[9] A. Gallineck and L. B. Kalinowsky, "Psychiatric aspects of multiple sclerosis," *Dis. Nerv. Syst.*, vol. 19, p. 77, 1958.
[10] D. R. Giblin, "Somatosensory evoked potentials in healthy subjects and in patients with lesions of the nervous system," *Ann. N.Y. Acad. Sci.*, vol. 112, pp. 93-142, 1964.
[11] J. I. Hall, "Studies on conduction in demyelinated peripheral nerves of the guinea pig," Ph.D. Dissertation, University of Edenburgh, 1964.
[12] —, "Studies of demyelinated peripheral nerves in guinea pigs with experimental allergic neuritis. A histological and electrophysiological study. II. Electrophysiological observations," *Brain*, vol. 90, pp. 313-332, 1967.
[13] A. M. Halliday and G. S. Wakefield, "Cerebral evoked potentials in patients with disassociated sensory loss," *J. Neurol. Neurosurg. Psychiat.*, vol. 26, pp. 311-363, 1963.
[14] A. L. Hodgkin, *The Conduction of the Nervous Impulse*. Liverpool, England: Liverpool Univ. Press., 1967.
[15] H. E. Kaeser and E. H. Lambert, "Nerve function studies in experimental polyneuritis," *Electroenceph. Clin. Neurophysiol.*, Suppl. no. 22, pp. 29-35, 1962.
[16] H. Krausz, "Identification of nonlinear systems using random impulse train inputs," *Biol. Cybernetics*, vol. 19(4), pp. 217-230, 1975.
[17] S. J. Larson, A. Sances, and P. C. Christenson, "Evoked somatosensory potentials in man," *Arch. Neurol.*, vol. 15, pp. 88-93, 1966.
[18] Y. W. Lee and M. Schetzen, "Measurement of the Wiener kernels of a nonlinear system by cross-correlation," *Int. J. Control*, vol. 2, pp. 237-254, 1965.
[19] R. P. Mackay and A. Hirano, "Forms of benign multiple sclerosis. Report of two 'clinically silent' cases discovered at autopsy," *Arch. Neurol. Chicago*, vol. 17, pp. 588-600, 1967.
[20] C. D. Marsden, J. C. Meadows, and P. A. Merton, "Isolated single motor units in human muscle and their rate of discharge during maximal voluntary effort," *J. Physiol.*, vol. 217, pp. 12-13, 1971.
[21] R. F. Mayer, "Conduction velocity in peripheral nerve during experimental demyelination in the cat," *Trans. Amer. Neurol. Assoc.*, vol. 91, pp. 294-296, 1966.
[22] R. F. Mayer and D. Denny-Brown, "Conduction velocity in peripheral nerve during experimental demyelination in the cat," *Neurology*, vol. 14, pp. 714-126, 1964.
[23] W. I. McDonald, "The effects of experimental demyelination on conduction in peripheral nerve. A histological and electrophysiological study. II. Electrophysiological Observations," *Brain*, vol. 86, pp. 501-524, 1963.
[24] W. I. McDonald and T. A. Sears, "Effect of demyelination on conduction in the central nervous system," *Nature (London)*, vol. 221, pp. 182-183, 1969.
[25] —, "Focal experimental demyelination in the central nervous system," *Brain*, vol. 93, pp. 575-582, 1970.
[26] —, "The effects of experimental demyelination, on conduction in the central nervous system," *Brain*, vol. 93, pp. 583-598, 1970.
[27] N. S. Namerow, "Somatosensory evoked responses in multiple sclerosis," *Bull. L.A. Neurol. Soc.*, vol. 33, pp. 74-81, 1968.
[28] N. S. Namerow and L. R. Thompson, "Plaques, symptoms, and the remitting course of multiple sclerosis," *Neurology*, vol. 19, pp. 765-774, 1969.
[29] N. S. Namerow, "The pathophysiology of multiple sclerosis," in *Multiple Sclerosis: Immunology, Virology, and Ultrastructure*. New York: Academic Press, 1972, pp. 143-172.
[30] N. S. Namerow, R. J. Sclabassi, and N. F. Enns, "The somatosensory response to stimulus trains: normative data," *Electroencephal. Clin. Neurol.*, vol. 37, pp. 11-21, 1974.
[31] H. Ogura, "Orthogonal functionals of the Poisson process," *IEEE Trans. Inform. Theory*, vol. IT-18, pp. 473-481, 1972.
[32] H. Risch, R. J. Sclabassi, C. Hinman, and J. S. Kroin, "Functional power series analysis of somatosensory evoked potentials," submitted to *IEEE Trans Bio-Med. Eng.*, 1977.
[33] R. J. Sclabassi, N. S. Namerow, and N. F. Enns, "Somatosensory response to stimulus trains in patients with multiple sclerosis," *Electroencephal. Clin. Neuro.*, vol. 37, pp. 23-33, 1974.
[34] K. Suzuki, J. M. Andrews, J. M. Waltz and R. D. Terry, "Ultrastructural studies of multiple sclerosis," *Lab. Inves.*, vol. 20, pp. 761-768, 1975.
[35] I. Tasaki, "New measurements of the capacity and resistance of the myelin sheath and the modal membrane of the isolated frog nerve fiber," *Am. J. Physiol.*, vol. 181, pp. 639-650, 1955.
[36] V. Volterra, *Theory of Functionals and of Integral and Integro-Differential Equations*. New York: Dover, 1959, pp. 1-39.
[37] N. Wiener, *Nonlinear Problems in Random Theory*. New York: Wiley, 1958.

Real-Time Detection of Brain Events in EEG

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Abstract—Evoked responses or event related potentials in human EEG have been mostly studied with off-line analog recording and averaging. It is shown here that, at least in some situations, it is possible to detect and classify individual evoked responses or "single epochs" with surprising reliability.

To do so, however, required thinking anew not only the data processing but the whole experimental strategy. The classification is done in real-time by treating the experiments as a signal detection problem in which the computer, in the position of impartial observer, assigns classes to incoming epochs according to a predetermined decision rule. Since data collection and processing are interleaved, each classification outcome can be a factor in experiment control as well as in subject feedback.

The discrimination performance, expressed in terms of mutual information, is shown to be both a practical index for procedure optimization and a concise and specific descriptor for the experiment results.

