SPECTRAL ANALYSIS TECHNIQUES AND PATTERN RECOGNITION METHODS

FOR ELECTROENCEPHALOGRAPHIC DATA

W. R. Adey

Brain Research Institute and Space Sciences Center, University of California, Los Angeles; and Veterans Administration Hospitals, Long Beach and Los Angeles

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1. Introduction

From the melting pot of relatively modest experiences in data processing that, in most aspects, began little more than five years ago, the neurophysiologist has progressed to substantial use of large computing systems, and has taken account of his need for rapid processing of large amounts of data by comprehensive computational techniques that go to the very fringes of the mathematical arts. Granted that this rapid growth in analytic capabilities has not arisen de novo, and that it has its origins in earlier methods of frequency analysis (Grey Walter, 1950) and simple averaging and correlation analysis (Dawson, 1950; Brazier and Barlow, 1956), the exponential growth in the armamentarium of the neurophysiologist's analytic capabilities represents a series of essentially new developments. They rest upon a trinity that will be a recurring theme in this paper: data acquisition systems using analog or digital magnetic tape recording techniques, with appropriate coding for stimuli and epoch marking; the use of statistically valid analytic techniques, that take account of uncertainties inherent in limited epochs of physiological data; and automated display techniques that achieve required degrees of compression of the primary records to provide an overview of long and complex epochs of data, while retaining fine resolution of subtle shifts in pattern within the epoch (Adey, 1965a,b).

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These exceptional requirements in neurophysiological analysis appear to transcend by an order of magnitude the current needs in most other areas of physiological research. It has become apparent that many vital bridges in our understanding of cerebral functions will only be built on the basis of carefully quantified analysis and detection of patterns that inherently escape mere observational techniques. The urgent need and "burning thorn of discontent" so engendered have been powerful stimuli to the pioneering by the neurophysiologist of new computational techniques and display methods, that now also have application in other areas of physiological research.

In like fashion, improved analysis of both gross EEG and cellular wave phenomena has provided the first firm basis for a series of realistic cerebral models, concerned with the genesis of the gross EEG from a population of neuronal generators (Elul, 1965, 1966) and also with the organization of larger generators in systems subserving the cortical mantle as a whole (Walter and Adey, 1965a,b; Adey, 1966).

This paper will describe essential aspects of computing systems currently in use in our Brain Research Institute together with main computational methods and associated display techniques. It will discuss their application to EEG records in animals and man, and for the latter, in relation to baseline characteristics of a population of individuals in a gamut of states in sleep and wakefulness. It will describe simple automated pattern recognition techniques applied to these records. Finally, it will describe computer applications to impedance measurements and cellular wave phenomena, where computational techniques have played a vital role in the formulation of physiological models, having aspects of seeming realism in their exemplification of the uniqueness of organization of cerebral tissue.

2. Computational techniques in neurophysiological research

Our analytic methods have involved digital computational techniques almost exclusively, with evolution of a hierarchical organization, both in computational devices and in analytic techniques, as reviewed in detail elsewhere (Adey, 1965a,b; 1966). Small special-purpose digital computers for averaging of evoked potentials and EEG wave trains, and for estimation of interval histograms in unit firing patterns, have been widely used in our laboratories. Their value is indubitable, but the need for more comprehensive analyses has led to developments that are the theme of this paper.

a. Data acquisition systems for computational analysis of EEG.

The laboratories of the Brain Research Institute share the facilities of a central Data Processing Laboratory, organized to provide services for about 40 laboratories, either through acceptance of data on-line in analog or digital format, or as analog records on multi-channel magnetic tape, usually in 7 channel, half inch, or 14 channel, one inch IRIG formats. These systems have been reviewed elsewhere (Adey, 1964).

The cornerstone of this central processing laboratory is an SDS 930 computer (Fig. 1), with 16,000 words of core memory, 16 priority interrupts, three time-multiplexed communication channels (TMCC, "C", "W" and "Y"), and one channel with direct access to the computer memory (DACC, "E"). In Fig. 1, those blocks enclosed by dotted lines are system additions planned for operation within the year. A remote console system with 64 keys has been developed as an input device to the computer with a storage oscilloscope for display (Fig. 2).

This remote console system, or Shared Laboratory Interpretive Processor System (SLIP), has been designed by L. Rovner, L. Betyar and R. T. Kado, to function on a time-shared basis involving five simultaneous users. A separate computer interface has been installed on each floor of the Institute building to provide analog-to-digital conversion, relay drivers and sense lines to the user's laboratory. The system enables the experimenter to convert analog data in real time and operate upon it with several standard analytic programs, or programs which he himself generates by use of the console. A system interface unit incorporates 24 bits of parallel input (PIN) and output (POT) from the computer memory, character buffer and address matrix for the console system, digital-to-analog converter, and analog-to-digital converter.

Two of the time-multiplexed channels (W and Y) serve as the input/output communication path for the standard computer peripheral equipment. The remaining channel (C) serves the analog-to-digital converter, accepting digitized information and storing it in memory under computer control. The direct access channel E services the digital-to-analog converter, and provides a terminal for an interface with the main data processor (currently an IBM 7094) in the adjacent Health Sciences Computer Facility (Fig. 3).

The digital-to-analog converter accepts the 24 bit output from the computer E channel and provides X, Y and Z analog output signals to the SLIP console, and other oscilloscope display functions. The analog-to-digital conversion system provides 16 analog inputs to the computer at sampling rates up to 30,000 conversions per second.

The relay drivers enable transmission of switchable control functions to the remote laboratory, under program control. In addition to serving the relay drivers, the 24 POT lines are used by the address matrix of the SLIP console to establish communication between remote locations and the computer. The basic time-sharing system involves two computer program functions, a commutator and the interrupt processors. Activation of the system causes the commutator to scan a number of memory cells, equal to the number of consoles sharing the computer. On finding a cell bearing a zero, machine control is transferred to the associated program until service is completed. With console generated interrupts, the interrupt processor causes the input character to be stored in memory, and resets the console. By adequate buffering, additional interrupts, arriving before storage of the first character is completed, are ultimately stored in memory.

Unlike a typewriter keyboard, where the keys are of a fixed context, those of the console have entirely variable upper and lower case meanings. Each set of 64 upper and lower case key definitions is referred to as a "context level", and there are 64 such levels. Generally, the upper case meanings are interpreted as an action (operator), with the lower case forming the object of that action (operand).

Development of this console has greatly facilitated utilization of the SDS 930 computer by operators in the computer room, and by the investigator in his laboratory. In summary, the combined system has proved a thoroughly feasible method for preparation of data for subsequent more extensive analysis on the larger IBM 7094 computer, and provides appropriate displays of computed outputs from that computer.

b. Time series analyses of EEG data; correlation functions, digital filtering and spectral analysis.

Extraction of periodic signals in noise has been a lasting requirement for the communications engineer (Lee, 1950). Baffled by the complexity and apparently random character of the EEG, the neurophysiologist applied it similarly in his search for concealed rhythms (Brazier and Barlow, 1956; Rosenblith et al.,1959). Essentially the product of the epoch of record multiplied by itself and progressively shifted in time, an autocorrelation function contains all the frequencies present in the original function. This function and the Fourier power spectrum are transforms of each other (Wiener, 1958). Cross-correlation of pairs of simultaneous EEG records during training provided the first opportunities to examine aspects of pattern between different brain regions (Adey, Walter and Hendrix, 1961).

Yet there are serious practical and theoretical difficulties in extended use of correlation functions in EEG analysis (Adey, 1965a), relating to errors arising in use of truncated series (Bendat, 1958) which do not fulfill the mathematical constraints of an infinitely long series. Although some phase information can be extracted, for practical purposes this is limited to phase relations at the dominant frequency of the cross-correlogram. A much broader window on the interrelations between different brain regions in the degree of sharing of a broad spectrum of frequencies can be obtained by cross-spectral analysis (Walter, 1963). Blackman and Tukey (1959) have emphasized that estimates of functions of lag, such as autocorrelations or autocovariances "have fluctuations that are so far from independence as to frequently fool almost anyone who examines tables or graphs of their values", and they advise the use of the autocorrelogram merely as an intermediate step in spectral analysis.

The key to successful application of the digital computer in spectral analysis lies in its ability to function as a narrow band filter, with precisely specified characteristics, which can also be modified at will with respect to flat-top, shoulder and skirt (Goodman, 1960). Problems of designing physical filters with appropriately narrow skirt characteristics have led to the development of these digital filters, in which the digital filter provides weighting functions by which the time function is multiplied. The sum of these products is taken as the output of the digital filter. The weighting function can be considered as having a narrow bandpass characteristic, as in an analog filter, or the application of a set of digital filters to a function of time can be viewed as a discrete version of a Fourier transform.

Tukey (1965), in a recent elegant review of the power of spectral analysis in solving geophysical problems, including the detection of long period ocean waves coming 20,000 kilometers from the Indian Ocean to the coast of California, has pointed out that just so long as the information needed about some phenomenon is expressed, at any one time and place, in a distribution of activity or energy or power over frequency, "we have a hope of going from the there-and-then to the here-and-now". In the frame of reference of the electroencephalographer, we can expect to learn thereby the relations between simultaneous brain wave activity in different brain regions, with precise preservation of information about shared frequencies and phase relations, not merely at the dominant frequencies in a spectrum of activities, as in the cross-correlogram, but with equal clarity and precision at each and every frequency in the cross-spectrum.

It is in our capacity to precisely specify the bandpass characteristics of the digital filter, particularly in the low frequency range between 0.5 and 10 cycles per second, that has established its superiority over analog methods. Since its phase shift is zero, it has become possible to measure for the first time the phase relations between EEG wave trains at each frequency across the spectrum, as well as shared amplitudes between them at each frequency. From pioneering studies by our colleague D. O. Walter (Adey and Walter, 1963; Walter and Adey, 1963; Walter, 1963), we have come to the routine calculation of the coherence function, as a measure of statistical variability in linear interrelationships between brain regions.

In our hands, the value of coherence calculations as a basis for sharp delineation of shifting EEG patterns in specified states of sleep and wakefulness has been paramount. The magnitude of the coherence function may be expressed:

$$coh(f) = MAGS(f)/ASX(f)ASY(f)$$

where MAGS(f) is the mean cross-spectral magnitude at frequency f, and ASX(f) is the autospectrum of X and ASY(f) is the autospectrum of Y, at the respective frequencies. The coherence function is expressed between 0 and 1, and is a measure of the linear predictability of activity in any area, on the basis of knowing the activity in any other area, or series of areas.

