# Talking off the top of your head: A mental prosthesis utilizing event-related brain potentials



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# Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials

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**Summary** This paper describes the development and testing of a system whereby one can communicate through a computer by using the P300 component of the event-related brain potential (ERP). Such a system may be used as a communication aid by individuals who cannot use any motor system for communication (e.g., 'locked-in' patients). The 26 letters of the alphabet, together with several other symbols and commands, are displayed on a computer screen which serves as the keyboard or prosthetic device. The subject focuses attention successively on the characters he wishes to communicate. The computer detects the chosen character on-line and in real time. This detection is achieved by repeatedly flashing rows and columns of the matrix. When the elements containing the chosen character are flashed, a P300 is elicited, and it is this P300 that is detected by the computer. We report an analysis of the operating characteristics of the system when used with normal volunteers, who took part in 2 experimental sessions. In the first session (the pilot study/training session) subjects attempted to spell a word and convey it to a voice synthesizer for production. In the second session (the analysis of the operating characteristics of the system) subjects were required simply to attend to individual letters of a word for a specific number of trials while data were recorded for off-line analysis.

The analyses suggest that this communication channel can be operated accurately at the rate of 0.20 bits/sec. In other words, under the conditions we used, subjects can communicate 12.0 bits, or 2.3 characters, per min.

**Key words:** P300; Event-related potential: Prosthesis; Self-help device; EEG

Several hundred studies have demonstrated that, when subjects are assigned a task that requires them to determine to which of 2 possible categories each item in a series belongs, and one of the categories occurs rarely, these rare items will elicit an event-related brain potential (ERP) with an enhanced positive-going component with a latency of about 300 msec, labeled the P300. This experimental arrangement has come to be called the 'oddball' paradigm. For reviews see Pritchard (1981), Hillyard and Kutas (1983) and Donchin et al. (1986a). It has been amply documented that the amplitude of the P300 varies directly with the relevance of the eliciting events and inversely with the probability of the stimuli. The elicitation of P300 depends critically, therefore, on the subject's ability to discriminate the events and assign them to the appropriate categories.

Note that it is not necessary that the subject report the occurrence of a target event by overt means (e.g., button press). Often the subject is required only to maintain a running mental count of the number of occurrences of the target. In other words, the appearance of the P300 signals the subject's recognition of the rare event without recourse to verbal or motor means of communication. This attribute of the P300 suggests that it may be possible to develop a 'mental prosthesis' utilizing the oddball paradigm that would permit communication by persons who, as a result of

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injury or disease, have been deprived of overt means of communication. Such a prosthesis would operate by allowing a subject to communicate a choice among a series of items. If the items consist of, say, the alphabet, then the subject can spell out a message by successively choosing from among the 26 letters and communicating his choices via the P300. While it is fairly obvious how such a system can be implemented in a standard oddball paradigm, it is also obvious that the process would be unacceptably slow. The system we describe in this report accelerated communication by using subsets of a matrix of characters as the critical eliciting events and by presenting these events at an unusually high rate. The purpose of the study was to determine if intact young adults could use this version of the oddball paradigm to communicate their choices to a computer and to determine the operating characteristics of such a system.

The need for systems that could allow disabled individuals to communicate with computers has spurred the development of numerous devices, all of which utilize one or another motor system. For example, quadriplegic patients with good control of the neck muscles can activate buttons with a rod attached to the forehead. Increasingly sophisticated prostheses have been developed to allow individuals with more severe disabilities to communicate through the extension of residual motor functions. These include a typewriter that can be operated by a light beam directed by head movements (Soede et al. 1974); a typewriter controlled by a key embedded in a dental palate operated with Morse code (Saarnio 1974; see also Hammond 1974; Torok 1974; Vasa and Lywood 1976; Shwedyk and Gordon 1977; Hardiman et al. 1979; Jardine et al. 1984).

As it is not unusual for the oculomotor system to remain functional when other voluntary motor systems are damaged quite severely, numerous devices operate by detecting eye movements or fixations as a means of communication (Rinard and Rugg 1976; Wardell 1977; Sutter 1983; ten Kate et al. 1984; Rubin and Stark 1984).

All of these systems substitute one motor system for another. In some patients, however, no functional voluntary motor systems remain sufficiently intact, even though these patients do retain sensory and cognitive abilities. For such individuals a 'mental prosthesis' that utilizes non-motor manifestations of mental activity for communication may be of use. The system we describe here allows the subject to push a metaphorical switch by focusing attention on one of a series of stimulus events. The discrimination between the event on which the subject is focusing and the other events in the series carries the information that the subject is communicating. By detecting which of the events in the series generates a P300, the appropriate computer-implemented algorithm can identify the message the subject is trying to communicate and send it for him or her (Farwell et al. 1986; Donchin 1987).

The system works as follows: a 6-by-6 matrix containing the letters of the alphabet and a few 1-word commands (Fig. 1) is displayed on a computer-controlled CRT screen. The 'stimulus events' that occur in the test consist of intensifications of either a row or a column of the matrix. The subject attempts, at any instant, to communicate the contents of 1 cell in the matrix. As the subject focuses attention on that cell, the column and the row containing the cell become 'relevant' events. There are 12 possible events (6 rows and 6 columns) only 2 of which are relevant. These events are therefore both task-relevant and rare. Thus, any flash that contains the cell on which the subject is focusing should elicit a P300. The amplitude of the P300 following each flash is assessed, and the attended cell is identified as the cell at the intersection of the row and column that elicit the largest P300s.

We report here a study in which 4 healthy volunteers used the system to communicate a 5-letter word to a computer. The primary purpose was to determine the number of trials and the rate of event presentation that are required to achieve a specified level of accuracy in communication.

## Methods

### *Subjects*

Four healthy subjects, 3 females and 1 male, 20–36 years old, participated in the study.

