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FEASIBILITY STUDY FOR DESIGN OF A BIOCYBERNETIC COMMUNICATION SYSTEM

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FEASIBILITY STUDY FOR DESIGN OF A BIOCYBERNETIC COMMUNICATION SYSTEM

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SUMMARY

The objective of this research is to test the feasibility of designing a close-coupled, two-way communication link between man and computer using biological information. The research plan is to conduct experiments to determine whether biological information from the central nervous system and muscles of portions of the vocal apparatus can be directly related to thought processes; whether this information can be recognized by a computer; and whether the biological processes (representing a particular thought) can be induced in a human user. Should such a close-coupling between man and machine prove to be feasible, an individual using such a biocybernetic communication system would be able to "talk" (i.e., both send and receive) with a computer at the speed of thought, rather than be limited by the speed of a teletype or other electromechanical device through which ideas in the form of questions and answers must normally pass.

The research plan was predicated on existing evidence that verbal ideas or thinking are subvocally represented in the facial muscles of the vocal apparatus (see Introduction, p. 4 , for details). If the patterns of this muscle activity are at all similar to those involved in normal overt speech, then it is reasonable to assume that the electrical activity of the brain during covert speech (verbal thinking) may be similar to that during overt speech. The objective of the first year of research was to establish the validity of this basic premise.

The general methodology was to record the electromyograph (EMG) of facial muscles involved in speech from volunteer human subjects during performance of language tasks. The electroencephalograph (EEG) from scalp electrodes overlying areas of the cerebral cortex involved in speech was recorded simultaneously (see Methods, p. 7 , for details). The resulting analog data were then digitized for computer processing, and several statistics that reveal patterns of cortical activity were calculated. These statistics were then used in a computer pattern recognition program designed to identify features in the physiological data associated with specific words, whether overtly or covertly produced.

This report describes results of computer analysis of EMG and EEG recordings from each of three subjects during performance of a language task on two separate occasions. The purpose was to determine whether the computer could correctly classify 15 overtly spoken English words based on the EMG and EEG electrophysiological patterns alone. Several statistics were later applied to the EMG and EEG responses that were coincident with the 15 word utterances (each repeated ten times at each of the two sessions), but only one statistic was found useful for successful pattern recognition. This was based on calculating an average response

for each electrode for the period three seconds before and three seconds after the onset of vocalization of a word. Each of the 15 average responses per electrode (six electrodes, or 90 average responses for the 15 words per subject per session) then served as a template against which individual responses were compared. These comparisons were made by calculating the RMS (root-mean-square) difference between a single response of each electrode and the 15 word templates for that electrode. The individual electrode response was then classified as the word for that template with which the RMS difference was a minimum (see the Appendix for details of mathematics).

The significant results were:

(1) Both EMG and EEG responses, taken separately or together, were used to classify any one or all of the 15 overtly spoken words. The percentage of correct classifications for all electrodes of the three subjects for two sessions each ranged from 9% to 84%.

(2) Out of 900 possible correct classifications across all subjects and sessions, 74% of the words were correctly classified by EMG responses alone, 63% by EMG plus all EEG responses, and 34% by EEG responses alone (see Table 6, p. 34 , for details). Chi square tests of significance showed that these correct classifications could have occurred by chance with a probability of less than 1 in 1000.

(3) Reliability within each subject from one session to the other was high. Templates for one session of a given subject could serve to correctly classify words based on EMG and EEG responses of the other session nearly as well as templates within a session. In addition, a higher rate of correct classifications was made on the second session for all three subjects than on the first, indicating a learning or habituation effect that lowered response variability.

(4) When templates of one subject were used to classify words based on individual responses of another subject, the percentage of correct classifications for EEG responses was no greater than chance expectation. The percentage of correct classifications for EMG was greater than chance, but not nearly so good as within subjects. Thus, it appears that each subject's biological patterns associated with speech are unique.

(5) Six possible sources of error in word classification were identified, and their relative contribution to decreased success was evaluated. It was determined that if all sources of error could be eliminated, significant gains in correct word classification using biological responses would be achieved (perhaps approaching 90% or better).

We conclude that it is <u>feasible</u> for a human verbally to communicate overtly with a computer using biological information alone, with a high degree of accuracy and reliability, at least with a small vocabulary. During the next year attempts will be made to eliminate all sources of error, to determine the optimum locations for EEG recording, and to communicate (i.e., recognize signals) with the computer during silent speech (verbal thinking) using biological information alone.

INTRODUCTION

Our approach is predicated on previous research conducted by the authors and others in the areas of psychophysiological measures of thought, computer processing of electrophysiological information, and development of computer pattern recognition techniques. This research is summarized below (see SRI Proposal LSU 71-145, dated 10 December 1971, for details).

Early work by Watson (1930) indicated that verbal cognitive processes may be represented in muscle activity of the vocal apparatus as subvocal speech. McGuigan (1970), reviewing studies of such covert oral behavior during the silent performance of a language task, concluded that covert oral behavior (as measured by the electromyograph, or EMG) increases significantly in amount and frequency of occurrence, compared with when the subject is not performing a silent language task. Thus, verbal ideas, or thinking, although unquestionably a central nervous system process (MacNeilage and MacNeilage, 1971), has some sort of peripheral representation in the muscles of the vocal apparatus.

If the patterns of this muscle activity are at all similar to those involved in normal overt speech, then it is reasonable to assume that the electrical activity of the brain during covert speech, or thinking, may be similar to that during overt speech. That is, a measure of the scalp-recorded electroencephalograph (EEG) of a human during verbal thinking should be similar to the EEG of the same individual when expressing the same thoughts vocally.

However, previous examination of the "raw" EEG has not revealed any obvious pattern related to overt or covert speech; it may be that only patterns of EEG activity between various areas of the brain at a given moment are related to speech. Several technical advances made in recent years have provided us with some tools to deal with this possibility. Most important is the use of computer techniques for frequency analysis of the real-time EEG and the development of multivariate statistical procedures (Donchin and Lindsley, 1966; John et al., 1964; and Rose and Lindsley, 1965). These procedures allow comparison of specific components of EEG waveforms that are known to reflect different neurophysiological processes. In addition, certain statistics, such as auto- and cross-spectral frequency analysis (Walter, 1963; Walter and Adey, 1965), the linear coherence function (Adey, Kado, and Walter, 1967), and the weighted-average coherence (Galbraith, 1967), may be used to determine the degree of interaction between two different brain regions. Thus, with these tools, the EEG waveforms from several areas of the brain that are neurophysiologically related to speech may be examined to determine whether their patterns of interaction are similar during overt speech and verbal thinking.

A thorough visual analysis of the statistical results of these EEG waveforms would be extremely complicated and time-consuming. Therefore, we have turned to machine pattern recognition techniques to analyze the patterns of the EEG interrelationships to be found in the average responses, cross-spectra, and coherence functions related to covert and overt speech. Most useful for this feasibility study are techniques for on-line pattern recognition (Hall et al., 1968). These techniques allow the user to process multivariate data by using all reasonably conceivable graphic plots, and manipulate the data further using appropriate numeric procedures available in the computer system. Thus, for our purposes, a set of statistics such as the average responses, coherence functions of the EEG, the patterns of the EMG changes with overt speech, and other measures may be plotted as a function of each other for specific covert language tasks (i.e., thinking).

The objective of the first year of this feasibility study was to establish the validity of the basic premise that patterns of biological information can be related to language behavior. This has been accomplished by:

(1) Measurement of EMGs of the vocal apparatus and EEGs overlying cerebral areas involved in speech during overt and covert language tasks.

(2) Computer processing and analysis of the averaged biological activity, the cross- and auto-spectra, coherence, and weighted-average coherence of the EEG and EMG as related to speech.

(3) Application of computer pattern recognition techniques to determine if the statistical patterns of biological activity from the EMGs and EEGs are similar during overt and covert speech, and to attempt to machine-identify silent language performance with the best pattern recognition method.

During the first year two experiments were conducted, designated Group I and Group II. A complete description of the methods and results for Group I data and preliminary results for Group II data were given in the First Semi-Annual Technical Progress Report, dated October 1972. This report describes details of the computer analyses of Group II data. To place the Group II results in perspective, a summary of the results from Group I follows.

In the first experiment (Group I data), EMG and EEG records were obtained during performance of a language task under various conditions of stimulus presentation, including: visual presentation, overt response; visual presentation, covert response (silent reading); auditory presentation, eyes open, overt response; and auditory presentation, eyes closed, overt response. (The last two conditions were chosen because the EEG is characteristically different when the eyes are open compared with closed.) The language task, recommended by a psychophysiological linguist consultant, consisted of words and sentences most likely to reveal patterns in the EMG during speech. In the second experiment (Group II data), similar records were obtained, but under slightly different stimulus conditions and with 20 repetitions per subject for reliability tests. These conditions included visual presentation with overt response of five selected monosyllabic words, and five bisyllabic words, with the accent on the first syllable and then on the second (to compare effects caused by ordering the emphasis), for a total of 15 words.

Significant results of the Group I data and preliminary analysis of the Group II data were:

(1) EMG patterns for each word were specific for that word.

(2) EMG patterns for a given word were consistent, showing less within subject variability than between subject variability.

(3) Averaged EMG patterns for a given word spoken by a given individual were sufficiently consistent for that averaged EMG to serve as a template for identifying the same word when it was imbedded in a sentence.

(4) There was some variability in EMG patterns for bisyllabic words between accent on the first or second syllable, but it was sufficiently small so that either pattern could be used visually to identify the same unaccented word imbedded in a sentence.

(5) The pattern recognition analysis carried out on the Group I data distinguished words beginning with "H" from all other words.

Thus, the results from Group I data and the results from Group II data before computer analysis showed that the EMG may be used to identify specific overtly spoken words of a given individual. The results also implied that patterns of EEG activity associated with these words may be used to identify the same word when covertly produced (as in verbal thinking).

METHODS FOR GROUP II EXPERIMENT

Subjects

Subjects were three adult, right-handed, human female volunteers, ages 21-41, hereinafter designated B, C, and D. A total of six experimental sessions, each of about 2½ hours duration, were all carried out using the same experimental paradigm. A given session for a given S is identified by the S's letter code and her chronological session; thus C5 was the fifth experimental session for subject C. Before conducting these sessions, several apparatus debugging sessions were carried out with a fourth S, A.

Apparatus

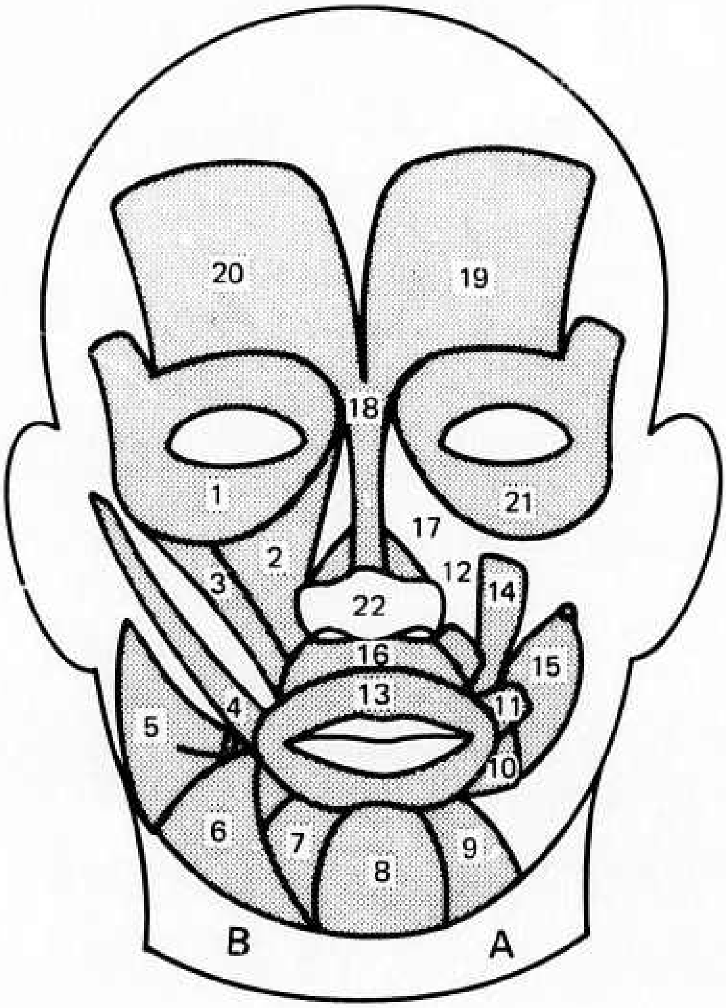
Electrodes and Electrode Placements

For surface recording of the EMG from facial muscles involved in speech production, Beckman silver, silver-chloride miniature disk skin electrodes (2-mm exposed) were used. EEG scalp electrodes, reference electrodes, and the ground electrode were Beckman silver, silver-chloride standard disk skin electrodes (8-mm exposed). Two reference sites were employed--the skin under the left mastoid for EMG recordings and the skin under the right mastoid for EEG recordings. All recordings were monopolar to record absolute potentials at the recording site.

Selected skin areas were first cleaned with acetone (alcohol on the face), then conditioned with Redox electrode paste by rubbing it into the skin, and followed by a second cleaning with acetone. A conductive, paste-filled electrode was then placed over each recording area and attached by a sticky collar to the underlying skin. Following a recording session, electrodes were removed, and the skin was cleaned with acetone or alcohol.

Figure 1 shows the facial musculature. Muscles involved in vocalization that are surface-recordable are 2, 3, 4, 6, 7, 8, 9, 10, 11, 13, and 16. Each of these locations was tested during preliminary experiments. In Experiment 1, combined sites 13/16 and 7/8 were found to produce the most reliable integrated EMG patterns during overt speech and so were used for collecting Group II data.

Figure 2 illustrates the 10/20 system of EEG recording (Penfield and Jasper, 1954). Locations F7, anterior C5, T5 and T6 were used for Group II. Three of these placements overlie areas thought to be involved in speech (Penfield and Roberts, 1959), as follows: F7, Broca's



1. Orbicularis oculi m. (right)
2. Quadratus labii superioris m. (right)
3. Zygomatic head of quadratus labii superioris m. (right)
4. Zygomaticus m. (right)
5. Risorius m. (right, cut)
6. Triangularis m. (right)
7. Quadratus labii inferioris m. (right)
8. Mentalis m.
9. Quadratus labii inferioris m. (left)
10. Triangularis m. (left, cut)
11. Zygomaticus m. (left, cut)
12. Quadratus labii superioris m. (left, cut)
13. Orbicularis oris m.
14. Caninus m. (left)
15. Buccinator m. (left)
16. Depressor septi nasi m.
17. Nasalis m. (left)
18. Procerus m.
19. Frontalis m. (left)
20. Frontalis m. (right)
21. Orbicularis oculi m. (left)
22. Nasalis m. (right)

FIGURE 1 MUSCLES OF THE FACE (AFTER VAN RIPER AND IRWIN, 1958)

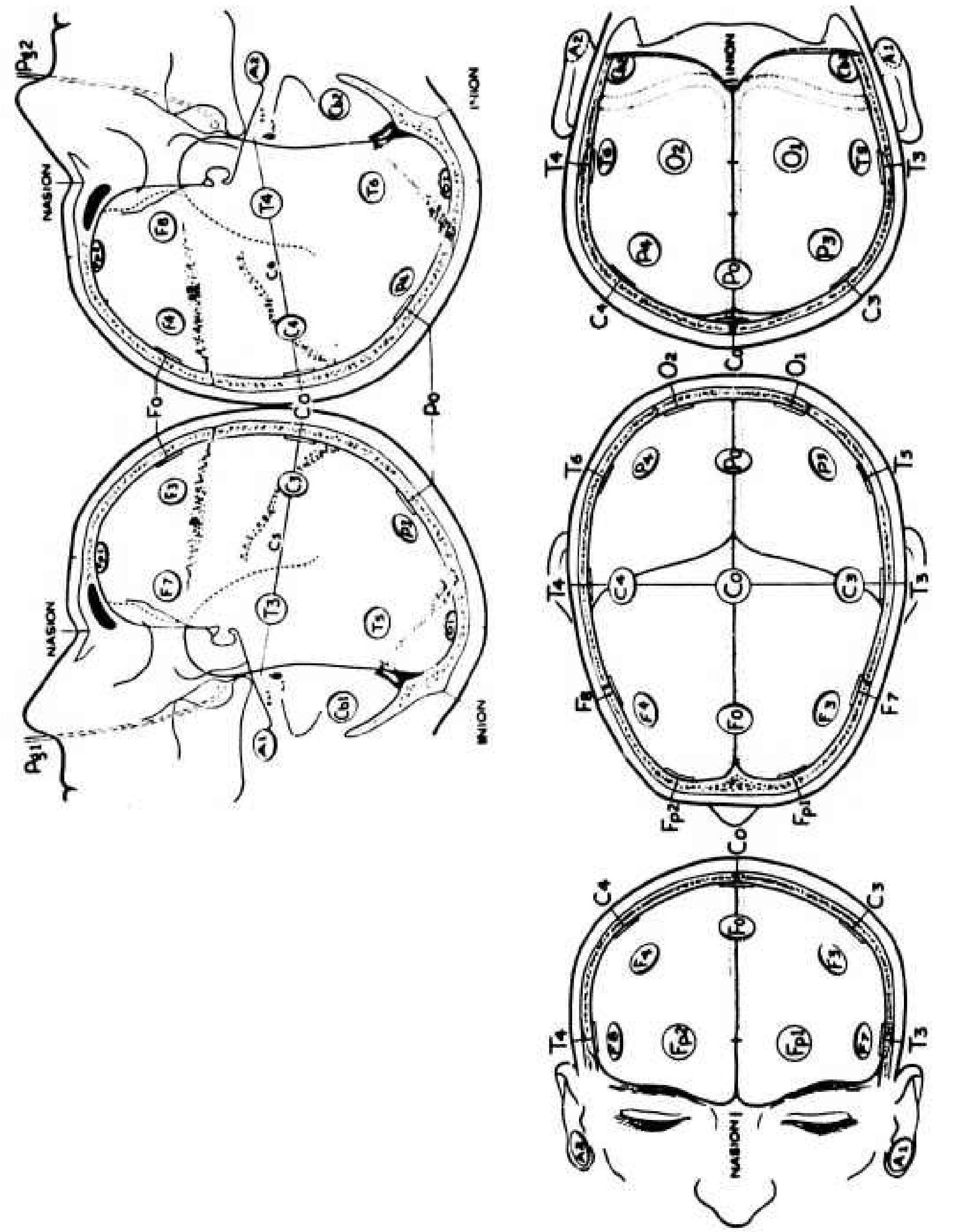


FIGURE 2 ELECTRODE PLACEMENTS FOR 10/20 METHOD OF EEG RECORDING (AFTER PENFIELD AND JASPER, 1954)

speech area; anterior C5, motor control of vocal musculature; and T5, Wierneki's area for speech organization and comprehension. In addition, location T6 on the right (nondominant) hemisphere, the homologue of T5 over the dominant hemisphere, was employed as a control.