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I. Introduction: Evoked Responses and Event Related Potentials

CONTEMPORARY VIEWS about the nature and origins of electroencephalographic (EEG) signals and evoked responses (ER's) are presented elsewhere in this issue and will not be discussed here. However, a brief review is given below of those characteristics of the signal that are most relevant to the present discussion.

EEG signals, collected on the human scalp are fluctuations of electrical potential that reflect activity in underlying brain structures and particularly in the cerebral cortex below the scalp surface. The signal energy appears confined mostly to low frequencies and especially around the 10-Hz alpha rhythm and below. Amplitudes vary typically in the 5 to 50-mV range. This continuous activity is spatially distributed over the scalp and can be described as a nonstationary or, at best, piecewise stationary time series. The "ER" or "event related potentials" (ERP's) discussed in the present paper are microscopic signals embedded in this continuous activity.

When a brief sensory stimulus such as a flash of light or a tap on the forearm is delivered to a subject, a perturbation of the on-going EEG takes place, starting after some delay following the initial event (stimulus) and spreading over half a second or less. The changes in signal amplitude, due to the perturbation, are small (a few microvolts at best), and buried in as well as interacting with the on-going activity. Because of these conditions, the existence and consistency of evoked response have been generally shown by averaging stimulus bound EEG epochs over a number of stimulations.

Fig. 1 illustrates the appearance of raw epochs, contrasted with their averages, for two scalp locations and identical visual pattern stimuli. The averages shows distinct waveshapes although one location is clearly more favorable than the other; individual epochs, however, fluctuate wildly.

Averaging has revealed the presence of potentials induced by stimuli other than sensory events, suggesting to Vaughan [12] the more general designation of ERP's rather than evoked potentials or ER's. A tentative classification of these ERP's can be made as follows:

1) Sensory ERP's: Responses that have been elicited by visual, auditory, somatosensory and olfactory stimuli as well as by direct electrical stimulation of the afferent pathways. Their presence is most prominent at short "latencies" (e.g., within 50 to 150 ms).

2) Motor ERP's: Responses found accompanying voluntary movement that may in fact precede the actual behavioral event. The phenomenon has been shown for limb movement as well as with phonation and eye movement.

3) "Long Latency" Potentials: These refer to potential changes taking place some 250 to 450 ms after the initial event. Most prominent in the literature is a positive deflection occurring around 300 ms. In experiments involving a behavioral task, they are enhanced both by the rarity (i.e., the low subject expectation) and the task relevance of the initial event.

4) Artifacts: Potential fluctuations of nonneural origin are called artifacts. These include electroocular potentials (EOG) and muscle potentials from neck, scalp and face (including eye blinks), as well as electrocardiographic signals (ECG).

Event related potentials have received considerable attention in recent years and have become an essential research tool in psychophysiology and human neurophysiology. A number of clinical applications have also made their appearance and lately sophisticated evoked response procedures have been developed to evaluate visual or auditory acuity, chart the progress of demyelinating diseases that impair nerve propagation and even to test brain functions for perceptual and cognitive disorders.

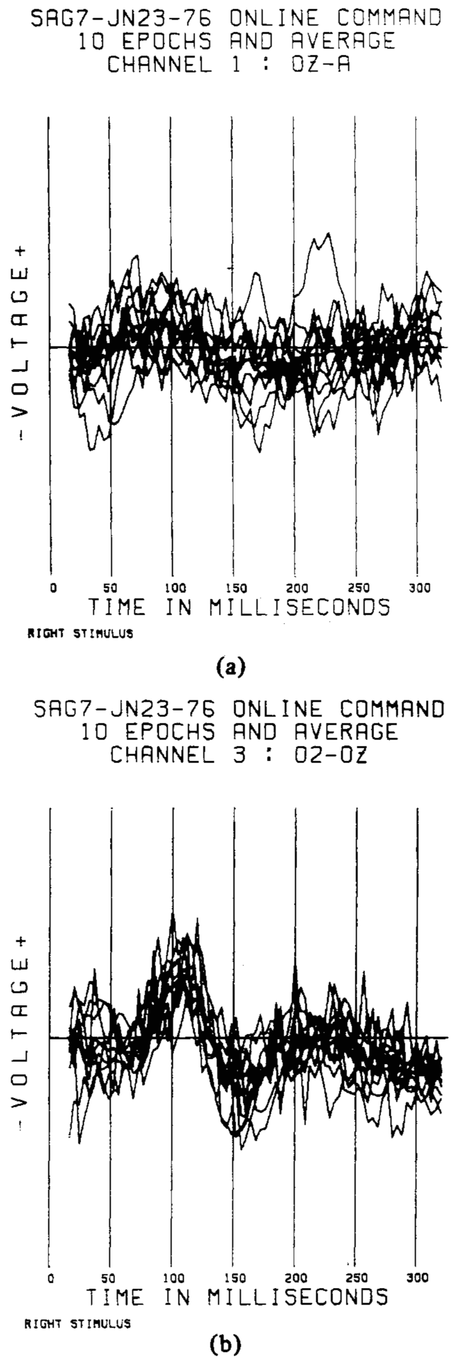

Fig. 1. Ten single epochs of visual evoked responses are superimposed. The average appears as a darker line in the cluster. Stimulus was a diamond shaped checkerboard pattern, flashed while the subject was fixating the right corner of the pattern border. (a) and (b) Show simultaneous epochs collected on two different electrodes (locations are illustrated on Fig. 3.

However, as more demand is put on this measure of brain activity the limitations and inadequacies of time-locked averages as descriptors of evoked events become more apparent. However, most investigators take it for granted that EEG signals are too noisy and the evoked event too small in amplitude to detect and measure in any other way. Yet this may not necessarily be the case. For the last four years, at the Brain Computer Interface Laboratory at University of California at Los Angeles (UCLA), our group has pursued the identification of EEG evoked responses based on the processing of individual responses or "single epochs" in real-time, i.e., as they occur during the experiment. We have determined unequivocally that under suitable conditions, reliable detection and classification can be performed. Pursuing the logical implications of this new paradigm leads to the introduction of completely different descriptors for the response, based on the investment of information within the evoked event, rather than on the actual potential fluctuation. This reformulation bypasses the largely idiosyncratic nature of potential waveforms in different subjects and bring experiment results at a semantic level that matches that of most of the psychophysiological experiments involving ERP's. The balance of the paper will be devoted to the rationale and general strategy in the new approach, i.e., keeping with the purpose of this issue, to the signal processing methodology. Sample results are given informally and for the purpose of illustration.

