Discriminant analysis of "activated" EEG

JOHN M. RHODES², DONALD O. WALTER AND W. ROSS ADEY

BRAIN RESEARCH INSTITUTE, UCLA

Samples of EEG activity from different experimental situations, ranging from rest to mild stress, were subjected to a spectral analysis and were then classified into their appropriate categories by a step-wise discriminant analysis program. While it was possible to discriminate among waking experimental situations for a given individual, this was not possible when 4 Ss were combined. When samples from different sleep stages were classified, it was possible to combine 4 Ss.

Since the first recognition of Berger's early studies, it has been hoped that electroencephalography would elucidate varying states of consciousness, as well as an array of general behavioral problems. Scalp recordings from humans have, unfortunately, been of little assistance except for identifying stages of sleep and aiding in clinical diagnosis. Computer technology, however, has recently been applied to EEG analysis. In general, this has involved the use of a large, general purpose computer in a minimal procedure, such as frequency analysis (Brazier, 1961; Remond, 1964); but it has also made possible an essentially microscopic approach (Rhodes, Reite, Brown, & Adey, 1965; Walter, 1963).

The current report is an outgrowth of one such approach—spectral analysis (Walter, 1963). Specifically, a broad-band spectral analysis was combined with a multivariate discriminant analysis in a preliminary attempt to classify electrical activity from scalp recordings during different psychological states.

Method

EEG records of high-performance Air Force pilots were taken on magnetic tape during an hour-long protocol (Walter, Rhodes, Brown, & Adey, 1966). The Ss were then given lunch and asked to take a nap. Recordings were made during this sleep period and classified into standard sleep stages. During a "stage three" sleep, the Ss were partially aroused by a tone; later they were completely awakened.

Samples of EEGs were taken for the purpose of discriminant analysis from five sleep stages, an awake stage, and two arousal stages. Samples were also taken from 11 different experimental situations: (1) eyes closed resting (ECR); (2) eyes closed photic stimulation at 1 cps (ECP); (3) eyes closed auditory stimulation at 1 cps (ECA); (4) eyes closed tactile stimulation at 1 cps (ECT); (5), (6), (7), and (8) corresponded to situations (1) through (4), respectively, but with eyes open (EOR, EOP, EOA, EOT); (9) a temporal conditioning task, excluding samples from test trials (TC); (10) a 3 sec. exposure to a Malmo Rapid Discrimination

Task (SRD); (11) a 1 sec. exposure to the same task (FRD). Samples were neither equated for length nor corrected for muscle or movement artifacts.

A modified 10-20 electrode placement system was used, and 18 EEG channels were arbitrarily selected. After digitization of the analog magnetic tape records, a spectral analysis was performed in each channel over four frequency bands (1.5-3.5, 3.5-7.5, 7.5-12.5, 12.5-25.5), roughly corresponding to the traditional delta, theta, alpha, and beta bands. For each band of each channel, the following information was obtained: (1) the sum of activity; (2) the mean frequency; (3) the band width, which can be considered a measure of the regularity (Rhodes et al, 1965); (4) the coherence with the other channels, within a given band. This latter measure is somewhat similar to obtaining a cross-correlation coefficient (Koopmans, 1964) and is a measure of shared components between channels, almost on a wave-by-wave basis.

These measures were then treated as variables for a step-wise discriminant analysis program (Anderson, 1958; Dixon, 1965), which was given the samples and asked to classify them by situation. The program does this, essentially, by choosing that single variable which can best be expected to categorize the segments into their appropriate situations. After the first step, it re-evaluates all the variables, partialling out the one chosen, and selects as the next variable that one which can be expected to add most to the discriminating power of the first. This process continues until the program is told to stop, or until all of the variables have been used.

For any given S there were 18 channels, each broken down into four frequency bands with three measures for each band, plus the possible combinations for coherence between channels. Thus, the total number of variables from which to choose was well over a thousand. At the present time, however, this program can deal with a maximum of only 80 variables.