3. Examples of spectral analyses of EEG data; use of contour plots and three dimensional displays

Continuous contour plots of spectral density and coherence have proved most useful tools in compression of long epochs of data into a single plot, while retaining all essential information relating to transitions occuring,

for example, during visual discriminations and auditory vigilance tasks. In Fig. 4 are plotted autospectra from simultaneous scalp leads during these performances, which covered a test period of approximately one hour. Differences in densities at 1 to 2 cycles per second in left and right centroparietal and left parietooccipital leads were associated with substantially greater difficulty of the task in the second performance. An even greater difference will be noted in all leads between records during visual discrimination and during an auditory vigilance task with eyes closed. These parameters form part of a scheme of automated pattern recognition described below.

Similar plots of coherence from scalp leads during auditory vigilance tasks (Fig. 5) provide a continuous measure of linear interrelationship between pairs of leads at all frequencies from 0.5 to 15 cycles per second (Adey, 1965a). Evidence from such plots suggests both longitudinal and transverse generators, since a high coherence in the alpha band characterizes interrelations between all pairs of longitudinal leads, but very little coherence was found between the bioccipital lead in any part of the spectrum, despite a powerful but unchanging alpha activity throughout the test. This question of generator function analysis on the basis of linear transfer functions has been discussed in detail elsewhere (Walter and Adey, 1965a, b).

Different types of displays of autospectral densities and associated coherence functions were used in studies in the monkey of the effects of whole body vibration on the EEG in surface and deep brain structures (Adey, Kado and Walter, 1965).

Results presented elsewhere have indicated the presence of a "driving" in EEG records from cortical and subcortical structures during whole body vibration, at certain frequencies in the test spectrum of 5 to 40 cycles per second, and 2G peak-to-peak in the range from 13 to 40 cycles per second

(Adey, Kado, Winters and DeLucchi, 1963).

More recent studies with extensive computer analyses (Adey, Kado and Walter, 1965) have shown little or no evidence of EEG driving below 9 cycles per second despite powerful head movements. Driving at the shaking rate was frequency selective and maximal in the range 10 to 15 cycles per second. However, in many instances, maximum EEG energy peaks occurred at other than shaking frequencies, and without harmonic relationship to shaking frequencies (Fig. 6). Calculations of coherence, or linear predictability, were high between cortical and subcortical leads at EEG frequencies unrelated to concurrent shaking frequencies, and absent from baseline records before or after shaking (Fig. 7). Coherence between head and table accelerometers and cortical and subcortical leads were below significant levels at fundamental driving frequencies below 11 cycles per second, although significant coherence peaks appeared at other EEG frequencies. Shaking in the range 11 to 17 cycles per second produced many coherent relationships at fundamental driving frequencies, and at harmonically related and unrelated EEG frequencies. These computed analyses have provided evidence not available by other means that the effects of vibration on concurrent EEG activity, including the frequency selective driving, do not arise in simple electromechanical artifacts, but may have their origins in physiological mechanisms. Much significance also attaches to the use of display techniques that allow ready interpretation of multi-dimensional data.

4. Applications of spectral methods in EEG baseline analysis; the normative library

It has long been a matter of concern that definition of EEG patterns has rested, not only on the subjective opinion of the investigator, but also on wide

individual variations in apparently normal subjects. We have, therefore, sought to establish by computer analysis the presence of common EEG factors in a significant population of astronaut candidates, both in relation to task performances and in assessment of sleep states.

In detailed studies to be reported elsewhere (Walter, Rhodes, Kado and Adey, 1966), a series of 200 astronaut candidates were tested in a series of perceptual and learning tasks, by means of a programming device, developed in our laboratory by Raymond T. Kado, and using a magnetic tape command system to ensure accurate timing in task presentation from one subject tc the next. Subject testing and EEG recording were performed by Dr. P. Kellaway and Dr. R. Maulsby, at the Methodist Hospital, Houston. Physiological data was recorded on magnetic tape, together with command signals, for subsequent computer analysis. This data constitutes a normative library, and includes not only 18 EEG channels from all scalp areas, but also the electrooculogram (EOG), electrocardiogram (EKG), galvanic skin responses (GSR) and respiration.

A series of 50 subjects were selected at random from the total of 200, and intensive spectral analyses performed. Each hour of subject data required 25 hours of main computation time, wherein multiplications were performed at approximately 500,000 per second. The scope of such an analysis appears to have been justified, in that it has allowed selection of variables for a possible on-line system that would be far less demanding in computer requirements.

To synthesize the data, an averaging procedure was adopted on the spectral outputs, covering all 50 subjects in the various test situations, and in selected sleep epochs. These averages were made for each scalp region, and are presented as a series of bar graphs (Fig. 8), covering the spectrum from 0 to 25 cycles per second. First, an average was prepared of spectral densities at each scalp

recording site for all test epochs (Fig. 8, top left), including sitting with eyes closed at rest, eyes closed during 1 per second flash stimuli, during an auditory vigilance task, during visual discriminations at 3 second intervals, and a similar series of more difficult discriminations at 1 second intervals.

The contours of these "lumped" spectra were then used as the mean for comparison with the spectra for the individual situations. The subsequent graphs in Fig. 8 thus show the variations about the mean established by the average over 12 situations in the top left figure. Spectral densities above the mean at any frequency have bars above the baseline, and vice versa. It will be seen that such a display clearly separates spectral density distributions for the 50 subjects in the five situations shown. In particular, the distributions for more difficult visual discriminations (Fig. 8, lower right) exemplify trends that already characterize discriminations made in three seconds (Fig. 8, lower middle). Pattern recognition techniques described below clarify differences between records in these two tasks. It is also possible to compare an individual with the mean for the group, or with his own mean, using a two-color display technique.

Similar averages were made for 30 subjects in various stages of sleep and drowsiness (Figs. 9 and 10). Here, the mean was established by an average over 7 stages of presleep, sleep and postsleep, and thus became the baseline for measurement of variance for individual sleep states. It will be noted that states of drowsiness, and light, medium and deep sleep can be readily distinguished from each other, but that separation of deep "slow wave" sleep from subarousal with "K-complexes" is less clear.

5. Application of simple pattern recognition techniques to spectral parameters for definition of states of attention

Discriminant analysis was applied to these spectral outputs in four subjects (Walter, Rhodes and Adey, 1965) covering five situations: eyes closed at rest, eyes open at rest, an auditory vigilance task, and the two visual discriminative tasks described above. A computer program attempted to assign each segment to the situation from which it came, using measurements derived from four EEG channels: left and right parieto-occipital (P3-01 and P4-02), vertex (F2-C2), and bioccipital (01-02). Each channel's activity was analyzed into 4 frequency bands, corresponding to the classical delta (1.5 to 3.5 cycles per second), theta (3.5 to 7.5 cycles per second), alpha (7.5 to 12.5 cycles per second) and beta (12.5 to 25 cycles per second) bands. In each band, measurements were made of the strength of activity in each channel, mean frequency within the band (the dominant frequency when present), bandwidth within the band (an expression of the regularity of the dominant frequency), and the coherence between pairs of channels.

This discriminant analysis program initially considers all the measurements for all the segments, and selects that parameter which best discriminates segments recorded in different situations. It then reexamines all measurements and chooses the parameter which will add most to the discriminating power of the first measurement. It calculates five linear functions of those two measurements whose values differ as much as possible among the situations. The program continues this iteration of selecting and calculating linear functions, until insufficient improvement is made by adding another parameter.

The four variables which best distinguish among the five situations are: left parieto-occipital alpha intensity, the mean frequency of theta-band activity in the vertex, the coherence in the theta band between left parieto-occipital

and vertex, and coherence in the beta band between vertex and bioccipital leads. A detailed account of the respective contributions of each of these variables to the identification of each of these situations is given elsewhere (Walter, Rhodes and Adey, 1965).

The separate analysis of each subject's records in the same way yielded a higher proportion of correct classifications than the group analysis. With his own best four measurements, between 62 and 69 per cent of a single subject's samples were correctly classified, as contrasted with 51 per cent for the subjects simultaneously (Fig. 11). An even greater disparity appeared after 15 measurements were selected. Individually, 95, 93, 96 and 90 per cent were correct, while for the subjects together, only 65 per cent were correctly classified. It would thus appear that each subject may have a spatially and numerically characterized individual EEG "signature", as to which measurements are most effective in distinguishing different situations.

6. Studies of the essential nature of the electroencephalogram: its cellular origins, and possible role in information transaction, storage and recall

It would indeed be disappointing if application of these computational techniques were confined to studies in grosser aspects of cerebral system organization, useful though this might be. We have, therefore, sought evidence for slow, wave-like processes at the level of single cells, occurring independently of actual neuronal discharge, and contributing to the process recorded as the electroencephalogram from larger domains of tissue.

Intracellular recording in unanesthetized cortical neurons in our laboratory (Elul, 1965; Adey and Elul, 1965) has revealed a large wave process, from 5 to 15 millivolts in amplitude, which appears to arise in the dendritic branches of the cell, rather than in the soma (Fig. 12). Spectral analysis of this wave process has indicated that its density distribution closely follows that of the EEG recorded grossly in the same domain of tissue. Despite this similarity of density contours, calculations of coherence between the intracellular and gross EEG records have shown that there is virtually no linear relationship between the two processes (Fig. 13), so that the population of neuronal generators appear to be independent and nonlinearly related (Elul, 1965). The wave process recorded extracellularly arises from generators no larger than cellular dimensions (Elul, 1962), and has an amplitude less than one hundredth of the intracellular wave process. Elul has suggested that the occurrence of a rhythmic EEG as the integral of activity in such a population of independent and nonlinearly related generators may be mathematically modeled in terms of the central limit theorem of Cramer (1955).

The patterns of EEG waves described above, and the indubitable evidence of comparable processes at the cellular level have suggested that they are concerned in the transaction of information. The evidence further suggests that, at the level of the individual neuron, the cell may function as a phase comparator for patterns of waves sweeping its dendritic surface in space and time. Moreover, the wave process may underlie the lasting physico-chemical changes associated with storage of information in cerebral tissue. In such a scheme, recall of information would depend on the reestablishment in that domain of tissue of wave patterns that resembled, but were not necessarily identical with, those associated with the initial experience (Adey and Walter, 1963).