After electrodes were attached, Ss were seated in a semi-dark, electrically shielded booth. All electrodes were plugged into a junction box leading to the recording equipment. Electrode resistances were checked; if any one electrode was found to be greater than 5000 ohms, it was removed, the skin further cleaned and conditioned, and the electrode replaced. When all electrodes checked correctly, the S was instructed in the experimental procedure, a microphone for recording speech as placed in front of the S's mouth, and the recording session begun.

Equipment

Figure 3 shows a diagram of the equipment setup. Electrodes from the facial musculature were led first to a Beckman Model 9852A EMG integrator coupler, with a fixed time constant of 0.25 sec, and pass band of 20 to 5000 Hz. For Group II, channels 1 and 2 of the Dynograph were used to record the integrated EMG. EEG electrodes were led to Beckman type 9806A couplers, within the pass band set to 2 to 22 Hz. flat; channels 3, 4, 5, and 6 recorded the instantaneous EEG. Channel 7 recorded the voice output of the microphone; channel 8 was not used. Amplitude normalization was carried out by setting all like channels (EMG or EEG) to the same gain.

All physiological signals were preamplified by Beckman Model 481B preamplifiers, and were then led in parallel to Beckman Model 482A power amplifiers with calibrated zero suppression and to an Ampex SP-300, seven-channel, analog instrument tape recorder. The output of the Beckman power amplifiers drove ink-writing galvanometers on chart paper moving at 25 mm/sec. The output on the chart paper could be set by a switch to record either the input to the Ampex tape recorder (i.e., "direct" recording) or the output of the Ampex; this feature enables the investigator to calibrate and monitor the permanent tape recording. EMG and EEG recordings were on channels 1 through 6 of the Ampex, using frequency modulation, at 1-7/8 in./sec (pass band dc-312 Hz.); voice was recorded on channel 7.

Group II data filled one 10-½-in. Ampex tape with analog data. These data were then sent through the data analysis system using the Linc-8 laboratory instrument computer and a CDC-6400 computer (see Data Analysis section below).

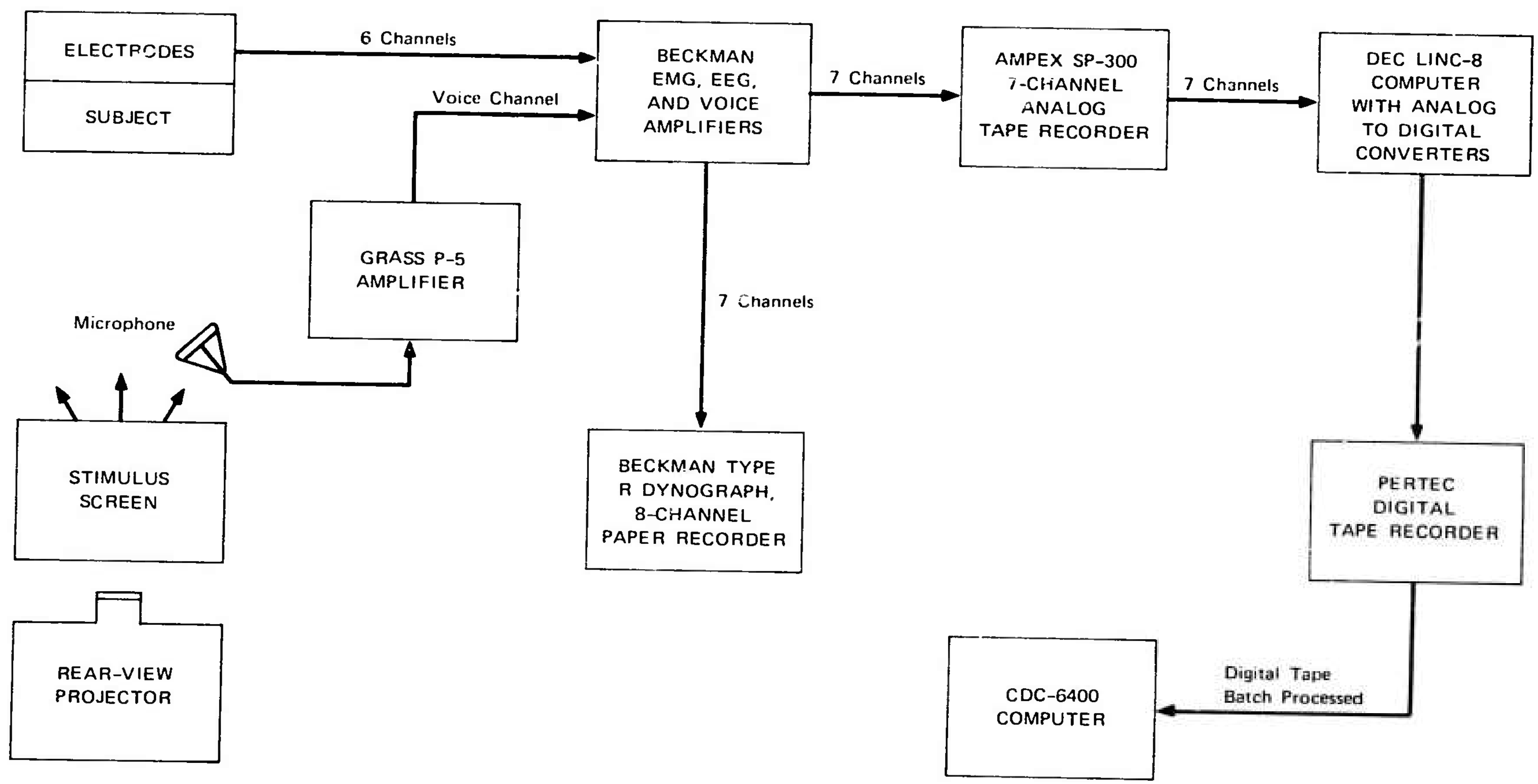


FIGURE 3 BLOCK DIAGRAM OF STIMULUS RECORDING AND DATA PROCESSING EQUIPMENT

Procedure

Language Task

On the basis of results from Group I data, 15 words were selected which had the greatest likelihood of reproducing reliable EMG patterns. The 15 words and a sentence containing all the words, which are shown in Table 1, consisted of five monosyllabic and five bisyllabic words. The latter are phonetically balanced words used in two groups; one group has the accent on the first syllable, and the other group has the accent on the second syllable. These 15 words were chosen to emphasize rounded lips, spreading lips, bilabials, and open lips in the case of the monosyllabic words, and to assess the effect of emphasis (pre- and post-) of one syllable on the other in the case of the bisyllabic words. No covert responses were obtained with Group II data.

Stimulus Presentation

Each of the individual words and the sentence in Table 1 was printed on a 35-mm slide (white on black to reduce glare) and presented to the S by projecting the word (or sentence) on a rear projection screen about 3 ft from the S's eyes. The subtended visual angle of the stimulus and its intensity in the semi-darkened room were chosen to avoid squinting, glare, or eye strain and to reduce eye movements.

After installation in the recording chamber, the S was instructed that she was to relax with eyes closed while the polygraph and tape recorder gains and filters were adjusted for proper EMG and EEG recordings. During that period, the S was to say her name when asked (to calibrate EMG gains and the voice channel) and to open or close her eyes when asked (to check for alpha in the closed-eyes EEG and alpha blocking, or desynchronization, with the eyes open and to check for eye movement artifact). Following these adjustments, the S was told that she would be presented with a list of 15 words, one at a time, for ten full presentations, plus one sentence at the end of each word list. The presentations would be visual. (The S was shown a test word on the screen as an example.) The S was to sit relaxed with her eyes closed. On hearing the statement "ready" from the experimenter, she was to open her eyes and look at the screen. In 2-3 sec. a stimulus word would be projected on the screen for about 3 sec, during which time she was to read the word aloud into the microphone. When the projected word was turned off, she was to close her eyes until the next word was presented, and wait until the next "ready" signal.

At the end of the 15 words (presented randomly to obviate any anticipatory effects in the EMG and EEG), the sentence was presented to the subject. On the signal "ready," the S was to open her eyes and look at the screen. When the sentence appeared, she was to read it aloud at her natural speed. The 15 words plus a sentence were then presented again; a total of ten such presentations were given each S per session.

Table 1

LANGUAGE TASK FOR GROUP II DATA

Monosyllabic	Bisyllabic	
	Accent First Syllable	Accent Second Syllable
TIP	BLACKBOARD	BLACKBOARD
HIT	SCHOOLBOY	SCHOOLBOY
HAD	COUGHDROP	COUGHDROP
PUT	SHIPWRECK	SHIPWRECK
COOL	MOUSETRAP	MOUSETRAP

Sentence:

THE SHIPWRECKED SCHOOLBOY HAD PUT A COOL COUGHDROP IN THE MOUSETRAP AND AIMED IT TO HIT AND TIP OVER THE BLACKBOARD.

Each of the three Ss was run a second time not less than one week nor more than one month following the first session. This set of measurements was recorded exactly the same as the first, and was run to determine within S reliability. Thus Group II data are based on six electrodes per S, for three Ss, two sessions each, where each session consisted of ten repetitions of 15 words and one sentence. This resulted in a total of 5400 electrophysiological responses (6 X 3 X 2 X 10 X 15) of 6 sec each (this total does not reflect analysis of the sentences, which has not yet been completed and will be described in a later report).

Data Analysis

Editing and Digitizing

As noted in the First Semi-Annual Technical Progress Report, editing and digitizing of the Group II data for the CDC-6400 computer processing was delayed while waiting for installation of a Pertec digital recorder. When this was received in early December 1972, a Linc-8 program written for this purpose, was used to edit and digitize the analog data.

A synchronization signal on channel 7 (voice channel) of the Ampex analog recorder, which preceded each stimulus presentation, caused the Linc-8 to begin sampling the six channels of data and the voice channel through analog-to-digital converters. A total of 7 sec of data were sampled at 42 samples/sec for each of the seven channels. The 7th sec of data was collected for time justification of the electrophysiological response as described below. The data were stored in memory, and on command any two of the six data channels or the voice channel could be displayed on a two-channel, cathode-ray oscilloscope driven by the computer. The display itself consisted of 6 sec of data, or 256 data points. In addition, the scope displayed a vertical cursor that was exactly centered to represent a zero point for time justification of the electrophysiological response.

Figure 4 illustrates the seven-channel dynograph recording of the EMG and EEG for one presentation of the word "COOL." Note the cursor line at the onset of vocalization (channel 7) which was used to time-justify all electrode responses. Any two of these channels could be displayed on the Linc-scope, as shown in Figure 5. In Figure 5A, an EMG response is shown on the top channel; the voice voltage and the centered cursor are shown on the second channel. Note that the vocal onset is off-centered on the scope, indicating that this particular response was not time justified for vocalization to occur at exactly 3 sec from the onset of the display. By use of a second Linc-8 command, all six channels of data and the voice channel could be rotated simultaneously into and out of memory with the extra 7th sec to place the onset of vocalization at any desired point. This feature was used to shift the data and voice channels (to the left in this case) so that the onset of vocalization occurred at the centered, 3 sec cursor, as shown

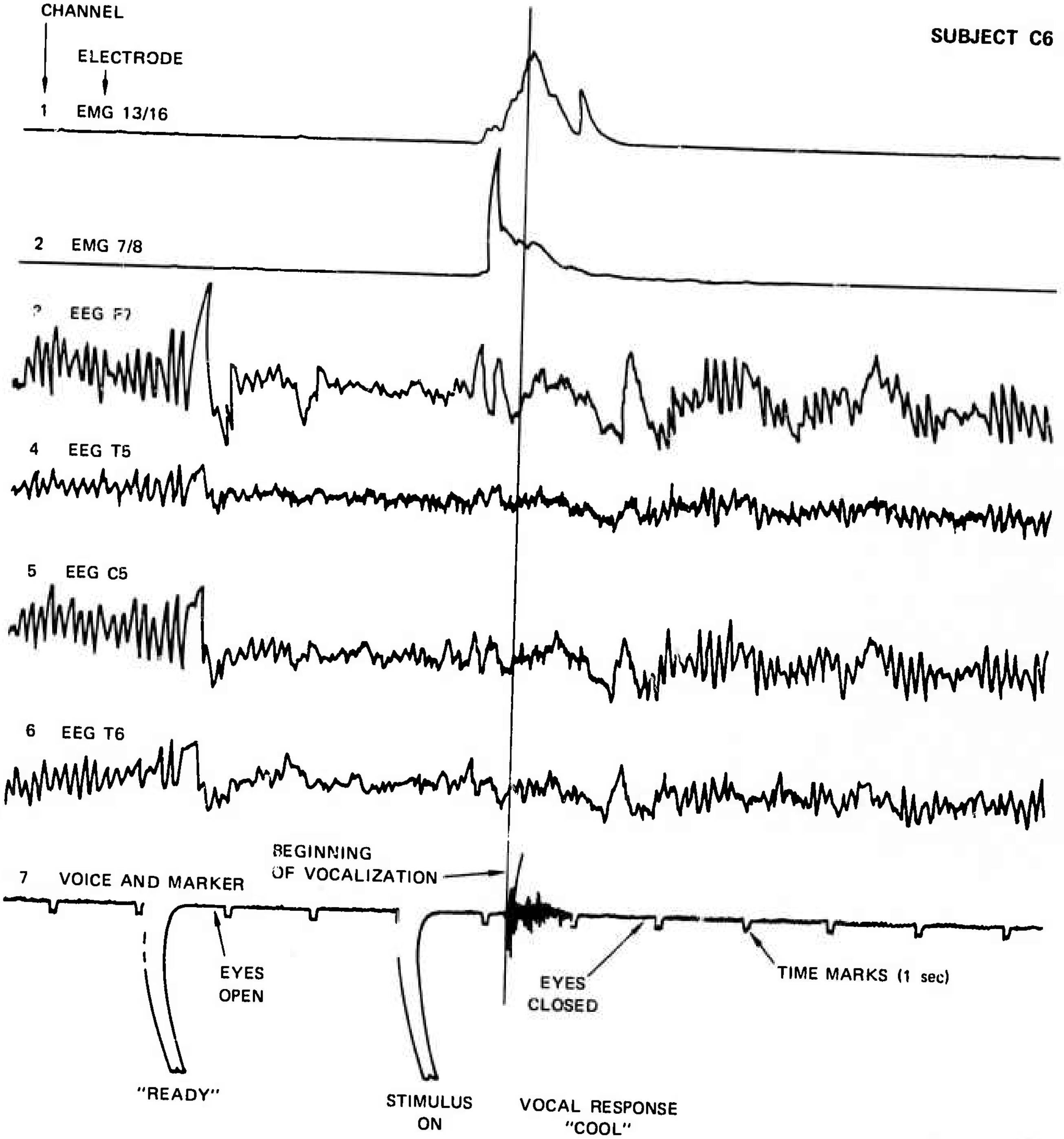


FIGURE 4 DYNOGRAPH RECORDING OF STIMULUS-RESPONSE OF EMG AND EEG FOR THE WORD "COOL"

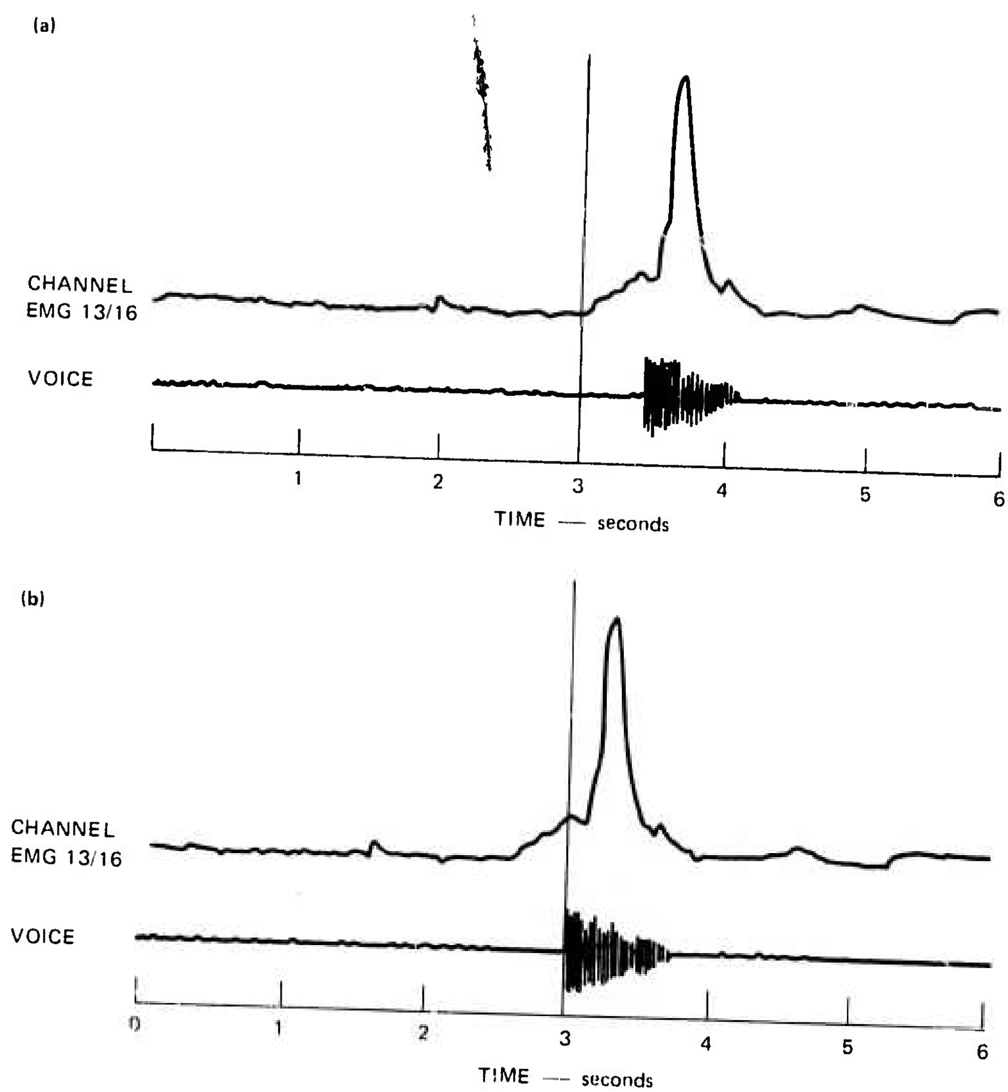


FIGURE 5 PLOTS OF LINC-8 CRT FOR TIME JUSTIFICATION OF ELECTROPHYSIOLOGICAL RESPONSE TO WORD TIP WITH ONSET OF VOCALIZATION AT t = 3 SECONDS

in Figure 5B. Thus, after time justification, 3 sec of data were displayed before the onset of vocalization and 3 sec after. On completion of time justification, the six channels of data were stored on Linc tape on the computer, one channel per block of tape. Then the next stimulus-word-response was sampled from the Ampex recorder, the responses were time justified, and the data stored.

