Computerized Clinical Electroencephalography in Perspective

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***Abstract*—Recent developments in the field of computerized clinical electroencephalography (EEG) are surveyed, with particular reference to techniques of analysis of background (stationary) EEG activity, transient (nonstationary) activity, and to integrated systems for multichannel clinical EEG's. A variety of approaches have been used for the basic EEG analyses. For background activity, the fast Fourier transform (FFT) and autoregressive approaches have predominated. For fast transients, segmentation, double differentiation, and inverse filtering have been prevalent. Some integrated systems, which provide a summary, and in some cases an evaluation of the basic EEG analyses, are limited to processing of only the background activity, whereas others include both background and transient activity. Some systems have been designed primarily to be an aid to the clinical electroencephalographer in the preparation of his report. A very few systems have been designed to provide a printed report similar to the conventional clinical EEG report. Although not considered extensively in this review, artifact rejection and/or compensation will necessarily be a major aspect of any fully computerized system. Overall, the field of computerized clinical EEG is now a relatively rapidly evolving one in which further progress is likely to be accelerated by the utilization of microprocessors and high-speed arithmetic processing devices.**

INTRODUCTION

THE total impact of computerized electroencephalography (EEG) analysis on clinical EEG (i.e., as carried out routinely in clinical EEG laboratories in hospitals, etc.) has remained quite limited despite rather extensive work [1]-[7]. (Excluded from this characterization, and not included in this survey, are the applications in EEG of sensory evoked responses—visual, auditory, somesthetic—which have indeed come into relatively widespread routine clinical use.) The overriding reason for this state of affairs is that the remarkable skill of the well-trained and experienced electroencephalographer, in his evaluation of the many facets of analysis and interpretation of recordings from the scalp of the electrical activity of the cerebral cortex, has not so far been matched by any single or any combination of computer techniques. Rapidly scanning a number of channels (16 being the current standard) and automatically and subconsciously eliminating artifact, the electroencephalographer can as a rule readily distinguish normal activity from localized or generalized abnormalities of particular types from many meters of an EEG tracing within minutes. In doing so, account is taken of waveform, frequency, amplitude, phase, the occurrence of brief patterns, their durations, similarities, and differences among channels, etc., in a large number of channels, and finally a suggestion made for the possible clinical significance of the findings.

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Two questions can therefore be asked of computer analysis and reporting of clinical EEG's: 1) would it be worthwhile if it were possible?, and 2) is it or will it be possible?

In relation to the first question, clinical EEG to a considerable degree remains an art rather than a science, and is very dependent on such factors as amount and kind of training and experience (and, it might be added, the individual or individuals from whom training was received). Thus, although there would be little disagreement, even by interpreters with minimal training, over such obvious EEG abnormalities as a generalized spike-and-wave pattern or gross slowing, there are characteristic EEG signs that can be misinterpreted as abnormalities by the occasional or inadequately trained electroencephalographer: vertex sharp waves or the parieto-occipital sharp transients of sleep, the minimal or even more than minimal changes with drowsiness, not to mention the high-voltage hypersynchrony of drowsiness in children. Even among experts, there can be differences, even pronounced ones, in identifying transients (e.g., spikes) as abnormal or not [8], [9]. Accordingly, there can on occasion be differences, even appreciable ones, in the reports of different electroencephalographers, even expert ones, and correspondingly greater variability and greater likelihood of error among reports of nonexpert EEG readers. In addition to interreader variability [9]-[11], the same reader may give different interpretations on the EEG of the same patient in a stable clinical setting [12], [13].

Therefore, if the analysis and reporting of clinical EEG's could be put on an objective basis, the groundwork could be laid for a greater degree of standardization that is not presently possible. Such objective reporting, with its attendant quantitative evaluation of EEG's, would obviously be useful in the clinical evaluation of serial EEG's, which at times can be of much greater value than a single test. In addition, objective EEG evaluation could in turn form a firm basis for a later electroclinical correlation so that diagnostic possibilities or probabilities, at least in certain types of EEG abnormalities, could accompany the clinical EEG report. At present, there are relatively few generally accepted specifically diagnostic EEG patterns.

Maulsby *et al.* [14] have pointed to the rapidly increasing load of clinical EEG's and the relative scarcity of qualified

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electroencephalographers as making it imperative that automation and computer techniques be initiated for routine diagnostic work. Kellaway [15] has indicated that automatic interpretation of the clinical EEG offers many attractive prospects, including an objective evaluation of the EEG, and the freeing of the well-trained electroencephalographer from the labor of evaluating a large number of easily classifiable EEG's so that he could focus on problems that make full use of his expertise.

In relation to the second question posed above, the fully automatic analysis and reporting of clinical EEG's is not presently being carried out on a routine basis on every EEG at any center, as will be apparent from the following review. It will, however, become apparent that, considering the work of a number of laboratories, considerable advances have been made in recent years toward this ultimate objective. Accordingly, the objective reporting of EEG's by computer (in the first instance, mimicking the clinical electroencephalographer) which seemed a remote possibility even just a few years ago, now does not appear to be quite so remote.

But even if computer analysis and reporting of clinical EEG's turns out in the end to be impractical, efforts toward that end can still have the effect of better standardization of conventional clinical EEG reporting. For example, in the glossary prepared by the Committee on Terminology of the International Federation of Societies for Electroencephalography and Clinical Neurophysiology [16], the definitions for a spike ("transient, clearly distinguished from background activity, with pointed peak at conventional paper speeds and a duration from 20 to under 70 ms, amplitude is variable") or for a paroxysm ("phenomenon with abrupt onset, rapid attainment of a maximum and sudden termination, distinguished from background activity") necessarily rely considerably on the experience and judgment of the electroencephalographer. As has often been pointed out by those who have worked on automatic spike recognition, such operational definitions of a spike as the one above intended for visual clinical EEG are not adequate [17], [18], and further specifications are needed.

In the same way that spectra have proved to be a valuable adjunct in clinical EEG, in particular for quantitative evaluation of background rhythms by the electroencephalographer, recent and further work in the area of computer analysis of EEG transients may prove to be a valuable aid to the clinical electroencephalographer in his interpretation and reporting of records. Moreover, computer studies on EEG nonstationarities or paroxysmal activity may prove valuable in relation to the problem of automatic detection of changes in continuous on-line EEG monitoring in ICU's and in similar settings.

So that the current status and future prospects of computer analysis and reporting of clinical EEG's can be viewed in perspective, the early history of instrumental EEG analysis will first be briefly reviewed. A survey of approaches that were developed to quantify EEG background (stationary) activity and to detect transients (nonstationarities), more specifically spikes and sharp waves, will then follow. A description of several recently described integrated computer systems for clinical EEG will then be presented. Although this review is extensive, it is not intended to be all-inclusive. Such relatively specialized areas as computer evaluation of drug effects, automatic sleep staging, monitoring during anesthesia, dialysis, and carotid endarterectomy, for example, are not covered. Indeed, with some exceptions, the discussion so far as background EEG activity is concerned is primarily focused on the adult waking EEG; consideration of transient activity (spikes and sharp waves) is however less narrowly limited. Within these limits, a reasonably complete overview of the current status of computerized clinical EEG is intended.

Attention is focused on computer processing of EEG *per se*, work on automatic artifact rejection in the main not considered; adequate discussion of the latter, with which there are still many difficulties, would virtually require a separate review. Indeed, it is the view of some workers, the present author among them, that with some exceptions (e.g., the removal by computer of electrocardiogram (EKG) artifact from referential recordings [19]), artifacts in all their diversity and complexity are for the present perhaps best identified and excluded by the well-trained EEG technologist or by the electroencephalographer. Of course ultimately, automatic artifact rejection, at least to some degree, would appropriately and even of necessity be a part of any completely automated EEG system.