The threshold for firing of the individual neuron would be critically dependent on computed evaluation of stochastic modes of operation in sizable populations of neurons, as well as at the level of the single cell. We are thus already far removed from simple concepts of pulse-coded nerve nets, or connectivity diagrams of intrinsic cerebral organization. A specific model of these processes is discussed elsewhere in terms of single, or limited numbers of generation processes, spatially organized and characteristically shared between different domains of cortical tissue (Walter and Adey, 1963; 1965b).

Yet even here, let us beware of any comfortable notion that storage of information in cerebral tissue, its unique and most characteristic function, occurs exclusively within its neuronal compartment. Our measurement of electrical impedance in small volumes of cerebral tissue in the course of alerting, orienting and discriminative stimuli, has revealed, with the aid of computational techniques, regional differences in "evoked" impedance responses accompanying learned responses, and their dependence on levels of learning in training and extinction trials. The extraneuronal course of the bulk of the impedance measuring current, presumably through extracellular fluid characterized by a substantial content of macromolecules and susceptibility to divalent cations, such as calcium, or through neuroglial elements surrounding nerve cells, has seriously implicated these two perineuronal compartments in the transaction and storage of information in brain tissue (Adey, Kado, Didio and Schindler, 1963; Adey, Kado, McIlwain and Walter, 1966).

What, then, of the future of computational applications in neurophysiological research? Our studies have emphasized the continuing role and still evolving power of spectral analysis to detect aspects of pattern in the seemingly random processes of the EEG, particularly when coupled with pattern recognition

techniques. Much remains to be done in this area of pattern recognition, and in display techniques arising therefrom. Only through diligent and challenging developments in these areas can we hope to see full consummation of the applications of spectral analysis to neurophysiological problems, and come within sight of Tukey's goal of passing "from the then-and-there to the here-and-now". Yet we may ask more fundamental questions about the precise nature of the physiological processes revealed by linear time series analyses of the spectral type. The evidence suggests that organization at the level of cellular domains involves essentially nonlinear processes, and that in broader aspects of cerebral system interrelations, nonlinear transfer functions may be of vital importance, and would tend to escape us completely with current forms of spectral analysis.

It is here that the physiologist comes face to face with the fringes of current arts in applied mathematics, for there are currently few techniques that offer even modest prospects of success in dealing effectively with nonlinear systems in massive data analysis. In seeking possible solutions to what promises to be a major confrontation in the progressive evolution of our analytic techniques, we may well ask whether to pursue further time series analysis in its current form, or whether, as recently suggested by Svoboda (1964), we would do better to consider analyses based on logical statements, and applied at the level of the simplest transforms of EEG data, as, for example, to the outputs of digital filters, proceeding thereby to develop a matrix that might uniquely describe a unique physiological situation, and one so complex as to not readily reveal its pattern in linear time series analysis.

Clearly, the optimal methods of data analysis for electrophysiological records remain for future devising, based on appropriate consideration of the unique complexities of cerebral organization. Nevertheless, we may reasonably claim to have taken the first halting steps in computer applications that have revealed novel aspects of central nervous organization, and which have, in turn, suggested new experimental designs and needs for new and different computational methods, wherein the flexibility of the general purpose digital computer, in minor sorties or major confrontations, is paramount (Adey, 1965a).

Summary

A data acquisition, analysis and display system for time-shared use by a group of neurophysiological investigators is described. Applications of spectral analysis to a normative library of EEG data in states of sleep and wakefulness is described, with establishment of baselines for adult males in the course of simple alerting, vigilance task performance and in visual discriminations of increasing difficulty. Simple pattern recognition techniques were applied to such data from individual subjects, with good accuracy in automated recognition of EEG states accompanying different levels of focused attention. The use of computer analysis in analysis of intraneuronal wave records is described, and a physiological model of genesis of the EEG in a population of neuronal wave generators having independent and nonlinear characteristics is discussed. Possible future trends in electrophysiological data analysis are reviewed.

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Legends to Figures

Fig. 1. A general schema of the system used in the Data Processing Laboratory of the Brain Research Institute, University of California at Los Angeles. Abbreviations: HSCF, Health Sciences Computing Facility, equipped with IBM 7094 computer; MTU, magnetic tape unit; TMCC, time-multiplexed control channel; DACC, direct access control channel; A/D, analog-to-digital converter; D/A, digital-to-analog converter.

Fig. 2. SLIP console for time-shared remote operation of SDS-930 computer. (See text).

Fig. 3. General arrangement of the system interrelations in the SDS 930 - IBM 7040 - IBM 7094 computers, showing main streams of data flow.

Fig. 4. Contour plots of autospectral density in six EEG channels recorded simultaneously during performance of visual discrimination tasks in 3 seconds (epochs 60 through 79), followed by more difficult visual discriminations each performed in 1 second (epochs 100-119), and leading to an auditory vigilance task presented at 5 second intervals (epoch 56). This condensed presentation covers an elapsed time of many minutes.

Fig. 5. Plots of contours of coherence between pairs of tracings taken from scalp locations indicated. Longitudinally oriented leads showed high coherences between all pairs, particularly in the alpha band at 10-11 cycles per second, but coherence between a bioccipital lead and all others remained low throughout the test. (From Adey, 1965a).

Fig. 6. Models of autospectral contours in normal monkey before and during shaking at decreasing frequencies from 17 to 5 cycles per second. EEG spectrum depicted on abscissae, vibration spectrum on ordinates, and spectral power on Z-axis (in microvolts squared per cycle per second) for visual cortex (A), amygdala (B), nucleus centrum medianum (C), midbrain reticular formation (D), and head accelerometer (E). (From Adey, Kado and Walter, 1965).

Fig. 7. Plots of coherence (linear predictability) between centrum medianum and visual cortex (A), vertical head accelerometer (B), and table accelerometer (C) during vibration. Similar plots are shown between visual cortex and midbrain reticular formation (D), head accelerometer (E) and table accelerometer (F). Abscissae show EEG spectrum, ordinates the vibration spectrum, and Z-axis the level of coherence. With 12 degrees of freedom, coherence levels were significant above 0.516. Significant coherence levels at the shaking frequency are shown in solid black, and at points away from the shaking frequency in stipple. (From Adey, Kado and Walter, 1965).

Fig. 8. Averaged spectral densities over the range 0 to 25 cycles per second for a population of 50 subjects, with each spectrum presented as a series of bars at 1 cycle per second intervals, and located at the appropriate location on the scalp. The top left figure is an average for all subjects across 12 situations (See text). The contour of this average was then used as the mean against which to measure deviations in the succeeding five situations, with powers at any frequency above the mean shown as a bar above the baseline and vice versa. Calibrations for average over 12 situations in microvolts squared per second per cycle; for the separate situations, in standard deviations. (From Walter, Rhodes, Kado and Adey, 1966).

Fig. 9. Averages prepared as in Fig. 8 for a population of 30 subjects in 7 stages of presleep, sleep and postsleep, and the separate averages, with display of deviation from the mean developed in Fig. 9A, in the succeeding heads for eyes closed awake, drowsy and light sleep records. (From Walter, Rhodes, Kado and Adey, 1966).

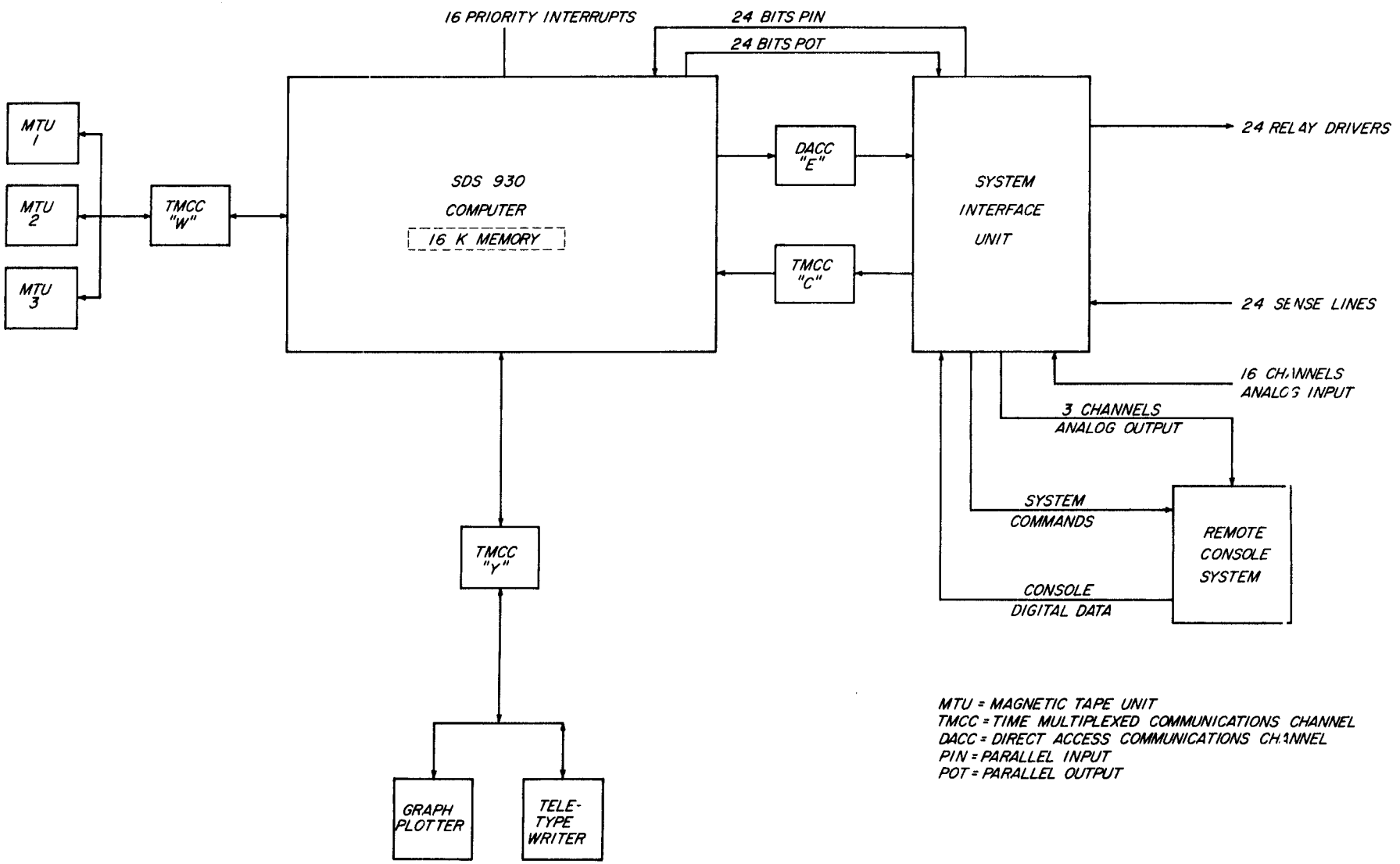
Fig. 10. Averages prepared as in Figs. 8 and 9 for medium sleep, deep sleep, subarousal, and arousal to auditory stimuli. (From Walter, Rhodes, Kado and Adey, 1966).