When responses to all 150 word utterances and the 10 sentences for a given subject-session had been stored on Linc tape (six channels per word and sentence, for a total of 990 tape blocks), another Linc-8 program was used to transfer this data to the Pertec digital tape recorder in ten files of 101 records per file (255 samples per block were transferred rather than the 256 collected because of an error in the transfer program). The Pertec tape was then unpacked on the CDC-6400 computer, and the data words were reordered in sequence for data processing.

CDC-6400 Response Classification by Averaging

As a first approximation for machine pattern recognition of the six electrophysiological responses for each word utterance, it was decided to use a method of averages to construct templates for response-word classification. (The rationale and mathematical equations for this, and all other computations described below, are given in the Appendix.) The data unit of analysis for classification was the individual 6-sec electrode response corresponding to a word. To determine whether the CDC-6400 computer could correctly classify the word by analysis of the electrophysiological response alone, the response was compared with 15 templates (one for each of the 15 words).

As shown in Figure 6, a given template was the average electrophysiological, 6-sec response for the ten repetitions of the word for a given S on each session. Each sample point of the 255 samples in a 6-sec epoch was added to each corresponding point of the other nine responses, and the result divided by ten for the average response for that point. Since there were six electrodes and 15 words, there were 90 templates altogether for each S on each session, or a total of 540 templates for the three Ss, two sessions each.

To compare a single electrode response for a single word utterance with each of the 15 templates for that electrode, a root-mean-square (RMS) difference was calculated between the single response and the template, as shown in Figure 7. In the top of the figure the EMG 13/16 electrode response to TIP 2 (second utterance of TIP) is compared with the template for COOL. That is, each sample of the 255 samples in the response was subtracted from the corresponding sample in the template. The difference for each sample point (only a few ficticious values were used in Figure 7 for illustration) was squared, and the squared differences were summed over the 255 samples. Dividing by 255 and taking the square root provided the single RMS number for that comparison.

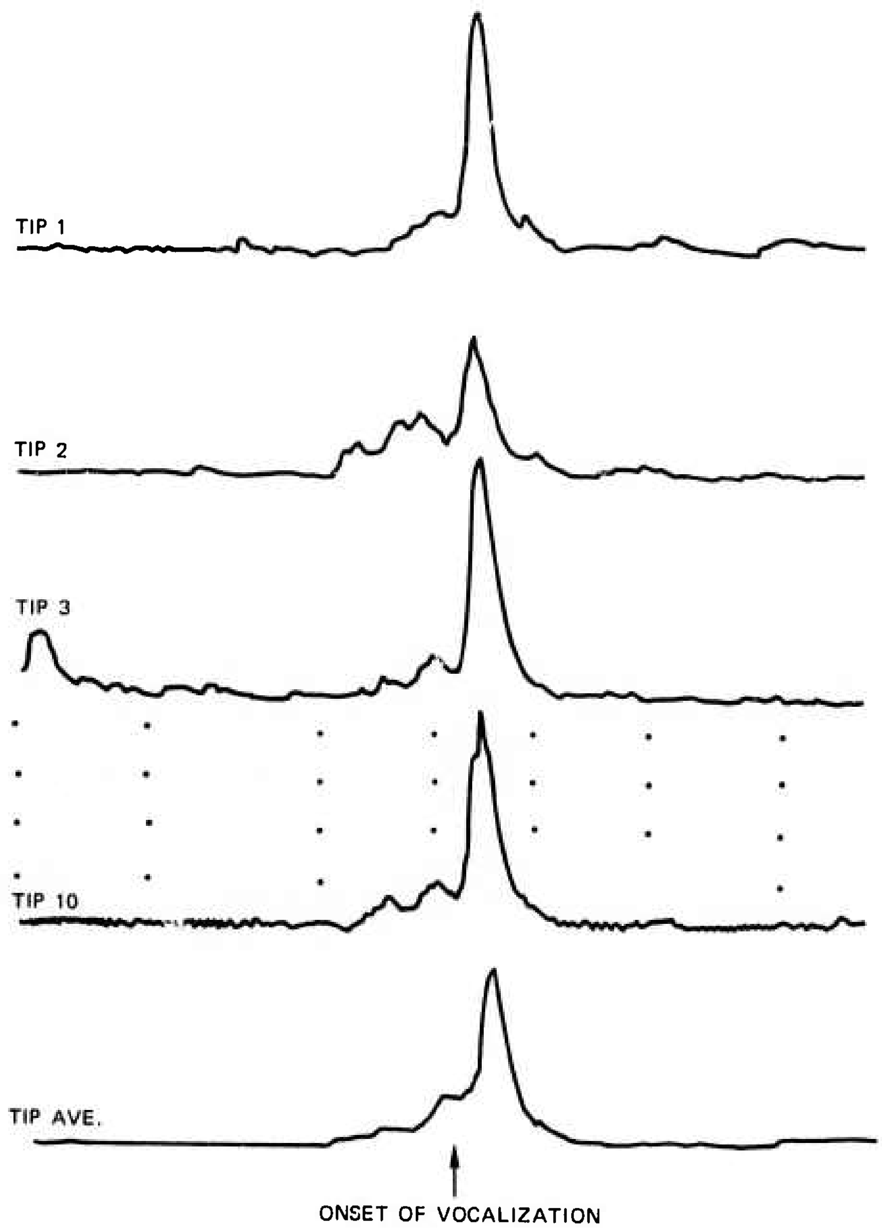


FIGURE 6 AVERAGING OF EMG RESPONSES (ELECTRODE 13/16) FOR WORD "TIP"

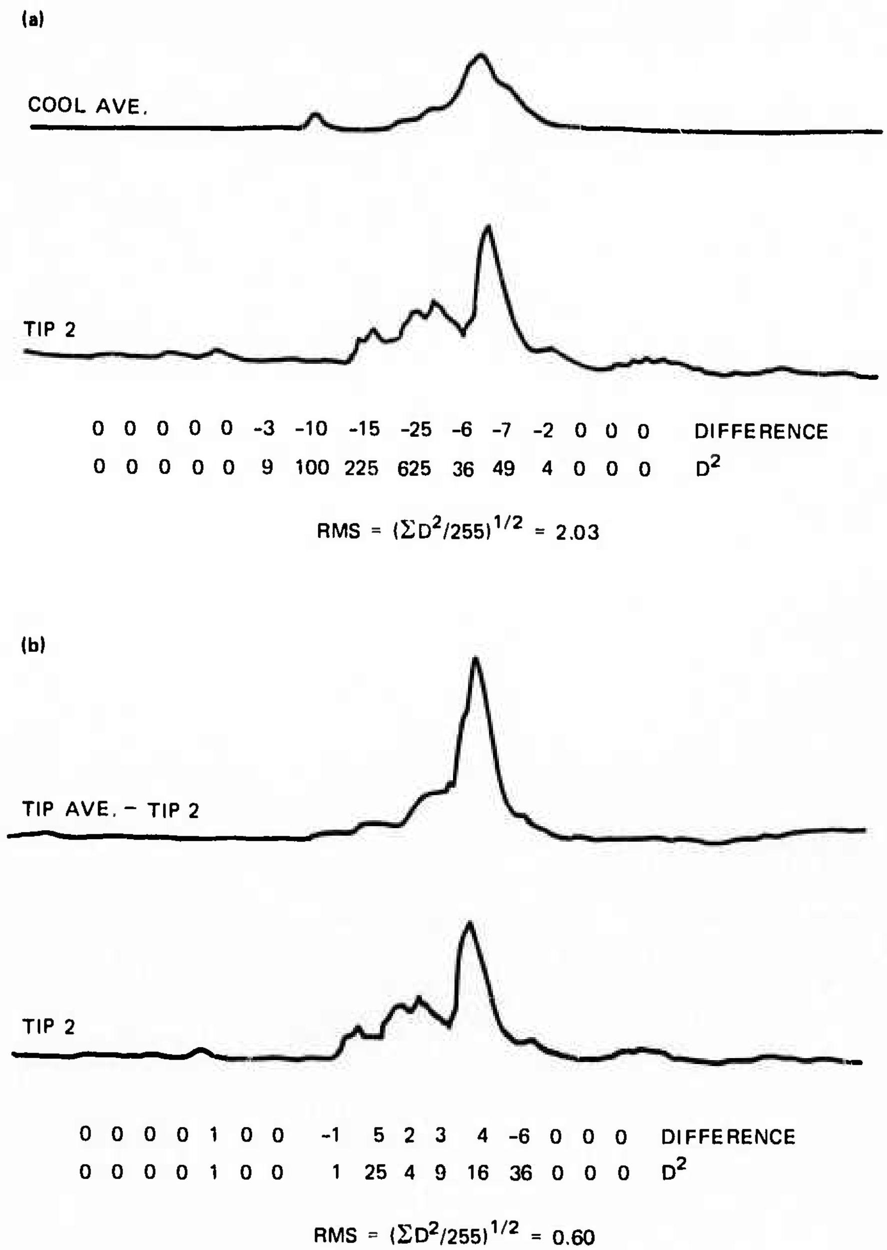


FIGURE 7 CLASSIFICATION OF TIP 2 AS TIP WITH RESPECT TO ANOTHER TEMPLATE (COOL) USING RMS DIFFERENCE

In the bottom of Figure 7, the <u>same</u> electrode response to TIP 2 is compared with the template for the word TIP. Since TIP 2 was included in making the template for TIP (see Figure 6), this template was necessarily biased in favor of classifying TIP 2 response as TIP. Therefore, for this response and all other responses compared with their own templates, the individual response was first subtracted from the template. The RMS difference was then calculated for the individual response against the <u>unbiased</u> average response for the other nine utterances of the word.

After calculating the RMS difference for a given electrode response for a given word against all 15 templates, the computer then classified the response as the word having the smallest RMS value. For example, in Figure 7, TIP 2 is classified as "TIP" rather than "COOL," since the RMS difference with TIP AVERAGE minus TIP 2 is less than the RMS difference with COOL AVERAGE. If this RMS difference remained the smallest when TIP 2 was compared with all 15 templates, then ultimately the TIP 2 response was classified as TIP.

In this way, response classifications were made for each of the 150 words per S per session per electrode (Within Subjects, Within Sessions classification). Two additional classifications were also made: (1) Within Subjects and Between Sessions (to assess within S reliability); and (2) Between Subjects (to assess individual differences). In the first case, the six electrode responses for each 150 words of one session for a given S were compared to the 15 templates for the <u>other</u> session for that S (e.g., C5 responses with C6 templates, and C6 responses with C5 templates). In the second case, the six electrode responses for each of the 150 words of a given S on a given session were compared with the 15 templates for <u>another</u> S on a given session (e.g., C5 responses with B5 templates, or D4 responses with C6 templates).

Finally, in addition to obtaining classification of responses for each electrode, it was decided to pool both EMG electrodes, all four EEG electrodes, and all six electrodes (EMG plus EEG) to assess the relative contribution of types and number of electrode responses to the computer classification.

<u>Determination of Critical Classification Period</u>

The electrophysiological recordings shown earlier in Figure 4 to the word COOL illustrate that only about 1 sec of the 6-sec epoch is actually involved in making the response. Since it is possible that computer classification of an electrophysiological response might be based on that portion of the response following stimulus onset, but <u>before</u> the onset of vocalization, it was decided to determine which parts of the 6-sec epoch contributed to the classification and to what extent. To do this, an F-ratio was calculated for each electrode for the Within Words variance and Between Words variance for each of the 255 data samples in the 6-sec epoch (see Appendix for details of computation). If a given sample point was not contributing to the computer classification of the word, then the ratio of the two variances (i.e., the F-statistic) should be small. On the other hand, if the Between Word variance was significantly higher than the Within Word variance for a given sample point, then it may be assumed with some confidence (given by statistical tables for the F-ratio) that the particular data point was contributing to the classification.

Examples of the F-ratio for the 255 samples in the 6-sec epoch for an EMG and an EEG electrode are shown in Figures 8 and 9, respectively, for Subject C, Session 5. Note that in both cases the F-ratio remains small and statistically insignificant for about the first 100 samples, but becomes and remains significantly larger from about sample 101 to about sample 200. For the EEG (Figure 9), another portion between about sample 205 through 230 barely reaches significance. This means that for both EMG and EEG responses taken separately, only that portion of the 6-sec epoch between samples 101 and 200 probably contributes significantly to classification of the response (that portion of the EEG from 205 to 230 may also contribute, although less significantly). F-ratios were calculated for all Ss, sessions, and electrodes, with essentially the same results.

The finding that the samples from 101 to 200 of a response are the only portion of the response contributing to the classification suggested that calculating sums of squared differences for RMS values across all 255 samples may produce undesireable errors. Accordingly, each electrode response was further divided into three subgroups, and RMS values were calculated and responses classified for each subgroup, as well as for the entire 255 samples. These subgroups were samples 1-100, 101-200, and 201-255. Thus, for each of the six electrodes taken separately, the two EMG electrodes taken together, the four EEG electrodes taken together, and all six electrodes taken together, there were four classification epochs for a total of 36 classifications per word per S per session.

CDC-6400 Response Classification by Other Statistics

As pointed out earlier, there is no *a priori* reason for believing that a particular statistic of the EEG and EMG will ultimately be a better classifier of the verbal response than any other. Consequently, several other statistics were computed, RMS differences were obtained in the same manner as with the averaged responses, and individual electrode responses were classified. These statistics were auto- and cross-spectra, linear coherence, and weighted-average coherence (see the Appendix for the meaning of these statistics and details of their computations). These statistics are presumed to be useful, since they involve frequency analysis of the EEG and may be used to determine the degree of interaction between two or more different regions of the brain. Such an analysis should provide information about cortical organization, and therefore may show patterns of organization that are specific for particular responses to the 15 stimulus words. Except for the actual calculation of the statistic itself, all other computations for response classification were the same as for the averaged responses described above.