Characterization of Background (Stationary) EEG Activity

In the earliest analyses of EEG's by automatic, nonvisual means, *frequency spectra* were obtained by means of Fourier transformation [20]-[23]. Following the development of the first spectral analyzer specifically designed for the EEG and its subsequent improvement and commercialization [24]-[26], there was an appreciable increase in the application of frequency analysis to the EEG [27].

Analysis of EEG's in the time domain, by *correlation analysis*, was originally carried out manually [28]. Electronic correlators originally designed for the analysis of communications signals were then used [29], [30] until the advent of the first correlator specifically designed for brain potentials [31]-[34].

Period analysis, or wave duration analysis (also termed interval analysis), in which the baseline crossings of the EEG and, additionally, of its first and second time derivatives are determined (in order to identify high-frequency waves superimposed on low-frequency ones), is a somewhat simplified method of EEG spectral analysis [35], [36] which has continued to be useful in limited applications (e.g., [37], [38]).

Carrie and Frost [39] used a period-amplitude measure, obtaining wave periods simultaneously for two channels from baseline crossings corresponding to frequency ranges of 6-18 Hz and also 3-7 Hz. A combined integrated amplitude-per-wave versus wavelength frequency was also available. Their small computer program (LINC 8) included a capability for determining various summary statistics, e.g., chi-square test for significant differences between, e.g., homologous recordings for the two hemispheres.

An alternative approach to identification of lower frequencies and of higher frequencies superimposed on the latter consists of successive segmentation of EEG curves according to their inflection points, the durations of the ensemble of segments being evaluated as inverse frequencies [40]-[42]. Zetterberg [6] has pointed out that, although interval analysis is simple to apply, the results are difficult to interpret.

The relationship of zero-crossing parameters to the correlation functions and the spectral density has been discussed by

Saltzberg [43], [44]. A spike-and-wave detector employing a baseline-crossing scheme which identified frequencies in the range of 2-33 Hz was described by Ehrenberg and Penry [45]. Another simplified approach to frequency analysis has been proposed by Hjorth [46] in the form of three descriptors, "activity, mobility, and complexity," based, respectively, on EEG amplitude, slope, and slope spread. The approach is one of limited applicability, however [47], and has not come into general use.

With the exception of frequency analysis, which was at times employed on a regular basis as an adjunct for selected clinical EEG's, the above described techniques have largely been applied to research problems in EEG.

Although *power spectra* (the square of frequency spectra) were occasionally computed by Fourier transformation of correlograms [34], the first systematic application of power spectral analysis by general purpose digital computers was reported in 1963 by Walter [48]. The introduction of the *fast Fourier transform* (FFT) [49] appreciably diminished [by a ratio of approximately $(2N \log_2 N/N^2)$] the necessary number of computations to obtain Fourier transforms. [The FFT requires only $2N(\log_2 N)$, in contrast to the N^2 operations required for a normal Fourier transform where N is the number of points in the original time series (i.e., the sampling rate in hertz times the duration of the epoch in seconds).]

The relevance to EEG of the development of the FFT was immediately appreciated [50]. Although an individual FFT is ordinarily calculated for a short segment of EEG data (a few seconds to several seconds), such segmentation of a signal with subsequent averaging over individual modified periodograms has been shown to lead to a consistent estimator of the spectrum [51]. Multichannel FFT's are used routinely as an aid to the electroencephalographer in some clinical laboratories [52].

To decrease the time-consuming computational procedure of the FFT, sets of orthogonal functions simpler than sine and cosine waves have been used, e.g., Haar functions, which have values of only +1 and -1 [53]. However, these may have the same limitations of accuracy as do Walsh functions, which also have values of only +1 and -1 and which do not provide a satisfactory estimate of EEG spectra [54]-[56].

The determination of spectra by *complex demodulation*, or heterodyning of an EEG with both sine and cosine versions of a given frequency [57], has not found widespread application in EEG analysis.

Extensive reviews of spectral analysis, correlation analysis, and period analysis have been published [58].

By plotting FFT's of successive short (e.g., 4 s) segments of EEG's a *compressed spectral array* (CSA) was obtained by Bickford and his coworkers [59]-[62], which is particularly useful for following EEG spectra over time, such as during anesthesia [63]. CSA's together with frequency difference arrays (FDA's) and amplitude histogram arrays (AHA's), were used by Chiappa and Young [64] for carotid endarterectomy monitoring.

A different approach to the determination of power spectra is by the use of an *autoregressive "model"* of the EEG [65]-[74], in which the current amplitude is expressed as a weighted sum of equally spaced samples of the immediately preceding EEG, plus an error term, the "prediction error." The weighting factors are the autoregression coefficients (which are determined from the autocorrelogram of a segment of the EEG itself) and the number of coefficients specifies the order of the autoregressive filter. The ensemble of them constitutes the autoregressive filter. The power spectrum of the EEG can be derived from the coefficients, and if wideband electrical noise is fed into the autoregressive filter, the output resembles the original EEG. The principle of autoregressive filtering has also been used to identify other types of nonstationarities or changes in EEG's, e.g., responses to sensory stimuli [75]. The time-varying case of the autoregressive approach (as Kalman or self-tuning filtering) was discussed by Isaksson and Wennberg [76].

It has been pointed out that autoregressive power spectral estimation has some advantages over the determination of spectra by the FFT: windowing (smoothing) procedures are not involved, and better estimates of the true spectra are obtained, or equivalently, for a given spectrum, the spectral estimate by autoregression requires smaller sample length than if obtained by FFT. Determination of the order (length) of the autoregressive filter requires careful attention however [73], [77], [78].

Wennberg and Zetterberg [79] pointed out that, in suitable cases at least, the power spectrum can be summarized by a small number of parameters (e.g., peak frequency, bandwidth, power content), thus the term "parameter analysis."

Intermediate between the analyses of background activity and of transient activity, respectively, was the *pattern recognition* computer program reported by Leader *et al.* [80] that evaluated and sorted into 13 categories the wave parameters from the time and amplitude values of maxima and minima for successive 4-s epochs. Spikes and sharp wave activity were not included in the analysis however, except as part of a spike-and-wave pattern. A somewhat similar approach was described by Goldberg *et al.* [81].

The technique of *discriminant analysis*, used earlier by Walter *et al.* [82] to classify the EEG in different states of consciousness in normal subjects, by Hanley *et al.* [83] to distinguish pre- and post-septal spike scalp EEG spectra, and by Sklar *et al.* [84] to the EEG of dyslexics, was applied by Serafini [85] to a limited number of stationary EEG patterns. Lloyd *et al.* [86] however, have noted that discriminant analysis makes no use of the existing body of knowledge concerning the clinical significance of particular EEG patterns.

Detection and Characterization of Transients (Nonstationarities)

Attempts at automatic identification of fast transients (spikes and sharp waves) in the EEG is a more recent development than the characterization of background activity, although the early automatic spike-wave detector of Bickford [87] employed a spike detector together with an independent slow-wave detector.

Kooi [88] stressed that rise time, fall time, and peak angle are all relevant features in classifying spikes, approximated by a steep triangular wave, as having slopes of more than 2 μV/ms.

For detecting biphasic identifying spikes from depth structures in epileptic patients, Brazier [89] specified a constellation of individually variable parameters which included peak-to-peak amplitude, duration (separation), and rise and fall times for the first and second peaks, respectively, in relation to one third of the amplitudes from the baseline to the peaks.