*Data acquisition and analysis*

The electroencephalogram (EEG) was recorded from Ag-AgCl Beckman Biopotential electrodes placed at the Pz (parietal) site (10/20 international system), referred to linked mastoids. This site was chosen because it is where the largest amplitude P300 is recorded in young adults (Pritchard 1981; Hillyard and Kutas 1983; Donchin et al. 1986a). Electro-oculogram (EOG) was recorded from sub- and supraorbital electrodes (above and below the right eye). The subjects were grounded at the forehead. Electrode impedance did not exceed 5 k$\Omega$. Brain electrical activity was amplified by Grass Model 12 amplifiers with low- and high-pass filters set at half-amplitude frequencies of 35 and 0.02 Hz, respectively. These signals were digitized at a rate of 50 Hz. Data were analyzed in real time in the pilot/training session and off-line in the assessment session, both of which are described in detail below.

Each subject participated in 2 sessions. The first served to assess the feasibility of the technique and to familiarize the subjects with the apparatus and procedures. In the second we obtained data that allowed us to assess the operating characteristics of the system.

*The communication system*

Subjects were presented with a 6-by-6 matrix whose cells contained the letters of the alphabet as well as several 1-word commands for controlling the system (see Fig. 1). The matrix was displayed on a computer-controlled CRT. In every 'trial,' each of the 6 rows of the matrix, or each of the 6 columns, was intensified for a period of 100 msec. In the first session the inter-stimulus interval (ISI) was 500 msec. In the second session data were acquired with both a 500 msec and a 125 msec ISI. The ISI was measured from the beginning of the intensification of each row/column and of the subsequent row/column to be intensified. The rows were selected for intensification in a random order, and then the columns were intensified in a similar manner.

Subjects were instructed to attend to a given letter and to keep a running mental count of the number of times it flashed. In the first session the

**CRT Display Used in the Mental Prosthesis**

MESSAGE

BRAIN

Choose one letter or command

| | | | | | |
|---|---|---|---|---|---|
| A | G | M | S | Y | * |
| B | H | N | T | Z | * |
| C | I | O | U | * | TALK |
| D | J | P | V | FLN | SPAC |
| E | K | Q | W | * | BKSP |
| F | L | R | X | SPL | QUIT |

Fig. 1. CRT display used in the mental prosthesis. The rows and columns of the matrix were flashed alternately. The letters selected by the subject ('B-R-A-I-N') were displayed at the top of the screen in the pilot study.

subjects completed 6 blocks of 120 trials each. The first session was concluded with a block of trials in which we used a real-time signal-detection algorithm to allow subjects to communicate the word 'BRAIN' to the computer.

Subjects selected each of the letters in the word 'BRAIN' in turn, and silently counted the flashes of the row or column containing the letter until the system displayed the letter it had selected in a specified position on the screen (see Fig. 1). After the letters spelling the word 'BRAIN' had been displayed, the subject selected the 'TALK' command, and the word was sounded by means of a Votrax speech synthesizer. In a few cases the computer displayed a letter other than the one on which a subject was focusing. The subject then focused on the BKSP ('backspace') command to correct the error.

The computer recognized the selections using the covariance algorithm described below. All subjects were able to spell the word and to activate the voice synthesizer.

*Analysis of the operating characteristics of the system*

The process required the computer to detect a P300 elicited by one of a series of rapidly changing events. It assumed that only the rows and columns containing the chosen character will elicit the P300. However, the detection of the P300 clearly requires the application of signal averaging, which depends, of course, on the presentation of many stimuli. The effectiveness of this procedure as a communication channel depends on the degree to which the message can be communicated with a small number of trials using an efficient, cost-effective, on-line detector of the P300. It is necessary, therefore, to determine the smallest number of trials in which the system can make the detections at different levels of accuracy. To determine this property of the system, we ran 10 blocks for each of the 4 subjects in the second session. Our purpose was to assess the accuracy with which the character selected by the subject was identified as a function of the number of trials used for the detection. Four different methods for detecting the P300 were assessed.

We compared 2 different rates of stimulus presentation. Half of the blocks were run with a 125 msec ISI between the onset of the intensification of a given row or column and the onset of the intensification of the next row or column to be flashed and half with a 500 msec ISI. As before, each row was intensified for 100 msec, and then each of the columns was intensified similarly. Fig. 2 illustrates the time course of events in the blocks

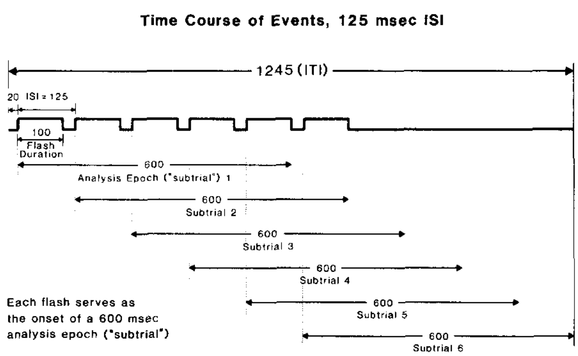


Fig. 2. Time course of events in the blocks using the ISI of 125 msec. Six columns (or 6 rows) were intensified ('flash') in a random sequence for 100 msec, at 125 msec intervals (ISI). EEG was recorded from 20 msec prior to the first flash until 600 msec after the last flash. Each flash served as the onset of a 600 msec analysis epoch ('subtrial'). A trial comprised 6 flashes (1 flash of each row or 1 flash of each column) plus the associated data collection time, a total of 1245 msec.

using the ISI of 125 msec.