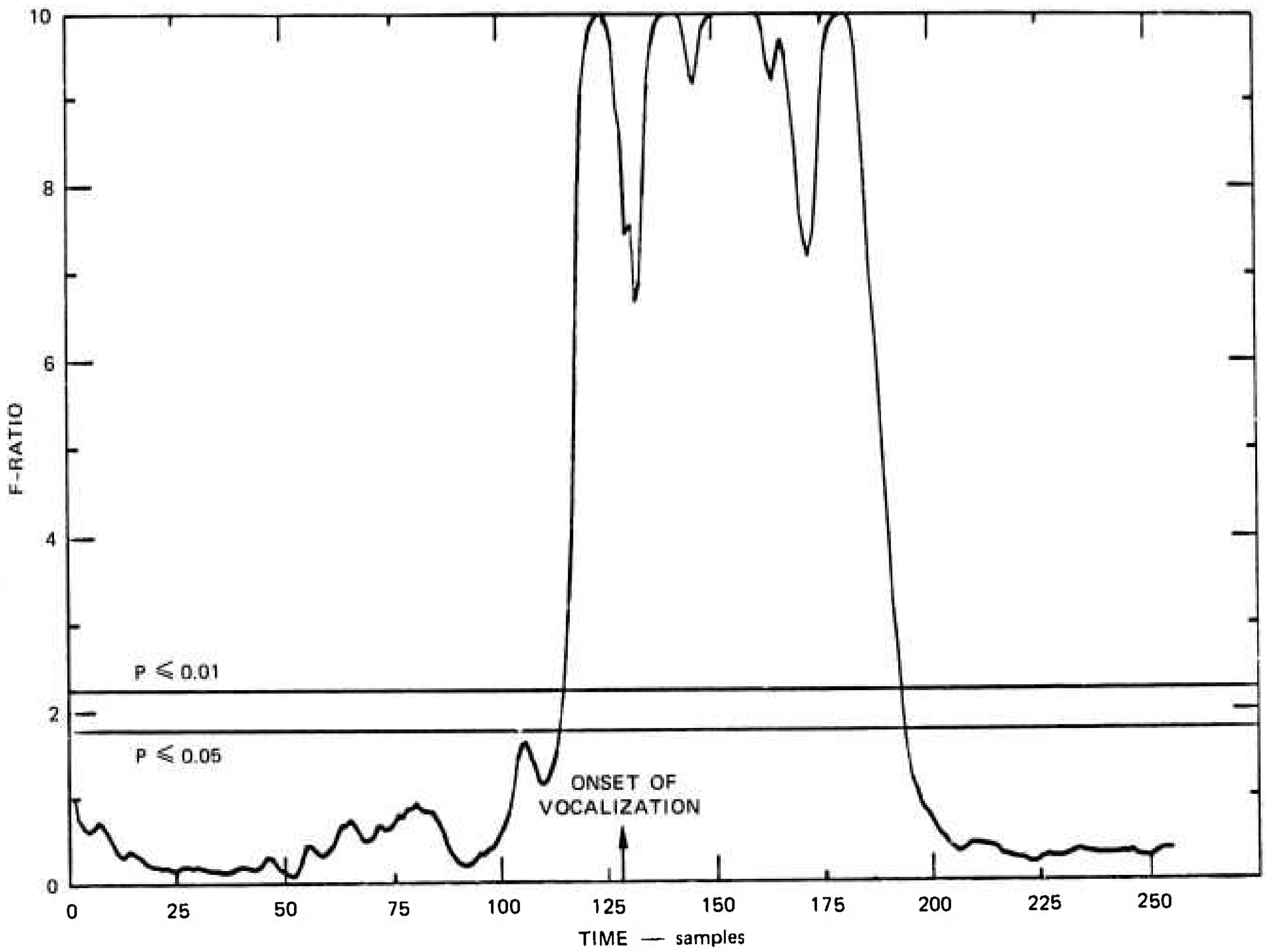


FIGURE 8 F-RATIOS FOR EMG ELECTRODE 13/16, SUBJECT C5, ALL WORDS

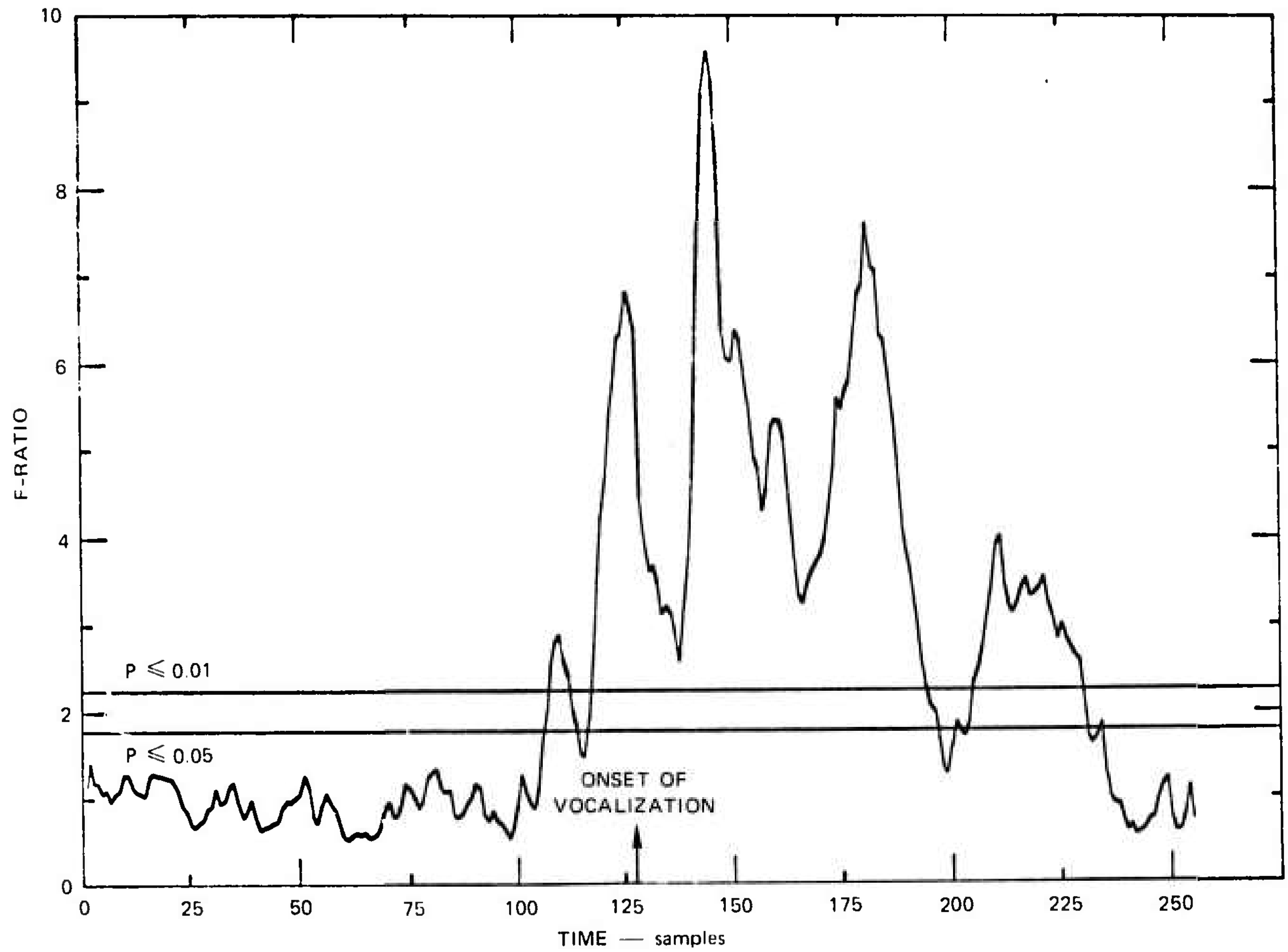


FIGURE 9 F-RATIOS FOR SUBJECT C5, EEG ELECTRODE F7, ALL WORDS

Tests for Statistical Significance

To show that correct classification of single electrode responses by the computer did not occur by chance, a chi square was calculated for each electrode subclassification for each S and each session, between sessions and between subjects. The "expected" frequencies for evaluating the chi square were based on classifications being randomly distributed across words (see the Appendix for details of computation).

Control of Artifact

In a working biocybernetic communication system, constraints on the user against eye or muscle movement may not be effective. Since such movements often produce artifacts in electrophysiological responses (especially in the EEG), it is imperative that a system be designed that is not unduly affected by such artifacts. That is, pattern recognition and classification should be carried out successfully whether artifacts are present or not. For this reason, it was decided to analyze Group II data without removing those responses with known artifacts present; that is, this was a "worst case" analysis.

Nevertheless, some effort was devoted to controlling and identifying artifacts, and to assessing their contribution to response classification. This was accomplished by obtaining responses in the four EEG electrodes to five words under conditions of both visual and auditory stimuli and with and without known eye movements and movement artifacts. The results of these controlled studies are described below under "Results, Group II Data, Sources of Error." Finally, during data collection proper, Ss were instructed to remain as relaxed as possible during the response period, with no more eye or body movement than necessary.

RESULTS OF GROUP II DATA

Classification by Averages

Individual Responses

Figure 10 illustrates the six electrode templates for Subject C, Session 5, for the word COUGHDROP, with the accent on the first syllable. Note that for both EMG and EEG records, significant changes occur primarily over computer samples 101 to 200, thus beginning about 0.5 sec before onset of vocalization (arrow at 3.0 sec).

Figure 11 shows the variability around the averages of Figure 10, the upper trace of each pair being the average plus one standard deviation, the lower trace the average minus one standard deviation. Note that the variability of each electrode signal is relatively small. Similar plots were made for all three Ss for the two sessions, each with essentially similar results, indicating that it should be feasible to identify a given spoken word by comparing the electrophysiological response to the templates.

As described in the previous section, for each S on each session, the individual electrode response for each of the 150 word utterances was compared with the 15 templates. These comparisons resulted in 15 RMS values, from which the CDC-6400 computer classified the response with the word for which the RMS value was a minimum. Tables of correct responses were then constructed for each S and each session, showing the number of correct classifications for the 150 words for each electrode and each subclassification.

Table 2 shows these results for Subject C, Session 5, and illustrates the method. Along the top row are the 15 words. The leftmost column gives the channel number (corresponding to Figure 4) for the six electrodes, the combination of both EMG electrodes, the combination of the four EEG electrodes, and the combination of all six electrodes. The second column on the left gives the four subclassifications for each electrode and combination--that is, the sample points of the 6-sec response over which classifications were made according to the findings of the F-ratios (see previous section). The table proper then gives the number of responses correctly classified for each electrode and each subgroup. For example, in Channel 1 (EMG electrode 13/16), in the portion of the response from sample 1-100, none of the utterances of TIP was correctly classified, while six out of ten were correctly classified for samples 101-200, none for samples 201-255, and five for the entire response (samples 1-255). The same interpretation can be made for all other words, electrodes, and combinations.

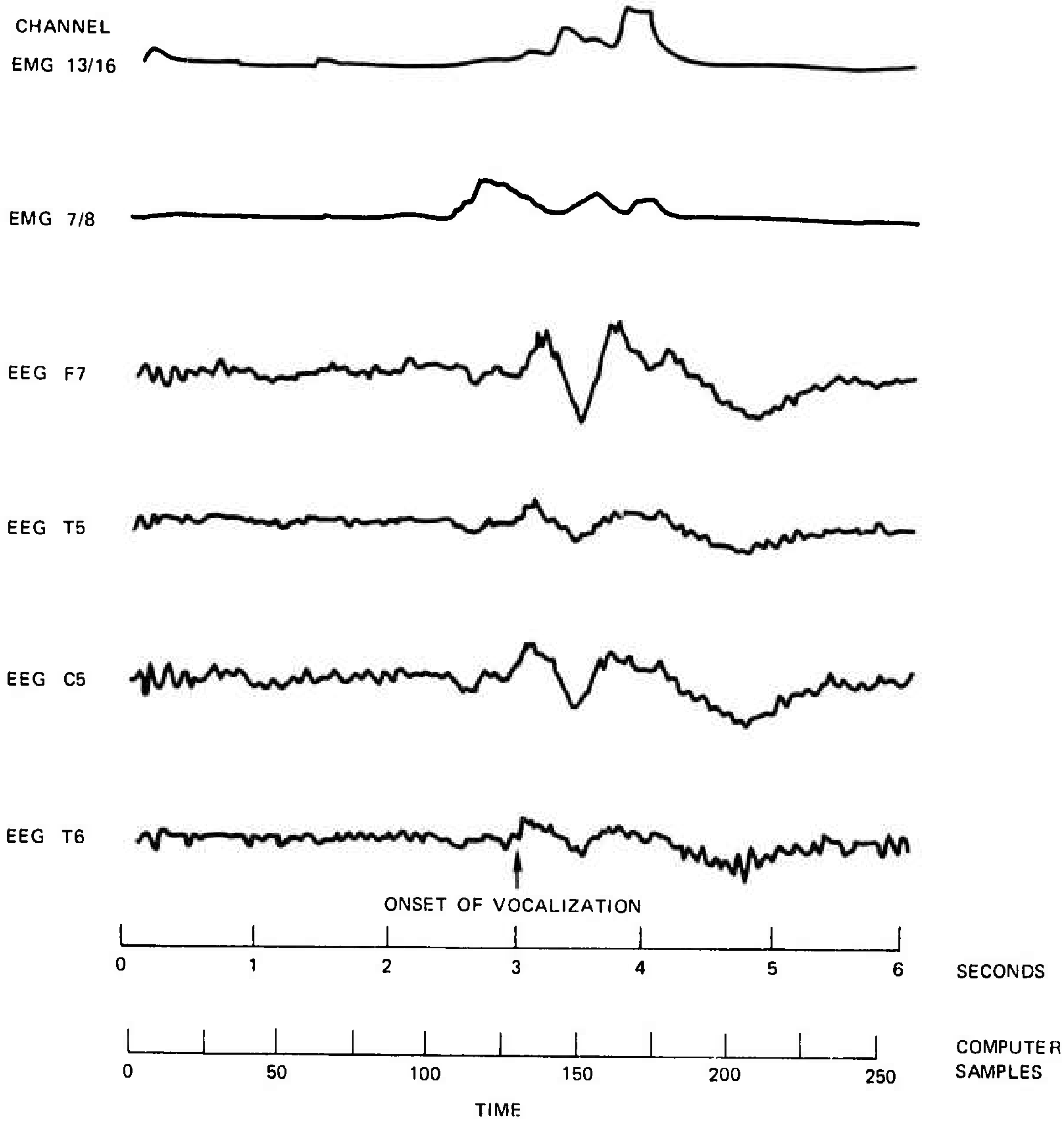


FIGURE 10 TEMPLATES (AVERAGES OF 10 RESPONSES EACH) FOR THE SIX ELECTRODES, SUBJECT C5, FOR THE WORD COUGHDROP

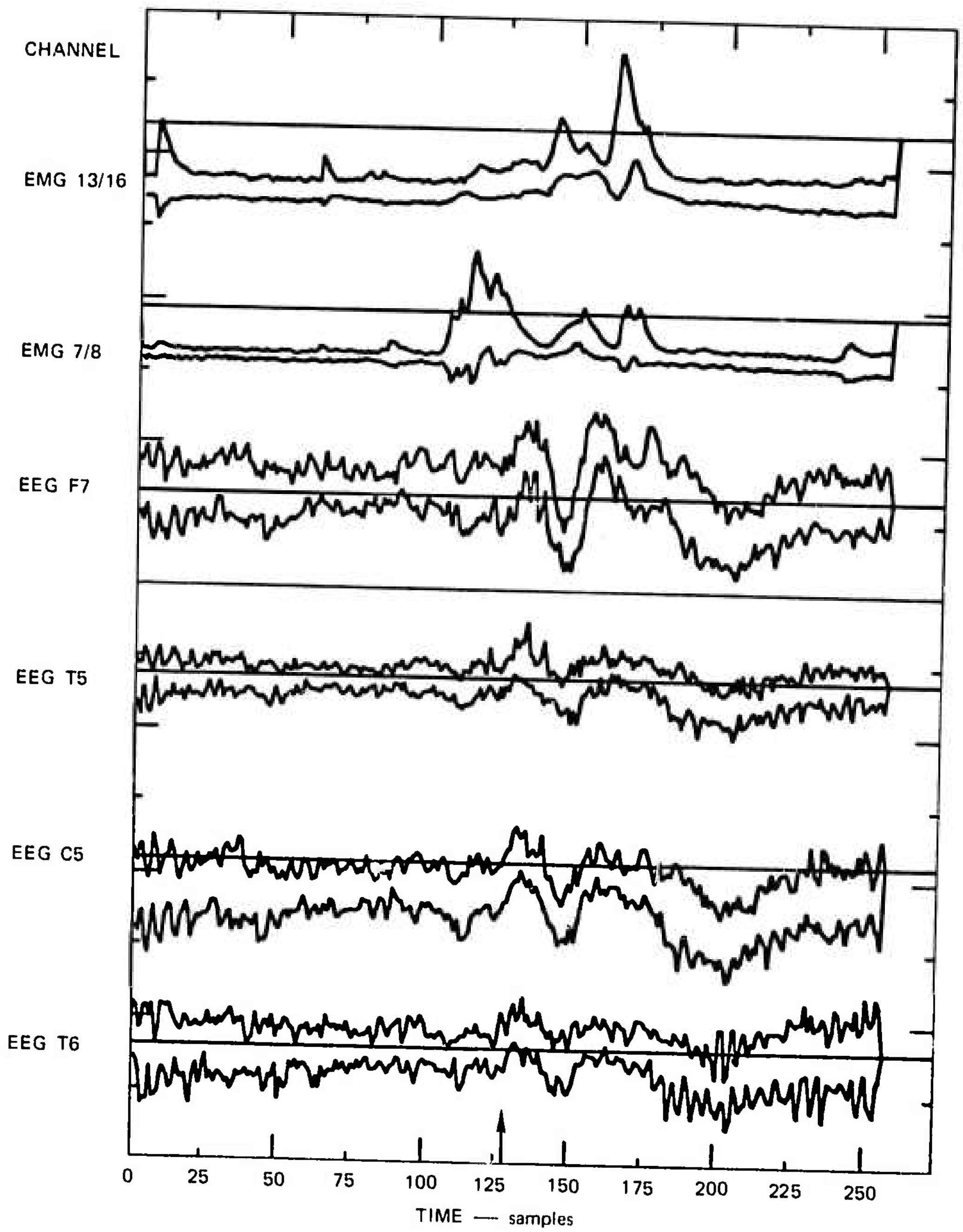


FIGURE 11 VARIABILITY OF AVERAGE RESPONSES OF THE SIX ELECTRODES, SUBJECT C5, FOR THE WORD COUGHDROP

Table 2

FREQUENCY OF CORRECT RESPONSE CLASSIFICATION, SUBJECT C5

SUMMARY TABLES, MARCH 7, 1973
WITHIN SESSION SUMMARY OF COMPARISON DATA

SB1=SCHOOLBOY 1	BB1=BLACKBOARD 1	SW1=SHIPWRECK 1	CD1=COUGHDROP 1	MT1=MOUSETRAP 1
SB2=SCHOOLBOY 2	BB2=BLACKBOARD 2	SW2=SHIPWRECK 2	CD2=COUGHDROP 2	MT2=MOUSETRAP 2

SUMMED OVER THE FOLLOWING DATA SETS
C5 DATA WITH C5 TEMPLATES 1-100,101-200,201-255

NUMBER OF RESPONSES CORRECTLY CLASSIFIED

CHAN	POINTS		TIP	HAD	PUT	COOL	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2	CORRECT	CHI1	CHI15
REPITITIONS			10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150		
1	1-100	1	0	0	1	0	0	0	0	0	1	0	2	0	0	0	0	4	3.86	11.79
	101-200	2	6	5	8	8	6	5	6	3	6	5	2	9	3	6	8	86	618.86	710.36
	201-255	3	0	0	0	0	0	0	0	0	3	0	4	0	0	0	0	7	.96	35.89
	1-255	4	5	5	8	8	5	5	5	3	6	5	3	9	2	6	8	83	570.96	663.75
2	1-100	5	0	2	0	1	1	1	0	0	0	0	2	0	0	1	0	8	.43	12.86
	101-200	6	5	1	2	5	6	4	5	4	2	8	2	4	4	5	8	65	324.11	419.46
	201-255	7	0	0	0	1	4	0	0	2	0	0	1	0	0	2	1	11	.11	30.54
	1-255	8	5	1	2	4	6	3	5	4	0	8	3	3	4	5	8	61	278.68	392.68
3	1-100	9	0	0	1	1	2	0	0	0	0	0	0	1	0	0	0	5	2.68	11.25
	101-200	10	6	5	6	4	1	4	5	3	3	5	5	4	5	4	8	68	360.43	417.86
	201-255	11	2	2	3	1	1	0	0	2	0	1	0	1	0	1	2	16	3.86	24.64
	1-255	12	6	4	5	2	3	1	3	2	3	5	1	3	4	4	5	51	180.11	230.89
4	1-100	13	0	1	0	0	0	0	0	1	0	0	0	0	0	1	2	5	2.68	11.25
	101-200	14	6	3	4	9	5	4	3	3	4	3	4	7	8	4	4	71	398.68	480.54
	201-255	15	1	0	2	0	4	0	1	4	0	1	0	1	1	0	1	16	3.86	43.93
	1-255	16	5	2	3	7	3	4	3	2	2	2	3	4	4	1	4	49	162.96	212.68
5	1-100	17	0	0	1	1	0	0	0	1	0	0	1	0	0	1	0	5	2.68	8.04
	101-200	18	7	5	5	6	2	3	3	3	3	1	3	5	3	4	4	59	257.25	313.39
	201-255	19	2	1	1	1	0	0	1	2	0	1	0	2	1	0	1	13	.96	13.39
	1-255	20	4	2	4	6	2	2	5	2	2	5	2	3	4	3	3	49	162.96	203.04
6	1-100	21	1	0	0	0	1	2	1	0	0	1	2	1	1	4	0	14	1.71	28.93
	101-200	22	4	1	2	3	2	3	3	1	4	2	2	4	3	2	3	39	90.11	111.96
	201-255	23	0	1	1	0	0	1	4	0	0	1	0	0	1	0	0	9	.11	25.18
	1-255	24	5	1	1	0	1	3	3	0	0	2	1	3	2	2	2	26	27.43	70.71
EMG	1-100	25	0	2	0	0	2	0	0	0	1	0	2	0	0	0	0	7	.96	16.61
1-2	101-200	26	5	5	8	9	6	8	7	3	6	7	2	9	4	7	9	95	774.11	882.32
	201-255	27	0	1	0	0	3	0	0	2	0	0	1	0	0	0	0	7	.96	19.82
	1-255	28	5	4	8	9	6	7	7	4	6	7	3	9	3	7	9	94	756.00	853.93
EEG	1-100	29	0	0	0	0	0	0	0	1	0	0	0	1	0	3	0	5	2.68	17.68
3-6	101-200	30	6	5	6	7	2	4	4	3	3	4	6	5	5	5	8	73	425.25	482.68
	201-255	31	2	1	1	0	0	0	1	0	0	1	0	1	2	0	1	10	.00	11.79
	1-255	32	6	3	4	3	1	1	4	1	3	3	3	3	5	4	4	48	15[illegible].71	200.36
ALL	1-100	33	0	0	0	0	1	0	0	1	0	0	0	1	0	3	0	6	1.71	17.14
1-6	101-200	34	8	5	8	9	7	8	8	5	8	7	4	9	5	5	9	105	966.96	1034.46
	201-255	35	1	0	1	0	0	0	1	1	0	1	0	1	2	0	1	9	.11	9.11
	1-255	36	7	4	8	9	6	5	8	4	6	7	4	9	4	7	8	96	792.43	868.93

On the far right, under the column labeled "Correct," the total number of responses across the 15 words that were correctly classified is listed for each electrode and combination for each subgroup. Thus, for Channel 1, 4 out of 150 individual responses were classified correctly for subgroup 1-100, 86 out of 150 for subgroup 101-200, 7 out of 150 for subgroup 201-255, and 83 out of 150 for the total response (1-255). Note that for all electrodes and combinations, the middle subgroup (101-200) is a better classifier than any other subgroup including the total response (1-255), as predicted by the F-ratio test. The latter result means that variation in the responses outside of the 101-200 sample period serves to decrease the accuracy of classification. Furthermore, all electrodes taken together (see "All" data at the bottom of Table 2), especially in the 101-200 subgroup, serve as a better classifier than any single electrode or combination. Thus, for the 101-200 sample subgroup, 105 out of 150 (or 70%) of responses were correctly classified. Table 2 also shows that for this S and session, the EMG responses (individually or taken together) were better classifiers than any (or all) of the EEG responses, and that the EEG of the nondominant hemisphere (T6, Channel 6) was the poorest classifier of all.

