Analysing electroencephalograms

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Computers have mainly been used to assist doctors in analysing electroencephalogram records by averaging responses to a repeated stimulus. Techniques are now being developed using computers which will assist the doctor to recognise epileptic activity in EEG records and to make quantitative estimates of the likelihood that a patient may suffer from fits.
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Introduction

It is now almost 50 years since a German doctor, Hans Berger (1929), at the Neuropsychiatric Institute of Jena, demonstrated the possibility of recording from the scalp of living conscious human patients and volunteers, as well as from animals, the tiny fluctuating electrical potentials which reflect the workings of the brain within the skull.

The patterns of these potentials have since been studied extensively, firstly in attempts to localise tumours and other lesions in the brain, later in attempts to find clues to the pathology of mental and nervous diseases. Always an overriding interest has been in the fact that electrical brain activity is linked to the phenomenon of consciousness.

The potentials are generally recorded by ink pens on a moving paper band, which is cheap and sufficiently accurate because the fluctuations are essentially repetitive although slightly irregular. The best known pattern and that first described by Berger is the alpha rhythm (illustrated in **Fig. 1**). This is a fairly regular potential fluctuation giving the appearance of more or less sinusoidal waves at a frequency of about 10 Hz, the fluctuations themselves being about 50 millionths of a volt in amplitude. Curiously—and to its discoverer's great surprise—this phenomenon is generally suppressed instead of being enhanced by increased mental activity and is best seen when the individual is resting quietly alert but with the eyes closed.

Many other patterns have been noted and described in more or less detail, but almost all of these are transient disturbances of the otherwise almost constant fluctuations.

The K-complex (**Fig. 2**) is a striking slow wave disturbance seen in a drowsy subject, usually provoked by a noise, but sometimes apparently spontaneous. Perhaps the best known of the transient EEG patterns is the spike and wave complex (**Fig. 3**), the electrical sign of a brief disruption of the stream of consciousness, which was recognised as a form of epilepsy by the early French neurologists and christened the 'Petit Mal' to distinguish it from the epileptic convulsion or 'Grand Mal'.

Why has it not yet been possible to program computers to compete with trained human observers in this kind of pattern recognition? A human being can comfortably 'read' an 8 channel EEG, like those shown in the figures, but of course when these 8 continuous signals are converted into digital form the amount of data is considerable. At a rough estimate over 1,000,000 bits are needed to define an ordinary clinical EEG record, but although this is a lot of information, it scarcely ranks as gigantic by modern computing standards. The major difficulty is that the signal is very messy, unstructured and to a large extent apparently composed of random noise-like fluctuations.

Evoked responses

One ingenious approach was suggested in the 1950s by G. Dawson (1947, 1954) working at the National Hospital for Nervous Diseases in London. As earlier indicated many

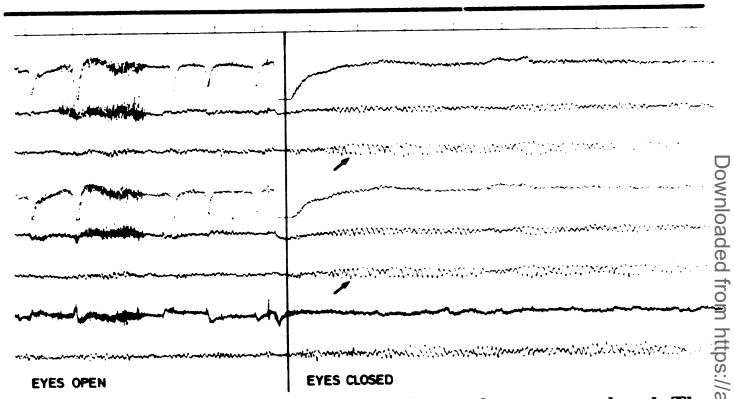

Fig. 1 Alpha rhythm (arrowed) appearing as the eyes are closed. The large potentials to the left of the vertical line which marks the moment of eye closure are eye blink potentials with some muscle potentials