Fig. 11. Pattern recognition techniques applied to spectral outputs from 4 subjects, separately and jointly, with development of a matrix display of automated classifications for five situations: EC-R, eyes closed resting; EO-R, eyes open resting; EC-T, eyes closed while performing an auditory vigilance task; EO-T-3, performing moderately difficult visual discriminations in 3 seconds; EO-T-1, performing difficult visual discriminations in 1 second. (From Walter, Rhodes and Adey, 1965).

Fig. 12. Simultaneous records of EEG from cortical surface (top trace in each pair) and intracellular wave activity (lower trace in each pair) in unanesthetized cat cortex. Upper two sets of records show large slow waves in both cortical and intracellular records during sleep, with faster records in waking state in lowest set of tracings. The depolarizing phase of the intracellular waves (upward) frequently exceed level at which firing of the cell can occur, without initiation of firing. Calibrations for EEG channel, 50 microvolts; for intracellular records, 50 millivolts. (From Elul, 1965).

Fig. 13. Plot of coherence over a 500 second epoch between intracellular wave records and EEG from cortical surface in same domain of tissue. Coherence levels are below statistically significant levels at all frequencies for the major part of the analysis epoch, and the incidence of significant levels of coherence (shown in black) remains at around chance levels throughout the analysis. The findings are interpreted as indicating origins of the EEG in a population of independent neuronal generators. (See text). (From Elul, 1966).

COMPUTER LABORATORY

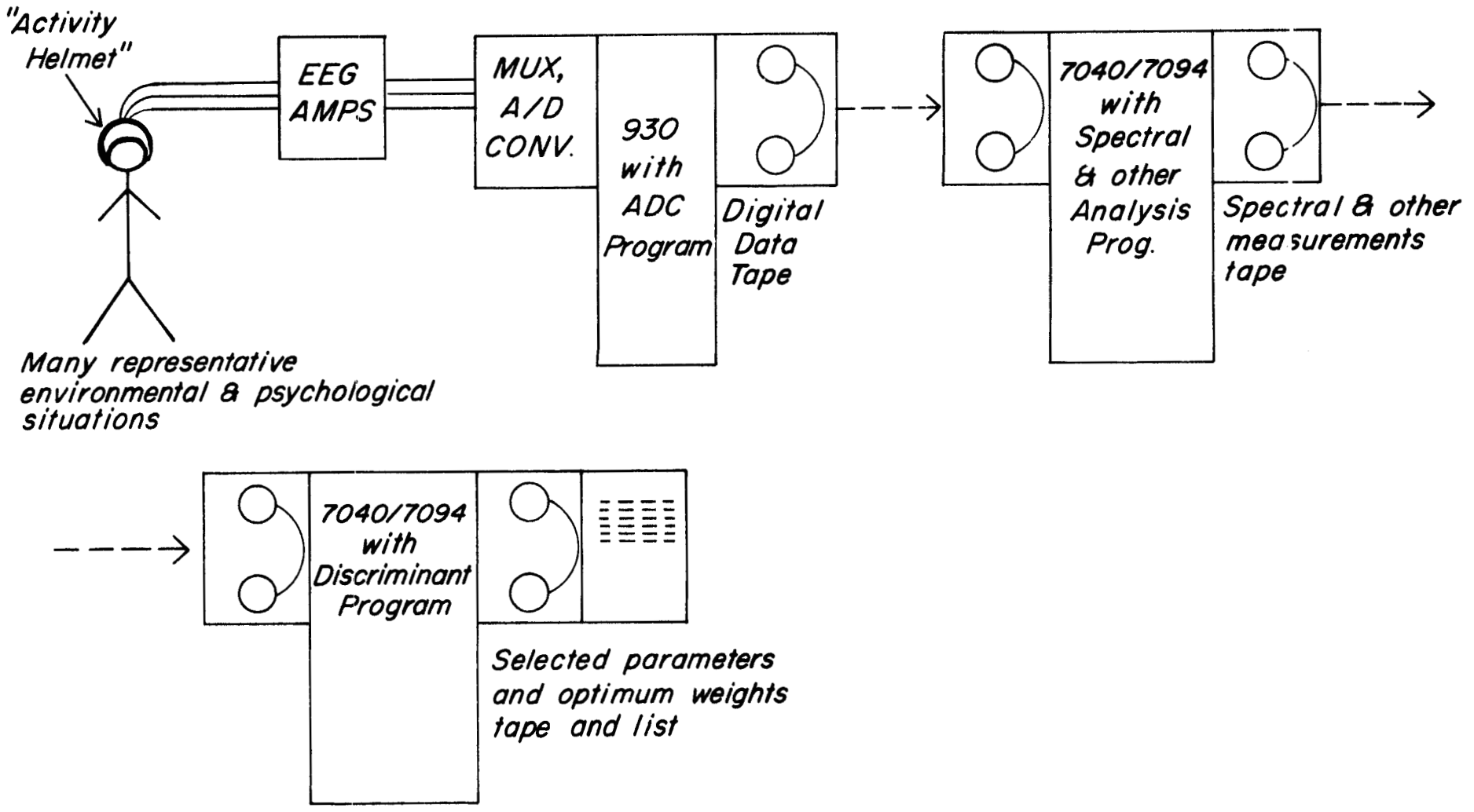


MTU = MAGNETIC TAPE UNIT
TMCC = TIME MULTIPLEXED COMMUNICATIONS CHANNEL
DACC = DIRECT ACCESS COMMUNICATIONS CHANNEL
PIN = PARALLEL INPUT
POT = PARALLEL OUTPUT