The relevant data consisted of the EEG digitized for 600 msec after the onset of each flash. The EEG was digitized continuously from 20 msec prior to the first flash in each trial to 600 msec after the sixth flash. The subsequent trial began approximately 620 msec after the sixth flash. The inter-trial intervals (ITIs) measured from the beginning of one trial to the beginning of the next trial, then, were 1245 and 3120 msec for the 125 and 500 msec ISIs respectively. Note the distinction between ISI — the time from the onset of the flash of one row or column to the onset of the flash of the next row or column — and ITI — the time from the onset of one trial (6 row or column flashes) to the onset of the next trial.

Each block consisted of 30 trials. Five blocks at 125 msec ISI were followed by 5 blocks at 500 msec ISI for 2 of the subjects, and the order was reversed for the other 2 subjects.

Subjects were instructed to keep a running mental count of the flashes of the letter 'B' until the 'choose one letter or command' instruction (Fig. 1) was turned off for 500 msec and then turned back on. They were then to count the letter 'R' until the same signal appeared, then the letter 'A,' then 'I,' and then 'N.' Trials with muscle or EOG artifact were eliminated. After 30 uncontaminated trials were accumulated, the 'choose...' instruction turned off for 500 msec, and then a new block began with the next letter to be attended. After 5 blocks at 1 ISI, the subjects received a short break, and then the next series was run.

Thus, in effect the subject spelled the word 'BRAIN' in each series of 5 blocks, with approximately 30 trials for each letter. When a trial was rejected for artifact, it was not recorded for inclusion in the signal-detection computations, and an additional trial was presented. Therefore, the total number of trials in each block viewed by the subject was sometimes a few more than 30, but the number of trials recorded was 30 in every case [2].

[2] We emphasize that this is not a 'biofeedback' experiment. Our interest is not to train subjects to control the display. Ours is a variant of an oddball paradigm, and our purpose is to determine the minimum number of trials at which a detectable P300 can be recorded.

*Data analysis*

The speed with which a subject can communicate the element he has chosen from the matrix depends on the speed with which the computer can detect the row and the column which elicit the P300. When presented with averages based on 30 trials presented at a 500 msec ISI, the computer can identify the correct element with complete accuracy using any one of several detection algorithms. However, presenting 30 trials at a 500 msec ISI requires 93.6 sec, reducing communication speed to about 0.01 characters/sec. If we choose to base the choice of the element on the minimum available data, 1 trial at 125 msec ISI, the system will communicate at the rate of 0.8 characters/sec, but many of the choices will be in error.

Clearly, therefore, one must improve the signal-to-noise ratio by averaging over a certain number of trials. Our purpose, then, was to estimate the smallest number of trials that must be used to reduce the signal-to-noise level in the ERP signal so that the character the subject has chosen could be communicated at a specified level of certainty. We addressed this question by examining the level of accuracy at which each of 4 detection algorithms that are used in computing the average will operate given the number of trials presented at a given ISI. This analysis yields also an estimate of the smallest number of trials that would yield a certain level of accuracy at a given ISI and for a given algorithm. By multiplying by the time required to present the trials, we also obtained an estimate of accuracy as a function of time — the speed/accuracy tradeoff function.

Each trial contained 6 distinct events, namely, the flashes of each of the rows or columns, only one of which was task-relevant. For analytical purposes, each trial was divided into 6 data windows or subtrials, each consisting of the data for 600 msec after onset of the flash of a row or column (see Fig. 2). Thus, since the ISI was less than 600 msec, these subtrials contained overlapping data. For each subtrial we computed a score that measured the magnitude of the P300 in the epoch following the presentation of the row or the column.

Four different algorithms were used to compute the scores: (a) stepwise linear discriminant analysis (SWDA), (b) peak picking, (c) area, and (d) covariance. We will briefly describe each of these algorithms. The interested reader can find detailed discussions of these procedures in Coles et al. (1986) and Donchin and Heffley (1976).

*(1) Stepwise discriminant analysis.* SWDA is a classification procedure. It yields a score that measures the 'distance' between each epoch and the mean of a group of trials known to include a P300. This score is obtained by applying a discriminant function to the data from each epoch. That function was developed on the basis of a 'training set' of trials recorded while the subject was focusing on the first 2 letters ('B' and 'R'). The remaining ERPs provided the 'analysis set.' We used the training set data to compute the discriminant function that distinguished between the 'attended' subtrials (600 msec following the flash of a row or column containing the attended cell) and the 'unattended' subtrials (600 msec following the flash of a row or column not containing the attended cell).

*(2) Peak picking.* The amplitude of P300 was computed as the difference between the lowest negative point prior to the P300 window (defined as the time range within which the average attended wave form in the training set for each subject was positive) and the highest positive point in the P300 window. The window for the P300 ranged typically between 220 and 500 msec.

*(3) Area.* The 'area' of P300 was calculated as the sum of the data points in the P300 window (as defined above).

*(4) Covariance.* A P300 template was computed as the average of the attended subtrials in the training set for each subject. P300 scores in the analysis set were derived by computing the covariance of each subtrial with this template. The covariance was computed using all of the points in the 600 msec epoch. (This is the detection procedure used in the first, pilot session.)

The values attained from the above analyses were then used to determine the letter upon which the subject was focusing attention. Row and column scores given by the respective algorithms were summed to compute a unique score for each cell in each pair of trials (1 trial in which rows were flashed and 1 trial in which columns were flashed). For example, the score for 'B,' which is located in the first column and the second row (see Fig. 1), was the sum of the score for the first column and the score for the second row. (By 'first' and 'second' here we refer to the spatial position in the matrix, and not the temporal position in the sequence of row or column flashes. Since flashes were in random order, the 'first' column would be flashed first about one-sixth of the time.)