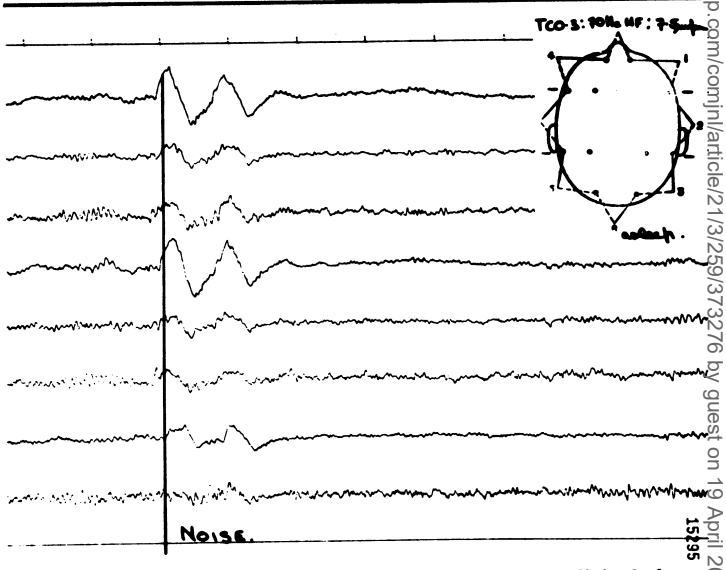

Fig. 2 K-complex, transient potential disturbance elicited by a noise which disturbs a drowsy patient

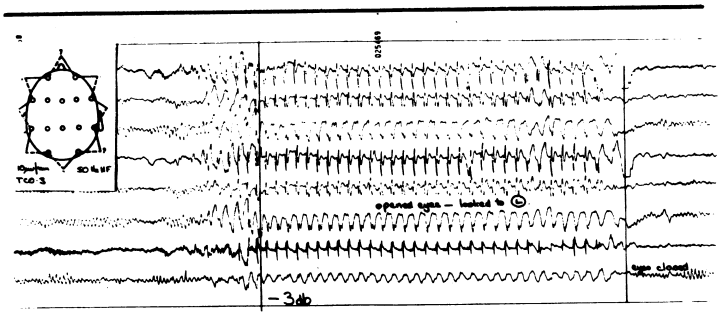

Fig. 3 Minor epileptic (Petit Mal) attack with characteristic spike and wave EEG pattern. Amplification is reduced (−3dB) at the start of the attack

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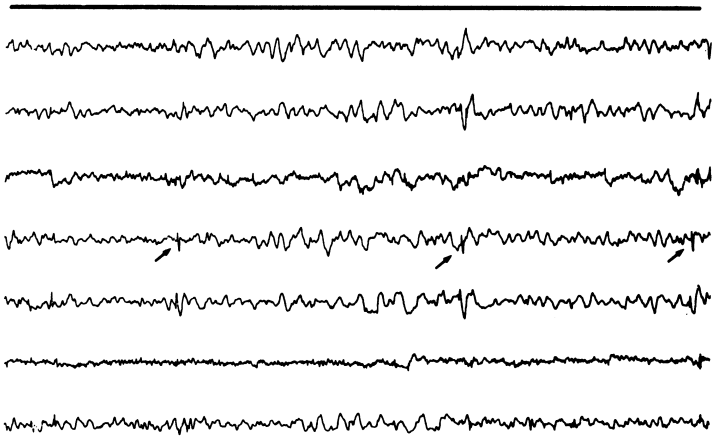

Fig. 4 Small transient potentials (arrowed) recorded in the left parietal region following an electrical stimulus to the right median nerve

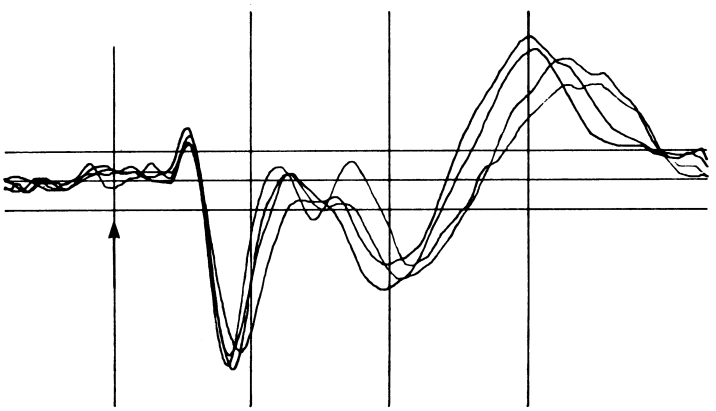

Fig. 5 Superimposed average responses. Two recorded from the Rt parietal area and two from the Lt. Each trace is the average of 100 trials
Note in Figs. 5, 6 and 7 the first vertical line (arrow) marks the instant at which the stimulus is given. The other vertical lines indicate 50, 100 and 150 milliseconds after the stimulus instant. The horizontal lines indicate ± 5 microvolts about the 0 volt baseline