II. Single ERP Epochs Versus Averages

As mentioned before, most of the research on event related potentials has been concerned exclusively with averaged potentials. These averages are obtained over a number of replications of the evoking stimulus. Before the routine availability of general purpose digital computers, waveform averages were the only attainable descriptors, obtained either by photographic superimposition or with special electronic averagers. Because of technical limitations, most investigations were limited to the recording of one electrode channel selected on a neuroanatomical basis, (the spatial distribution of simultaneous activity around the recording electrode or over the scalp was considered only by very few researchers.) Within the last few years however, the general availability of economical, laboratory-sized general purpose computers has tremendously extended the capability of many laboratories and more sophisticated approaches are becoming increasingly common.

The opportunities afforded by the new equipment have prompted a search for alternatives to averaging. Clearly averaging is an essential and powerful tool for the detection of ERP's but it is easy to show that it may mask as many relevant phenomena as it enhances, depending on the signal properties. It will for instance, show the presence of prominent amplitude features but without regard for their consistency in the epoch population. On the other hand, averaging would be clearly indicated if evoked responses were deterministic signals superimposed in an linearly additive manner to independent noise. Whenever this additive model is valid, averaging is indeed an efficient way to recover the signal. Instrumentation noise is a case in point and because of that property is not a particularly worrisome cause of error in the measurement of averaged potentials. To a somewhat lesser extent the same can be said of EOG and ECG artifacts. The evoked signal itself, however, can be considered deterministic only as a crude approximation.

Most investigators have been using loosely defined models to articulate their findings. These models are usually expressed in terms of "components": those peaks and valleys in the waveform that can be detected by eye in the averages. Peak to peak measurements provide a simple and convenient way to reduce the data. However, these components are seldom well defined or reproducible and stochastic variations in amplitudes and latencies combined with component overlap makes positive identification often very difficult. The influence of the concurrent ongoing activity is also extremely complex, and has been the object of considerable controversy. On-going activity, unrelated to the event of interest, competes with the ERP for "signal space" and as such constitutes or plays the role of noise. The evoked signature, moreover, is not independent of the EEG state at the time of the evoking event; this has been shown for instance by delivering stimuli at fixed times within the alpha cycle [3], [11]. To this day however, there is still no clear understanding of the nature and extent of the interaction.

Thus, because "components" need not be time locked to the initial event and because the ERP signal is generated by unknown processes that may exhibit branching and multiple modes influenced by unobservable factors, averaging can produce a signal prototype that is not representative of any of the single epochs that entered the average. Another limitation of averaging is that, in principle, it requires the stationarity of the target phenomena with a concommitant inability to reflect rapid changes. Neural states change continuously and should be expected to do so over the time required to deliver the necessary number of repetitions (often 50 to 100). In other words, the elusive evoked potential does not necessarily remain the same from the beginning to the end of a stimulation series. Habituation, shifts of attention, drowsines and boredom are only a few of the possible causes that could mediate waveform changes.

Finally, the misrepresentation of single events and the loss of information is magnified when averaging is made, as it often is, across a population of subjects. This is a most severe limitation that cannot be obviated as long as results must rely on the presence of common trends and "components" in the observed waveforms. Indeed, intersubject variability is much larger than that measured with data from the same subject (Fig. 2).

Thus it is obvious that, ideally, one would like to recover the event related information from the electrical potential on the base of single events. To accomplish this however, presents an enormous challenge in view of the elusive nature of most ERP's. Also the effects of instrumentation noise and of artifacts become far more critical without the benefit of averaging.

Single epoch identification is now being done successfully on a limited scale at the UCLA's Brain Computer Interface Laboratory but required thinking anew the whole experimental strategy (and not just the data processing) as well as developing an ambitious computer facility specifically for this program [13], [14], [16]. The overall approach will be discussed in some detail in Section V.

III. Real-Time Identification of ERP's

The real fascination of single epoch identification rests, however, with the possibility to perform it in "real-time." With this provision, a door opens to a whole new realm of experiments in which cognitive variables that vary from trial to trial may be manipulated and sorted out.

Indeed the need for repetition is definitely inimical to experiments dealing with stimulus meaning since meaning will shift inevitably and often uncontrollably where the