The scores computed for each letter were summed across trials to determine which cell was identified as the cell selected by the subject. Each test could yield 1 correct response or 1 of 35 possible errors. The test was considered a 'hit' if the algorithm yielded the largest total score, summed across trials, for the letter on which the subject was focusing. For example, if the subject was attending to the letter 'B' and 6 trials were being considered in the analysis, a correct response would be achieved if the total of the 6 'B' scores — the scores for the rows and columns containing 'B' — was greater than the total of the 6 scores for any other cell in the matrix.

## Results

The principal aim was to determine the speed with which the letter on which the subject is focusing can be determined, given the detection technique employed for analyzing the trials. To accelerate the transmission rate, the ISI was shortened and the data-collection epochs were overlapped.

A rather distinct P300 is elicited by the attended letter, as can be seen in Fig. 3. This figure presents ERP responses to intensifications of attended, or correct, letters and of unattended letters, averaged across all trials for each subject. The amplitudes of the P300s for all subjects at both ISIs are presented in Table I [3].

[3] It is evident that in this presentation mode many ERP components are included in an overlapping fashion. Thus the time window we record may include many components in addition to the P300. However, this is not a matter of concern in the present context. As long as we discriminate the correct letter, we have achieved our purpose.

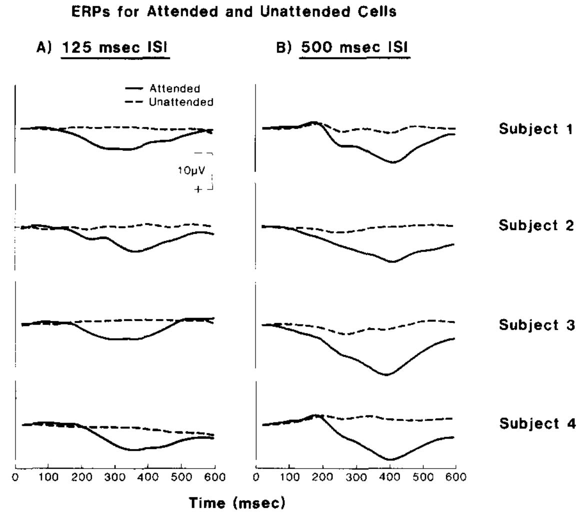


Fig. 3. Average wave forms for attended vs. unattended cells for each of the 4 subjects. A: 500 msec ISI. B: 125 msec ISI.

In the present context, however, the question is, how detectable would be the P300 elicited by a much smaller number of trials? More precisely, we try to estimate the degree to which signal averages based on sample size X will yield accurate detection of the attended letter. In other words, we had to estimate proportion of correct determinations for different sample sizes. We therefore examined the accuracy with which the attended letter could be detected as a function of the number of trials at each ISI for each of the 4 detection algorithms.

Detection accuracy was estimated by means of an iterative sampling technique akin to bootstrapping (Efron 1979). Bootstrapping provides an estimate of a parameter in the absence of adequate data on its sampling distribution by obtaining many random sub-samples from the available data and computing the parameter afresh for each of these sub-samples. The distribution of these values approximates the actual distribution.

We randomly chose 1000 sets of 2 trials, 1000 sets of 4 trials, and so on up to 1000 sets of 40 trials from the analysis set. (Recall that the analysis set consisted of 30 trials for each of 3 letters, a total of 90 trials.) We applied the 4 signal-detection algorithms, computed scores for each of the 36 stimuli, and determined how many times out of 1000 the stimulus that the subject was attending to

TABLE I

P300 amplitude ($\mu$V). Amplitude of the average P300 elicited by attended and unattended cells in the matrix, at 125 msec and 500 msec ISI. (A) Peak-to-peak amplitude; (B) base-to-peak amplitude.

| Subj. no. | ISI (msec) | (A) Peak to peak 125 Attended | 125 Unatten. | 500 Attended | 500 Unatten. | (B) Base to peak 125 Attended | 125 Unatten. | 500 Attended | 500 Unatten. |
|---|---|---|---|---|---|---|---|---|---|
| 1 | | 6.4 | 1.5 | 12.5 | 3.5 | 5.0 | 1.1 | 9.8 | 1.8 |
| 2 | | 7.6 | 0.9 | 10.1 | 1.7 | 5.9 | 0.1 | 8.6 | 1.1 |
| 3 | | 5.6 | 1.5 | 14.1 | 2.9 | 4.3 | 0.7 | 11.5 | 2.4 |
| 4 | | 8.1 | 2.6 | 14.2 | 2.9 | 7.2 | 2.4 | 11.1 | 1.3 |

was assigned the highest score. This analysis was repeated for each of the 4 algorithms.

Fig. 4 illustrates the iterative sampling analysis procedure. It presents the results of only *one* iteration in each of 2 specific cases. For illustrative purposes we have included 1 set of data where the discrimination between the attended and unattended stimuli is quite clear and another set