The two columns on the right of Table 2 give the chi square values for Within Words (CHI 1=1 degree of freedom) and Between Words (CHI 15=15 degrees of freedom). These indicate how likely the total number of correct classifications was obtained by chance. The chi square for significance at the $p<.01$ level is 30 for this distribution and 15 degrees of freedom. Thus, all correct classifications in the "Total Correct" column having a chi square greater than 30 occurred by chance with a probability of less than 1 out of 100. Examination of this column shows that only the 101-200 and 1-255 sample subgroups were at high levels of significance for all electrodes and combinations.

Finally, the third row from the bottom of Table 2 ("All electrodes," subgroup 101-200, the best classifier of all) shows the frequency of the words that were correctly classified for Subject C, Session 5. Thus, three words (COOL, BLACKBOARD, and MOUSETRAP) were correctly classified nine times out of ten, while five words were correctly classified 80% of the time, two 70%, four 50%, and one 40%.

Within Subjects

To test the reliability of measurements and response classification, all three Ss were run on two sessions each. The sessions were no less than one week and no longer than one month apart. Tables of correct classifications were constructed for each S and each session (as in Table 2), and comparisons were made for both Within Subjects/Within Sessions, and Within Subjects/Between Sessions.

Table 3 summarizes the Within and Between Sessions comparisons for Subject C, for the best classifier subgroup (101-200) for all electrode combinations (Tables 4 and 5 give the results for Subjects B and D, respectively). The nearest percentage correct responses and the rank

Table 3

NEAREST PERCENTAGE CORRECT RESPONSES AND RANK ORDER OF ELECTRODES AS CLASSIFIERS, SAMPLE POINTS 101-200, SUBJECT C, WITHIN AND BETWEEN SESSIONS

	Within Sessions				Between Sessions			
	C5 with C5*		C6 with C6		C5 with C6**		C6 with C5	
Channel	% Correct	Rank	% Correct	Rank	% Correct	Rank	% Correct	Rank
1	57	3	76	2	39	3	53	3
2	43	7	56	4	33	4	40	4
3	45	6	48	5	22	7	15	9
4	47	5	46	7	31	6	29	6
5	39	8	36	9	14	9	28	7
6	26	9	37	8	21	8	25	8
EMG	63	2	79	1	42	2	64	2
EEG	49	4	47	6	31	5	31	5
All	70	1	75	3	50	1	65	1

* C5 data compared with C5 templates.

** C5 data compared with C6 templates.

Table 4

NEAREST PERCENTAGE CORRECT RESPONSES AND RANK ORDER OF ELECTRODES AS CLASSIFIERS, SAMPLE POINTS 101-200, SUBJECT B, WITHIN AND BETWEEN SESSIONS

	Within Sessions				Between Sessions			
	B5 with B5*		B6 with B6		B5 with B6**		B6 with B5	
Channel	% Correct	Rank	% Correct	Rank	% Correct	Rank	% Correct	Rank
1	49	3	57	4	32	4	52	3
2	59	2	59	3	56	3	51	4
3	9	9	22	8	19	9	23	9
4	29	7	14	9	23	8	24	8
5	31	6	27	7	25	6	37	5
6	38	5	29	5	29	5	30	6
EMG	67	1	74	1	61	2	67	1
EEG	12	8	29	6	24	7	28	7
All	47	4	67	2	63	1	65	2

* B5 data compared with B5 templates.

** B5 data compared with B6 templates.

Table 5

NEAREST PERCENTAGE CORRECT RESPONSES AND RANK ORDER OF ELECTRODES AS CLASSIFIERS, SAMPLE POINTS 101-200, SUBJECT D, WITHIN AND BETWEEN SESSIONS

	Within Sessions				Between Sessions			
	D3 with D3*		D4 with D4		D3 with D4**		D4 with D3	
Channel	% Correct	Rank	% Correct	Rank	% Correct	Rank	% Correct	Rank
1	66	3	72	2	56	3	56	4
2	67	2	71	3	59	2	65	2
3	19	7.5	27	8	11	8.5	11	8.5
4	27	5	30	7	12	7	11	8.5
5	16	9	33	6	15	6	16	7
6	19	7.5	19	9	24	5	17	5.5
EMG	74	1	84	1	67	1	71	1
EEG	25	6	37	5	11	8.5	17	5.5
All	65	4	70	4	50	4	57	3

* D3 data compared with D3 templates.

** D3 data compared with D4 templates.

order of electrodes as classifiers are given by classifying each response first with the templates of its own session, and then with the templates from the other session. The following may be concluded from inspection of Tables 3, 4, and 5:

(1) In all three Ss, a greater number of responses were correctly classified on the second session (Within Sessions comparison) than on the first (by rank order and not necessarily for a particular electrode or combination). Thus, an habituation or learning effect is present that, presumably, reduces the variability from one session to the next.

(2) Again in all three Ss, when the second session responses are compared with the first session templates (Between Sessions comparisons), a greater number of responses were classified correctly than when the first session responses are compared with the second session templates. This is also probably due to a decreased variability in the individual responses of the second session, further strengthening the conclusion that habituation or learning operates to improve performance in response classification.

(3) In all three Ss, the EMG responses, taken separately or together, are better classifiers than any EEG response or the EEG responses taken together. However, there appears to be no consistency, either within a S or across Ss, for any particular EEG response being a better classifier than any other.

(4) The range of percentages of correct classifications across Ss is from 9% to 84%, with all EMG and all electrodes generally in the higher ranges, EMGs separately and all EEGs in the middle range, and EEGs separately in the lower ranges.

(5) Comparisons among percentages of correct responses among the three Ss indicate that responses from Subject C are better classifiers, in general, than either B's or D's, with B slightly better than D. Examination of either raw data or templates shows that this result is probably due to variability (larger in D, less in B, still less in C).

Tables 6 and 7 give summaries for all Ss and sessions together for Within Subjects/Within Sessions comparisons, and Within Subjects/Between Sessions comparisons, respectively. These tables are to be interpreted as is Table 2. They show that for all Ss and sessions, the results are essentially the same as for Subject C, Session 5. That is, the number of correctly classified responses (out of a possible 900) is 74% for EMGs, 63% for all electrodes, and about 34% for EEGs. Again, this is true only for subgroups 101-200 and 1-255, the former being the better classifier of the two. All chi squares for these two subgroups (last two columns on the right for 1 and 15 degrees of freedom, respectively) were significant at p well below .001.

Table 6

SUMMARY OF CORRECT RESPONSE CLASSIFICATIONS FOR ALL SUBJECTS AND SESSIONS, WITHIN SUBJECTS AND WITHIN SESSIONS

SUMMARY TABLES, MARCH 7, 1973
WITHIN SESSION SUMMARY OF COMPARISON DATA

SB1=SCHOOLBOY 1	BB1=BLACKBOARD 1	SW1=SHIPWRECK 1	CD1=COUGHDROP 1	MT1=MOUSETRAP 1
SB2=SCHOOLBOY 2	BB2=BLACKBOARD 2	SW2=SHIPWRECK 2	CD2=COUGHDROP 2	MT2=MOUSETRAP 2

SUMMED OVER THE FOLLOWING DATA SETS

B5 DATA WITH B5 TEMPLATES	1-100,101-200,201-255
B6 DATA WITH B6 TEMPLATES	1-100,101-200,201-255
C5 DATA WITH C5 TEMPLATES	1-100,101-200,201-255
C6 DATA WITH C6 TEMPLATES	1-100,101-200,201-255
D3 DATA WITH D3 TEMPLATES	1-100,101-200,201-255
D4 DATA WITH D4 TEMPLATES	1-100,101-200,201-255

NUMBER OF RESPONSES CORRECTLY CLASSIFIED

REPITITIONS CHAN POINTS		TIP 60	HAD 60	PUT 60	COOL 60	HIT 60	SB1 60	BB1 60	SW1 60	CD1 60	MT1 60	SB2 60	BB2 60	SW2 60	CD2 60	MT2 60	CORRECT 900	CHI1	CHI5
1 1-100	1	2	1	9	0	2	8	1	1	6	7	6	2	5	1	1	52	1.14	35.36
101-200	2	45	31	39	28	32	40	40	30	40	42	38	46	39	32	45	567	4590.16	4717.77
201-255	3	4	1	4	3	8	7	5	3	9	5	5	1	0	2	3	60	.00	25.18
1-255	4	4	29	38	25	26	38	40	28	41	39	39	46	39	32	44	544	4183.14	4345.18
2 1-100	5	4	4	0	1	2	4	0	3	3	3	3	2	6	3	3	41	6.45	15.80
101-200	6	36	30	37	35	28	35	39	34	33	48	29	41	31	33	44	533	3995.16	4112.41
201-255	7	1	2	4	6	11	3	8	4	0	6	2	0	6	3	7	63	.16	36.70
1-255	8	39	29	37	34	28	31	38	31	30	48	30	40	31	31	44	521	3795.02	3929.73
3 1-100	9	4	4	10	4	6	5	1	2	2	7	2	2	7	[illegible]	7	63	.16	29.20
101-200	10	12	19	19	9	17	20	20	16	22	20	12	19	22	11	17	255	479.02	743.30
201-255	11	4	4	3	3	4	1	2	7	1	2	2	6	3	2	14	58	.07	40.18
1-255	12	10	11	18	10	14	12	16	16	18	21	7	13	20	8	14	228	391.14	459.64
4 1-100	13	4	4	3	2	3	3	1	8	2	4	2	4	4	2	8	54	.64	16.07
101-200	14	20	16	17	30	19	17	16	21	24	49	14	21	25	11	16	316	1170.29	1678.57
201-255	15	6	4	5	3	4	2	3	13	3	32	3	5	1	2	2	88	14.00	240.00
1-255	16	14	13	12	22	14	13	12	18	17	43	10	13	19	7	13	240	578.57	838.93
5 1-100	17	3	3	7	6	5	3	2	7	2	5	4	0	4	5	10	66	.64	23.57
101-200	18	20	9	20	20	18	22	21	19	23	18	14	19	19	10	21	273	910.16	872.95
201-255	19	5	7	5	1	4	0	2	8	2	7	4	5	2	0	3	55	.45	24.37
1-255	20	13	10	18	12	13	12	19	17	23	16	12	13	19	9	14	220	457.14	513.21
6 1-100	21	4	5	2	1	2	3	4	1	5	4	4	1	6	9	7	58	.07	20.36
101-200	22	18	10	13	17	27	21	22	10	23	19	16	16	14	10	16	252	658.29	753.75
201-255	23	2	4	9	3	4	3	9	7	7	4	5	5	7	4	4	77	5.16	22.77
1-255	24	13	9	10	7	13	15	18	12	17	15	14	15	11	10	14	193	315.87	350.62
EMG 1-100	25	2	4	6	0	3	8	1	2	5	5	6	2	6	0	0	50	1.79	26.79
1-2101-200	26	48	34	50	46	32	48	47	37	44	47	44	50	41	44	51	663	6493.02	6620.62
201-255	27	[illegible]	3	2	4	10	7	0	4	1	6	1	3	2	1	6	60	1.79	32.68
1-255	28	40	31	51	46	33	48	46	36	43	46	45	49	40	39	51	650	6216.07	6362.14
EEG 1-100	29	3	3	6	2	2	4	1	4	1	6	2	2	4	5	7	52	1.14	14.46
3-6101-200	30	17	22	18	19	19	19	26	17	23	25	17	20	21	13	21	297	1003.02	1045.45
201-255	31	5	6	1	1	3	1	3	5	4	6	0	4	6	1	8	54	.64	22.50
1-255	32	10	12	15	14	13	13	18	18	20	19	8	10	19	11	15	215	429.02	482.95
ALL 1-100	33	3	4	6	2	4	3	1	3	1	6	2	2	5	5	7	54	.64	13.93
1-6101-200	34	42	33	46	41	36	36	47	37	42	49	34	42	36	30	41	592	5054.00	5165.89
201-255	35	4	5	1	2	3	1	3	6	3	6	0	5	5	1	8	53	.87	20.62
1-255	36	39	28	40	36	30	26	40	34	36	44	31	30	29	22	38	494	3363.50	3498.75

Table 7

SUMMARY OF CORRECT RESPONSE CLASSIFICATIONS FOR ALL SUBJECTS AND SESSIONS, WITHIN SUBJECTS AND BETWEEN SESSIONS

SUMMARY TABLES, MARCH 7, 1973
COMPARISON BETWEEN SESSIONS FOR THE SAME SUBJECT

SB1=SCHOOLBOY 1	BB1=BLACKBOARD 1	SW1=SHIPWRECK 1	CD1=COUGHDROP 1	MT1=MOUSETRAP 1
SB2=SCHOOLBOY 2	BB2=BLACKBOARD 2	SW2=SHIPWRECK 2	CD2=COUGHDROP 2	MT2=MOUSETRAP 2

SUMMED OVER THE FOLLOWING DATA SETS

B5 DATA WITH B6 TEMPLATES	1-100,101-200,201-255
B6 DATA WITH B5 TEMPLATES	1-100,101-200,201-255
C6 DATA WITH C5 TEMPLATES	1-100,101-200,201-255
C5 DATA WITH C6 TEMPLATES	1-100,101-200,201-255
D3 DATA WITH D4 TEMPLATES	1-100,101-200,201-255
D4 DATA WITH D3 TEMPLATES	1-100,101-200,201-255

NUMBER OF RESPONSES CORRECTLY CLASSIFIED

	TIP	HAD	PUT	COOL	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2	CORRECT	CHI1	CHI15
REPITITIONS	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60	900		
CHAN POINTS																		
1 1-100 1	2	3	9	3	2	5	4	2	7	13	9	0	9	5	2	75	4.02	53.84
101-200 2	27	24	31	26	27	28	35	31	31	35	26	39	12	30	31	433	2684.45	2626.34
201-255 3	5	1	6	5	7	2	9	4	8	4	8	3	2	3	7	74	3.50	26.79
1-255 4	26	28	32	26	25	24	37	32	31	32	25	39	12	28	32	429	2431.45	2583.48
2 1-100 5	3	5	5	3	9	6	2	1	3	11	7	3	3	16	2	79	6.45	68.30
101-200 6	24	24	33	35	29	25	35	28	23	43	31	37	21	29	41	458	2828.64	2996.79
201-255 7	6	2	4	4	7	3	8	2	7	6	5	9	0	6	3	72	2.57	26.25
1-255 8	26	23	32	35	23	24	34	27	26	44	36	35	21	26	41	453	2758.02	2944.02
3 1-100 9	9	1	0	2	0	11	1	4	1	2	15	2	4	1	8	61	.02	77.95
101-200 10	21	9	11	11	3	5	15	7	9	10	13	14	4	8	11	151	147.87	227.95
201-255 11	12	3	0	0	0	3	1	15	8	9	1	10	1	4	6	73	3.02	91.87
1-255 12	17	8	10	11	7	12	20	14	12	8	14	8	2	9	8	160	179.57	251.79
4 1-100 13	5	4	1	1	4	2	9	0	10	2	2	1	2	2	4	49	2.16	33.48
101-200 14	13	11	15	16	15	6	15	9	18	13	13	12	15	10	13	194	320.64	355.18
201-255 15	1	4	11	8	9	2	2	0	5	10	3	3	1	2	10	71	2.16	56.52
1-255 16	7	13	19	20	16	5	16	4	16	11	13	11	10	7	13	181	261.45	350.62
5 1-100 17	5	8	2	4	1	1	3	2	3	4	4	1	4	2	4	48	2.57	15.54
101-200 18	20	18	6	16	14	13	21	12	20	15	12	11	11	5	8	202	360.07	452.68
201-255 19	4	0	8	9	8	5	1	1	[illegible]	5	4	4	2	3	11	65	.45	43.66
1-255 20	16	12	9	27	9	5	17	7	22	13	11	7	10	3	9	177	244.45	399.37
6 1-100 21	2	4	0	8	3	1	4	2	4	6	8	4	3	0	6	55	.45	24.37
101-200 22	13	17	15	18	22	12	21	9	14	16	13	16	15	6	13	220	457.14	520.71
201-255 23	4	7	8	7	9	3	1	3	1	5	1	5	0	2	7	63	.16	31.87
1-255 24	10	17	11	15	14	6	11	7	13	13	7	14	5	5	13	161	182.16	238.66
EMG 1-100 25	2	4	4	3	9	3	6	2	3	11	12	0	10	4	3	76	4.57	55.18
1-2 101-200 26	39	26	40	40	33	35	41	39	37	46	40	46	18	33	45	558	4428.64	4641.43
201-255 27	3	3	6	5	12	2	7	4	3	8	11	3	1	4	4	76	6.57	42.86
1-255 28	40	28	39	40	32	33	41	37	37	46	39	46	18	34	46	556	4393.14	4601.25
EEG 1-100 29	6	1	0	2	3	8	1	5	3	2	14	2	2	1	11	61	.02	61.87
3-6 101-200 30	22	11	20	20	6	8	24	8	16	16	16	16	7	10	11	213	418.02	536.52
201-255 31	11	8	7	4	5	3	2	6	8	6	0	4	1	5	7	77	5.16	37.23
1-255 32	22	12	12	21	8	7	25	12	19	11	12	9	4	5	11	190	301.79	451.07
ALL 1-100 33	6	1	0	2	2	6	2	4	3	2	14	2	2	2	12	60	.00	60.54
1-6 101-200 34	48	40	37	47	31	22	43	29	32	43	31	40	18	32	34	527	3894.45	4172.95
201-255 35	13	10	8	4	5	3	1	6	8	6	0	2	2	5	7	80	7.14	54.11
1-255 36	47	30	27	43	30	16	43	21	35	36	29	33	11	24	27	452	2744.00	3116.25

The comparison of Between Session (Table 7) with Within Sessions (Table 6) for all Ss and sessions repeats the findings shown in Tables 3, 4, and 5--namely, that Within Sessions responses are correctly classified with a higher frequency than the Between Sessions responses. The results of these five tables also show that intrasubject reliability is good.