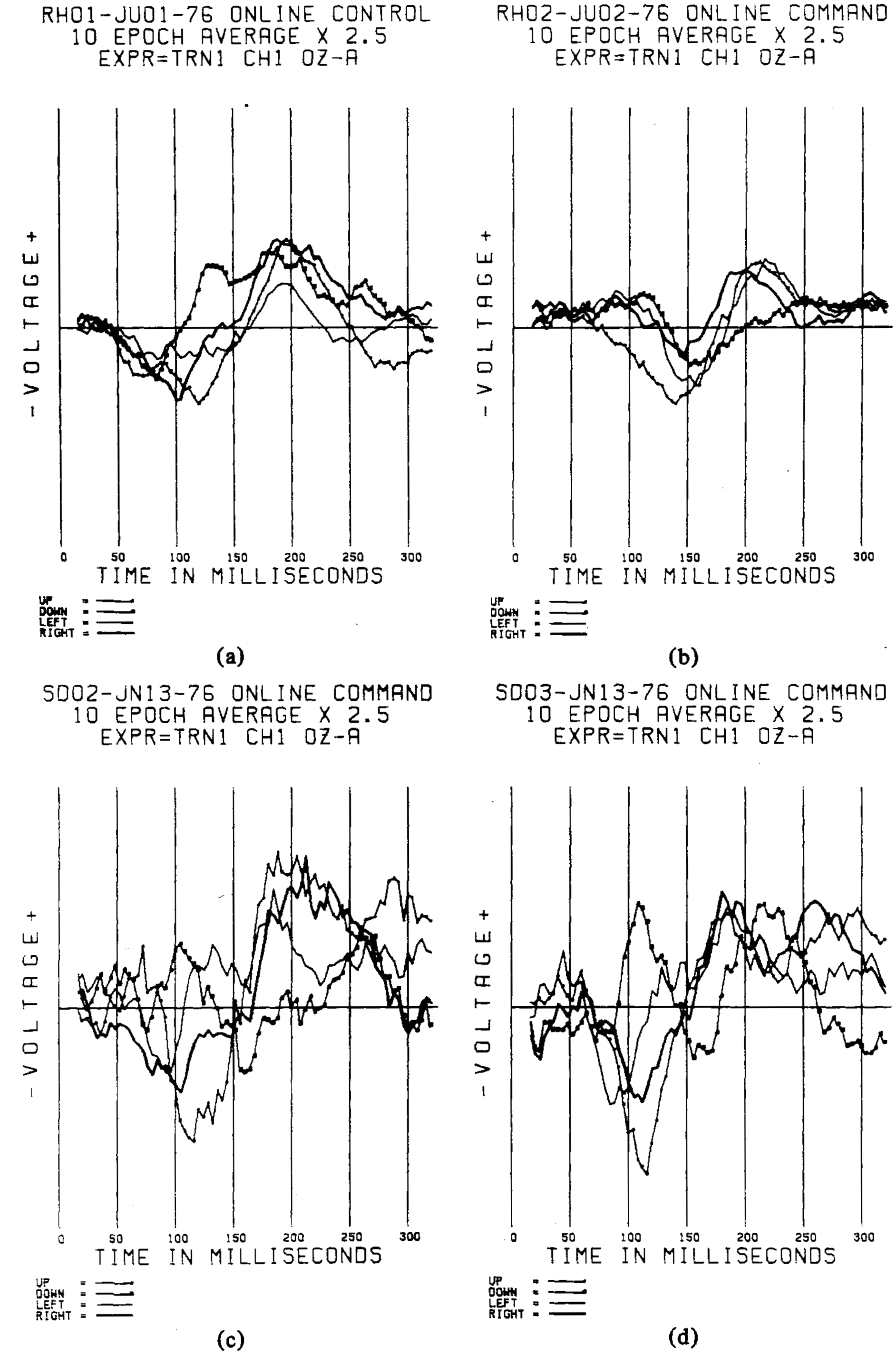

Fig. 2. Variability of response averages with same and different subjects. Averages of visual evoked responses for two different subjects are shown superimposed. The four curves in each graph correspond to four different stimuli (identical for each graph). While averages from the same subjects vary in such replications, there are much more pronounced idiosyncratic differences in data collected from different subjects.

same "message" is repeated. The study of cognitive brain function is presently at the forefront of experimental psychophysiology. The possibility that ERP's could provide an objective measure of the brain processes involved in learning and problem solving is tantalizing. To bring about real-time discrimination would provide a quantum increase in the power of the psychophysiological method. Indeed, if ERP "codes" can be read in context, and translated by the computer into a perceivable change in the environment, the specific brain activity becomes a "behavior," open to conscious validation. Thus biofeedback with respect to Event Related EEG codes brings to the field the same advantages enjoyed by other behavioral experiments, i.e., the subject's conscious participation and verbal reporting.

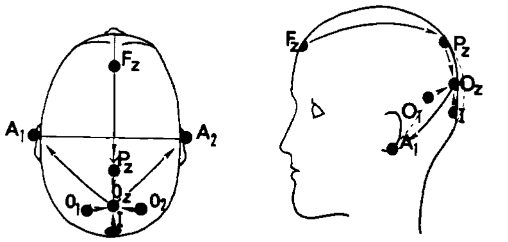

Fig. 3. Electroae locations in pattern experiments. Electrodes are applied at five scalp locations and to the connected ears. The ERP data is collected from the occipital and parietal areas with four bipolar channels: P_Z-O_Z, O1-O_Z, O2-O_Z, I-O_Z and one monopolar channel (to the ear reference): O_Z-A. The frontal electrode is used for artifact detection only (F_Z-P_Z).

The experiment campaign conducted in our laboratory with visual evoked responses involved single epoch classification in real-time, i.e., the identification for each epoch of the value or class of the input stimulus. Stimulus parameters included flash intensity and color, background intensity and color (retinal adaptation) and finally pattern shape. The real-time paradigm in every case lead to a nontrivial elaboration of the experiment design.

IV. Example of Experiment Design

One of these experiment series, dealing with parafoveal pattern stimuli, will be briefly described here to illustrate the general paradigm.

Subjects are seated in a shielded room, in front of a multiple field display. Electrodes are applied on the scalp at five locations and on the earlobes for electrical reference. Four of the scalp locations are in the occipital–parietal area which receive the primary afferent pathways from the visual system. The fifth location is on the frontal pole and serves as a channel for the artifact detection process discussed in the next section. ERP data is collected from five channels comprising monopolar (to ear reference) and bipolar combinations of the electrodes (Fig. 3). Ordinary EEG amplifiers with approximate bandwidth of 1 to 70 Hz are used. Data epochs consist of digitized samples taken every 4 ms. Epoch duration is typically 400 ms including 50 ms of data taken before the stimulus event. Stimuli consist of brief (30 μs) flashes from a xenon light source illuminating a red checkerboard with alternating red and black (opaque) squares against a dimly lit yellow background.

Fig. 4 illustrates the outline of the stimulus target. The small dots at each of the vertices of the diamond serve as visual fixation points for the subject during the experiment. As will be explained below, these fixation points are changed from trial to trial, which in effect changes the physical stimulus and the resulting evoked response. Depending on which of the fixation points has been in use at the time of each flash, one of four nonoverlapping parafoveal areas receives the stimulus. In other words, the diamond-shaped checkerboard "lands" on four different retinal positions depending on which dot has been selected. This very simple arrangement provides an alternative to the more traditional approach of presenting the four different patterns to a passive subject [10]. An important difference however, is that the subject has control of stimulus selection, a control that will be directed by a new entity introduced in the experiment design: an independent cognitive task that performs several important functions. In the present experiment, this outside task is provided with the help of a simple maze, simulated on a CRT (Fig. 5), and visible

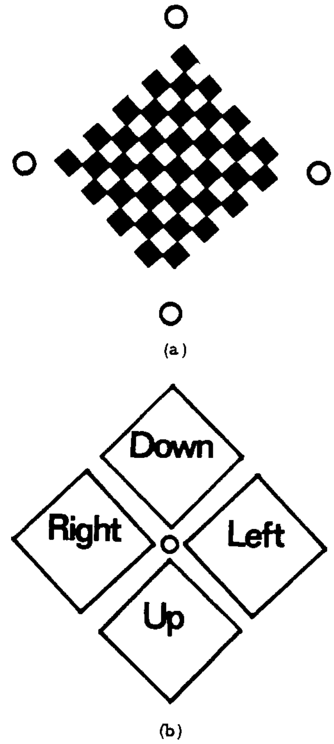

Fig. 4. Stimulus target in real-time visual ERP experiments. The target consists of a fixed diamond shaped red cherckerboard illuminated with a xenon flash to provide visual stimulation. (a) The four dots at the corner of the diamond are fixation points. For each point the stimulus target lands on a different retinal position with respect to the fovea and thus distributes neural activity on different sites of the primary visual cortex. (b) From the subject's view the target appears as one of the four options shown.