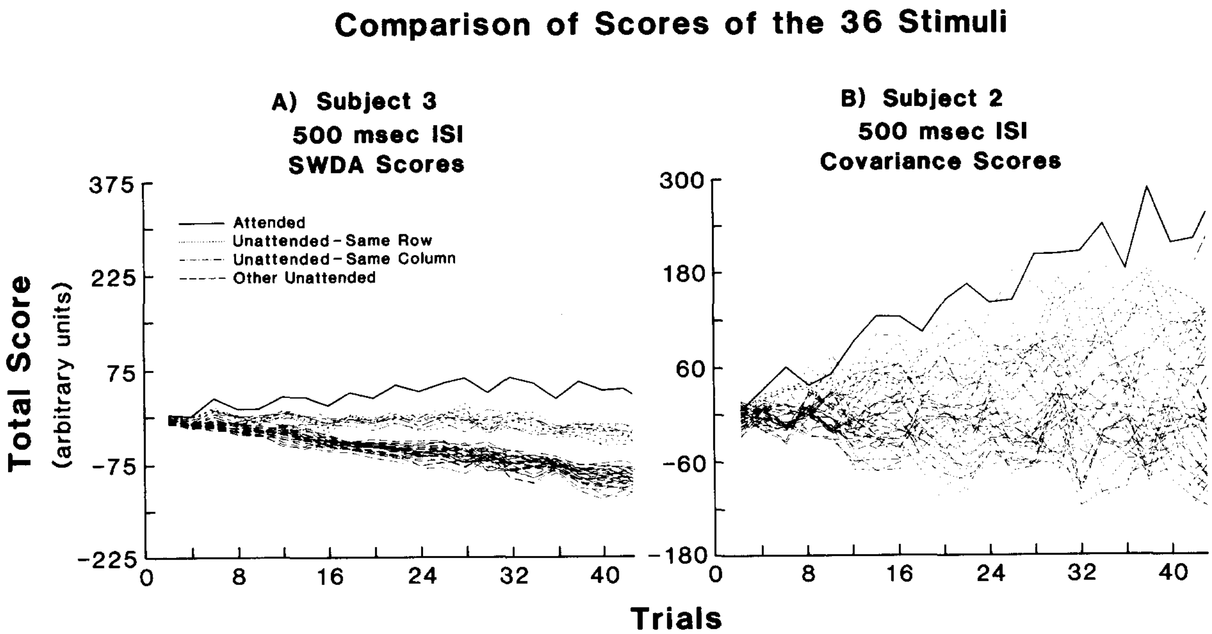


Fig. 4. Examples illustrating the comparison of scores generated by the analysis algorithms, with different numbers of trials included in the analysis. This figure provides an example of the data that went into the speed/accuracy calculations, and is provided for the sake of illustration. In this figure we plot (A) SWDA scores for subject 3 in the 500 msec ISI condition and (B) covariance scores for subject 2 in the 500 msec ISI condition. Each line represents the score obtained for 1 letter as sample size was varied systematically from 2 to 40 trials/sample. Scores fall into 3 groups: (1) the 'attended' subtrials (solid line), which begin with a flash of the attended letter (and its row or column); (2) 'unattended' subtrials that begin with the flash of a letter (and its row or column) that shares a row or a column with the attended letter (dotted and chained lines); and (3) other unattended subtrials (dashed line). A correct identification was made whenever the attended stimulus received the highest score. Note that this figure includes data from only *one* iteration of the analysis procedure, i.e., it represents only 1 random sample of each size and therefore includes only 1 score for each letter at each sample size. Speed/accuracy results (see Fig. 5) were obtained by repeating this sampling and analysis procedure 1000 times for each sample size and tallying the proportion of iterations in which the attended cell resulted in the highest score at each sample size. It can be seen that in these particular samples the attended cell did generally achieve the highest score. It can also be seen that there was considerable individual variability.

where the discrimination is much less clear. In each of these 2 figures we plot the scores assigned to each of the 36 letters by the application of 1 detection technique: (a) SWDA scores for subject 3 in the 500 msec ISI condition, and (b) covariance scores for subject 2 in the 500 msec ISI condition. We emphasize the illustrative purpose of this figure. Each plot in Fig. 4 displays the results of 1 out of 1000 separate iterations.

Each line in the figure is a plot of the scores assigned to one of the characters plotted against the size of the sample used for computing the score. The scores of each of the 36 characters at each sample size appear to fall in 3 groups: (1) 1 'attended' letter (solid line); (2) 10 unattended letters that share a row or a column with the attended letter — and therefore are flashed at the same time as the attended letter (dotted and chained lines); and (3) 25 other unattended letters — which are never flashed concurrently with the attended letter (dashed lines).

Note that the highest score was generally obtained for the attended cell. The scores for unattended cells that were in the same column or the same row with the attended cell are higher, in general, than the scores for the other unattended cells. The decision algorithm is, of course, 'correct' whenever the attended letter is assigned the highest score. It can be seen that this is generally the case, though there are differences among the subjects.

As we noted, the analysis procedure was repeated 1000 times for each combination of sample size (2–40 trials) and algorithm (SWDA, peak picking, area, and covariance), at each ISI (125 and 500 msec). In each of the 1000 iterations, for each sample size, we picked a new random sample of the trials for inclusion in the analysis. For a particular iteration, at any given sample size, each analysis procedure provided either a correct or an incorrect determination. We tallied the number of correct determinations for each sample size, for each subject, at each ISI, employing each analysis algorithm.

In Fig. 5 we plot the proportion of correct decisions out of the 1000 iterations of the procedure at each sample size. To allow comparison of the data obtained with the 2 ISIs, the accuracy data are plotted against the *time* required to present a given number of trials rather than against the number of trials. As can be seen in Fig. 5, subjects differ in their ability to use the system