Saltzberg *et al.* [90] and Buckley *et al.* [91] described a *spike detector* that signaled an event if the second time derivative (i.e., its curvature in the mathematical sense) exceeded a preset threshold. Carrie [92] reported a hybrid A/D method, in which the threshold was not fixed, but was continuously adapted to a moving average value of selected measurements of the EEG signal. Carrie noted that the second derivative (i.e., the curvature) after filtering (to diminish noise introduced by the differentiation of the EEG with respect to time) was found to be a more efficient discriminator of sharp transients than the first derivative, i.e., the slope. Walter *et al.* [93] full-wave rectified the second derivative prior to determining whether the threshold for curvature were exceeded.

Hill and Townsend [94] formulated a computer program to determine the angle at the peak of spikes in the electrocorticogram of rats by determining the angle between straight lines fitted by the computer to four sample points of the EEG on either side of the peak. Smith and Ktonas [95], [96] proposed digital computer evaluation of 6 *parameters characterizing spikes*: 1) and 2) maximum slopes of the leading and trailing edges, respectively; 3) and 4) the times of occurrence of these relative to the peak, respectively; 5) the sum of the latter two, which is inversely proportional to the spike sharpness (curvature); and finally 6) spike duration, for those spikes which exhibit a well-defined triangular shape. The latter authors found that pretreatment of EEG's by low-pass filtering, with a cutoff frequency of 50 Hz (18 dB/octave), did not significantly distort the prominent features of abnormal spikes.

In the special case in which the specific waveform of a transient is known, it can be used for *template matching or matched filtering* to search for similar events in the background. Saltzberg *et al.* [97] applied this technique to the detection of focal depth spiking from the scalp EEG of monkeys. Using the above-mentioned spike detector that operates on a curvature threshold principle, and actual depth spiking as a trigger, these authors obtained an averaged scalp waveform time-locked to the depth spiking. The resultant waveform was then either used directly as a template, or to optimize the signal-to-noise ratio, was Fourier transformed and the resulting spectrum divided by an approximation to the power spectrum of the background scalp EEG (approximated by a $1/f$ function). The modified spectrum was then inverse Fourier transformed, and a running convolution (multiplication) of the modified template carried out. The technique was also applied to surface and depth recordings from schizophrenic patients [98], [99]. A procedure similar to the latter steps was described by Herolf [100] (see also [101] and [102]). Template matching has been applied by Barlow and Dubinsky [103] to the detection of epileptic spikes (Fig. 1) and vertex sharp transients of sleep. Saltzberg [104], [105] has suggested techniques for the detection of intermittent transients of unknown waveform.

The previously mentioned *autoregressive technique* has also been used to detect fast transients in the EEG. Lopes da Silva *et al.* [106], [107] first formed an autoregressive filter to model the EEG (in epochs of 10–12 s) which included occasional transients. An inverse autoregressive filter was then formed through which the same EEG epoch, with the nonstationarities, was passed. The *inverse filter* essentially eliminated the stationary or background EEG. Nonstationarities (spikes) were identified by the computer program as peaks (amid the random output of the filter) for which there was a chance occurrence of less than some predetermined value, e.g., 0.001. In a comparison of inverse autoregressive filtering with the aforementioned second derivative method, these authors found that the latter appeared to exhibit a tendency to report more false positives (Fig. 2). The program also plotted out the nonstationarities, which could then be used for template-matching or matched filtering.

Birkner *et al.* [108] obtained a more reliable detection of spikes by combining the methods of double differentiation and of inverse autoregressive filtering, i.e., by double differentiation of the output of the inverse filter (the prediction error signal). In this combined approach, these authors argued that the method of double differentiation makes use of the spectral difference between spikes and background activity, whereas the method of inverse autoregressive filtering utilizes the difference in the predictability of stationarity of the spikes and background signals. Accordingly, if the methods utilize independent sources of information, then their combined use should yield greater reliability of spike detection. Greater reliability of spike detection was obtained by Pfurtscheller and Fischer [109] by combining inverse filtering with matched filtering (template matching).

Praetorius *et al.* [110] have recently extended the autoregressive approach to obtain spectral estimates and to detect fast transients, but also, after transients are detected and eliminated, to segment the resultant EEG when the spectral error measure (a running average computed from the output of the autoregressive filter) [111], [112] exceeds a preset threshold value. The onset of a new background pattern is thus signaled, making the autoregressive model adaptive (Fig. 3). (The autoregression coefficients are redetermined from the first 2 s of each new segment.)

A different approach to the use of an inverse filter for the detection of both fast and slow transients has been described by Barlow [113]. The inverse filter [103], [114], [115] was formed on a computer by inverse Fourier transformation of the inverse of the square root of the power spectrum. Passage of the original EEG through the resulting filter eliminated the stationary background, leaving both fast (Fig. 4) and slow nonstationarities in the filter output.

For on-line automatic recognition and quantification of interictal spike and sharp wave activity, Gotman and Gloor [17] used a sequential *pattern recognition* technique. The EEG of each of the 16 channels was broken down into half-waves, each of which was characterized by the durations and amplitudes of its two component half-waves, by the second derivative at the apex (both relative to a weighted mean of

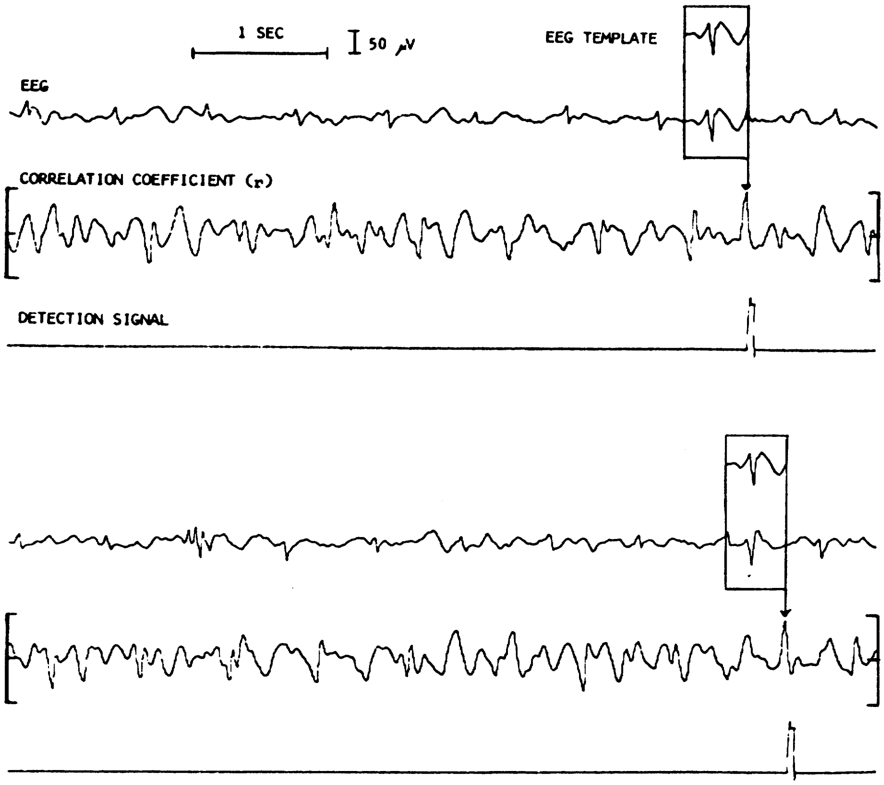


Fig. 1. Spike detection by template-matching. A running cross-correlation coefficient is computed between one channel of an ongoing EEG and the template, the latter having been taken from the spike on the top line. Note that EKG transients are not detected (from Barlow and Dubinsky 1976 [103]).