of the transient phenomena can be provoked by an external stimulus. In Dawson's case the interesting feature was a small potential which could be recorded over the central scalp area and provoked by an electrical stimulus to the main nerve in the forearm. **Fig. 4** shows these potentials (arrowed) recorded from a patient suffering from a variety of myoclonic epilepsy, similar to that affecting Dr. Dawson's patient. Even in such patholgical cases where the potentials are greatly exaggerated the deflections can only just be seen and tend to be more or less distorted by the ongoing irregular fluctuations. By using a digital computer to sample the potential and to build up a graph showing the average potential (averaged over say 100 repetitions of the stimulus) at each of the times 1, 2, 3, etc. up to 250 mS after the instant of stimulus application, a much clearer picture of the response can be obtained. **Fig. 5** shows four superimposed recordings of such averaged potentials; two of these are obtained by stimulating the left arm and recording from the scalp on the right side, the other two by stimulating the right arm and recording from the scalp on the left. (Remember that the right hand side of the brain controls the left hand side of the body and vice versa.) The superimposition gives an idea of how accurate and consistent is the average picture obtained. In this case the responses are almost identical on the two sides except where the late slow waves are slightly different.

This technique turned out to be very powerful and easy to apply. Notice the implied 'model'.

(*a*) The brain is continually producing potential fluctuations which are not in any way related to the stimuli.

(*b*) The stimulus produces a transient potential fluctuation of constant shape which is linearly combined with, and does not alter, the continuous potential fluctuations.

Under these conditions the continuous activity can be regarded as noise and the transient as signal. It can be shown that the ratio of signal/noise is increased in proportion to the square root of the number of trials averaged. We have been interested in applying this method, following Halliday *et al.* (1972) to the study of transient responses recording from the back of the head following a sudden change in a pattern that the subject is watching. A normal response is shown in **Fig. 6.** The pattern changes at the instant represented by the first vertical line. The first sign of a response is 50 mS later at the second vertical line, and the main downward going (positive) wave occurs just before the third vertical line from the left—i.e. about 80 mS after the stimulus. Once again several responses have been superimposed, this time two responses when the pattern is viewed with the right eye and two responses when the pattern is viewed with the left eye. **Fig. 7** shows an obviously abnormal response recorded from one eye (three superimposed averages), contrasting with a normal response from the other eye. It is most interesting and surprising to find that the patient was totally unaware of any impairment of vision in the affected eye and that no disturbance could be shown by the normal clinical eyesight tests.