COMPUTER-ASSISTED ASTRONAUT MONITORING METHOD

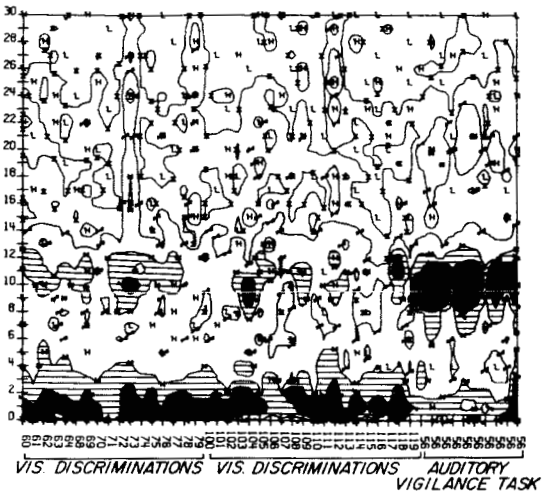
I. Comprehensive Data Collection Phase



ASTRONAUT F.B. NORMATIVE STUDY
VISUAL DISCRIMINATIVE and AUDITORY VIGILANCE TASKS

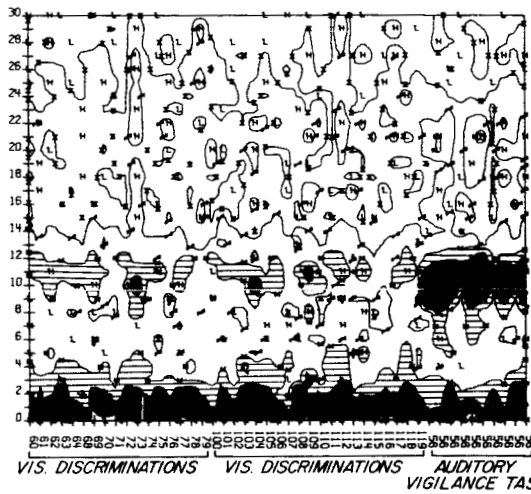
1. L. PARIETO-OCCIPITAL

A1
LP-LO



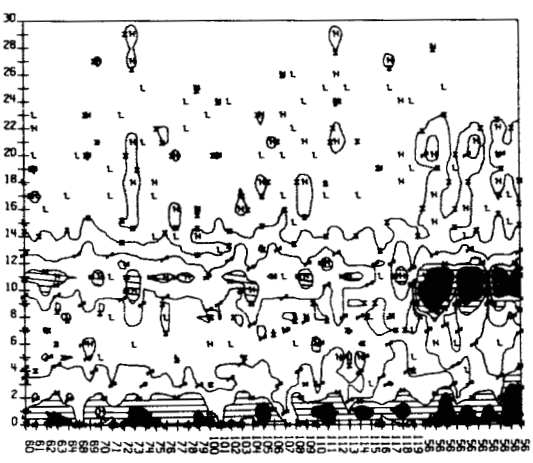
3. L. CENTRO-PARIETAL

A1
LC-LP



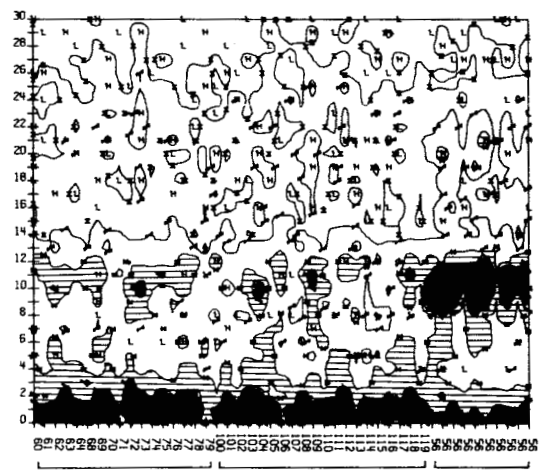
2. R. PARIETO-OCCIPITAL

A1
RP-RO



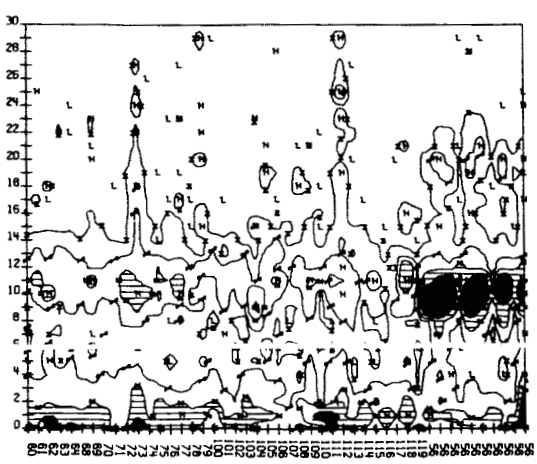
4. R. CENTRO-PARIETAL

A1
RC-RP



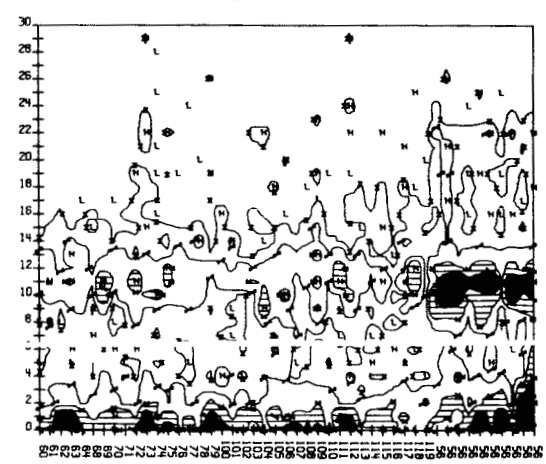
5. VERTEX

A1
FZ-CZ

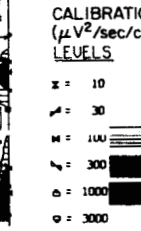


6. BI-OCCIPITAL

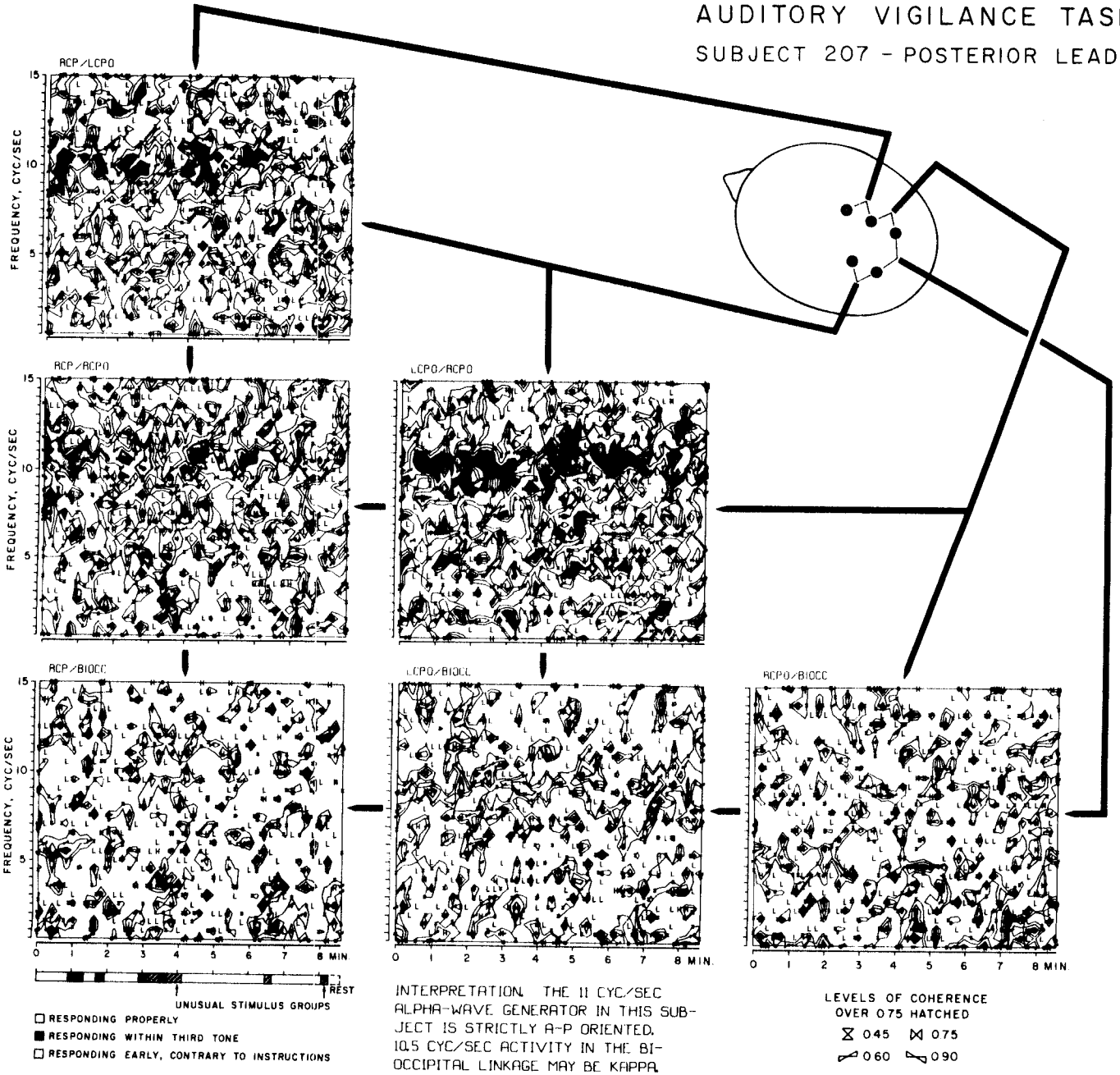
A1
LO-RO



CALIBRATIONS
(μV^2/sec/cycle)
LEVELS



CONTOURS OF COHERENCE (LINEAR PREDICTABILITY)
AUDITORY VIGILANCE TASK
SUBJECT 207 - POSTERIOR LEADS



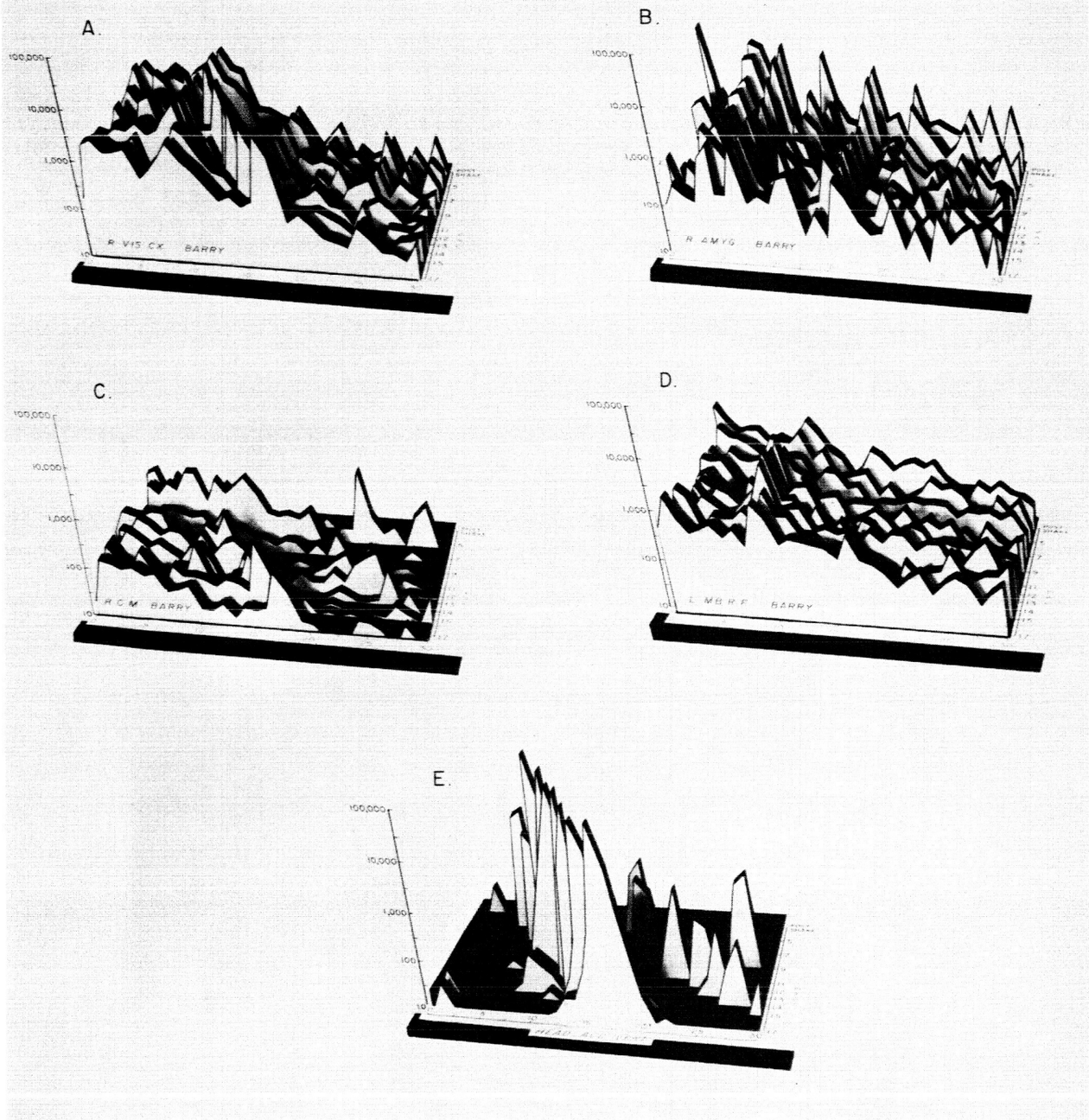
INTERPRETATION. THE 11 CYC/SEC ALPHA-WAVE GENERATOR IN THIS SUBJECT IS STRICTLY A-P ORIENTED. 10.5 CYC/SEC ACTIVITY IN THE BI-OCCIPITAL LINKAGE MAY BE KAPPA.

