the EEG and interpretation of computer-extracted features in patients with supratentorial brain lesions. *Electroencephalography and Clinical Neurophysiology*, 1975, 38, 623-639.
- HANLEY, J., & SKLAR, B. Electroencephalographic correlates of developmental reading dyslexias: Computer analysis of recordings from normal and dyslexic children. In G. Leisman (Ed.), *Basic visual processes and learning disability*. Springfield, Ill: Thomas, 1976.
- ITIL, T. M., MARASA, J., SALETU, B., DAVIS, S., & MUCCIARDI, A. N. Computerized EEG: Predictor of outcome in schizophrenia. *Journal of Nervous and Mental Diseases*, 1975, 160, 188-203.
- JENKINS, G. M., & WATTS, D. G. *Spectral analysis and its applications*. San Francisco: Holden-Day, 1968.
- JOHN, E. R. *Neurometrics: Clinical applications of quantitative electrophysiology*. New York: Wiley, 1977.
- KILOH, L. G., MCCOMAS, A. J., & OSSELTON, J. W. *Clinical electroencephalography*. New York: Appleton-Century-Crofts, 1972.
- KOOI, K. *Fundamentals of electroencephalography*. New York: Harper & Row, 1971.
- KUNKEL, H. Historical review of principal methods. In A. Remond (Ed.), *EEG informatics. A didactic review of methods and applications of EEG data processing*. New York: Elsevier, 1977.
- LEVINE, P. H., HERBERT, J. R., HAYNES, C. T., & STROEBEL, O. *EEG coherence during the transcendental meditation technique*. Weggis, Switzerland: MERU Press, 1975.
- ORR, W. C., & NAITOH, P. The coherence spectrum: An extension of correlation analysis with applications to chronobiology. *International Journal of Chronobiology*, 1976, 3, 171-192.
- OTNES, R. K., & ENOCHSON, L. *Digital time series analysis*. New York: Wiley, 1972.
- OTNES, R. K., & ENOCHSON, L. *Applied time series analysis*. New York: Wiley, 1978.
- SCAMMON, M. E. *Coherence analysis of the electroencephalogram in chronic alcoholism*. Unpublished master's thesis, University of Hartford, 1980.
- SHAW, J. C., O'CONNOR, K. P., & ONGLEY, C. The EEG as a measure of cerebral functional organization. *British Journal of Psychiatry*, 1977, 130, 260-264.
- STEADMAN, J. W., & MORGAN, R. J. Use of a spectral ratio in lateralization of CNS lesions. *Electroencephalography and Clinical Neurophysiology*, 1974, 37, 399-402.