The problem of epilepsy

Epilepsy is a symptom, sometimes resulting from damage

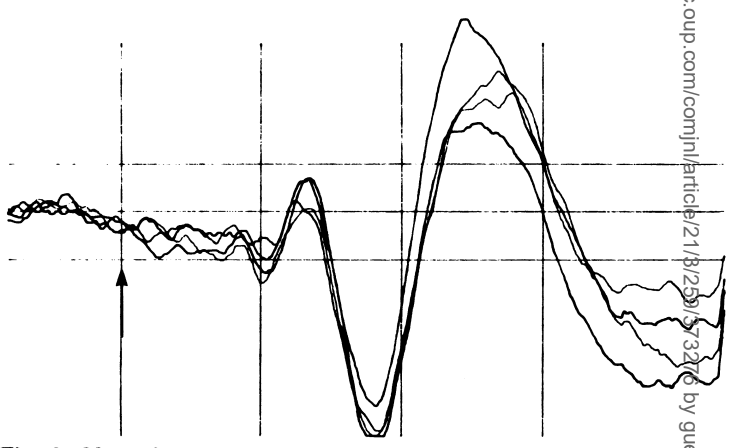

Fig. 6 Normal responses to a patterned stimulus

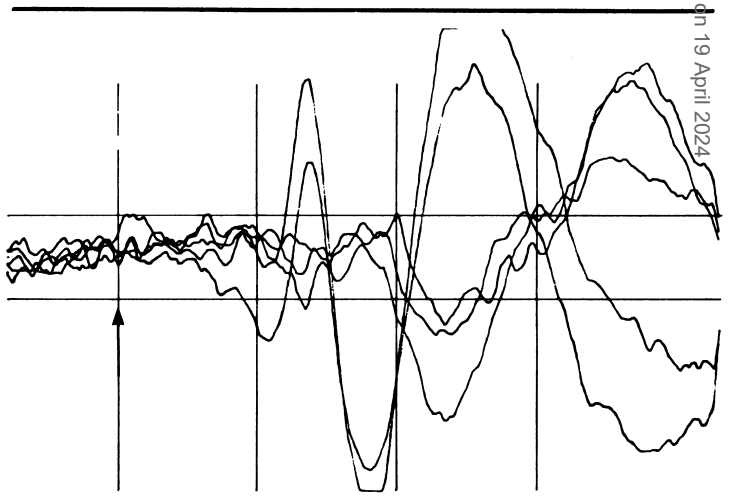

Fig. 7 Delayed response to a patterned stimulus (three repeats) in one eye contrasting with normal response from the other eye. Patient is unaware of any disturbance of vision

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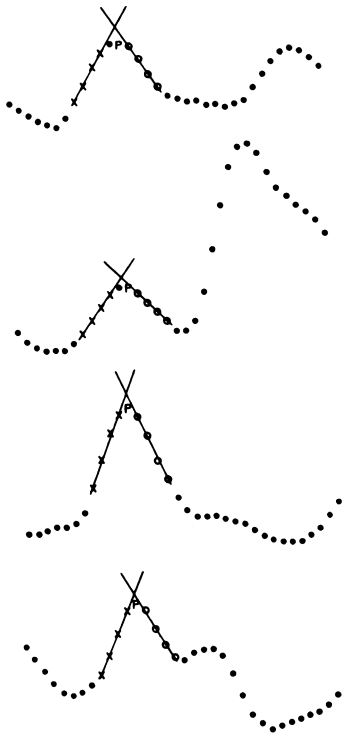

Fig. 8 The 'Peak Angle' of a wave is measured by fitting straight lines to the rising and falling limbs of the wave and measuring the angle between the two fitted lines

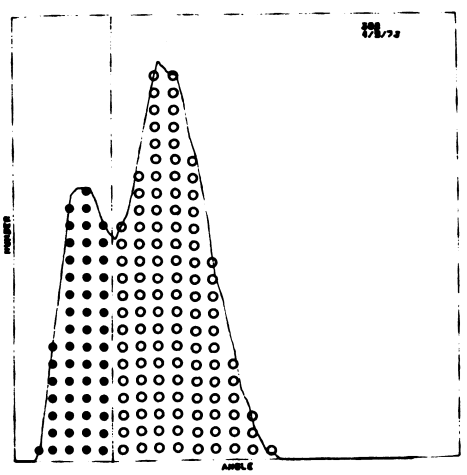

Fig. 9 A histogram of 'Peak Angle' measurements shows a bimodal form. The spikes are those waves (filled circles) whose peak angle exceeds a threshold determined so as optimally to separate the two overlapping distributions

to the brain, apparently due to a failure in the control of brain activity which becomes briefly and catastrophically disorganised from time to time. The EEG is a sensitive indicator of brain activity and not only is it disrupted during an epileptic fit, but small apparently spontaneous disturbances may occur indicating instabilities in the system and providing signs which can help the doctor in formulating a diagnosis. The commonest such pattern is the spike potential. When studying the EEGs of laboratory rats (Dow *et al.*, 1972) using the number of spikes in a given time interval as a measure of 'epileptic activity', we have developed a method of automatic analysis because of the large volume of data and the need to ensure consistent estimates.

Other workers trying to automate spike counting have made use of the fact that spikes are generally larger than the other waves in the record and that because they are fast phenomena selective filtering or differentiation enhances their apparent amplitude, so that they may be detected by a simple threshold. These techniques proved unsuitable for our data not least because they are very sensitive to 'artefact' potentials caused by physical movement of the electrodes and connecting wires. On searching the literature we were impressed by a suggestion of Kooi (1966): 'Peak angle is an attractive measure because it interlocks duration and amplitude. It may quite accurately signal equivalence of low to moderate amplitude short duration waves of 80 mS, and high amplitude discharges of similar form but exceeding 80 mS in duration. Intuitively one accepts such a statement readily, and in point of fact the distinction between a spike and sharp wave in clinical practice is probably largely based on this parameter, . . .' .