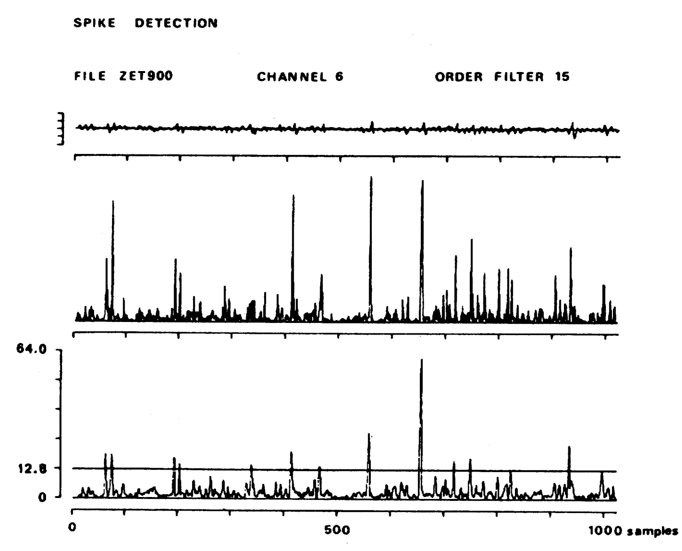


Fig. 2. Comparison of transient detection by inverse autoregressive filtering and by the second time derivative method. The first signal is the EEG epoch (1024 samples; sampling frequency 80 Hz). The second trace gives the rectified second derivative. The third gives the detection signal obtained using the autoregressive method ($p = 15$). The probability level $p \leq 0.005$ is indicated. Note that there are several clusters of sample points which exceed that level. In these cases it can be concluded that the null hypothesis, i.e., that those samples belong to a stationary normally distributed filtered noise signal, can be rejected (figure and caption from Lopes da Silva *et al.* 1975 [106]).

the amplitude of the background activity of the immediately preceding 5 s), and by the duration and amplitude of the following half-wave. The decomposition of the EEG in this manner (Fig. 5) is not too different from the scheme of sequences and segments of Rémond and Renault [40]. It was found that spikes and sharp waves could be characterized by particular combinations of these parameters, and areas of maximal epileptogenicity could be identified by interchannel comparisons. The computer program routines for rejection of artifacts from eye blinks and muscle potentials were found to perform with a high level of reliability.

Gevins *et al.* [2], [116], [117] employed basically a curvature (second derivative with respect to time) criterion after initially subjecting the EEG to digital low-pass filtering (at 20 Hz, with 21 dB/octave attenuation of higher frequencies) and then imposing additional criteria to reduce false detections from muscle potentials and fast background activity. An improved program for spike detection which utilizes curvature, period, rise time, and amplitude is currently being tested [118].

Multichannel Integrated Computer Systems for Clinical EEG

The systems to be described are in general of two types: 1) those which are primarily intended to generate summary data or displays to facilitate the task of the electroencephalographer

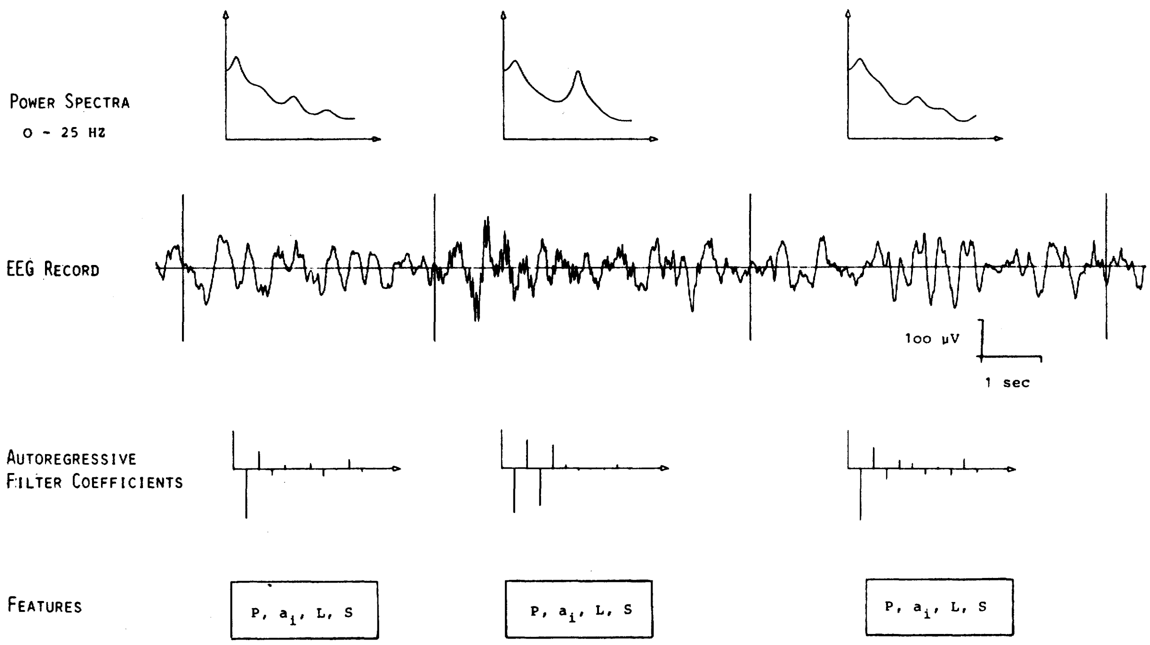


Fig. 3. Feature extraction scheme by autoregressive analysis. For each detected segment the total power P, the autoregressive filter coefficients a_1–a_{10}, the segment length L, and the location and form of the transient S are stored. The log power spectra computed from the autoregressive filter coefficients are shown at the top. Note that the 14 Hz component clearly seen in the middle segment shows up in the middle spectrum and not in the other two. Child, age 8, sleep stage III (figure and caption from Praetorius *et al.* 1977 [110]).

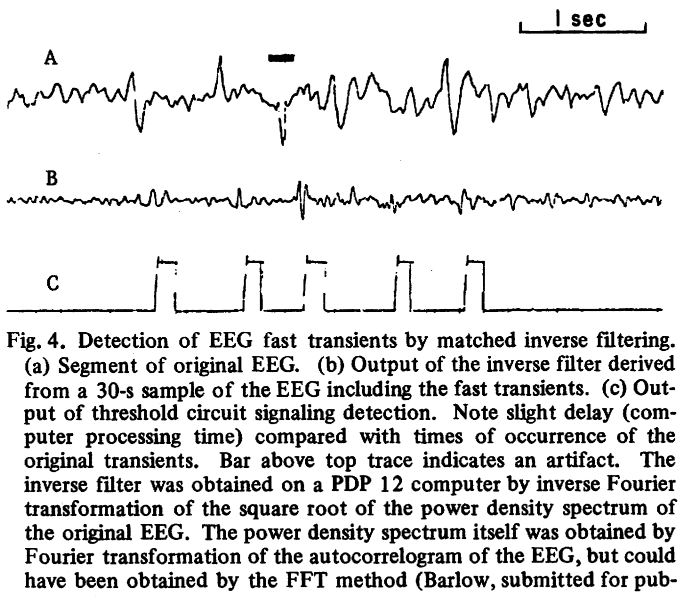


Fig. 4. Detection of EEG fast transients by matched inverse filtering. (a) Segment of original EEG. (b) Output of the inverse filter derived from a 30-s sample of the EEG including the fast transients. (c) Output of threshold circuit signaling detection. Note slight delay (computer processing time) compared with times of occurrence of the original transients. Bar above top trace indicates an artifact. The inverse filter was obtained on a PDP 12 computer by inverse Fourier transformation of the square root of the power density spectrum of the original EEG. The power density spectrum itself was obtained by Fourier transformation of the autocorrelogram of the EEG, but could have been obtained by the FFT method (Barlow, submitted for publication).

in the interpretation and reporting of EEG's, and 2) those which in addition have as their objective the automatic generation of a conventional descriptive EEG report.