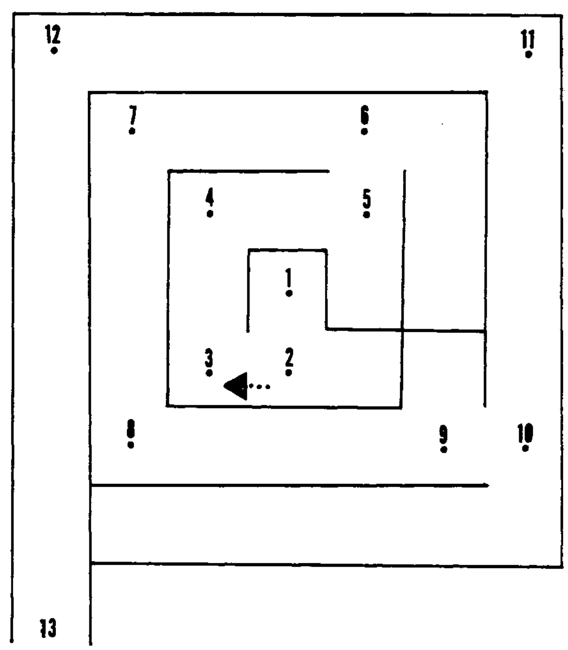

Fig. 5. Maze feedback display for real-time ERP classification experiment: The display, generated on a computer graphic terminal, shows a fixed maze containing a triangular mobile. This continuous display and the intermittent stimulus pattern of Fig. 4 share the same visual field. The subject task is to see the mobile through the maze by selecting before each stimulus time the appropriate fixation point. Four fixations dots are provided: left, right, up and down. The ERP's are classified and the result is translated into the corresponding mobile motion to provide subject feedback.

continuously in the background of the subject display. The task here is to move a symbol through the maze and out, from an initial position at the maze center. The subjects conveys each desired move, (in one of four possible up, down, left and right directions), by fixating the corresponding dot (which remains visible in the display unlike the checkerboard which appears only at stimulus times). Actual movement of the symbol on the CRT however, is implemented by the computer system according to its classification (in one of the four expected classes) of each incoming ERP. Thus, single epoch identification is the key to the subject feedback that simultaneously delivers implicit instructions for each successive selection, maintains a steady level of attention by keeping the task meaningful and provide the learning clues that will minimize artifacts by rewarding clear signals. The last function is further enhanced by an audible reporting of detected artifacts which functions as a second level feedback.

This cybernetics modus operandi and the general broadening of experimental perspective afforded by the real-time identification approach have far reaching implications. They will be further discussed in Section VI after the presentation of the essential aspects of experiment control and data processing.

V. Experiment Control and Data Processing

Under the experimental conditions tested so far the program has been remarkably successful: rate of correct classification over small sets of stimuli [4]–[10] now exceeds 90 percent consistently with average subjects. Even when one includes early experiments, where performance was degraded because of various mishaps with instrumentation, the procedure consistently averaged more than 80 percent of correct classifications. Fig. 6 shows the results of the thirteen first experiments using parafoveal stimuli as described in the preceeding section. The percentage of correct classification is shown for each experimental session relative to the 80- and 90 percent levels. The coordinate axes and the mutual information scale $I(i, j)$ are discussed below and in the next section.

This rewarding level of discrimination performance has been achieved through successive refinements of the experimental strategy and of the data processing. Each multichannel epoch was submitted to several processing steps that will be reviewed below in chronological order. There is little doubt that these procedures is still suboptimal, and the present performance level should be viewed as a lower bound rather that as a limit on what could be theoretically attained.

1) A Priori Artifact Rejection: This procedure detects electroocular and movement artifacts before and during the ERP epoch. On-line artifact rejection is a fundamental tenet of the real-time approach and probably the most effective and rewarding step in the overall strategy.

EOG artifacts, blinks and head movements create sharp disturbances of the EEG baseline that produce oversized peaks in the waveform. Detection is made by amplitude averaging over a sliding time window, comparing the difference between each sample and the current average to a preset threshold. A peak detection algorithm is also used, that tracks the waveform and looks for alternations where the difference between maximum and minimum exceeds a given value. The width of the window and the threshold value are adjustable parameters. The computer controlled data acquisition schedule on Fig. 7 shows the time sequence and the position of artifact rejection in the overall scheme.

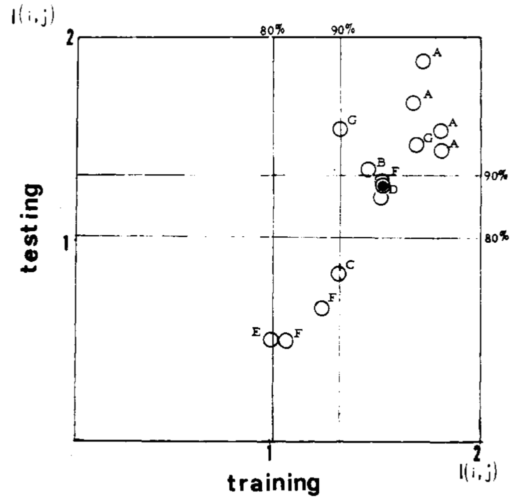

Fig. 6. Parafoveal experiments: Summary of discrimination performance. Discrimination performance is shown for thirteen parafoveal stimulation experiments. Each circle identifies one experiment session. Different letters correspond to different subjects. The full circle locates the average.