After trying several methods of estimating the 'sharpness' of the given wave, the most satisfactory seemed to be to fit straight lines to the rising and falling limbs of the wave close to, but not necessarily passing through the peak, and using the angle between these two lines as the parameter by which to quantify sharpness (**Fig. 8**). This procedure is of course to a considerable extent arbitrary, but only in its detailed implementation. When the results of a large number of such sharpness measurements are gathered together in the form of a histogram, there is clear evidence of a clustering tendency. Normal animals, or animals treated with effective anti-epileptic drugs, show only a single peak. Epileptic animals show a double peaked histogram as illustrated (**Fig. 9**), and there is good evidence to associate the smaller left hand peak with the presence of spikes in the EEG. A simple partitioning technique places a cut-off, separating the histogram into two regions, and the area of the left hand region which corresponds to the number of waves exceeding a certain degree of sharpness is taken as a measure of the amount of epileptic activity. This technique has now been used for a number of years and has proved robust and reliable. (Hill and Townsend, 1973).

A model for EEG activity

The alpha rhythm was described above and its more or less regular shape suggests some form of sinusoidal oscillation generator analogous to a swinging pendulum. Another kind of oscillator, a relaxation oscillator, is exemplified by the primitive mill in which water flowing into a bucket raises a beam slowly until the water spills out and the beam comes down with a thump. The analogy of epilepsy with such a gradual build-up and sudden discharge, in the form of a fit, is irresistible.

The swinging pendulum is the simplest example of a linear oscillatory process and it has been found that a general class of such linear oscillatory processes fits the EEG very well. It is assumed that the electrical brain activity recorded as the EEG arises initially from a random input, perhaps derived from the multitude of small uncorrelated stimuli arising in a quiet environment, which is modified by the structure of the brain. What we record is 'brain noise', electrical potentials generated as a by-product of the brain's analysing activity, reflecting essentially the instantaneous metabolism of the cells as items of information are processed and passed from cell to cell. A mathematical model of this kind of process can be built up as follows:

1. We obtain a suitable sample of EEG record from a subject under the usual recording conditions of lying relaxed but alert in a quiet environment.
2. Then we construct an optimum filter which when applied to the sample of EEG will remove all the rhythmic components. This filter is the *inverse* of our proposed brain model, i.e. when EEG activity is fed into the filter, random activity is produced. The EEG signal is sampled at regular intervals and S_{n-1}, S_{n-2}, etc. are successive samples of the

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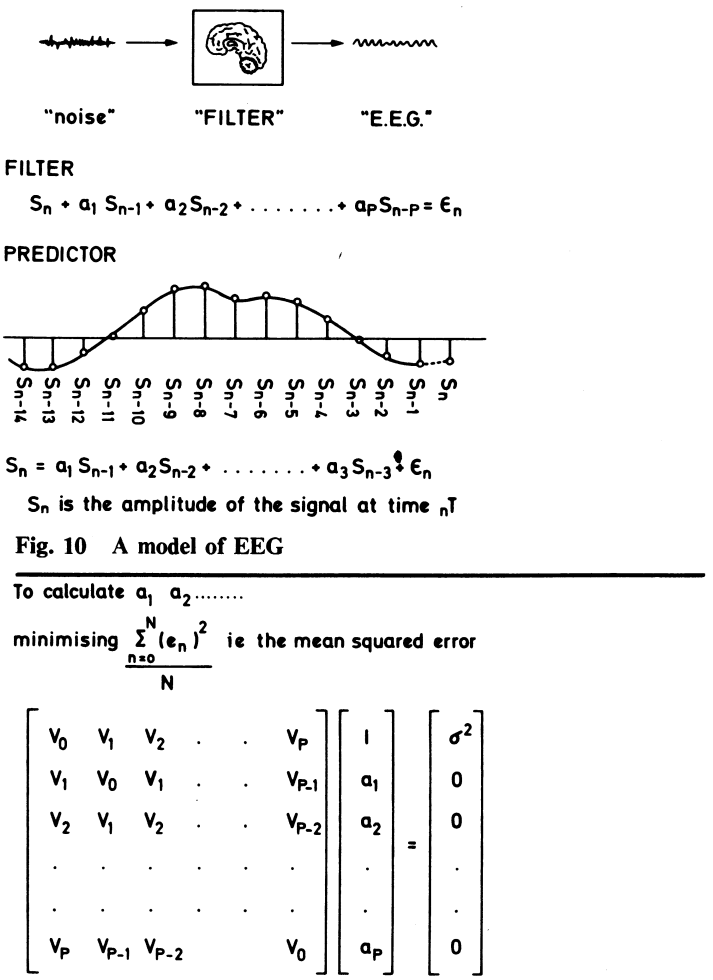

Fig. 10 A model of EEG

Fig. 11 Calculating the weights

EEG extending backwards in time. Quantities a_1, a_2, . . . are the weights which characterise the particular filter ($a_0 = 1$) and the summed products of weights and amplitudes gives the filter output which should be 'random noise'.