LEVELS OF COHERENCE OVER 0.75 HATCHED

0.45 0.75

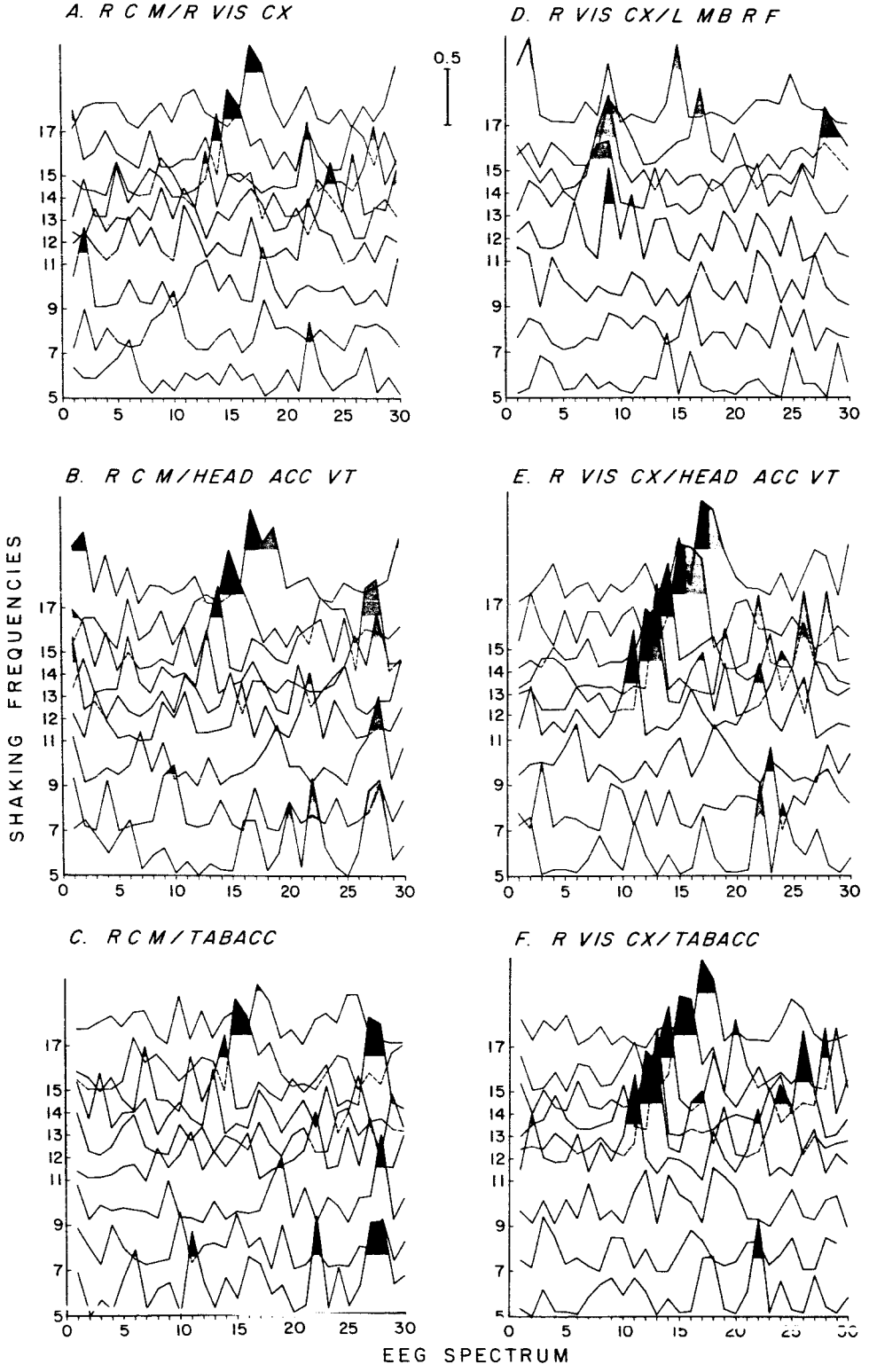
0.60 0.90

AUTOSPECTRAL CONTOURS DURING VIBRATION
NORMAL MONKEY



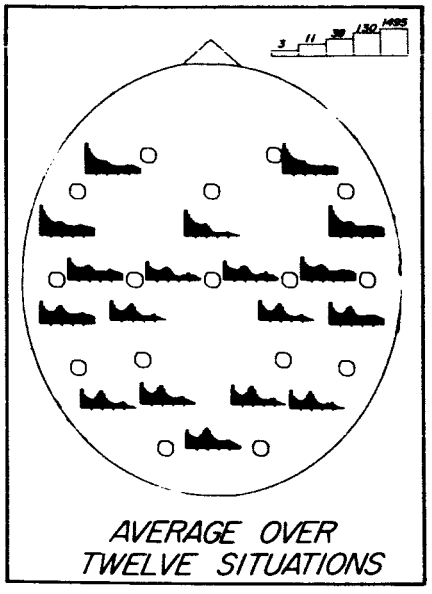
PLOTS OF COHERENCES (LINEAR PREDICTABILITY)
DURING VIBRATION – NORMAL MONKEY

SIGNIFICANT LEVEL AT 0.516

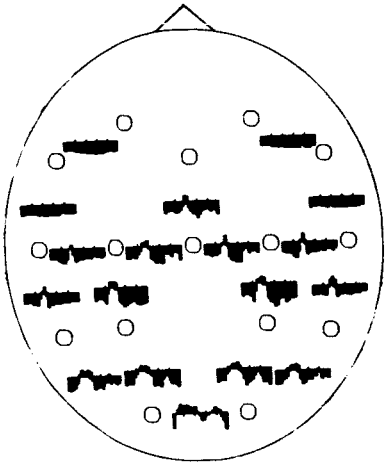


RESPONSES OF ELECTROENCEPHALOGRAM TO DIFFERING SITUATIONS

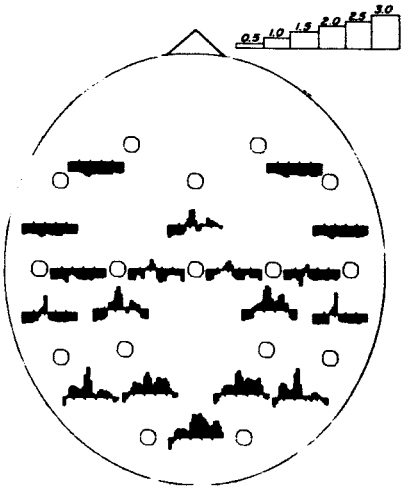
TOPO-SPECTROGRAPHIC VARIATIONS OF
AVERAGES OVER FIFTY ASTRONAUT CANDIDATES



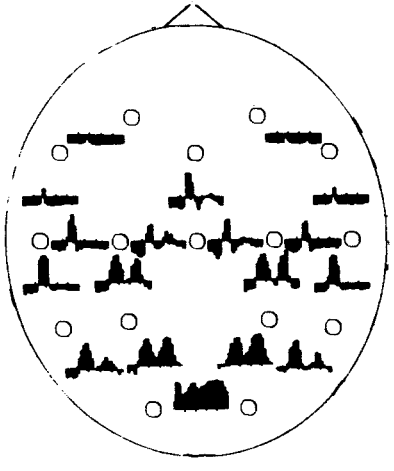
AVERAGE OVER
TWELVE SITUATIONS



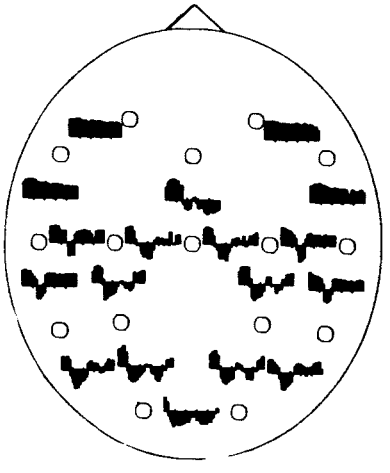
EYES CLOSED
INTERSTIMULUS RESTS



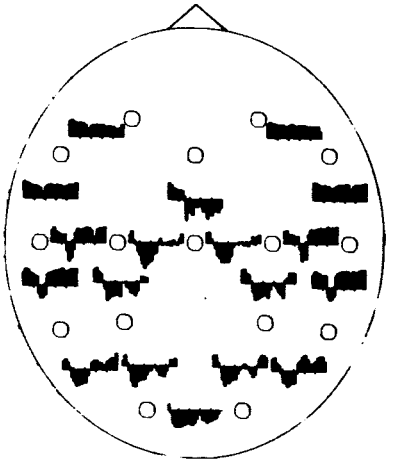
EYES CLOSED
FLASHES, ONE PER SEC.