Performance levels are indicated with respect to the 80 and 90 percent levels of correct classification. The coordinate axis and the mutual information scale $I(i, j)$ are explained in Sections V and VI.

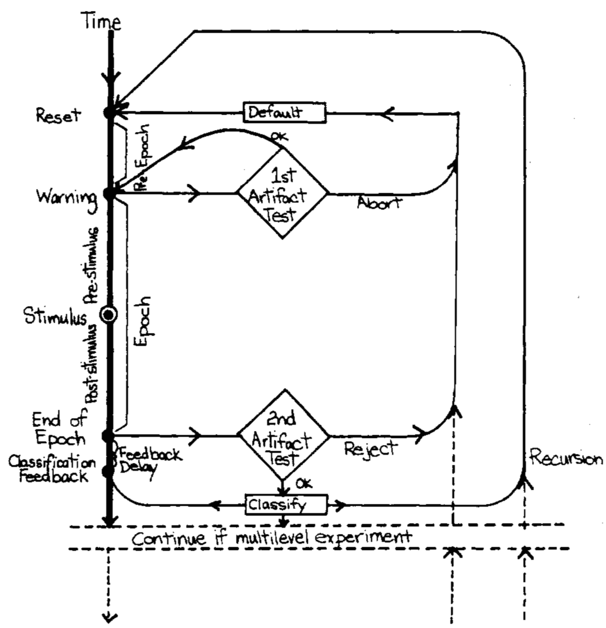

Fig. 7. Real-time computer scheduling in experiments. Real-time scheduling of stimulus cycle. Multilevel experiments are possible where the result of one classification, i.e., the classification feedback becomes the stimulus for a second level ERP.

Artifact monitoring starts before stimulation and continues throughout a period called the pre-epoch. The detection of an artifact during the pre-epoch aborts data acquisition and reschedules the stimulus event. After the beginning of the epoch proper, data acquisition is completed but the affected epoch is "rejected."

2) Preprocessing–Wiener Filtering: Real-time filtering is performed to improve the signal-to-noise ratio based on covariance information. Wiener filtering of evoked response has been suggested by a few researchers and used with some success in an earlier off-line study [2].

The filter evaluates smoothed estimates X of the unknown ERP signal S from the measured raw amplitude vector Z. For the present purpose, Z is assumed to be made up of true signal and additive zero-mean noise U:

$$Z = S + U. \tag{1}$$

However S is considered here as a stochastic vector. The signal mean $E[S]$ and the covariance matrices. $W(U)$ and $W(S + U)$ are evaluated from ensemble data using data preceding the stimulus for the evaluation of $W(U)$. The estimate is given by

$$X = E[S] + A \cdot (Z - E[S]) \tag{2}$$

where

$$A = W(S) \cdot [W(S + U)]^{-1}$$

X is the minimum mean-square error estimate of the signal vector under the assumptions.

The operational validity of the procedure can be evaluated objectively by comparing classification performances. The results at this time are still unconclusive, mostly because of statistical errors in the evaluation of $W(S)$, due the the unknown level of covariance between S and U.

3) Selection of a Feature Vector: The features used in all the aforementioned experiments were simply the filtered amplitude samples (i.e., the X vector). It is the simplest possible feature vector and a logical choice because of the sequential nature of ERP's which demands preservation of time ordering. Obviously, a number of transformations of the original vector would be possible and in that light the current procedure can be viewed as a particular case of the linear class of spectral transformations, where the basis functions are an orthogonal set of impulses, one for each sample time.

4) Step-Wise Selection of Best Samples: Sampling intervals in the experiments discussed were 4 ms. Thus the acquisition of a half-second epoch generates initially a large measure vector made of adjacent filtered samples. Considerations of statistical stability demands that dimensionality be reduced before attempting classification. Here again many linear operators, and particularly the Karhunen-Loéve transformation which would yield the principal components, could achieve a drastic reduction of dimensionality in the highly correlated sample vector. Several authors have used principal component analysis in combination with coordinate rotations, to analyse average evoked responses [5], [9]. Yet most spectral transformations will to some extent blur timing information.

In the current experiments, a step-wise discriminant procedure similar to that described by Dixon [4] was applied to the components of the X vector itself. This procedure is actually related to the principal component strategy. It selects a small subset of the original components that simultaneously achieve the best F-ratios and maximum statistical independence. Fisher's F-ratio [7] is computed as a ratio of data variance computed with respect to the overall mean across the classes versus the relative variance to each class mean. Thus the F-ratio offers a measure of class separability (for each sample time) by measuring how much each component of X varies across the classes in relation to its variations within each class. The discriminant analysis method requires therefore a "training set," i.e., a set of labelled epochs of known classes (50 epochs in the current experiments), to guide the data reduction. After reduction of the data vector, the F statistics are given by

$$F = \frac{(N - K)\, V^T\, W(X)\, V}{(K - 1)\, V^T\, U(X)\, V} \tag{3}$$

where N is the number of epochs, K is the number of classes, $W(X)$ and $U(X)$ are, respectively, the covariance matrices relatively calculated with respect to the within group and the across group means, V is the "thinning" vector, a set of weights set to zero for all but the "surviving" samples in the selection, "T" denotes the transpose of the corresponding matrix. The problem is then to select V in such a way as to maximize F.

Differentiation yields a linear system of equations to be solved:

$$[U(X)^{-1} \cdot W(X) - zI] \cdot V = 0 \tag{4}$$

where

$$z = \frac{V^T\, W(X)\, V}{V^T\, U(X)\, V}$$

and I is the identity matrix.

The step-wise method of Effroymsen [6] is used to solve these equations and select the samples one by one into an ordered subset of preassigned dimensionality D (D was equal to ten in the present application), with monotonically decreasing F ratios. From that point on, the reduced vector Y becomes the epoch descriptor and the only ERP information retained in subsequent computations.

5) Epoch Classification and Recursive Outlier Rejection: A linear Bayesian decision rule is calculated for each class over the reduced vector. The classification is based on Bayes posterior probabilities:

$$p[i \mid Y] = \frac{p[i]\, p[Y \mid i]}{\sum_k p[k]\, p[Y \mid k]}, \quad i = 1, 2, \cdots, K;$$

$$k = 1, 2, \cdots, K. \tag{5}$$

The classification procedure starts with the same training population used to perform the dimensionality reduction.