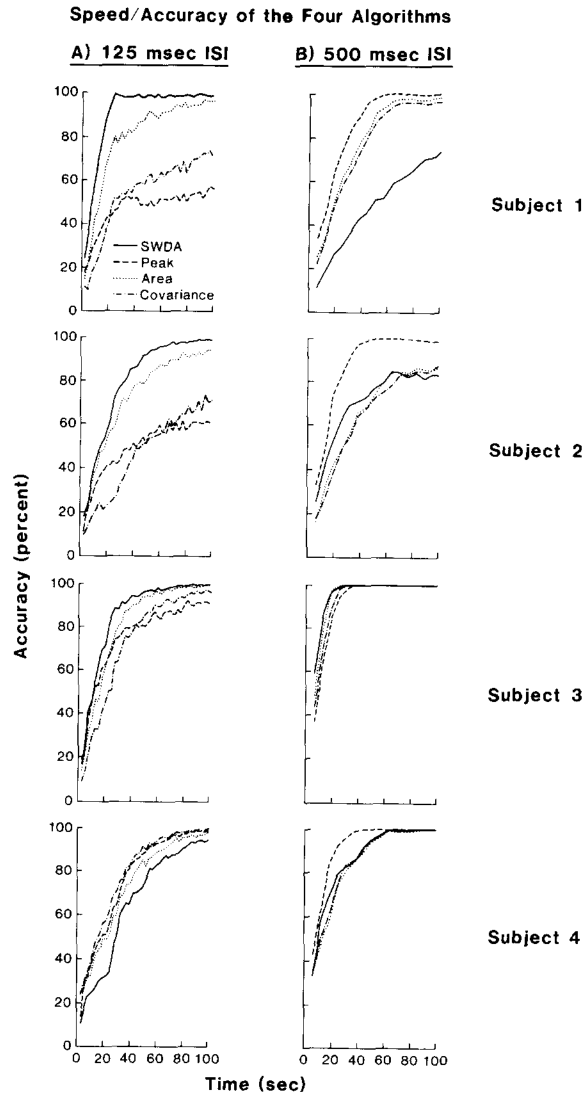


Fig. 5. Graphs of the accuracy of each of the 4 algorithms in identifying the attended stimulus, as a function of the number of trials cosidered in the analysis. Each of the graphs presents the increase in the accuracy of the algorithm as sample size increases. To facilitate the comparison of the 2 ISIs and the analysis of the speed of the system, the number of trials has been transformed to the time required to present the trials. Time is the product of the number of trials considered and the duration of a single trial (ITI). Accuracy is the percent of correct identifications of the attended cell out of 1000 iterations of 1 of the 4 algorithms.

TABLE II

Speed/accuracy: fastest algorithms. Times required to obtain (A) 80% and (B) 95% accuracy, by subject and ISI, using the fastest algorithm in each case. Accuracy is the percent of correct identifications of the attended cell out of 1000 iterations of the signal-detection algorithm. Time is the product of the number of trials considered and the duration of a single trial (ITI). (Times have been interpolated when the least number of trials required to reach 80% or 95% accuracy not only reached but in fact exceeded that level.) Times for the fastest combination of an algorithm and an ISI for each subject are followed by two asterisks ( * * ). Time in sec; ISI in msec.

| Subj. no. | ISI | (A) 80% accuracy | | | | (B) 95% accuracy | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 125 | | 500 | | 125 | | 500 | |
| | | Time | Algo. | Time | Algo. | Time | Algo. | Time | Algo. |
| 1 | | 15.7 * * | SWDA | 28.2 | Peak | 21.6 * * | SWDA | 42.5 | Peak |
| 2 | | 33.4 | SWDA | 23.3 * * | Peak | 57.5 | SWDA | 35.5 * * | Peak |
| 3 | | 22.3 | SWDA | 11.1 * * | SWDA | 46.4 | SWDA | 17.6 * * | SWDA |
| 4 | | 36.7 | Cov | 17.7 * * | Peak | 64.0 | Area | 29.3 * * | Peak |
| Mean | | | 27.0 | | 20.1 | | 47.4 | | 31.2 |
| Mean time to 80% accuracy, fastest ISI and algorithm for each subject | | | | | 20.9 | Mean time to 95% accuracy, fastest ISI and algorithm for each subject | | | 26.0 |

and in the relative effectiveness of the different detection algorithms. All subjects, however, were able to achieve a high level of accuracy in communicating their choices to the system at a speed of some seconds per choice.

Table II presents speed and accuracy figures for the fastest algorithm for each subject at each ISI. When the subjects' optimal ISIs and signal-detection algorithms were used, the mean time required to achieve 80% accuracy of determination of the 1 stimulus out of 36 that the subject was attending was 20.9 sec. For 95% accuracy, the mean time required was 26.0 sec. A choice of 1 out of 36 contains 5.2 bits of information, so the speed at 95% accuracy was 0.20 bits/sec, or 12.0 bits/min. By using the 'BKSP' (backspace) command (see Fig. 1) with the same speed and accuracy, a subject could correct errors and achieve over 99.9% accuracy with a speed of 0.18 bits/sec, or 10.8 bits/min.

SWDA and peak picking proved to be the most efficient algorithms. At 125 msec ISI, SWDA was the fastest algorithm to reach both 80% and 95% accuracy in 3 out of 4 cases. At 500 msec ISI, peak picking was fastest to reach both 80% and 95% accuracy in 3 out of 4 cases. (A possible explanation of this difference in algorithm effectiveness as a function of ISI is discussed below.) When considering the 4 subjects, 2 ISIs, and 2 accuracy criteria (80% and 95%), SWDA yielded the fastest times to reach the accuracy criterion in 8 cases out of 16, and peak picking in 6 cases. Area and covariance were each fastest in 1 case.

Table III shows the times taken by each of the 4 algorithms to reach 80% and 95% accuracy for each subject at each ISI. As shown in Tables II and III and Fig. 5, different signal-detection algorithms were more effective for different subjects. This is a result of differences in the characteristic ERPs for different subjects and differences in the information utilized by the algorithms.