Between Subjects

The results of the EMG analysis from Group I data (see Introduction) showed that an individual's electrophysiological responses accompanying speech are unique to that individual. Therefore, a comparison was made Between Subjects for one session for all combinations. The results of this comparison are shown in Tables 8 and 9. Table 8 gives the number of correct classifications for all subgroups, and their associated chi squares, while Table 9 compares percentage correct responses and electrode rank order for all Ss over all sessions. Table 8 shows that a significant number of EMG responses were correctly classified above chance level.

Table 9 shows that even though the EMG responses are significant at $p<.01$, the highest frequency (both EMG) is only 39%, compared with 74% Within Subjects/Within Sessions, and 62% Within Subjects/ Between Sessions. These results suggest that homologous muscles act more like each other between Ss than homologous brain sites. Table 9 also shows that, although EMGs taken separately or together are better classifiers than the EEGs taken separately or together, no EEG electrode is preferred for classification purposes.

Sources of Error

As indicated in Data Analysis section of Methods, no special attempts were made to remove artifacts or other known sources of error, because we wanted to see how well the computer would perform in classifying responses under the "worst case" condition. Several known sources of error existed, including time and amplitude variations and muscle and eye movement artifacts. Each of these is demonstrated below, and an evaluation made as to their relative contribution.

Confusion Matrices (Bisyllabic Confusion)

To determine why those responses not correctly classified were confused with other templates, a set of confusion matrices was constructed for each electrode, for each S, and for each session. Table 10 shows such a confusion matrix for Subject C, Session 5, for the "All Channels" category, for each of the four sample subgroups. The confusion matrix shows how each electrode response was classified. Note that for subgroups 1-100 and 201-255 (left side of table), the rates of correct classifications are quite low and appear to be randomly distributed. This is in contrast with subgroups 101-200 and 1-255 (right side of table),

Table 8

SUMMARY OF CORRECT RESPONSE CLASSIFICATIONS FOR ALL SUBJECTS ONE SESSION EACH, BETWEEN SUBJECTS

SUMMARY TABLES, MARCH 7, 1973
GROUP 2 DATA -- BETWEEN SESSIONS FOR DIFFERENT SUBJECTS

SB1=SCHOOLBOY 1 BB1=BLACKBOARD 1 SW1=SHIPWRECK 1 CO1=COUGHDROP 1 MT1=MOUSETRAP 1
SB2=SCHOOLBOY 2 BB2=BLACKBOARD 2 SW2=SHIPWRECK 2 CO2=COUGHDROP 2 MT2=MOUSETRAP 2

SUMMED OVER THE FOLLOWING DATA SETS
R5 DATA WITH C5 TEMPLATES 1-100,101-200,201-255
C6 DATA WITH D3 TEMPLATES 1-100,101-200,201-255
D4 DATA WITH R6 TEMPLATES 1-100,101-200,201-255

NUMBER OF RESPONSES CORRECTLY CLASSIFIED

REPITITIONS CHAN POINTS			TIP 30	HAD 30	PUT 30	COOL 30	HIT 30	SB1 30	BB1 30	SW1 30	CO1 30	MT1 30	SB2 30	BB2 30	SW2 30	CO2 30	MT2 30	CORRECT 450	CHI1	CHI15
1	1-100	1	0	0	1	4	3	2	0	3	0	11	2	0	1	1	0	24	.14	61.07
	101-200	2	11	7	4	6	14	2	1	15	8	8	6	15	2	14	10	123	308.49	684.82
	201-255	3	2	1	2	1	2	0	6	9	3	2	4	0	1	2	3	38	2.24	43.93
	1-255	4	12	9	4	8	13	2	1	14	8	8	5	15	2	15	11	127	336.04	506.25
2	1-100	5	1	0	1	1	0	4	0	2	1	2	2	2	0	14	2	32	.14	90.00
	101-200	6	8	1[illegible]	5	5	2	9	14	1	11	9	2	13	9	3	9	11[illegible]	225.57	354.64
	201-255	7	3	1	2	0	0	1	1	3	1	2	1	1	0	5	1	3[illegible]	.00	33.21
	1-255	8	7	8	6	5	2	8	14	2	13	9	3	13	8	4	11	113	265.04	363.75
3	1-100	9	10	2	1	1	2	5	0	0	2	0	6	1	2	1	0	33	.32	58.39
	101-200	10	0	0	1	2	0	1	0	5	0	1	8	3	4	6	7	38	2.29	61.07
	201-255	11	2	1	5	1	1	0	0	0	1	1	0	1	1	3	4	21	2.99	19.82
	1-255	12	2	1	0	5	0	2	0	1	0	0	5	3	4	2	6	31	.74	32.68
4	1-100	13	1	3	2	2	1	1	1	0	5	1	3	1	0	1	2	24	1.29	13.93
	101-200	14	1	1	4	3	5	1	0	1	0	0	2	0	2	2	[illegible]	3[illegible]	.00	37.50
	201-255	15	2	1	8	4	2	2	0	0	0	2	0	0	0	1	0	22	2.29	37.50
	1-255	16	2	2	6	8	3	1	0	1	2	0	4	1	1	1	5	37	1.75	42.32
5	1-100	17	1	0	0	0	2	0	10	3	1	1	0	2	1	1	0	22	2.29	50.36
	101-200	18	1	1	2	3	5	0	0	0	0	0	4	1	1	4	10	32	.14	56.79
	201-255	19	2	0	10	8	2	0	0	0	1	0	1	0	4	3	3	34	.57	70.71
	1-255	20	0	4	2	7	7	1	0	3	0	0	0	4	1	[illegible]	2	31	.04	45.54
6	1-100	21	0	0	5	1	0	0	0	3	3	9	5	2	3	0	1	32	.14	51.43
	101-200	22	1	3	5	0	6	3	1	0	2	0	4	2	1	2	7	37	1.75	38.04
	201-255	23	4	0	3	1	7	1	1	2	2	2	5	1	0	1	2	32	.14	27.86
	1-255	24	2	2	3	6	4	3	1	0	2	0	5	3	0	0	5	36	1.29	31.07
EMG 1-2	1-100	25	0	0	1	4	3	4	0	2	0	9	3	0	1	3	0	30	.00	46.07
	101-200	26	14	18	4	12	8	4	11	15	13	13	13	16	4	14	14	173	730.32	881.25
	201-255	27	2	2	3	2	0	3	3	7	4	4	5	0	2	1	3	41	4.32	29.46
	1-255	28	14	18	4	13	8	6	11	15	12	13	13	16	4	15	14	176	761.29	901.07
EEG 3-6	1-100	29	10	2	0	0	3	1	4	2	2	1	0	1	0	1	1	28	.14	48.21
	101-200	30	0	1	3	2	1	2	0	3	0	1	8	4	2	5	10	42	5.14	69.64
	201-255	31	2	1	9	3	4	0	0	0	1	0	0	0	3	1	4	28	.14	46.07
	1-255	32	4	3	1	9	0	1	0	3	2	1	4	3	2	2	6	41	4.32	46.61
ALL 1-6	1-100	33	10	2	0	0	3	1	4	2	2	1	0	1	0	2	1	29	.04	47.68
	101-200	34	6	6	0	9	1	3	5	12	3	4	17	10	4	14	7	101	180.04	355.18
	201-255	35	2	1	9	3	4	0	0	0	1	0	0	0	3	2	4	29	.04	45.54
	1-255	36	12	7	2	12	2	2	2	5	2	2	11	10	3	8	5	85	108.04	227.68

Table 9

NEAREST PERCENTAGE CORRECT RESPONSES AND RANK ORDER OF ELECTRODES AS CLASSIFIERS, SAMPLE POINTS 101-200, ALL SUBJECTS, ALL SESSIONS

	Within Sessions/ Within Subjects		Between Sessions/ Within Subjects		Between Subjects	
Channel	% Correct	Rank	% Correct	Rank	% Correct	Rank
1	63	3	48	4	27	2
2	59	4	51	3	24	3
3	28	8	17	9	8	6.5
4	35	5	22	7.5	7	8.5
5	30	7	22	7.5	7	8.5
6	28	9	24	5	8	6.5
EMG	74	1	62	1	39	1
EEG	33	6	24	6	9	5
All	65	2	58	2	22	4

Table 10

CONFUSION MATRIX, SUBJECT C, ALL CHANNELS

```
SUMMARY TABLES, MARCH 7, 1973
        WITHIN SESSION SUMMARY OF COMPARISON DATA

SUMMED OVER THE FOLLOWING DATA SETS
        C5 DATA WITH C5 TEMPLATES        1-100,101-200,201-255

NUMBER OF REPETITIONS PER WORD
        TIP  HAD  PUT  COOL  HIT  SB1  BB1  SW1  CD1  MT1  SB2  BB2  SW2  CD2  MT2
        10   10   10   10    10   10   10   10   10   10   10   10   10   10   10
```

C O N F U S I O N   M A T R I X

ALL CHANS DATA, (CATEGORIES 33-35)

SAMPLES 1-100

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CO2	MT2
TIP	0	0	1	0	2	0	1	0	0	0	3	0	1	1	1
HAD	0	0	2	0	0	0	0	1	1	0	3	1	1	0	1
PUT	1	1	0	0	1	0	1	2	1	1	1	0	0	1	0
COOL	0	0	1	0	0	2	1	0	0	2	2	0	1	0	1
HIT	2	1	1	0	1	0	0	0	0	1	0	1	2	1	0
SB1	0	0	0	1	0	0	0	4	0	0	1	0	3	0	1
BB1	0	0	2	0	0	0	0	0	1	2	0	0	1	2	2
SW1	0	0	1	0	0	4	1	1	0	1	1	0	0	0	1
CD1	0	1	0	1	2	1	1	1	0	0	0	0	2	0	1
MT1	1	1	0	1	0	0	1	2	0	0	1	1	1	0	1
SB2	1	1	1	1	0	2	0	1	0	0	0	0	0	2	1
BB2	1	0	1	0	0	3	2	0	0	0	0	1	1	0	1
SW2	2	1	0	0	0	1	0	1	0	0	1	3	0	1	0
CD2	1	0	0	0	1	0	1	0	1	0	1	0	0	3	2
MT2	0	0	1	1	1	0	1	0	0	1	1	1	0	3	0

SAMPLES 101-200

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CO2	MT2
TIP	8	0	0	1	0	0	0	1	0	0	0	0	0	0	0
HAD	0	5	0	0	5	0	0	0	0	0	0	0	0	0	0
PUT	1	0	8	0	1	0	0	0	0	0	0	0	0	0	0
COOL	0	1	0	9	0	0	0	0	0	0	0	0	0	0	0
HIT	0	3	0	0	7	0	0	0	0	0	0	0	0	0	0
SB1	0	0	0	0	0	8	0	0	0	0	2	0	0	0	0
BB1	0	0	1	0	0	0	8	0	0	1	0	0	0	0	0
SW1	0	0	1	2	0	0	0	5	0	0	0	0	2	0	0
CD1	0	0	0	0	0	0	0	0	8	0	0	0	0	2	0
MT1	0	2	0	0	0	0	1	0	0	7	0	0	0	0	0
SB2	0	0	0	0	0	5	0	1	0	0	4	0	0	0	0
BB2	0	0	0	0	0	0	1	0	0	0	0	9	0	0	0
SW2	0	0	0	0	0	0	0	5	0	0	0	0	5	0	0
CD2	0	0	0	0	0	0	0	0	4	0	0	0	0	5	1
MT2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	9

SAMPLES 201-255

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CO2	MT2
TIP	1	2	1	1	1	0	0	2	0	0	0	0	2	0	0
HAD	1	0	3	1	0	0	2	3	0	0	0	0	0	0	0
PUT	0	5	1	1	2	0	0	1	0	0	0	0	0	0	0
COOL	1	1	4	0	0	0	1	0	0	1	0	0	2	0	0
HIT	0	1	4	1	0	0	0	1	0	0	0	1	2	0	0
SB1	0	2	0	0	0	0	1	1	1	1	0	0	2	0	2
BB1	0	1	0	1	0	1	1	0	1	1	0	1	1	0	2
SW1	1	1	0	0	1	2	0	1	0	1	0	0	3	0	0
CD1	0	1	0	0	0	0	2	1	0	2	1	1	0	2	0
MT1	0	0	0	0	0	0	1	0	0	1	0	1	2	2	3
SB2	0	0	0	2	1	0	0	1	1	0	0	1	0	1	3
BB2	0	0	0	0	0	1	0	0	1	2	1	1	2	1	1
SW2	2	2	0	0	0	0	0	0	0	1	1	0	2	0	2
CD2	0	0	0	0	0	2	0	0	1	1	0	2	1	0	3
MT2	0	1	0	0	0	1	2	0	0	4	0	0	0	1	1

SAMPLES 1-255

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CO2	MT2
TIP	7	0	0	2	0	0	0	1	0	0	0	0	0	0	0
HAD	0	4	0	0	6	0	0	0	0	0	0	0	0	0	0
PUT	1	0	8	0	1	0	0	0	0	0	0	0	0	0	0
COOL	0	1	0	9	0	0	0	0	0	0	0	0	0	0	0
HIT	1	2	0	0	6	0	0	0	1	0	0	0	0	0	0
SB1	0	0	0	0	0	5	0	1	0	0	3	0	1	0	0
BB1	0	0	1	0	0	0	8	0	1	0	0	0	0	0	0
SW1	1	0	0	2	0	0	0	4	0	0	0	0	3	0	0
CD1	0	0	0	0	0	0	0	0	6	0	0	0	0	4	0
MT1	0	0	0	0	0	0	1	0	0	7	0	0	0	0	2
SB2	0	0	0	0	0	5	0	0	0	0	4	0	0	0	1
BB2	0	0	0	0	0	0	1	0	0	0	0	9	0	0	0
SW2	0	0	0	0	0	1	0	5	0	0	0	0	4	0	0
CD2	0	0	0	0	0	0	0	0	2	0	0	0	0	7	1
MT2	0	0	0	0	0	0	0	0	0	2	0	0	0	0	8

where a strong diagonal begins at the upper left, each cell of the diagonal representing the number of correct responses.

The diagonal is seen even more clearly in Tables 11 and 12, which present the confusion matrices for all Ss Within sessions and Between Sessions, respectively. There are also two strong subdiagonals in subgroups 101-200 and 1-255. The first begins at the junction of SB2 (column) and SB1 (row); the second begins at the junction of SB1 (column) and SB2 (row). These subdiagonals represent a strong confusion by the computer between two identical bisyllabic words with different accents, suggesting that the effect of emphasis on classification is not large. This result further suggests that the percentage of correct classifications can be materially increased if emphasis is not taken into account by the computer. That is, we can regard confusions of emphasis not as errors, but as correct classifications of responses. For example, the number of total correct responses in the main diagonals for subgroup 101-200 in Tables 11 and 12 are 592 and 527, or 63% and 59%, respectively. By disregarding the confusions of emphasis on the bisyllabic words in classifying responses, these figures increase to 689 and 594, or 76% and 63% correctly classified responses, respectively.

Table 13 is the confusion matrix for the Between Subjects comparison. This shows that although there were sporadic incidences of relatively high correct response classifications in subgroups 101-200 and 1-255 (due to the EMG classification described above), in general the classifications were randomly distributed. Examination of the three confusion matrices in Tables 11, 12, and 13 reveals no consistent confusion of one word with another or one electrode with another.

Time Shift and Amplitude Variation

Two additional sources of error are illustrated in Figure 12. The first, an EMG response to TIP 8, was a slight shifting in time (to the left) of the electrophysiological response with respect to the onset of vocalization. Since the onset of vocalization was taken as the time zero reference, then any such shift would cause an incorrect classification even though the waveform of the individual response is very similar to the template. In this case, TIP 8 was confused with COOL. The second source of error was due to amplitude variation, as shown in an EMG response to TIP 9, so that TIP 9 was also confused with COOL (note that although there was also a time shift in TIP 9, it was shifted relative to both templates).

Another possible source of temporal error is contraction or expansion in time of an individual response with respect to the template. So far, no examples have been found in the raw data, although they may exist. A computer program designed to detect such errors and to correct for them is now being devised.