In the interactive system at the *Langley Porter Clinic* [2], [116], real-time spectral (FFT) and transient analysis (based primarily on determination of curvature or sharpness, as previously noted) are performed simultaneously on up to 16 channels. The bandwidth is up to 25 Hz and the system is interactive, with capability of on-line alteration of analysis and display parameters. There is also a capability for obtaining interchannel cross spectra and coherence. The PDP11-PDP 15-based system is intended as a first step in replacing the traditional ink recording and as an aid to facilitate the reporting of clinical EEG's, as well as to provide the data base necessary for automated classification of clinical EEG's.

The PDP 12-based system at the *Montreal Neurological Institute* [17], [119], [120] is intended to be an interactive system, to summarize the salient features of an EEG recording, and to assist the clinical electroencephalographer in his reporting of the record. Background activity (a 40-s sample) of 16 channels is analyzed by an FFT algorithm and displayed as plots of amplitude spectra (i.e., the square root of power spectra). A summary pictorial display is used, derived from weighted ratios (canonograms) of delta-plus-theta in relation to alpha-plus-beta activity, in weighted amounts for each (Fig. 6). A hemispheric symmetry-asymmetry factor is also displayed. Spikes and sharp waves are analyzed as previously described, supplemented by interchannel comparisons. Validation tests on EEG's with slow wave abnormalities from a series of 87 patients with suspected supratentorial tumors indicated that interpretations based on the canonograms were in general of about the same accuracy as the conventional EEG report [121]. Analogous validation of spike/sharp wave activity on 2-min sections of 16-channel waking recordings from 50 epileptic patients, and a control group of 30 normal and 30 slow wave EEG's, showed a correlation of approximately 60 percent between interpretations based on the computer analyses and those based on the ink recordings. A higher correlation (84 percent) was obtained for reports of two observers based on the computer displays alone [9].

In the system reported from the *Tulane University School of*

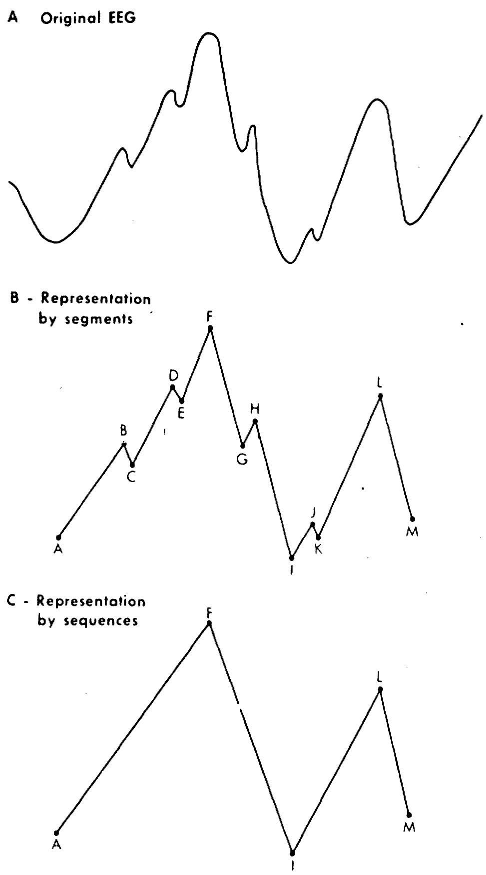


Fig. 5. Representation of an EEG by segments and sequences. (a)-(c) Segments, sequences, waves: upgoing sequence *AF* terminates at *F* because downgoing segment *FG* cannot be included, being larger than preceding segment *EF*. Downgoing sequence *FI* terminates at *I* because upgoing segment *IJ* cannot be included, being followed by downgoing segment *JK* of smaller amplitude. Upgoing sequence *IL* terminates at *L* because it cannot include a downgoing segment of very large amplitude *LM*. Waves *ABC*, *BCD*, *EFG*, *GHI*, and *HIJ* are examples of waves composed of 2 segments; *AFI*, *FIL* are waves composed of 2 sequences; *AFG*, *EFI*, and *FIJ* are waves composed of a segment and a sequence (figure and caption from Gotman and Gloor 1976 [17]).

Medicine [14], which was intended as a step toward an EEG screening test, 30 s (three 10-s segments) of 8-channel records in a pseudoreferential montage, manually selected to be relatively artifact-free, were subjected to power spectral analysis (Time Data Corporation TD 100 computer). Recordings with eyes closed and with eyes open were used. The spectra were then summated within the conventional EEG frequency bands (alpha, theta, delta, and beta), and displayed on a summary sheet as horizontal bar graphs (eyes open as X's, eyes closed as O's, the two superimposed on an outline of the head). No attempt was made to include detection and display of transient EEG activity in the system.

The system at the *Institute for Clinical Neurophysiology and Experimental Neurology of the Medical School at Hannover, West Germany* [54] has been primarily concerned with background EEG activity (up to 12 channels) which is analyzed in terms of spectra for each channel (autospectra) and between channels (cross spectra), calculated by means of the FFT on 20 epochs totaling some 125 s of recording, from which tables and graphs are displayed. More recently, linear and quadratic discriminant analysis of power spectra of background activity and of pattern (waveform) recognition of transients have been explored by the Hannover group [122].

In the PDP 15-based system at the *Sahlgren Hospital in Göteborg, Sweden* [123], [124] for quantification of background activity (the system has not been extended to include EEG transients), frequency spectra are computed by FFT for 100 s (ten 10-s samples) of manually selected artifact-free recordings of 8-channel EEG's. From these spectra, 20 secondary parameters are then computed, from which in turn age-dependent ratios are determined for each EEG channel by means of equations formulated from previous studies on 650 normal subjects of age range 1-22 years [125]. The upper limit of age change was considered to be 20 years. The resultant quotients ("EEG ages," expressed as percentages) are then printed out in columns alongside a diagram of the head (primarily useful in comparison of serial recordings) on which the presence of any abnormally slow activity is indicated by shading, the intensity of which is roughly proportional to the degree of slowing (Fig. 7). Below the head diagram, the system also prints out a verbal report with a conclusion. Good agreement with visual findings was obtained in 80-92 percent of a series of approximately 100 EEG's of which 30 percent were normal. Age-dependent quotients have been used by John *et al.* [126] as a part of their "numerical taxonomy method of neurometrics," in which an extensive battery background EEG and evoked responses are assessed. Recently Matoušek [127] has expressed the view that one of the principal advantages of computerized EEG will be in the comparison of serial EEG's with the differences tested statistically.

A more recent version of the Sahlgren Hospital system [128] incorporates an option for automatic preselection of artifact-free (muscle, movement, electrode, and drowsiness) portions of the record for which specific frequency criteria are employed (e.g., muscle artifact, on the basis of a disproportional increase in high-frequency content). The system, at least at present, is intended to function as an aid to the clinical electroencephalographer in summarizing the principal features of the background EEG, exclusive of transients.

The system developed at *St. Bartholomew's Hospital, London* [7], intended as an aid to the electroencephalographer and concerned primarily with background activity, utilizes power spectrum feature extraction (found to be more reliable than visual analysis and the previously mentioned Hjorth descriptors) in combination with a multivariate pattern recognition technique to distinguish normal and abnormal EEG's and to localize any normalities detected. For display of the latter, a topogram somewhat similar to that of the canonogram displays at the Montreal Neurological Institute (see above) was used.