3. Re-arrangement of this formula gives a predictor which forms a 'best estimate' of the present amplitude of the signal S_n as a weighted sum of past values S_{n-1}, S_{n-2}, etc.
4. The predictor may be used to simulate the process of EEG generation by assuming an arbitrary set of values for S_{n-1}, S_{n-2}, etc. and using the formula to predict a value to which is added a random component ε_n to give the value S_n, the first sample of the model EEG.

The predictor has the form:

$S_n = \varepsilon_n - a_1 S_{n-1} - a_2 S_{n-2} \ldots - a_p S_{n-p}$ (see **Fig. 10**).

Time is now advanced so that S_n becomes S_{n-1}, S_{n-1} becomes S_{n-2}, and so on. A new S_n is generated and the process iterated indefinitely producing a steady stream of samples which constitutes the simulation.

The weights a_1, a_2, etc. may be calculated from the matrix equation shown in **Fig. 11.** The quantities V_0, V_1, etc. are the terms of an autocorrelogram of the original sample of EEG. The autocorrelogram is a function of lag, each term V_i is formed as a sum of the products of a sample amplitude S_n with the corresponding sample S_{n-i} obtained i time intervals earlier (or later because the autocorrelogram is symmetrical about $i = 0$) and summed over the entire sample.

Because these weights constitute a model of the EEG generating process, other descriptive parameters such as the familiar frequency spectrum may be derived directly. Notice, however, that the model contains no information about changes in the pattern with time and therefore assumes that the EEG, or at least the sample we are considering, looks the same for all values of T. This is the property of stationarity.

The relaxation type of phenomenon which we have tentatively designated as epileptic may be termed a *non-stationarity* because it cannot be treated by the simple linear model.

If the EEG is filtered by an optimum filter calculated as described above, and the output of the filter examined, it will consist of random noise except where such non-stationarities occur. Lopes da Silva (1975) with others, has used this technique to recognise spikes in the EEGs of epileptic patients. He found that the technique, when tuned to recognise all phenomena characterised by experienced electroencephalographers as spikes, indicated the existence in his samples of many more non-stationarities. He suggests that these may not be 'false positives' because he was able to show in about one quarter of the instances that the non-stationarities although undetectable by the human eye, actually indicated the presence of a large spike discharge in the depths of the brain.

More work needs to be done to confirm these findings, but it does seem as though the technique offers a promise of computer pattern detection which is significantly more sensitive than the traditional methods of visual inspection.

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References

BERGER, H. (1929). Uber das Elektrenkephalogramm des Menschen, *Arch Psychiat Nervenkrankheiten*, Vol. 87, pp. 527-570.

DAWSON, G. D. (1947). Investigations on a Patient subject to Myoclonic Seizures after Sensory Stimulation, *J. Neurol. Neruosurg. Psychiat.* Vol. 10, p. 141.

DAWSON, G. D. (1954). A Summation Technique for the Detection of Small Evoked Potentials, *Electroenceph. Clin. Neurophysiol*, Vol. 6, p. 65.

DOW, R. C., MCQUEEN, JUDITH K. and TOWNSEND, H. R. A. (1972). The Production and Detection of Epileptogenic Lesions in Rat Cerebral Cortex, *Epilepsia* (Amst.), Vol. 13, pp. 459-465.

HALLIDAY, A. M., MCDONALD, W. I. and MUSHIN, J. (1972). Delayed Visual Evoked Response in Optic Neuritis, *Lancet*, Vol. 1, pp. 982-985.

HILL, A. G. and TOWNSEND, H. R. A. (1973). The Automatic Estimation of Epileptic Spike Activity, *Bio-Medical Computing*, Vol. 4, pp. 149-156.

KOOI, K. A. (1966). Voltage-time characteristics of spikes and other rapid electroencephalographic transients: semantic and morphological considerations, *Neurology* (Minneap.), Vol. 16, pp. 59-66.

LOPES DA SILVA, F. H., DUQUESNOY, A., VAN HULTEN, K. and LOMMEN, J. G. (1975). Analysis of nonstationary electroencephalograms, in *Quantitative Analysis of the EEG*. ed. M. Matejcek, G. K. Schenk. Sandoz Med. Biol. Res. Dept. Basle, pp. 421-432.