EYES CLOSED
VIGILANCE TEST
TONES & BUTTON PRESSING



EYES OPEN
VISUAL DISCRIMINATION
5 SEC. EXPOSURE

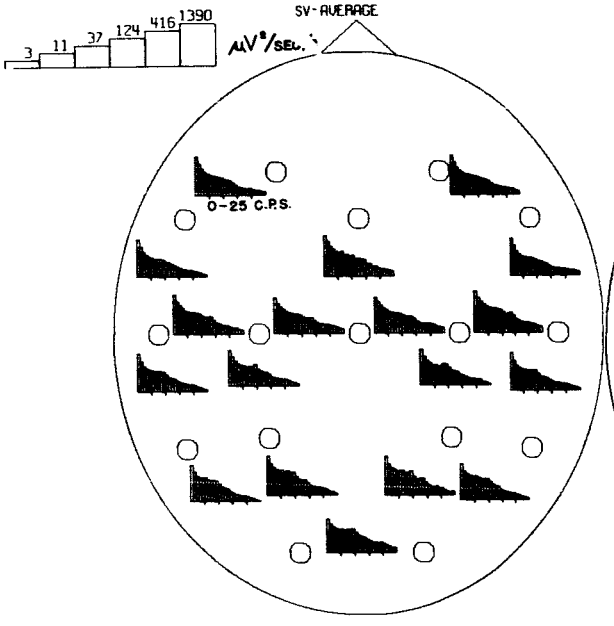


EYES OPEN
VISUAL DISCRIMINATION
1 SEC. EXPOSURE

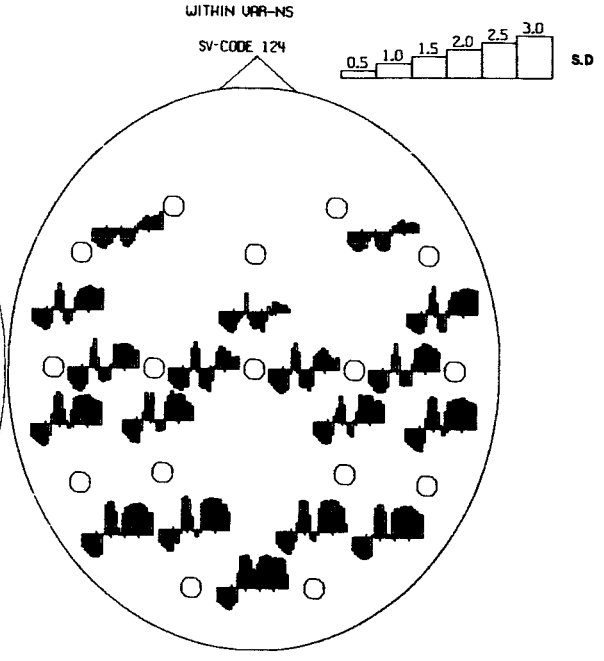
ELECTROENCEPHALOGRAPHIC CHARACTERISTICS OF SLEEP

TOPOSPECTROGRAPHIC VARIATIONS OF AVERAGES OVER 30 ASTRONAUT CANDIDATES

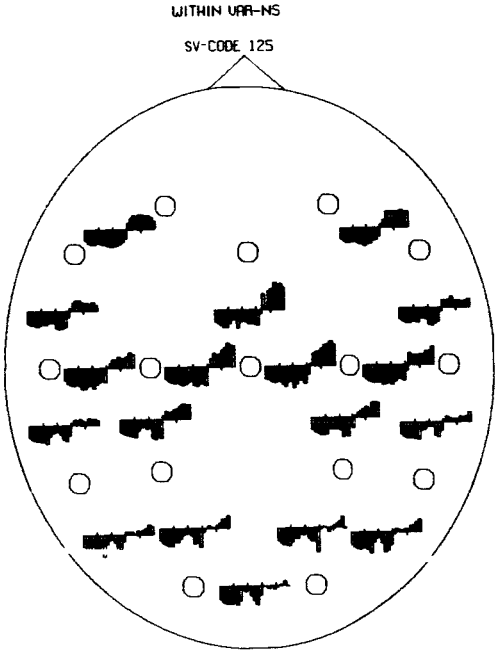
A. AVERAGES OVER 7 STAGES OF PRESLEEP, SLEEP & POSTSLEEP



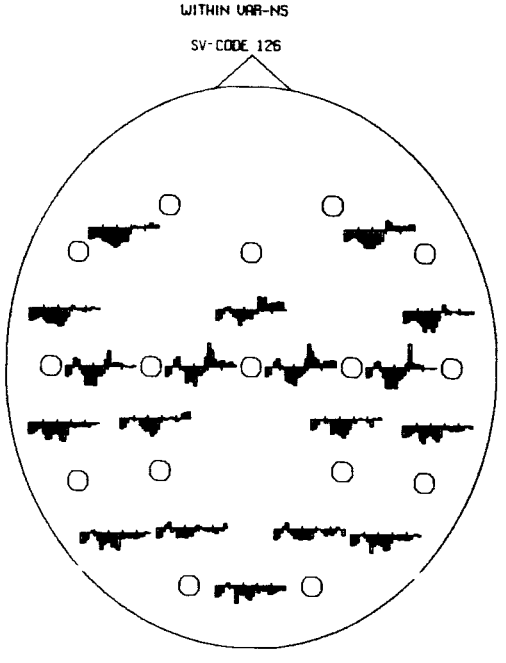
B. SLEEP Ø — EYES CLOSED, AWAKE



C. SLEEP I. "DRIFTING" OR DROWSY



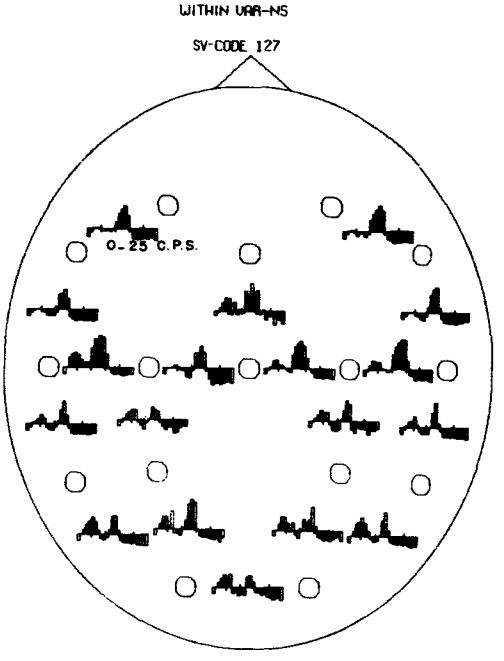
D. SLEEP II. LIGHT SLEEP—"PARIETAL HUMPS"



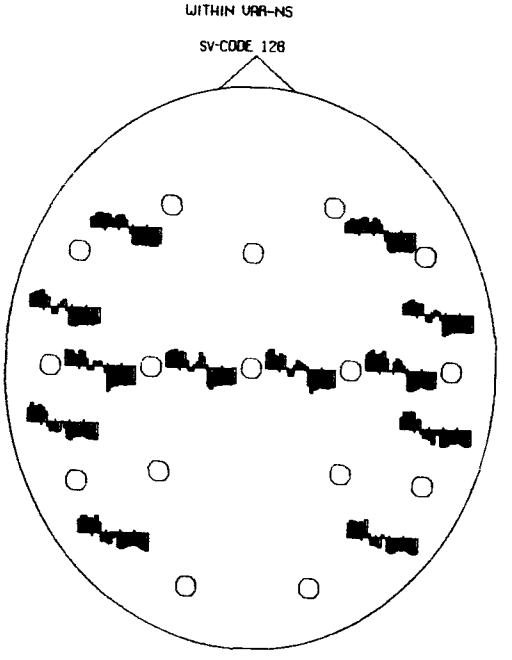
ELECTROENCEPHALOGRAPHIC CHARACTERISTICS OF SLEEP

TOPOSPECTROGRAPHIC VARIATIONS OF AVERAGES OVER 30 ASTRONAUT CANDIDATES

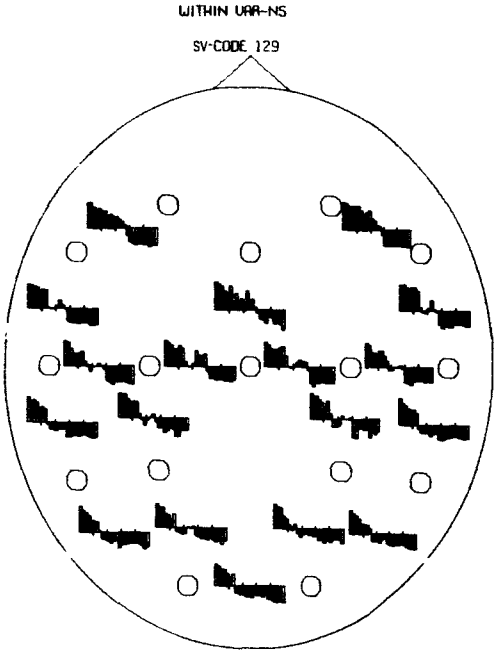
E. MEDIUM SLEEP — 14/SEC SPINDLES IN VERTEX