## Discussion

This study addressed 2 distinct questions. We sought to determine if it is indeed the case that the P300 can be employed as a switch by means of which the subject can toggle a choice. This question is clearly answered in the affirmative. The specific arrangement used to present choices to the subject amplifies the power of the P300 to act as a binary switch, as the series of choices allows for the reliable identification of 1 choice among 36 distinct items. In principle, this method can be

TABLE III

Speed/accuracy: 4 algorithms. Times required to obtain (A) 80% and (B) 95% accuracy, by subject and ISI for the 4 signal-detection algorithms. Accuracy is the percent of correct determinations of the attended cell out of 1000 iterations of the algorithm. Time is the product of the number of trials considered and the duration of a single trial (ITI). (Times have been interpolated when the least number of trials required to reach 80% or 95% accuracy not only reached but in fact exceeded that level.) Times for the fastest algorithm at each ISI for each subject are followed by an asterisk (*). Times for the fastest combination of an algorithm and an ISI for each subject are followed by two asterisks (**). Cases where the algorithm did not result in 80% (A) or 95% (B) accuracy after 80 trials are indicated by 'X.'

| Subj. | (A) Time to 80% accuracy | | (B) Time to 95% accuracy | |
|---|---|---|---|---|
| no. | 125 msec ISI | 500 msec ISI | 125 msec ISI | 500 msec ISI |
| *Peak picking* | | | | |
| 1 | X | 28.2 * | X | 42.5 * |
| 2 | X | 23.3 ** | X | 35.5 ** |
| 3 | 39.8 | 17.3 | X | 26.0 |
| 4 | 38.8 | 17.7 ** | 70.4 | 29.3 ** |
| *SWDA* | | | | |
| 1 | 15.7 ** | 114.8 | 21.6 ** | 202.8 |
| 2 | 33.4 * | 56.9 | 57.5 * | X |
| 3 | 22.3 * | 11.1 ** | 46.4 | 17.6 ** |
| 4 | 54.4 | 26.7 | X | 49.5 |
| *Area* | | | | |
| 1 | 29.1 | 39.9 | 76.7 | 59.3 |
| 2 | 49.0 | 56.6 | X | X |
| 3 | 29.3 | 12.6 | 55.8 | 17.9 |
| 4 | 45.5 | 44.9 | 82.2 | 52.9 |
| *Covariance* | | | | |
| 1 | X | 42.9 | X | 62.4 |
| 2 | X | X | X | X |
| 3 | 41.8 | 15.5 | 82.2 | 22.6 |
| 4 | 36.7 | 28.6 | 64.0 | 52.0 |

used in a manner that would allow for a choice among more items, as the number of rows and columns can be increased. However, such an increase would entail a cost in that the total number of flashes required for each choice would be increased. The optimal size of the matrix remains a matter for further investigation.

The answer to this first question was not entirely surprising. There is by now an extensive literature that establishes the reliability with which the P300 is elicited by rare, task-relevant events within the framework of the oddball paradigm. It is quite clear that almost any arrangement that would impose a categorization on a series of events, however abstract the categorization, can be used to elicit sizeable P300s, provided that the 2 categories are presented in a Bernoulli sequence, that the stimuli play an important role in the subject's information processing, and that one of the categories occurs with a somewhat lower frequency (see Fabiani et al. 1988, for a discussion of the varieties of the oddball paradigm). The use of very short ISIs — considerably shorter than the latency of P300 — did not interfere in any significant manner with elicitation of the P300 in the oddball paradigm. Our data thus confirm that the P300 can be used as a communication channel by taking advantage how it responds to task-relevant events in the oddball paradigm, as used in the arrangement described above.

There is, however, a second question the answer to which was by no means self-evident. The utility of a communication channel based on the P300 depends, as do all communication channels, on the signal-to-noise ratio. It is evident that the P300 on which this channel is based is buried in the 'polyneural roar of the EEG,' to use Ross Adey's felicitous phrase. The detection and measurement of the P300, as is true for other ERP components, requires signal averaging. Thus, it was conceivable that while the P300 can in principle serve as a switch, its reliability under usual signal-to-noise conditions would have been insufficient for actual use. Our main purpose in this study, then, was to examine the operating characteristics of the communication channel.

The prime task of the channel is to communicate the choice the subject has made among the 36 options. Thus, the performance index for the channel is the accuracy with which this choice is communicated as a function of the speed with which the channel operates. The speed is controlled by the rate at which the stimuli are presented. The accuracy is controlled by the efficiency of the signal-to-noise reduction achieved by the detection algorithms. It is for this reason that we used as independent variables the inter-stimulus interval within each trial and the various detection procedures.

The conclusions are quite clear. The channel can operate reasonably well at the speed of 12 bits/min. A character, chosen from among 36 items, can be detected with 95% accuracy within 26 sec.

The inter-stimulus interval proves to be an important variable. To obtain accurate discrimination of the attended stimulus, a certain signal-to-noise reduction is required. This can be achieved by increasing the interval between stimuli from 125 to 500 msec, allowing for a better definition of the P300. Alternatively, the signal-to-noise reduction can be achieved by an increase in the number of trials. Which of these methods is more effective depends on the subject and the signal detection algorithm.

The results show that different detection methods varied in their effectiveness when applied to the data of the different subjects. The differences in effectiveness are due to an interaction between the nature of the procedures and the specific attributes of the subject's data. It is useful to consider the differences among the detection algorithms.

*Comparison of the different algorithms*

Covariance computes, essentially, how similar the individual ERPs are to a template consisting of the average wave form for the attended cell in the training set. All time points are included, and each point is weighted according to the mean amplitude of that point in the training set.

SWDA involves much more extensive computations on the training set data than covariance, but it is in general more efficient because it gives greater weight to time points that were more effective in distinguishing between attended and unattended cells in the training set.

The primary weakness of both SWDA and covariance is that they are sensitive to latency variability. If an ERP component, such as P300, appears in a given trial with longer or shorter latency than the modal latency in the training set, then the discriminant weights (or, similarly, the weights in the covariance algorithm) will not be applied to the points that best characterize the P300, and accuracy will be lost. Latency jitter during the training set, also, will add noise to the system and result in less effective weights.