Table 11

SUMMARY CONFUSION MATRIX, ALL SUBJECTS, ALL CHANNELS, WITHIN SESSIONS

SUMMARY TABLES, MARCH 7, 1973
WITHIN SESSION SUMMARY OF COMPARISON DATA

SUMMED OVER THE FOLLOWING DATA SETS

B5 DATA WITH B5 TEMPLATES	1-100,101-200,201-255
B6 DATA WITH B6 TEMPLATES	1-100,101-200,201-255
C5 DATA WITH C5 TEMPLATES	1-100,101-200,201-255
C6 DATA WITH C6 TEMPLATES	1-100,101-200,201-255
D3 DATA WITH D3 TEMPLATES	1-100,101-200,201-255
D4 DATA WITH D4 TEMPLATES	1-100,101-200,201-255

NUMBER OF REPETITIONS PER WORD

TIP	HAD	PUT	COOL	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
60	60	60	60	60	60	60	60	60	60	50	60	60	60	60

C O N F U S I O N   M A T R I X

ALL CHANS DATA, (CATEGORIES 33-36)

SAMPLES 1-100

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
TIP	3	2	3	4	4	7	2	2	2	6	6	0	7	6	6
HAD	2	4	2	3	2	6	5	3	4	4	9	6	5	3	4
PUT	4	5	6		3	3	3	7	5	4	5	0	5	4	6
COOL	3	7	4	2	3	2	3	1	5	7	9	2	2	2	8
HIT	3	2	4	4	4	3	4	7	1	7	4	2	6	7	2
SB1	4	4	2	4	0	3	4	7	5	3	5	3	5	5	6
BB1	4	3	4	3	2	1	1	3	2	7	8	4	8	6	4
SW1	2	2	4	2	2	9	3	3	4	2	8	3	5	4	7
CD1	2	4	7	2	3	4	6	5	1	5	4	3	3	3	8
MT1	4	6	2	4	4	2	2	4	2	6	6	5	4	5	4
SB2	2	6	5	4	3	4	3	5	3	1	2	6	2	9	5
BB2	2	7	4	2	1	5	7	6	1	7	3	2	4	3	6
SW2	2	3	3	2	2	2	3	5	2	6	8	4	5	4	9
CD2	6	4	2	1	3	3	3	2	2	7	6	3	5	5	8
MT2	2	3	5	3	3	2	2	6	2	5	5	5	5	5	7

SAMPLES 101-200

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
TIP	42	2	2	2	5	1	0	2	2	1	0	0	1	0	0
HAD	0	33	2	7	13	0	2	0	1	1	1	0	0	0	0
PUT	1	2	46	1	5	0	1	1	0	2	0	0	0	0	1
COOL	1	8	0	41	2	1	0	0	2	0	2	0	1	2	0
HIT	3	15	3	1	36	0	0	0	0	2	0	0	0	0	0
SB1	1	0	0	2	0	36	0	2	11	1	6	0	0	1	0
BB1	0	1	2	0	0	0	47	1	2	1	0	6	0	0	0
SW1	3	3	1	3	0	1	4	37	0	0	0	0	8	0	0
CD1	0	1	0	2	2	5	0	0	42	0	0	0	0	8	0
MT1	0	2	0	0	0	1	2	1	1	49	0	0	0	0	4
SB2	2	0	0	1	0	15	0	2	0	0	34	2	1	3	0
BB2	0	0	0	0	0	0	11	0	0	0	3	42	1	2	1
SW2	2	2	0	0	1	1	0	12	0	0	4	0	36	1	1
CD2	0	2	0	1	0	2	0	0	18	1	3	1	0	30	2
MT2	0	1	0	0	0	0	0	0	2	9	2	1	1	3	41

SAMPLES 201-255

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
TIP	4	4	8	7	6	4	4	5	3	2	2	1	6	4	[illegible]
HAD	7	5	9	6	4	2	4	4	3	2	4	0	1	3	6
PUT	5	10	1	4	10	2	2	3	3	2	3	2	6	3	4
COOL	6	5	10	2	3	2	5	0	4	5	5	2	5	2	4
HIT	6	5	13	7	3	3	3	3	5	0	1	2	6	1	2
SB1	4	5	3	7	1	1	2	5	3	5	5	5	5	1	[illegible]
BB1	4	3	1	3	1	1	3	1	9	8	2	6	6	1	11
SW1	9	2	2	1	4	4	3	6	7	4	2	3	5	4	4
CD1	2	3	4	3	6	0	6	4	3	11	3	3	3	5	4
MT1	3	5	0	6	0	2	4	0	3	6	5	2	8	6	10
SB2	6	1	2	3	2	2	1	3	4	8	0	7	6	4	11
BB2	3	0	3	2	5	3	7	2	3	7	6	5	4	4	6
SW2	4	3	4	5	4	2	2	3	5	5	9	2	5	1	6
CD2	4	3	4	4	4	2	3	3	5	5	5	7	3	1	7
MT2	3	4	4	5	2	3	4	3	6	9	6	0	2	1	8

SAMPLES 1-255

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
TIP	30	6	1	5	10	1	0	2	2	1	0	0	1	1	0
HAD	2	28	2	6	18	0	1	0	0	1	2	0	0	0	0
PUT	1	6	40	2	6	0	1	1	0	2	0	0	0	0	1
COOL	1	11	0	36	3	2	0	1	2	1	2	0	1	0	0
HIT	4	13	3	6	30	0	0	1	1	2	0	0	0	0	0
SB1	0	0	0	3	0	26	0	6	14	0	9	0	1	1	0
BB1	0	0	2	0	0	0	40	2	3	3	0	10	0	0	0
SW1	4	3	1	2	0	1	4	34	1	0	0	1	9	0	0
CD1	0	1	1	4	1	9	0	0	36	1	1	0	0	6	0
MT1	0	1	0	1	0	1	2	0	2	44	0	0	0	1	8
SB2	2	0	0	1	0	15	0	1	0	1	31	1	3	3	2
BB2	1	5	0	0	0	0	14	3	0	0	4	30	2	1	0
SW2	1	1	0	0	2	4	0	11	0	1	8	0	29	3	0
CD2	2	2	0	1	1	3	0	2	16	1	4	0	1	22	5
MT2	0	1	0	0	0	0	0	1	2	11	2	1	1	3	38

Table 12

SUMMARY CONFUSION MATRIX, ALL SUBJECTS, ALL CHANNELS, BETWEEN SESSIONS

SUMMARY TABLES, MARCH 7, 1973
COMPARISON BETWEEN SESSIONS FOR THE SAME SUBJECT

SUMMED OVER THE FOLLOWING DATA SETS

B5 DATA WITH B6 TEMPLATES	1-100,101-200,201-255
B6 DATA WITH B5 TEMPLATES	1-100,101-200,201-255
C6 DATA WITH C5 TEMPLATES	1-100,101-200,201-255
C5 DATA WITH C6 TEMPLATES	1-100,101-200,201-255
D3 DATA WITH D4 TEMPLATES	1-100,101-200,201-255
D4 DATA WITH D3 TEMPLATES	1-100,101-200,201-255

NUMBER OF REPETITIONS PER WORD

TIP	HAD	PUT	COOL	HIT	SH1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
60	60	60	60	60	60	60	60	60	50	50	50	60	60	50

C O N F U S I O N   M A T R I X

ALL CHANS DATA, (CATEGORIES 33-36)

SAMPLES 1-100

WORD	TIP	HAD	PUT	COO	HIT	SH1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
	GETS	CLASSIFIED	AS	IF	IT	WERE - - -									
TIP	6	2	1	2	2	5	2	6	2	2	11	3	4	5	7
HAD	5	1	1	3	2	12	3	5	1	3	13	1	6	1	3
PUT	5	1	0	3	3	11	4	6	3	1	11	0	3	4	5
COOL	10	2	0	2	1	9	0	0	2	0	17	1	5	2	9
HIT	8	1	2	1	2	7	1	7	4	1	12	3	5	2	4
SH1	6	1	0	1	2	6	3	4	4	8	9	4	6	3	3
BB1	9	2	0	3	4	9	2	1	3	2	13	1	6	3	2
SW1	8	1	4	1	2	6	1	4	3	2	8	1	4	6	9
CD1	7	1	1	3	0	7	2	0	3	4	13	3	4	5	7
MT1	8	2	3	1	1	7	5	2	1	2	11	1	0	5	11
SB2	8	5	2	0	2	8	3	0	2	2	14	2	3	1	8
BB2	7	1	4	1	4	7	2	3	3	4	8	2	4	4	6
SW2	8	0	1	2	1	7	2	8	3	3	12	2	2	4	5
CD2	7	0	0	1	1	6	1	8	3	2	13	3	8	2	5
MT2	8	1	2	0	0	2	1	5	6	6	7	1	5	4	12

SAMPLES 101-200

WORD	TIP	HAD	PUT	COO	HIT	SH1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
	GETS	CLASSIFIED	AS	IF	IT	WERE - - -									
TIP	48	2	1	2	0	1	0	1	1	2	1	1	0	0	0
HAD	1	40	2	1	8	1	2	0	1	0	1	0	1	1	1
PUT	2	1	37	7	7	0	3	0	0	1	0	1	0	0	1
COOL	3	2	1	47	1	3	0	0	1	0	0	0	0	1	1
HIT	4	14	4	2	31	0	2	1	1	1	0	0	0	0	0
SB1	4	0	0	15	0	22	0	5	6	2	1	0	2	3	0
BB1	2	2	1	0	1	0	43	2	0	2	0	7	0	0	0
SW1	11	4	1	4	0	3	2	29	0	1	1	1	2	1	0
CD1	0	5	0	6	0	2	0	0	32	1	2	0	0	12	0
MT1	4	0	0	2	0	1	3	0	2	43	1	0	0	0	4
SB2	5	2	0	1	0	4	0	1	1	2	31	5	4	4	0
BB2	1	1	0	0	0	0	6	2	0	1	6	40	1	2	0
SW2	12	1	0	1	0	1	0	9	0	1	10	4	18	2	1
CD2	0	4	0	3	0	3	0	0	11	0	4	0	1	32	2
MT2	0	0	0	2	0	0	1	1	3	14	2	0	1	2	34

SAMPLES 201-255

WORD	TIP	HAD	PUT	COO	HIT	SB1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
	GETS	CLASSIFIED	AS	IF	IT	WERE - - -									
TIP	13	7	7	6	6	1	3	6	6	2	0	1	1	1	0
HAD	9	10	3	5	6	2	4	5	9	0	2	0	2	2	1
PUT	16	8	8	0	7	2	2	5	5	2	1	1	0	3	0
COOL	11	5	2	4	5	3	3	7	8	4	0	2	1	3	2
HIT	11	12	4	3	5	2	3	4	8	1	0	1	0	2	4
SB1	12	7	4	7	6	3	3	2	11	0	0	0	2	2	1
BB1	16	5	1	4	10	0	1	0	10	4	2	3	1	2	1
SW1	13	10	2	4	8	0	1	6	7	0	0	2	4	1	2
CD1	12	4	4	8	8	0	7	2	8	0	0	2	3	2	0
MT1	12	1	1	10	9	3	4	1	7	6	0	1	1	3	1
SB2	10	8	4	8	5	3	2	3	8	4	0	1	1	2	1
BB2	11	2	4	5	2	5	4	2	11	3	0	2	4	3	2
SW2	14	8	1	6	6	1	1	6	8	3	0	2	2	2	0
CD2	10	8	3	8	6	2	1	3	5	3	0	3	1	5	2
MT2	13	2	3	6	9	3	1	0	8	4	1	1	1	1	7

SAMPLES 1-255

WORD	TIP	HAD	PUT	COO	HIT	SH1	BB1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
	GETS	CLASSIFIED	AS	IF	IT	WERE - - -									
TIP	47	3	1	2	0	1	0	3	0	2	0	0	0	1	0
HAD	3	30	1	4	12	0	2	1	2	0	2	0	1	2	0
PUT	6	2	27	5	9	0	5	1	0	2	0	1	0	1	1
COOL	1	4	1	43	1	6	0	1	1	1	0	0	0	1	0
HIT	8	14	1	1	30	0	3	1	1	1	0	0	0	0	0
SB1	5	0	1	13	0	16	0	7	9	2	2	0	2	3	0
BB1	2	2	1	0	0	0	43	1	1	2	0	6	1	0	1
SW1	16	5	1	3	1	2	2	21	0	1	1	1	4	2	0
CD1	0	5	0	6	1	1	0	0	35	0	2	0	0	10	0
MT1	1	1	0	4	0	1	7	0	5	36	1	0	1	0	3
SB2	6	1	0	2	1	11	0	0	2	1	29	2	2	3	0
BB2	3	1	0	0	0	0	12	0	0	1	6	33	1	3	0
SW2	16	0	0	1	0	3	0	17	0	0	10	1	11	0	1
CD2	0	5	0	3	0	4	0	1	15	1	6	0	0	24	1
MT2	1	2	0	3	0	0	2	0	5	13	1	0	1	5	27

Table 13

SUMMARY CONFUSION MATRIX, ALL CHANNELS, ALL SUBJECTS, BETWEEN SUBJECTS

SUMMARY TABLES, MARCH 7, 1973
GROUP 2 DATA -- BETWEEN SESSIONS FOR DIFFERENT SUBJECTS

SUMMED OVER THE FOLLOWING DATA SETS
H5 DATA WITH C5 TEMPLATES 1-100,101-200,201-255
C5 DATA WITH D3 TEMPLATES 1-100,101-200,201-255
D4 DATA WITH H6 TEMPLATES 1-100,101-200,201-255

NUMBER OF REPETITIONS PER WORD

TIP	HAD	PUT	COOL	HIT	SH1	BH1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
30	30	30	30	30	30	30	30	30	30	30	30	30	30	30

C O N F U S I O N   M A T R I X

ALL CHANS DATA, (CATEGORIES 33-36)

SAMPLES 1-100

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SH1	BH1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
TIP	10	2	1	2	2	1	3	1	4	1	0	2	1	0	0
HAD	9	2	1	2	2	2	3	1	4	0	0	3	0	1	0
PUT	10	1	0	3	3	3	3	2	2	0	0	1	1	0	1
COOL	8	0	0	0	2	4	4	5	1	4	0	0	0	1	1
HIT	8	1	0	2	3	3	4	1	4	1	0	2	1	0	0
SB1	9	2	1	1	1	1	3	3	6	1	1	0	0	0	1
BB1	10	1	0	1	2	0	4	0	6	4	0	1	1	0	0
SW1	9	1	0	2	2	2	2	2	4	0	0	1	4	1	0
CD1	10	1	1	5	3	1	3	1	2	1	1	0	1	0	0
MT1	7	1	0	3	6	0	3	3	2	1	0	1	1	1	1
SB2	8	1	0	1	1	3	6	2	2	2	0	1	2	1	0
BB2	10	1	1	0	3	1	3	1	4	1	0	1	3	1	0
SW2	10	1	1	2	1	4	5	1	0	0	0	4	0	1	0
CD2	8	0	2	1	1	3	4	0	3	2	0	2	0	2	2
MT2	7	0	0	4	3	1	5	1	3	3	0	2	0	0	1

SAMPLES 101-200

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SH1	BH1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
TIP	6	6	0	0	0	0	1	5	2	2	4	0	2	2	0
HAD	1	6	1	4	0	1	0	0	5	6	0	0	0	5	1
PUT	0	0	0	3	0	0	1	5	0	8	1	4	8	0	0
COOL	1	4	1	9	0	0	0	7	3	2	1	0	0	2	0
HIT	1	15	1	2	1	0	1	0	3	1	0	0	1	4	0
SH1	7	1	0	1	0	3	0	0	1	0	12	1	0	4	0
BB1	4	0	2	2	0	0	5	3	1	0	4	5	2	2	0
SW1	5	0	2	3	0	0	0	12	1	2	1	2	1	0	1
CD1	0	0	0	4	0	2	0	0	3	0	8	0	0	13	0
MT1	2	1	0	3	0	0	0	2	2	4	3	0	0	5	8
SB2	1	0	0	0	0	1	0	0	4	0	17	2	1	4	0
BB2	0	0	0	0	0	2	8	0	1	0	3	10	5	0	1
SW2	7	0	1	0	0	0	0	7	0	5	1	5	4	0	0
CD2	0	0	0	1	0	3	0	0	5	0	5	2	0	14	0
MT2	2	0	0	0	0	1	1	0	3	6	3	0	4	3	7

SAMPLES 201-255

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SH1	BH1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
TIP	2	0	11	3	3	0	2	1	0	3	0	1	3	1	0
HAD	1	1	9	5	5	0	2	2	1	2	0	0	1	0	1
PUT	0	1	9	6	4	0	1	1	1	3	0	0	2	0	2
COOL	3	1	9	3	6	0	1	0	1	1	0	1	2	2	0
HIT	2	0	7	3	4	1	1	1	1	4	0	0	4	1	1
SB1	7	1	5	3	3	0	1	0	4	0	1	0	3	0	2
BB1	11	2	5	0	1	1	0	2	1	1	0	1	2	1	2
SW1	4	3	10	2	2	1	0	0	4	2	0	0	2	0	0
CD1	4	6	7	3	3	1	0	0	1	2	0	0	1	1	1
MT1	6	0	10	6	4	1	0	1	0	0	0	0	0	1	1
SB2	8	1	10	2	3	1	1	1	2	0	0	0	0	1	0
BB2	9	3	7	2	1	0	0	1	2	0	0	0	2	3	0
SW2	8	1	10	3	1	0	0	1	0	1	0	1	3	1	0
CD2	8	1	8	5	2	1	0	1	0	1	0	1	0	2	0
MT2	7	0	5	4	3	1	0	4	0	1	0	0	0	1	4

SAMPLES 1-255

WORD GETS CLASSIFIED AS IF IT WERE - - -

WORD	TIP	HAD	PUT	COO	HIT	SH1	BH1	SW1	CD1	MT1	SB2	BB2	SW2	CD2	MT2
TIP	12	5	0	2	1	0	0	3	1	0	2	0	3	0	1
HAD	0	7	1	6	0	2	0	0	9	1	0	0	0	3	1
PUT	4	2	2	7	1	0	4	4	0	1	1	0	4	0	0
COOL	5	1	1	12	1	1	0	3	4	1	1	0	0	0	0
HIT	2	10	1	6	2	0	0	0	5	0	0	0	1	1	2
SB1	9	0	0	6	1	2	0	1	2	0	6	1	0	2	0
BB1	9	0	0	6	0	0	2	4	0	0	3	4	0	1	1
SW1	11	3	3	3	1	0	0	5	0	0	0	2	0	0	2
CD1	2	3	0	6	0	1	0	0	2	0	5	0	0	10	1
MT1	7	1	0	6	0	0	0	2	0	2	0	0	0	3	9
SB2	2	2	0	3	0	2	0	0	4	0	11	5	0	1	0
BB2	2	0	0	1	0	2	5	1	1	0	2	10	4	1	1
SW2	12	2	1	1	0	1	0	2	2	1	0	5	3	0	0
CO2	4	2	0	2	0	5	0	0	4	0	2	1	0	8	2
MT2	5	0	0	0	0	2	0	0	3	6	5	0	2	2	5

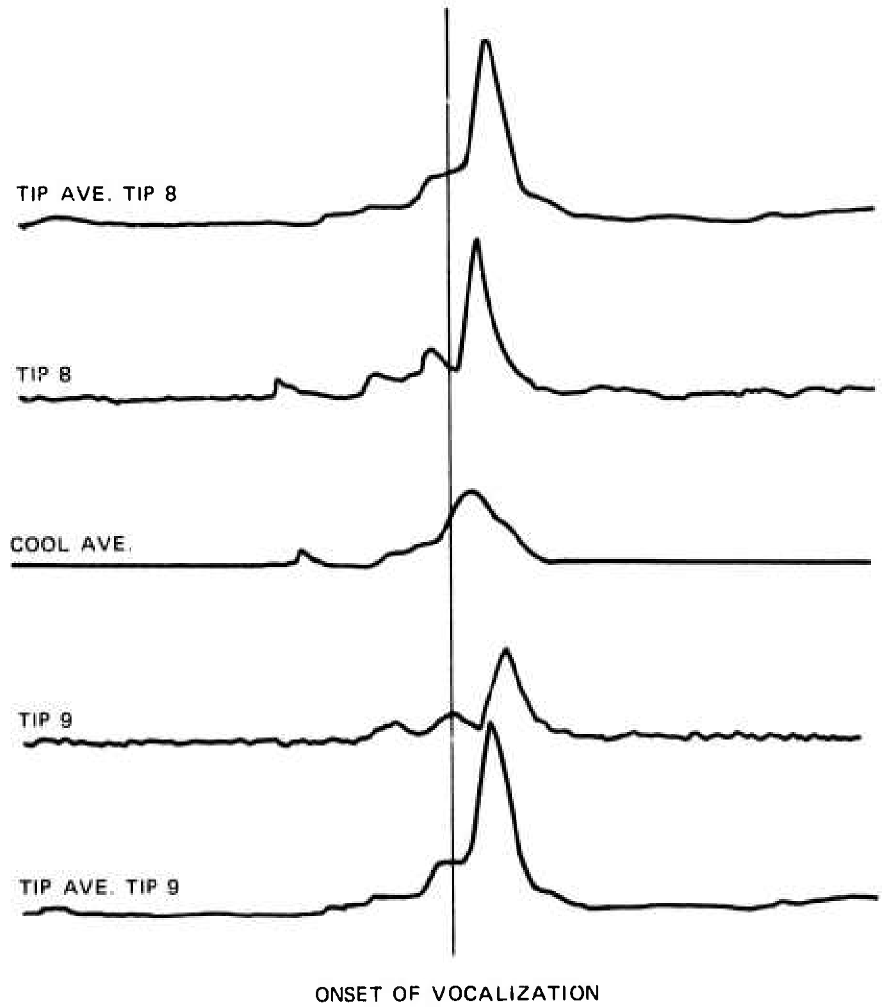


FIGURE 12 TWO EMG RESPONSES (ELECTRODE 13/16, SUBJECT C5) TO TIP CONFUSED WITH COOL DUE TO TIME SHIFT AND AMPLITUDE VARIATION

Artifacts

By definition, artifacts are: (1) potentials causing a disturbance not methodically related to the original biological response being measured; or (2) potentials that are methodically related to the response from a source other than that which is assumed to produce the response. The former disturbances are random and cannot contribute to computer recognition of the response, although they can degrade the recognition as random noise. The latter are true consistent disturbances and imply that a particular assumption about the physiological origin of the response is incorrect. However, from a practical point of view, if the computer can recognize the biological response produced by any source, including one whose origin may be mistaken, then biocybernetic communication may still function adequately even though all the sources of the response cannot be identified. Several such artifacts are discussed below.