The decision rule is then built on the assumption that the Y-vector population should distribute into K classes. As a first approximation, the data distribution within each class is conveniently assumed to be multivariate normal with the same covariances:

$$f(Y \mid i) = \frac{\exp\,[-0.5(Y - \overline{Y}_i)^T [W(Y)]^{-1} (Y - \overline{Y}_i)]}{\sqrt{(2\pi)^D\, |W(Y)|}}. \tag{6}$$

Because the class covariance are equal, equation (6) can be simplified by eliminating the quadratic term, yielding a simple expression for the *posteriori* probability:

$$p(i \mid Y) = \frac{p(i) : \exp\,[a(i) + B(i) \cdot Y]}{\sum_k p(k) \cdot \exp\,[a(k) + B(k) \cdot Y]} \tag{7}$$

Equation (7) varies monotonically with the linear term in the numerator which becomes the "decision rule" for group i:

$$d(i) = a(i) + B(i)Y \tag{8}$$

In addition, a $(K + l)$th class is defined, the outlier class, containing those epochs Y for which the Mahalanobis distance to the group mean exceeds a given threshold. This nonlinear test overrules any assignment made by (8) i.e. the training set is examined for outliers regardless of whether they have been initially misclassified or correctly classified. The program offers the option of removing these outliers before returning to the stepwise discriminant selection in order to obtain an updated selection and thus a corrected decision rule.

6) Real-Time Defaulting: Once the initial decision rule has been established on the training set, real-time classification ("testing") can proceed with a minimum or computing between epoch acquisition. The only calculations involve the evaluation of the linear decision rule (one expression must be computed for each class) and a comparison of the results to identify the largest value. This again is followed by distance calculation to detect outliers. When present, outliers now create a default or "don't know" class, which during the real-time experiment will cause the system to label the epoch as such and to repeat the stimulation cycle (a posteriori artifact or outlier rejection). Here again, because classification in the default class results in no change in the display, (probably against the subject's expectation), specific feedback is provided on the discrimination outcome.

7) Decision Rule Updating: By making the procedure recursive, blocks of epochs, (epoch strings) sequentially serve as training sets for the next string. Thus the decision rule can be tracked as it undergoes changes due, for instance, to task learning, operant conditioning or any other cause.

VI. The Cybernetics Viewpoint

The real-time interactive mode of ERP experimentation made possible by single epoch identification brings the experimental process into a new light.

It is first observed that the single epoch classification is essentially a signal detection problem in which the computer, in the position of an impartial observer, assigns classes to incoming epochs according to a given decision rule. Each experiment trial can therefore be viewed as a communication process in which an enciphered message is retrieved in the ERP signal. The "message," which usually changes with each individual trial, is the position of the stimulus event in the input set, i.e., the class label. Thus, the set of class labels can be regarded as an alphabet of symbols or characters, one for each of the K stimulus types.

Simple ERP experiments, such as described earlier, realize the transmission of one such character every time an epoch is classified, which, amounts to log K bits of information at the input, if stimuli are equiprobable.

The output set likewise forms an alphabet. Indeed, the components of Y, the reduced ERP data vector may be viewed as the euclidean coordinates of a signal space. This signal space is initially divided into K compartments by the decision rules, one compartment for each input character. Subsequently, a default region is defined that includes all the points that lie beyond a given distance from any of the class means, and thus cannot be placed confidently into any of the original slots. The default class brings the number of output characters to $K + 1$.

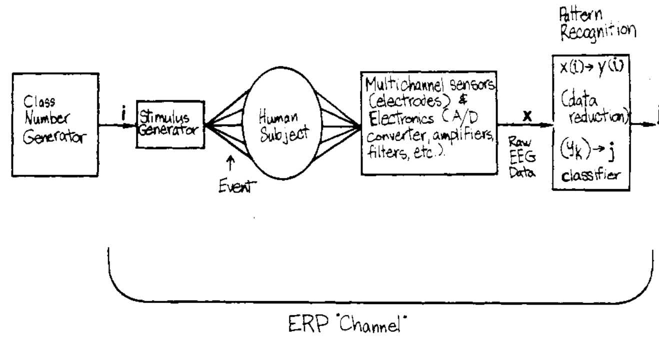

Fig. 8.

The ERP identification therefore maps the input alphabet into the output alphabet [1]. The resulting information "channel" is represented in Fig. 8. The efficiency of this mapping can be quantified conveniently:

Let i and j be the respective indexes for the input and output alphabets; the mutual information $I(i, j)$ is a measure of the efficiency of the transfer defined as the difference between average information and equivocation received at the output.

Average output information:

$$I(j) = -\sum_j p(j) \log p(j) \tag{9}$$

but since

$$p(j) = \sum_i p(i)p(j \mid i)$$

$$I(j) = -\sum_j \sum_i p(i) \cdot p(j \mid i) \log p(j). \tag{10}$$

Similarly the equivocation yields:

$$E(j) = -\sum_i \sum_j p(i) \cdot p(j \mid i) \log p(j \mid i). \tag{11}$$

The difference between (10) and (11) yields the mutual information measure

$$I(i, j) = \sum_j \sum_i p(i) \cdot p(j \mid i) \log \frac{p(i, j)}{p(i)p(j)}. \tag{12}$$

The probabilities in (12) can be estimated from the observed discrimination performance, i.e., by the "confusion matrix" generated by the accumulated trials; $I(i, j)$ expresses (in bits when the logarithms in (12) are in base 2), the average amount of information that survives the enciphering and decoding process. It provides an objective and unassailable index that can be used to compare different experiments, or to heuristically optimize the discriminant procedure.