Peak picking, on the other hand, is not sensitive to latency variability. The P300 peak can be located anywhere in a relatively wide time window. All of the information contained in the other points, however, is lost in this procedure. Moreover, at a short ISI, insensitivity to latency variability becomes a weakness instead of a strength. Since the peak picking algorithm locates a maximum value at any point within a considerable range, it is susceptible to falsely attributing a P300 peak generated by a previous or subsequent flash to the stimulus being considered. This fact undoubtedly accounts for a large part of the interaction between algorithm and ISI shown in Tables II and III, where peak was the most accurate algorithm at 500 msec ISI and one of the least accurate at 125 msec ISI.

The area analysis algorithm, like the covariance algorithm, considers all of the points in a broad range, but it is a purely additive, rather than multiplicative, procedure and does not use a training set. Therefore it misses some information contained in a consistent distinctive ERP shape and time course but also avoids some of the noise introduced into SWDA and covariance by variability in the time course and shape of ERPs. It takes advantage of information contained in a broad flat ERP that is lost in the peak picking algorithm, but by the same token it is influenced by noise at points at a distance from the peak.

Because of these differences, different algorithms are more effective in different cases. For a subject whose P300s have a distinct peak with considerable latency variability, peak picking is likely to be the most efficient algorithm, at least when a relatively long ISI is used. For a subject whose ERPs have a distinctive shape and little latency variability, SWDA is likely to be the most efficient. For a subject whose P300s tend to be broad and flat, without much of a peak and with considerable latency variability, the area measure is likely to be the most effective. In a clinical application, data such as those reported here could be collected and analyzed, and the optimal algorithm and timing parameters for the individual could be determined and utilized for real-time signal detection.

*Conclusions, applications, and potential improvements*

The above differences notwithstanding, the general conclusion is sustained by the data. It is quite possible to use the P300 as an effective communication switch, and the communication channel can be organized so that the choices can be communicated using a relatively small number of trials. We can assume for the rest of this discussion that the characters can be communicated with reliability at the rate of 1 character every 26 sec, or 2.3 characters/min.

This is, of course, rather a low rate for a communication channel. Even a slow typist can type 150 characters/min. Voice communication is even faster. However, it is equally clear that when no other channel is available because the skeletal musculature is completely disabled, the ability to communicate even at the rate of a few characters/min would be most welcome.

The value of the P300 channel may be further enhanced if the procedure is used as a method for choosing from a menu of commands rather than as a method for spelling words. The elements in the matrix may well be words such as 'nurse,' 'water,' 'pain,' or 'dinner.' Each of these choices may in turn call for another menu. In such a paradigm the rate of communication would be enormously amplified, even though the domain of the communication would be constricted. Furthermore, the communication speed we have assessed in this study examined the channel without any attempt to benefit from a number of obvious procedures for accelerating the communication. As a computing device must be a part of the system, it is relatively trivial to incorporate in the channel the known constraints of the language. With each letter presented the number of actual options is reduced, as combinations of characters appear with quite uneven probabilities in English. The system may be allowed to 'guess' to that, for example, having detected a 'TH' pair it is relatively certain that the following character will be one of the vowels.

It may also be possible to enhance the speed of the system by incorporating additional components of the ERP. If, for example, we were to present the rows and columns in a regular sequence, one would expect to see a CNV develop as the time for the appearance of the correct column, or row, neared. The relative effectiveness of a random presentation utilizing the P300 solely and a presentation that capitalized on both a CNV and the P300 is a matter for further research.

We are well aware that the application of this system in a clinical context will present severe logistical problems that do not arise when we test young, healthy adults. In one preliminary test we conducted with 1 locked-in patient, we discovered that it was necessary to add a differential amplifier that subtracted electrical activity generated by his continual involuntary eye movements from the EEG before the patient could use the system. It is clearly necessary to examine the effectiveness of the system we propose with patients as subjects.

The procedures we describe in this paper and the data we adduce serve to illustrate the feasibility and the limitations of the 'biocybernetic' concept. The term 'biocybernetics' has been used to describe an attempt sponsored during the 1970s to develop a 'biocybernetic' channel. That channel was intended to enhance the communication between people and machines by adding channels of communication that employed psychophysiological mechanisms. Several appraoches were proposed (Gomer et al. 1979). There were several attempts to use the ERP as a switch. Vidal and his associates have, for example, used the differences between responses to different checkerboards which flashed on different parts of the screen to create an EEG-driven joystick that controlled the movements of a displayed 'mouse' (Hickman and Vidal 1976). Donchin and his colleagues, within the framework of the biocybernetic program and in subsequent work, used the P300 as an index of mental workload (Donchin et al. 1986b for a review). In the assessment of workload, however, the P300 is used as a metric rather than as a switch.

A caveat may be in order. The biocybernetic concept has often been mistaken, especially in the popular press, as an attempt to use the computer to 'read the mind' of a subject. Here, too, it is possible to be deceived by the appearance of a subject 'writing to the screen' or 'speaking through the computer' with the brain waves. One may be tempted to see this as a direct communication between the computer and the mind that somehow bypasses the control that people have over the inner workings of their minds. Such an innovation would be treated with dismay by many, and with glee by some. We emphasize that this paper does not report the development of a means by which one can eavesdrop on the mind (Donchin 1987).

The procedure we describe above accomplishes no more than to provide the subject with a switch that can be wielded at the subject's discretion. The recording would be of no use whatsoever if the subject chose to ignore our instructions and to focus attention elsewhere. Furthermore, the probes we attach to the head record signals that can be interpreted solely within the framework of the stimulus arangement we have provided. Thus, there is no more 'mind reading' in the procedures we describe than there is when a person is handed a pencil and asked to record impressions. The contents, and the reliability, of the information obtained will depend to a degree on the sharpness of the pencil; but the subject's willingness to report and the accuracy of these reports will be the factors that ultimately determine the utility of the communication. We report here that the P300 can serve as a pencil, and that the pencil is actually rather sharp. The mind, however, retains control over the use of the pencil.

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