In the PDP 11/40-based system [comprehensive EEG analysis and reporting system (CEARS)] at the EEG laboratory of the *University of California at San Diego* [129], CSA's are computed in real time for 16 channels (Fig. 8). A spike-detection routine is based on measurements of slope, amplitude, frequency, and duration, and artifact-reduction programs for

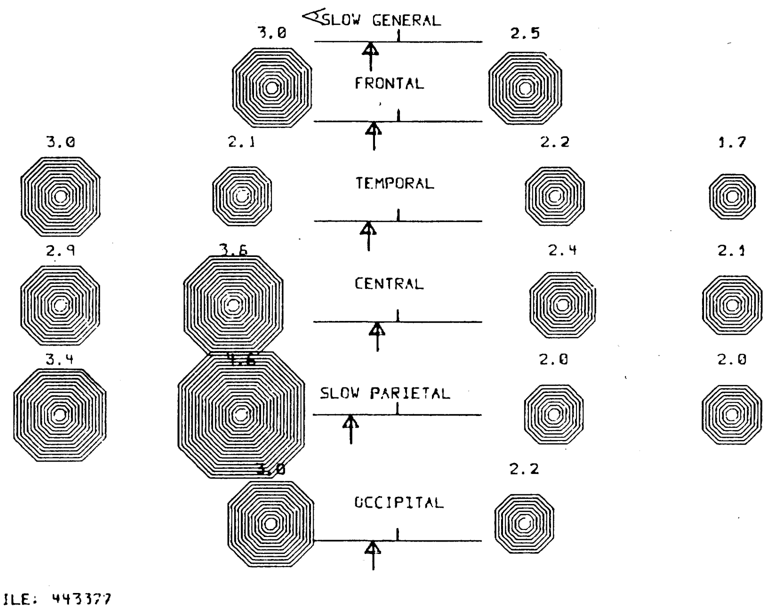


Fig. 6. Canonogram from subject with large tumor in left posterior Sylvian region. Referential montage with average reference. Frontal region at top, occipital at bottom. The arrows under the horizontal line indicate the asymmetry in slow activity. The arrows deviate towards the most abnormal side (more slow waves, less fast waves) (figure and caption from Gotman *et al.* 1975 [121]).

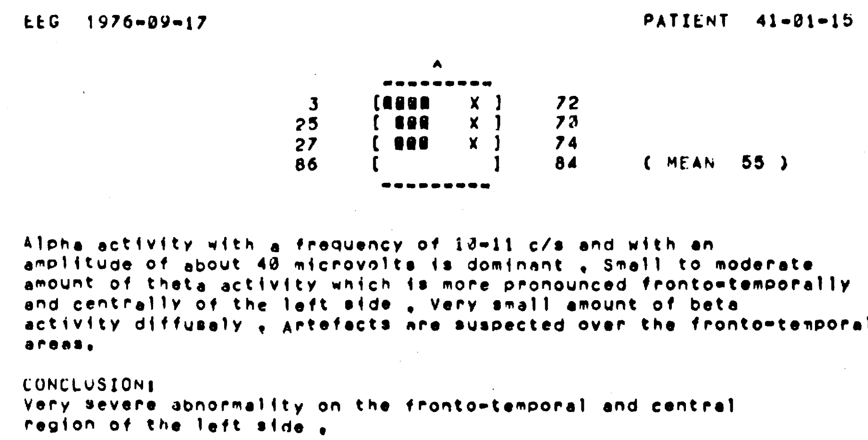


Fig. 7. Example of automatic EEG assessment where both verbal and quantitative information have been included. The assessment is understandable even for an unexperienced clinician, but the numerical results are still available for the better informed electroencephalographer (figure and caption from Matoušek 1977 [124]).

eyeblink and electromyographic (EMG) potentials are included [130]. Semiautomatic compilation of clinical EEG reports is envisaged.

In the PDP 8-based "sequential analysis" system at the *Graduate Hospital of the University of Pennsylvania in Philadelphia* [131]-[133], peak-to-peak time intervals and peak-to-trough amplitudes for 8 channels of EEG's are determined. The resultant photographic plots (one dot for each wave) from the display oscilloscope for background activity show clustering for well-defined dominant activity and diffusion for less well-defined activity. Transient or paroxysmal events (identified as being of twice the amplitude of "quasi-stable" waves of the same frequency class) fall outside the cluster of background activity, and are intensified to aid in distinguishing them from the background. The authors note that the method does not take into account any superimposition of waves, and assume that fast activity occurring in the region of the baseline (zero-crossing) is representative of all fast activity in the sample. (In actual practice, this limitation does not appear to be a major one.) Eye movement, EKG, and muscle artifact tend to have characteristic signatures on the plots; provision for eliminating eye movement and EKG artifact by analog pretreatment of the input EEG is included. A printout from the system includes a head diagram, on which is shown the mean frequency from baseline crossings for four regions of the head on each side, and a tabulation of the relative amount, amplitude, and average frequency within each of the conventional EEG frequency bands (alpha, beta, theta, and delta). In a more recent development, the totality of individual waves in the alpha-beta and theta-delta bands, respectively, are separately displayed topographically on outlines of the head ("computerized EEG topography"—Fig. 9) [134]. A somewhat similar display in the form of a dot-density topogram, for depicting localized EEG abnormalities,

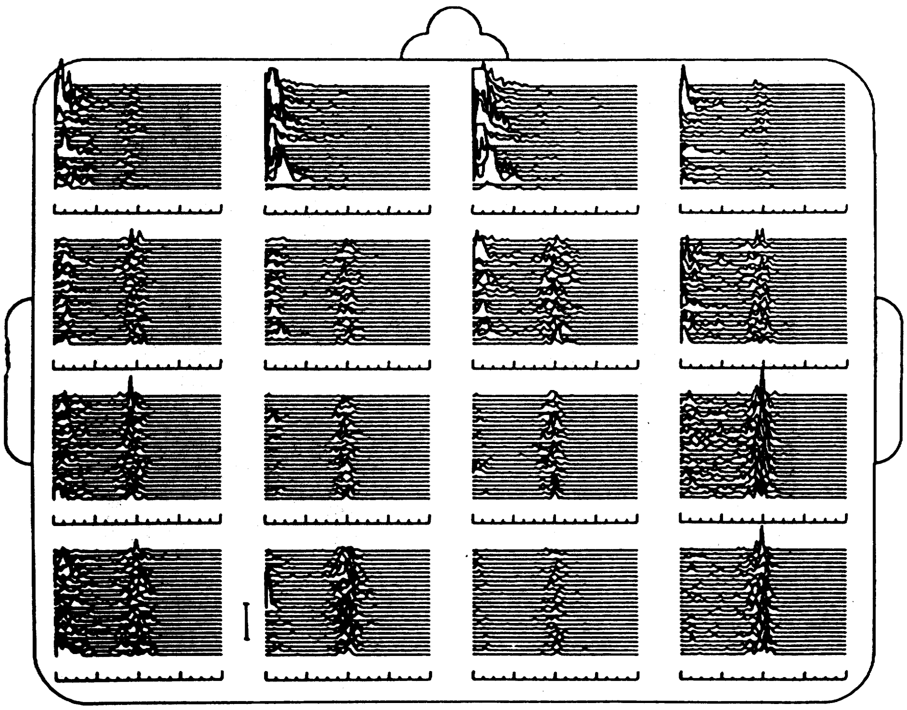
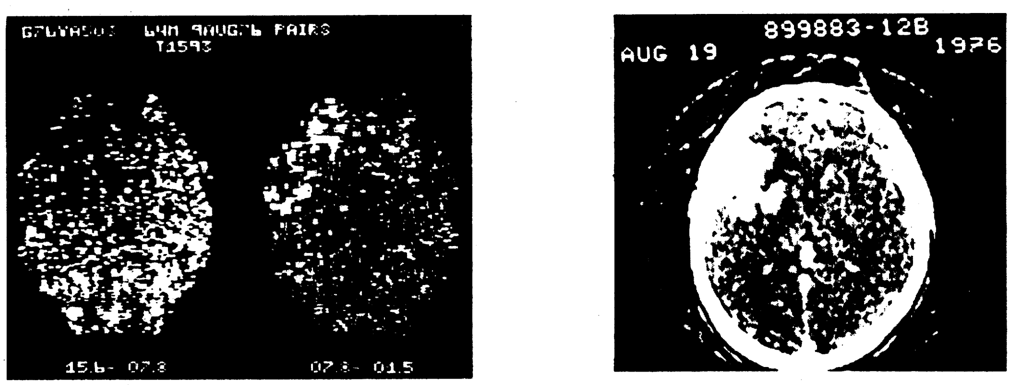