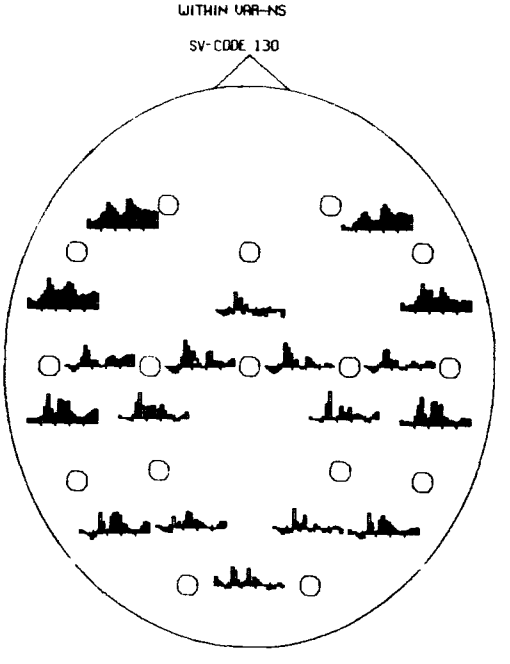
F. DEEP SLEEP — HIGH VOLTAGE SLOW WAVES

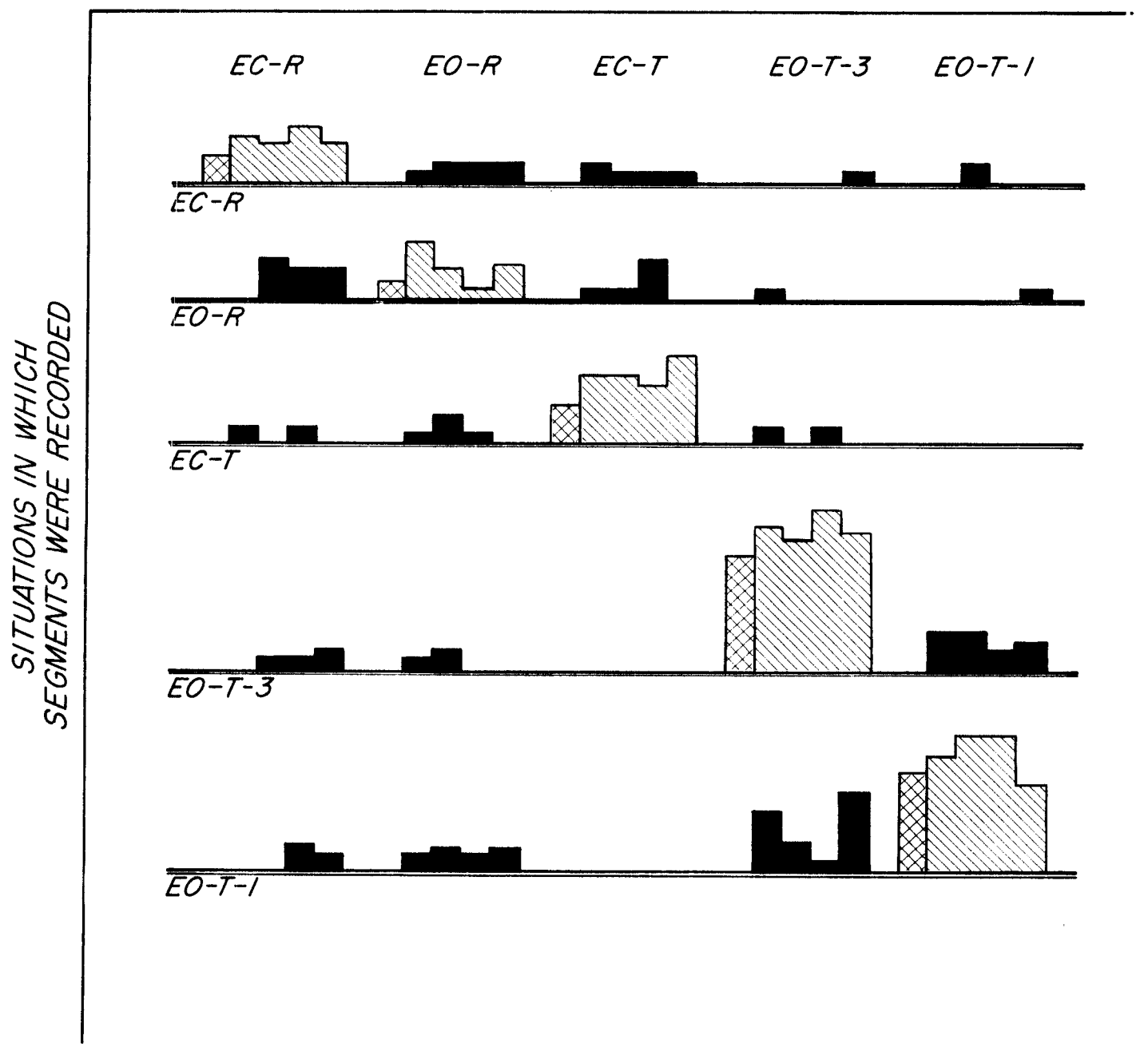


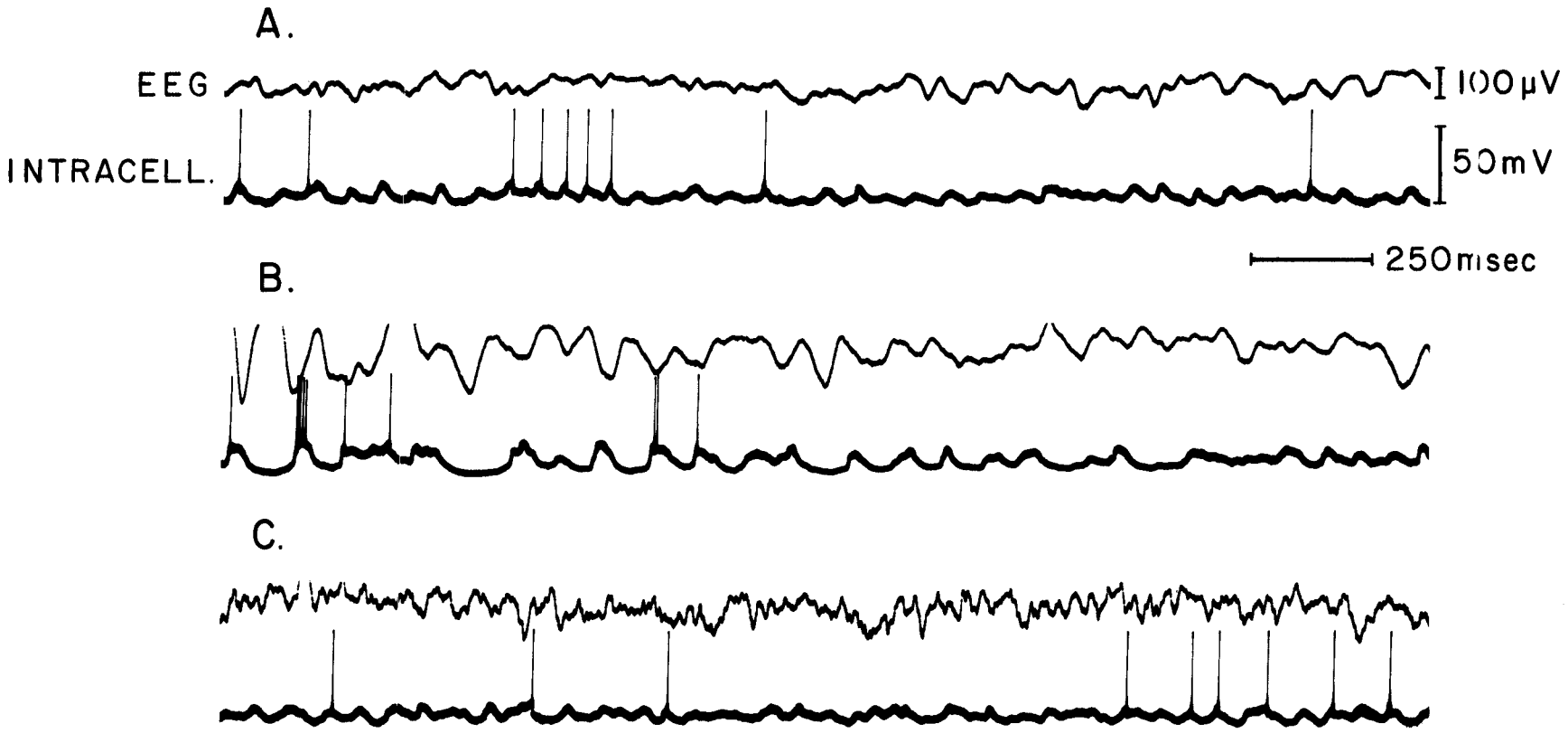
G. SUB-AROUSAL — "K-COMPLEX" TO AUDITORY STIMULI

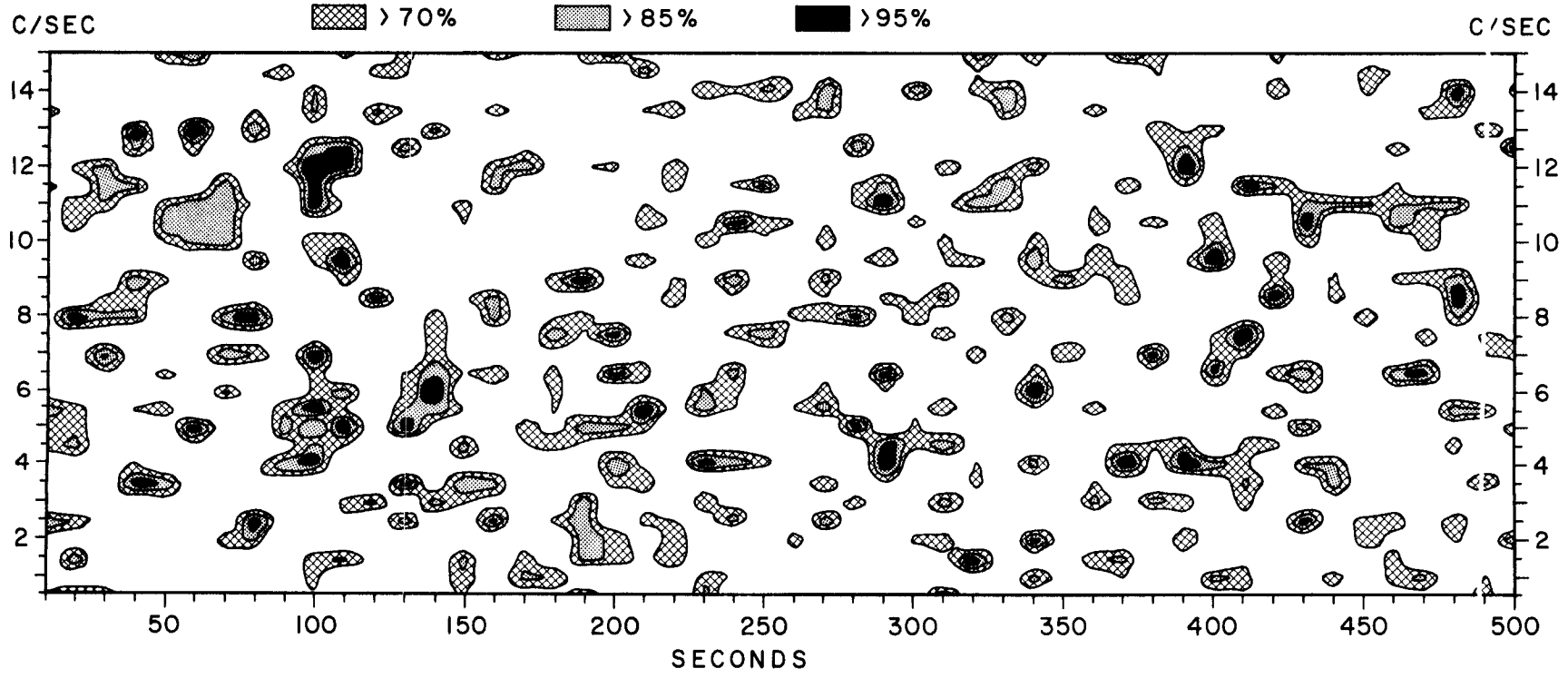


H. AROUSAL TO AUDITORY STIMULI




AUTOMATIC CLASSIFICATION BY BEST 4 MEASUREMENTS
EC-R
EO-R
EC-T
EO-T-3
EO-T-1
SITUATIONS IN WHICH SEGMENTS WERE RECORDED
EC-R
EO-R
EC-T
EO-T-3
EO-T-1


A.
EEG
INTRACELL.
100μV
50mV
250msec
B.
C.



COHERENCE (LINEAR PREDICTABILITY RELATIONSHIP)
BETWEEN NEURONAL WAVES AND EEG