Results

For exploratory purposes, one S was analyzed with two sets of variables, 80 in the first, 72 in the second. These variables were selected on the basis of past clinical and experimental EEG experience. The first set of variables, set A, was composed of bilateral frontal channels, bilateral temporals, left temporal to central, left temporo-parietal to occipital, coherence between left frontal and temporo-parieto-occipital, and coherence between left temporo-central and temporo-parieto-occipital. The second set of variables, set B, was composed of bilateral parieto-occipital, bi-occipital, vertex, coherence between bilateral parieto-

Fig. 1. Comparison between the ability of the two sets of variables to classify correctly EEG samples from a single subject.

occipital, coherence between left parieto-occipital and bi-occipital, coherence between right parieto-occipital and bi-occipital, coherence between vertex and bi-occipital, coherence between vertex and left parieto-occipital, and coherence between vertex and right parieto-occipital.

A comparison of the results obtained with these two sets of variables is shown in Fig. 1, where the number 96 total for set B) is plotted against steps completed. The second set of variables, even though fewer in number, achieved proper classification of all cases ten steps prior to the first set.

In an attempt to see whether results could be obtained for a group of Ss, as well as for an individual, four Ss were combined and treated as one. The total number of cases for five different experimental situations was 258, with 34 cases in ECR, 28 cases in EOR, 38 cases in TC, 80 cases in SRD, and 78 cases in FRD. Seventy-two variables were used, approximating set B above. The result was that, even when all 72 variables had been used, the program was still unable to classify properly 15 percent of the cases. Since this result implied that an individual could be characterized, but that groups could not be; it was decided to try the same procedure on cases from four individuals, but using sleep stages as the experimental situations. For sleep, perfect categorization was achieved after 55 steps.

Discussion

In view of the difficulties experienced in the past with computer analysis of "activated" EEG records, the present results, although of a preliminary nature, are highly encouraging. However, these results also suggest

that extensive work may be necessary to define a minimum adequate set of variables. Such an investigation might require an expansion of the discriminant analysis program to select from among many more variables, an extension now becoming operational. Furthermore, if the suggestion that an individual is consistently easier to define than is a group is confirmed by future investigations, it will be interesting to analyze the consistency of extensive replications for the same individual. Of course, further exploration of groups of Ss may reveal a different set of variables, having cross-S applicability, which would be capable of discriminating waking situations as accurately as sleep stages. At present, it is difficult to extrapolate. It is, however, already known that an eyes closed resting record and an activated record from the same S are likely to differ more than do two activated records from different Ss.

At present, replications of the present study in other subjects are in progress and have, so far, been confirmatory. In addition, applications to mentally ill patients and to animals are being investigated. Clearly this technique can be applied to a wide variety of experimental areas, including learning, stress, and sleep.

References

- Anderson, T. W. *Introduction to multivariate statistics*. New York: Wiley, 1958. Pp. 142-153.
- Brazier, M. A. B. (Ed.) *Computer techniques in EEG analysis*. *EEG clin. Neurophysiol.*, 1961, Suppl. No. 20.
- Dixon, W. J. (Ed.) *BMD Biomedical computer programs*. (3rd ed.) Los Angeles: Health Sciences Computing Facility, Dept. Preventive Medicine and Public Health, School of Medicine, UCLA, 1965. Pp. 587-605.
- Koopmans, L. H. On the coefficient of coherence for weakly stationary stochastic processes. *Ann. math. Statist.*, 1964, 35, 532-549.
- Remond, A. Level of organization of evoked responses in man. *Ann. N. Y. Acad. Sci.*, 1964, 112, 143-159.
- Rhodes, J. M., Reite, M. L., Brown, D., & Adey, W. R. Cortical-subcortical relationships in the chimpanzee during different phases of sleep. In M. Jouvet (Ed.), *Aspects Anatomofonctionnels de la Physiologie du Sommeil*. Editions du CNRS, Paris, 1965. Pp. 451-473.
- Walter, D. O. Spectral analysis for electroencephalograms: Mathematical determination of neurophysiological relationships from records of limited duration. *Exp. Neurol.*, 1963, 8, 155-181.
- Walter, D. O., Rhodes, J. M., Brown, D., & Adey, W. R. Comprehensive spectral analysis of human EEG generators in posterior cerebral regions. *EEG clin. Neurophysiol.*, 1966, 20, 224-237.

Notes

1. This work was supported in part by USPHS Grant NB02501 AFOSR Contract AF 49(638)-1387, ONR Contract 233 (91, MASA Contract 9-1970, and NASA Grant NSG 237-62). Those computations made on the Health Sciences Computing Facility were partially supported by NIH Grant FR-3.
2. Current address: Department of Psychology, University of New Mexico, Albuquerque, New Mexico.