Fig. 8. Illustration of CSA developed for clinical EEG report. Patient was a 61 year old man with progressive dementia and an old cerebrovascular accident (CVA) with left hemiparesis. The CSA shows the following features. (a) Alpha asymmetry with reduction on the right as seen in the posterior parasagittal spectral displays. (b) Widespread theta activity which runs into the alpha band and is most evident in the right posterior, temporal, and midtemporal areas. (c) Widespread delta activity most marked in the temporal areas bilaterally (some of the parasagittal frontal delta is eye movement). On comparing the midtemporal (lateral) areas on both sides the increased activity at 3–5 Hz is evident on the right. The CSA findings were considered compatible with an old CVA and matched features evident in the primary record, including alpha asymmetry, predominant theta, etc. Montage–bipolar. Frequency scale under each spectral derivation: large markers–4 Hz (0–16 Hz), small markers–1 Hz. Amplitude calibration: 20 μV peak-to-peak continuous (figure and caption from Bickford [62]).



(a) (b)

Fig. 9. "Computerized EEG topography" (left) in cerebral infarction, showing marked left frontotemporal slowing (in plot of frequencies in the range 7.8–1.5 Hz) with depression of alpha activity throughout the left hemisphere (in plot of frequencies in the range 15.6–7.8 Hz). EMI (computerized axial tomography) scan (right) shows a circumscribed area of contrast enhancement (figure and caption from Harner 1977 [132]).

has been described by Dubinsky and Barlow [135] (Fig. 10). Duffy and Lombroso [136] have used three-color displays for spectral components.

The system at the *Toranomon Hospital in Tokyo* reported by Homma *et al.* [137] employed a wave-by-wave analysis in 1-s epochs for duration and amplitude, additional measurements of curvature being taken on maxima and minima. The waves were then categorized according to duration of spikes, or as waves of the conventional EEG frequency bands (alpha, etc.). A summary printout indicated the categorization (normal/borderline/abnormal), the period of the basic rhythm (in milliseconds), the number and location of spikes, and an indication of the degree of symmetry for the 12 channels for each of the EEG frequency bands. Special measures were taken against EMG and 60 Hz interference. In a later version, digital filtering was used and spikes were detected by parameters of duration, slope, curvature, and amplitude ratio compared with average reference curvature and amplitude during the pre- and

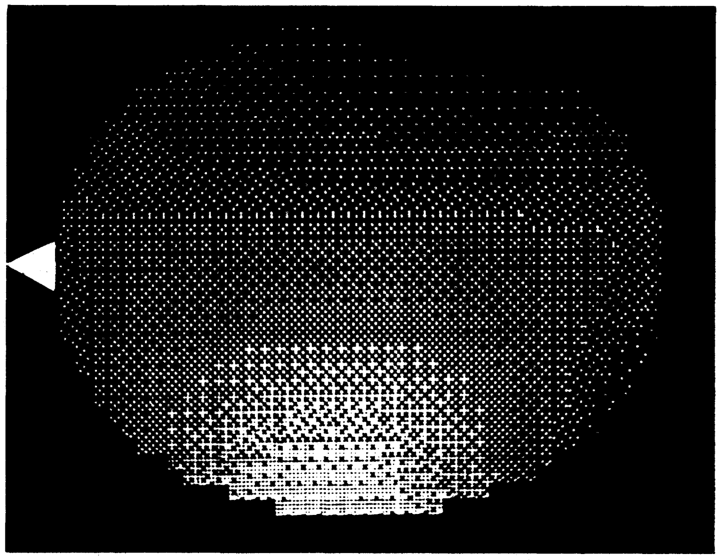


Fig. 10. Dot-density topogram for an EEG slow-wave event in the left temporal region. The potential distribution on the scalp at the peak amplitude of the event is depicted on a gray scale of 16. White triangle at top indicates the nose (from Barlow and Dubinsky [135]).

post-spike periods [138], [139]. For sleep, vertex sharp waves and sleep spindles were detected, level of sleep was taken as the ratio (theta + delta)/(alpha). A Hitachi-10 computer was used.

The system at the *Royal Free Hospital, London* [18], [140] is designed with the specific objective of implementing on a small computer the processing of a routine clinical EEG to the point of diagnosis, i.e., the determination of the presence or absence of abnormalities, their distribution, location, and nature. The system uses a Hewlett-Packard 2100A computer. Artifacts, marked by the EEG technologist as the paper record passes a point 12 cm (4 s) from the pens, are incorporated in the EEG recording and are used as part of the computer program for artifact rejection (supplemented by detection of excessive amplitudes and excessive low or high frequencies). A 3-min baseline recording is used. From FFT's of overlapping 1-s segments, bands of frequencies approximating the conventional EEG frequency bands are combined and used to sort portions of the record into quasi-stationary and nonstationary or transient-containing (more than two standard deviations departure) portions. A spike-detection routine is based initially on threshold criteria for duration and slopes for leading and trailing edges, supplemented by additional contingencies to exclude false positives from muscle activity and from sharp rhythmic background. The system prints out a summary of the activity in the conventional frequency bands, the dominant frequencies, and of any spiking for each of the 16 scalp locations, as well as a summary verbal (printed) report (Fig. 11). The authors stated that extensive clinical validation of the system had not yet been undertaken.

The 8-channel system at *Baylor College of Medicine* and the *Methodist Hospital in Houston, TX* [141] is based on the approaches to analysis of background and transient EEG activity used by Carrie and Frost [39], [42] which has already been discussed. The implementation is a hierarchical one, in which initial processing is carried out by hybrid subprocessors and microprocessors, second-order analysis is accomplished by multiple microprocessors, and final data processing and integration is under the control of a dedicated PDP 11/40 computer. The background activity is separated into the conventional EEG frequency bands (delta, theta, alpha, and beta) for each of which determinations of wavelength (baseline crossings) and peak-to-peak amplitudes are made. Mean and modal frequencies and average amplitude measures, as well as measures of asymmetries (and their significances) for the two sides of the head are obtained. The detection of spikes and sharp waves is based in the first instance on curvature (second time derivative) in relation to a running threshold derived from the immediately preceding background activity. Derivation of the parameters (e.g., durations of component segments) of transients is carried out in the second-order analysis. Evaluation in relation to artifact (e.g., muscle potentials) is accomplished at the third-order of analysis (PDP 11/40). At the latter level, interchannel comparisons are also carried out (work currently in progress). It has been found that spike/sharp wave detection by the system compares quite favorably with that of clinical electroencephalographers (e.g., 89 percent agreement in one study). Automatic report generation, currently limited to a description of background activity, employs the phraseology of conventional clinical EEG reports. Inclusion in the report of the probable medical significance of the findings is ultimately envisaged.