Finally the dynamic, spatio-temporal distribution of the mutual information can be analyzed. Indeed, all the probabilities in (12) are implicitly conditioned on the ERP data vector X at the input of the pattern recognition procedure. Until now X was taken to contain the entire multichannel epoch, however, since the time boundaries of the epoch are arbitrary as well as the inclusion or removal of any subset of data sensors, mutual information can be evaluated, conditioned on any subset of components from the original data vector. At the limit $I(i, j)$ can be computed for each single electrode site and sample time if the data base is large enough to insure

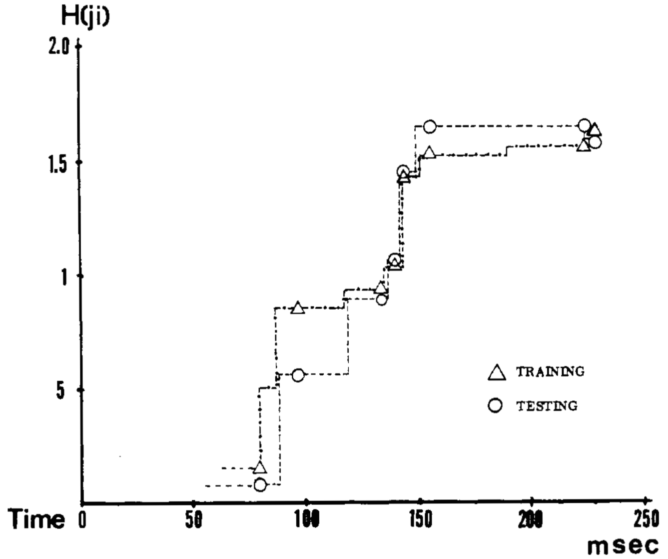

Fig. 9. Mutual information function–Time distribution: Mutual information function $H(ji)$ computed in function of time from stimulus. The distribution shows that no information is provided before 75msec and that it subsequently appears in two separate waves at about 80 and 145ms. Pattern experiment–SAD7–200 epochs.

statistical stability. Specifically, if these components are partitioned into subsets, $I(i, j)$ will in theory, i.e., except for statistical errors, form a nondecreasing function of the number of such subsets entered one by one in the calculation. In using the stepwise discriminant procedure, the samples or features surviving the selection process at each step must be pooled with each additional data subset to compute each new value of I. What emerges then, is the concept of an "event related information wave" (ERIW) indicating the presence of experiment relevant information in space (electrode location) and time.

This approach can be used to tackle fundamental questions in ERP research regarding time and space distribution. For instance, in Fig. 9 the time arrival of information has been traced by cumulatively computing $H(ji)$ over adjacent bins in time, corresponding to the optimal Y components across all channels for this experiment. The plot clearly shows the arrival of information in two successive waves, respectively around 80 and 145 ms.

This analysis translates the fluctuations of electrical potential in the ERP into a direct answer to the specific quest contained in the experiment paradigm. As mentioned earlier, the ERP waveforms are subject specific to such an extent that pooling data between subjects is often of doubtful value and certainly amounts to a reduction of the signal structure to some lower common factor. Thus the informational approach will recognize a commonality in the overall timing and anatomical location of the evoked neural processing without requiring that the fine structure of the electrical activity be comparable on a one-to-one basis.

In this perspective, the method lies at the proper semantic level with regard to the questions that motivate most evoked response research, at least with human subjects, such as determining delays between stimulus and cortical response or finding whether a given process favors one side of the brain over the other.

Until very recently, the considerable amount of computation required by this approach would have ruled it out as a practical approach. These days are over.

References

[1] N. Abramson, *Information Theory and Coding*. New York: McGraw-Hill 1963.
[2] J. I. Aunon and C. D. McGillem, "Techniques for processing single evoked potentials," *Proc. S.D. Biomedical Symp.*, Feb. 1975.
[3] E. Callaway and R. S. Layne, "Interactions between the visual evoked response and the spontaneous biological rhythms: the EEG alpha cycle and the cardiac arousal cycle," *Ann. N.Y. Acad. Sci.*, vol. 112, p. 421, 1964.
[4] W. J. Dixon, "BMDP, Biomedical computer programs," Health Science Computing Facility, Univ. California, Los Angeles, pp. 411-451, 1975.
[5] E. Donchin, "A multivariate approach to the analysis of average evoked potentials," *IEEE Trans. Biomed. Eng.*, vol. BME-13, pp. 131-139, 1966.
[6] M. A. Efroymsen, "Multiple regression analysis," in *Mathematical Methods for Digital Computers*, A. Ralston and H. S. Wilf, Eds. New York: Wiley, pp. 191-203, 1960.
[7] R. A. Fisher, "The use of multiple measurements in tax onomic problems," *Ann. Eugenics*, vol. 7: pp. 179-188, 1936.
[8] O. S. Halpeny and D. G. Childers, "Composite wavefront decomposition via multidimensional digital filtering of array data," *IEEE Trans. Circuits Syst.*, June 1975.
[9] E. R. John *et al.*, "Factor analysis of evoked potentials," *Electroencephal. Clinical Neurophysiol.*, vol. 34, pp. 33-34, 1973.
[10] W. F. Michael and A. M. Halliday, "Differences between the occipital distribution of upper and lower field pattern evoked responses in man," *Brain Research*, vol. 32, pp. 311-324, 1971.
[11] J. L. Trimble and A. M. Potts, "Ongoing occipital rhythms and the VER. I. Stimulation at peaks of the alpha-rhythm," *Investigative Ophthalmology*, vol. 14, no. 7, pp. 537-545, July 1975.
[12] H. G. Vaughan and S. R. Korey, "The relationship of brain activity to scalp recordings of event-related potentials," in *Average Evoked Potentials, Methods, Results, and Evaluations*, E. Donchin and D. B. Lindsley, Eds., Washington, DC: Govern. Printing Office., 1969.
[13] J. J. Vidal, "Toward direct brain-computer communications," *Annu. Rev. Biophys. Bioeng.*, vol. 2, pp. 157-180. Annual Reviews, Inc., Palo Alto, CA 1973.
[14] J. J. Vidal *et al.*, "Sensory stimuli are identified accurately in single epochs of visual evoked responses recorded on scalp," in *Neurosci. Abstr., Society for Neuroscience, 5th Annu. Meet.* (New York City), Nov. 1975.
[15] J. J. Vidal, "Neurocybernetics and man-machine communication," in *Proc. Int. Conf. Cybernetics and Society* (San Francisco, CA), Sept. 1975.
[16] J. J. Vidal and R. H. Olch, "Computer system architecture at the UCLA Brain Computer Interface Laboratory," in *Computer Technology in Neurosciences*, P. B. Brown, Ed. Washington, DC: Hemisphere Publ., ch. 26, pp 411-438, 1976.