Discussion and Conclusions

From the preceding survey, it is evident that, for the analysis of EEG background or stationary activity, the FFT has become the most generally used method, the autoregressive technique and period analysis being less frequently used, along with other still less frequently used methods. Techniques of obtaining spectra by using orthogonal series that are simpler than trigonometric (sine, cosine) functions, despite their relatively greater saving computationally in comparison with the FFT,

```
D7016

  DATE        RUN
241 8176       1

STEADY STATE ACTIVITY
MEAN VALUES

        ALPHA              DELTA              THETA              BETA
   72  65 183 113     73  59 106  71     68  64 172 110     74  78 147 104
   75 101 274 117     52  44 103  66     54  84 222  99     84 100 231 118
  148 163 192 192     63  63  69  73     96  97 121 135    153 172 163 174
  169 166 204 170     65  62  66  68    105 112 184 132    220 234 203 178

% ABOVE NORMAL LIMITS

      ALPHA         DELTA         THETA          BETA          SPIKES        DOM FREQ       RHYTHM
   -  -  A  A    -  -  -  -    -  - 99 64    -  - 18  M    -  -  -  -    -  -  7  -    -  -  R  -
   -  A  A  A    -  - 27  -    - 23 99 54    -  - 99  -    -  -  4  -    -  9  8  -    -  -  -  -
   -  -  A  A    -  -  -  -    4  2 19 33   14 23 10 18    -  -  -  1    9 12  8 11    -  -  -  -
   -  -  A  -    -  -  -  -    9 16 76 36   56 67 34 26    2  3  -  -   11 12  -  8    -  -  -  -

NORMAL VOLTAGE RECORD
POOR ALPHA BLOCKING , ASYMMETRICAL

% ASYMMETRY

      ALPHA         DELTA         THETA          BETA
   -  - 64 35    2  - 44  -    -  - 62 38    -  - 46 29
   -  - 63 36    -  - 57 21    -  - 62 45    -  - 56 25
   -  - 15 23    -  -  8 13    -  - 19 28    -  4  - 12
   -  - 18  -    -  -  7  5    -  - 39 19   18 13  -  -

              EEG REPORT ON PATIENT NUMBER 87016

              ---------------------------------------------------------------

              NAME ---     J ELDRED
              AGE  ---     30
              DATE OF RECORDING ---    241 8:76

              ---------------------------------------------------------------

              THE RECORD CONTAINS ABNORMAL BACKGROUND ACTIVITY ,
              WITH MODERATE VOLTAGE DOMINANT 8 TO 11 HZ ALPHA ACTIVITY ,
              PREDOMINANT ON RIGHT SIDE AND PRESENT IN RIGHT ANTERIOR
              QUADRANT , LEFT FRONTO- CENTRAL , RIGHT ANTERIOR TEMPORAL ,
              RIGHT PARIETAL , RIGHT OCCIPITAL AND RIGHT TEMPORAL REGIONS .
              POOR ALPHA BLOCKING OCCURRED ON EYES OPENING ON RIGHT SIDE .

              EXCESSIVE BETA ACTIVITY WAS SEEN IN RIGHT FRONTO- CENTRAL AND
              POSTERIOR QUADRANTS .

              ABNORMAL CONTINUOUS MODERATE VOLTAGE DELTA AND THETA ACTIVITY
              WITH MODERATE RIGHT-SIDED ASYMMETRY IN FRONTO- CENTRAL REGION .
              ABNORMAL CONTINUOUS MODERATE VOLTAGE THETA ACTIVITY WITH
              MODERATE RIGHT-SIDED ASYMMETRY IN FRONTAL , FRONTO- TEMPORAL ,
              ANTERIOR TEMPORAL , OCCIPITAL AND TEMPORAL REGIONS .
              ABNORMAL MODERATE VOLTAGE SYMMETRICAL ACTIVITY IN THIS BAND IN
              PARIETAL AND TEMPORO- OCCIPITAL REGIONS .
              HIGHLY VARIABLE DOMINANT 8 TO 12 HZ ACTIVITY IN POSTERIOR
              QUADRANTS .
              RHYTHMICAL 7 HZ ACTIVITY WAS SEEN IN ANTERIOR QUADRANTS .

              10 SPIKES WERE DETECTED IN THE BACKGROUND ACTIVITY IN RIGHT
              FRONTO- CENTRAL , LEFT OCCIPITAL , LEFT TEMPORO- OCCIPITAL AND
              RIGHT TEMPORAL REGIONS .

              EXCESSIVE MUSCLE ARTEFACT WAS PRESENT IN RIGHT FRONTO- TEMPORAL
              REGION .

              PAROXYSMAL DELTA AND THETA ACTIVITY WAS SEEN IN LEFT FRONTO-
              CENTRAL , RIGHT FRONTO- TEMPORAL , RIGHT ANTERIOR TEMPORAL ,
              LEFT PARIETAL AND TEMPORAL REGIONS .
              14 SPIKES WERE DETECTED WITHIN THE PAROXYSMAL ACTIVITY IN RIGHT
              FRONTO- CENTRAL , LEFT OCCIPITAL AND TEMPORO- OCCIPITAL REGIONS
```

Fig. 11. Facsimile of computer data output display for a routine clinical EEG recording. The figures are arranged to correspond to the topographic location of recording sites, anterior above, for 16 channels. The numerical values are arbitrary. Percentage asymmetries refer to the highest value with reference to the lower. *M* is muscle artifact. *R* is rhythmical activity. There is an additional similar display of paroxysmal activity (parasagittal meningioma) (figure and caption from MacGillivray 1977 [18]).

have not in general proved satisfactory. Of course, obtaining of spectra is only the first step in the clinical classification of background EEG activity with respect to normality and abnormality, but by now appreciable experience has been accumulated in the further evaluation of spectra in this respect, at least for the waking adult EEG, and, to a lesser degree, for the EEG of children.

The detection and classification by computer techniques of fast transients or nonstationarities (spikes, sharp waves—70 ms being the conventional division between the durations for the two) has been a later development than the characterization of background activity, and perhaps correspondingly, there is at present a greater diversity of techniques, from among which the optimum choices are not yet apparent. Thus, techniques based on segmentation, double differentiation, and inverse filtering have all been used with greater or lesser success. But the clinical validation of the results of any method of detection of transients poses a greater problem than the classification of background EEG activity because of the previously mentioned areas of disagreement among EEG experts on what constitutes abnormal fast transients. Nonetheless, appreciable progress has been made on the problem of fast transients. (It should be noted in passing that the difficulty of classification of EEG background activity increases in childhood and infants, and particularly in premature infants.)

On the other hand, mixed fast and slow transients, such as spike and slow-wave complexes, and particularly slow transients such as single slow waves or brief runs of slow waves, have received rather less attention, and hence, this is an area especially requiring further work since these kinds of events are also very much a part of clinical EEG.

Formal template-matching or matched filtering, in which a specific waveform is continuously searched for in the EEG, is of limited general usefulness because of the great biological variability from patient to patient, and for the same patient at different times. Nonetheless, template-matching may be useful in the classification of nonstationarities already detected by some other technique.

The use of the background EEG as a basis for searching for transients, as in the various inverse filtering techniques, has the appeal of being specifically derived for each original EEG (and hence, the term "matched inverse filtering" might be appropriate), but in this case the potential problem of very frequent transients and the corresponding effect on the characteristics of the inverse filter require careful attention.

Despite these limitations, several systems have been developed, as noted previously, which include analysis and classification of both background and transient EEG activity. Some of these are intended only as aids to the electroencephalographer in summarizing the salient features of an EEG, which can then be utilized in the preparation of the conventional report. But other systems are so designed that a typed out report is provided similar to the conventional clinical EEG report. The latter systems truly constitute the beginning of fully computerized systems for clinical EEG.

But much more experience will be required with these and other systems currently being formulated before their appropriate place in clinical EEG can be determined. Fully computerized evaluation and reporting of every kind of clinical EEG, normal and abnormal, is hardly just over the horizon. Nonetheless, the field has evolved very rapidly in recent years, as the technology has progressed from large to medium to minicomputers, and it seems likely that in the era of microprocessors and fast arithmetic processor arrays, which so far have hardly had an impact on this field, the principal problems may be primarily conceptual rather than computational.

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