Muscle artifacts were controlled by having Ss relax as much as possible throughout the experimental trials, with the allowance to move around between trials. Examination of the temporal changes of EMG records in comparison with any muscle artifacts in the EEG revealed little contamination from this source.

Figure 13 illustrates a relatively rare occurrence of EMG artifact, in which an EMG response (electrode 7/8) to TIP 1 was classified as MOUSETRAP. The artifact itself is due to a larger voltage response than usual for the amplifier gain, resulting in saturation. The response was misclassified simply because the minimum RMS difference was obtained, by chance, with MOUSETRAP, even though the signal value more closely resembles the form of the TIP template. The confusion has no other significance.

One of the more prevalent artifacts in EEG data is the corneal-retinal-occipital potential due to eye movements. In reading the stimulus words used in this project, such eye movements are practically impossible to eliminate completely. Nevertheless, their contribution may be assessed in various ways. For example, in the collection of Group I data, two stimulus inputs (visual and auditory) were used. In the visual input, both overt and covert responses were obtained to assess the contribution of EMG artifacts caused by speech (overt response). During the auditory input, responses were obtained during eyes open and eyes closed conditions to assess both the contribution of visually evoked responses and eye movements, both presumably absent under these conditions. Results showed that under all four conditions, certain potential changes were present in the EEG that could only be interpreted as true EEG potentials related to verbal behavior (overt or covert), and not attributable to auditory or visually evoked potentials, muscle or movement artifacts, or eye movements (see Figures 3, 4, 5, and 6 of the First Semi-Annual Technical Progress Report and the discussion regarding artifacts on pages 13-19 of that report).

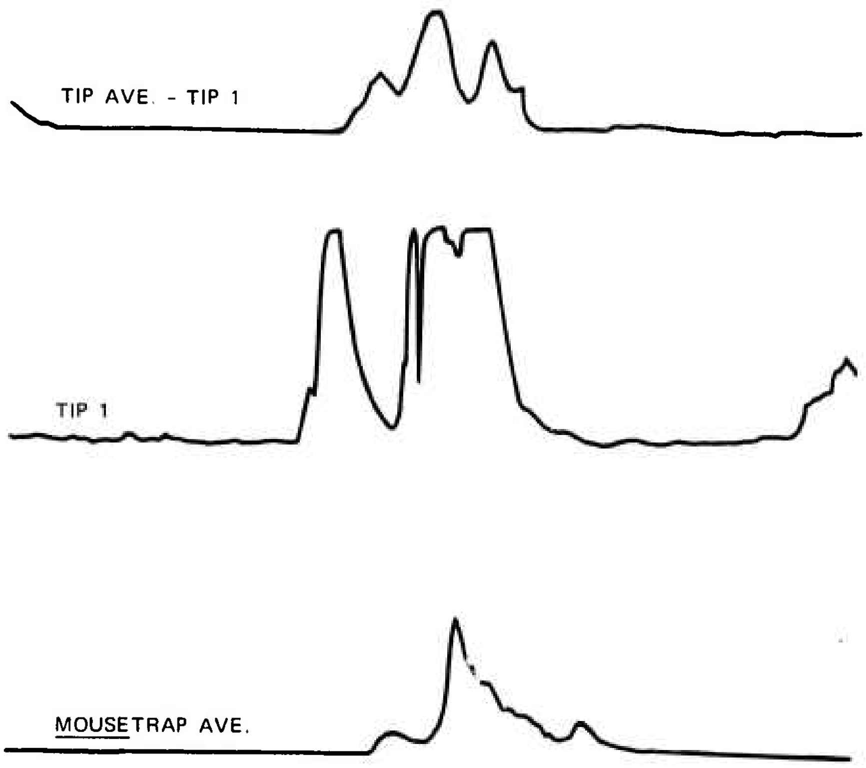


FIGURE 13 MISCLASSIFICATION OF EMG RESPONSE (ELECTRODE 7/8, SUBJECT C5) DUE TO AMPLIFIER SATURATION

Nevertheless, we cannot know from that data what contribution eye movements may have made to the current data. Therefore, a control study using five words from Table 1 was conducted, where eye movements *per se* were measured along with the EEG. Six types of stimulus-response combinations were obtained for each of the five words, each repeated five times. The words were TIP, HAD, PUT, COUGHDROP, and SCHOOLBOY. The conditions were:

(1) Visual stimulus presentation, overt response, eyes open.

(2) Visual stimulus presentation, covert response (silent reading), eyes open.

(3) Auditory stimulus presentation, overt response, eyes open.

(4) Auditory stimulus presentation, covert response, eyes open.

(5) Auditory stimulus presentation, overt response, eyes closed.

(6) Auditory stimulus presentation, covert response, eyes closed.

The S was instructed to remain as relaxed as possible between and during trials. On hearing a warning click (CLK) in her earphones for eyes open conditions, S was to fixate on a spot in the center of the stimulus screen. A visual or auditory stimulus was presented 1 sec later, followed in 1 sec by another CLK. On hearing the second CLK, the S was to respond either overtly or covertly according to the condition. Approximately 30 sec later, the next trial began, with a rest of 2 min between conditions. In all trials, eye movements were detected by two pairs of electro-oculograph (EOG) electrodes (one pair for vertical movement, one pair for horizontal) placed around the eyes.

The results may be summarized as follows:

(1) For the 25 visual stimuli, overt response (worse case for eye movements), eye movements were detected on both the EOG and the four EEG channels when S attended to the fixation point on hearing the warning CLK.

(2) Of these 25 presentations, nine (38%) had eye movement artifacts in the EEG record as confirmed by the EOG electrodes. Of these nine, only four could be associated with the actual response period; the remainder were randomly distributed. Thus, only 16% of the eye movement artifacts could have contributed to a correct classification, *if* all of the artifacts occurred in the same way for a given word, which they did not.

(3) For all other conditions, the amount of eye movement artifacts decreased so that by condition six (auditory stimulus, eyes closed, covert response), no artifacts were obtained at all.

(4) In all of the records, even those containing a fair amount of artifacts and those containing no artifacts, a specific potential change in the EEG was identifiable in the raw record that could be related to the verbal behavior, whether overtly or covertly produced. In many instances, this potential change had the time course and waveform of those often seen as eye movement artifacts, even when the EOG electrodes showed that no eye movements occurred and even when the response was covert (and therefore was not due to EMG or other jaw movement artifacts). Although artifacts of some sort, such as subvocal tongue movements, cannot be completely ruled out, the probability is high that the potentials we claim to be EEG signals are indeed EEG signals.

Figures 14 and 15 illustrate some of these results for Subject B. Figure 14 illustrates an (A) overt and (B) covert response to the visual stimulus SCHOOLBOY, under conditions of no eye movement artifacts of significance during the response period. The top two channels are the vertical and horizontal EOG electrodes; the next four are the four EEG channels; the last is the CLK code and voice channel. Note that there are definite EOG potentials and artifacts in the EEG in Figure 14A following the first CLK when Subject B attends to the fixation point. Preceding the onset of vocalization, a definite slow-wave negative-positive shift is obtained in the EEG that continues during vocalization. This slow-wave is also seen during the covert response in Figure 14B. This potential is evidently the patterned EEG change (more obvious in electrode F7 and T5) associated with SCHOOLBOY, whether overtly or covertly produced. In Figure 14A and B, there is a small EOG deflection on the horizontal electrode (channel 2) during portions of the vocalization and presumed silent reading. However, since it is not of significant size in either the overt or the covert response, and lasts only during a small portion of either the EEG response or the actual vocalization, it cannot contribute much either as an artifact or in response classification.

In contrast, Figure 15 shows the same overt and covert responses to SCHOOLBOY but, in both cases, accompanied by marked eye movement artifact as confirmed by the EOG electrodes. Note that in the overt responses (Figure 15A), the eye movements occur variably throughout the recording period, not just in association with the verbal response. Thus, they are more likely to produce confusion during classification than aid in classification. However, during vocalization, the EEG response of F7 and T5 which was seen in Figure 14A and B is clearly discernible in Figure 15A and to a reduced extent in Figure 15B (covert response), and is not associated with a particular EOG deflection. This suggests that if response classification were only carried out on the period from about 1 sec before vocalization for about 1.0 to 1.5 sec (corresponding to our best subgroup classifier of sample points 101-200), the response in 15A would be correctly classified despite the artifact.

In addition to the above results with eye movement artifacts, the following points show, on logical grounds, that eye movement artifacts

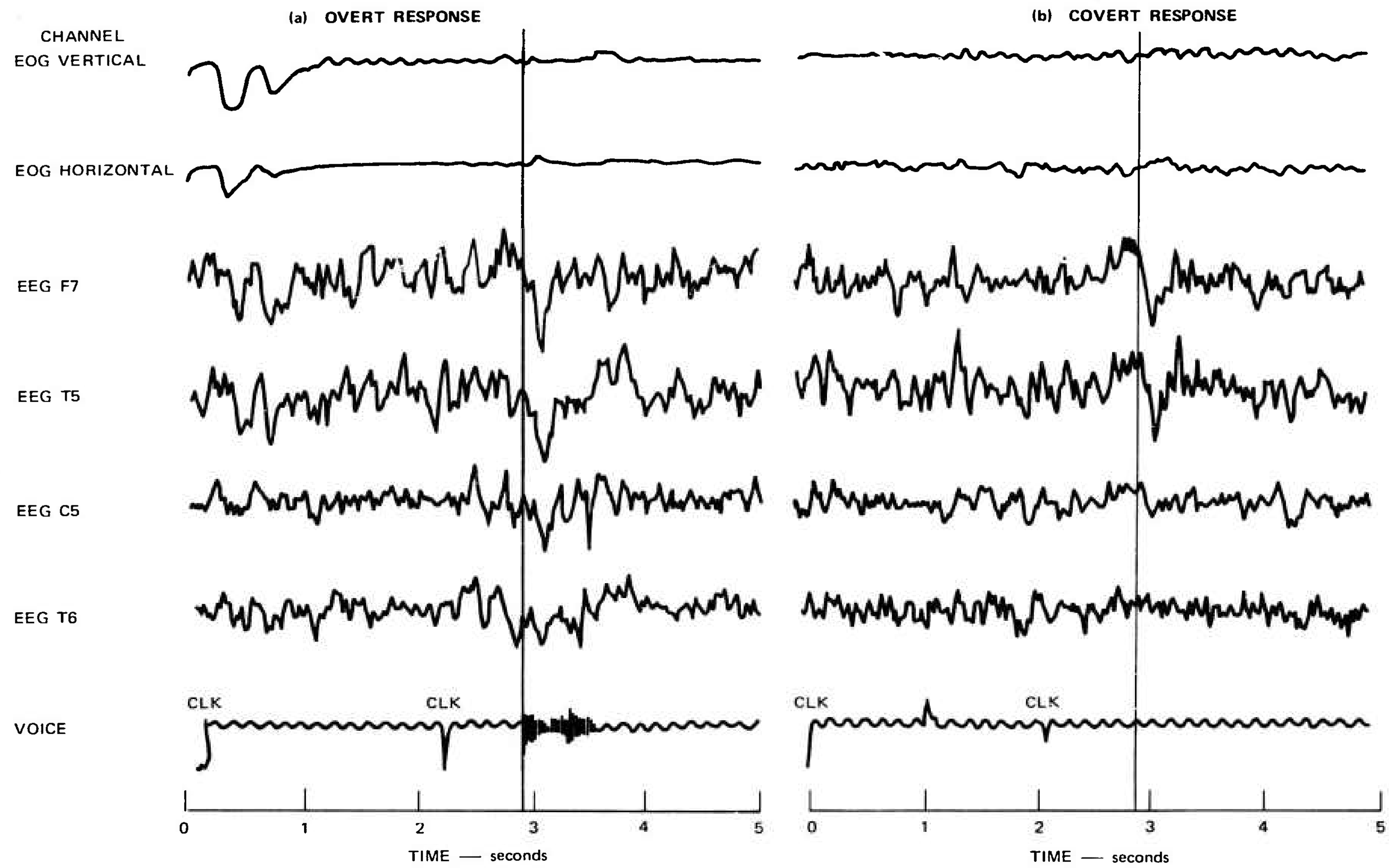


FIGURE 14 EEG IN ABSENCE OF EYE MOVEMENTS, OVERT AND COVERT VERBAL RESPONSE TO SCHOOLBOY, SUBJECT B7

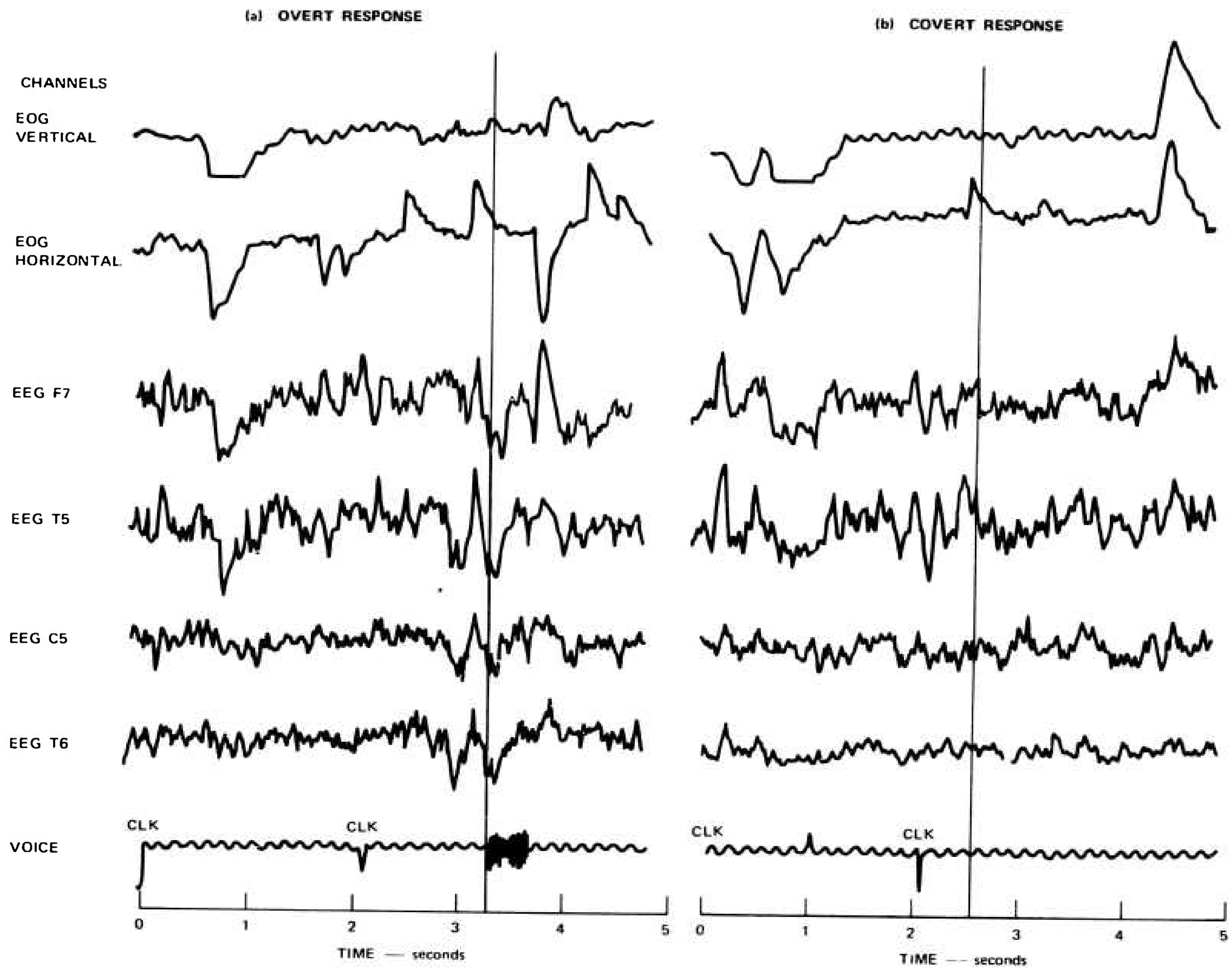


FIGURE 15 EEG IN PRESENCE OF EYE MOVEMENTS, OVERT AND COVERT VERBAL RESPONSE TO SCHOOLBOY, SUBJECT B7

did not contribute significantly to <u>correct</u> computer classifications in this project (although they may well have contributed to confusion).

(1) Figure 16 shows the EEG templates (electrode F7) for Subject C, Session 5, channel 3, for the words TIP and COOL. It also shows, between the templates, three individual EEG TIP responses on channel 3 that were confused with COOL. It appears that all three--TIP 2, TIP 3, and TIP 4--were probably confused with COOL because of a <u>time</u> shift in their responses to the right (see "cursor") with respect to the TIP template that made their slow-wave responses more coincident with the slow-wave of COOL than with TIP.

(2) Eye movement artifacts, when they occur, produce a fair amount of variability during a given response period (Figure 15A) and between response periods. Therefore, this variability should show up on the averaged records. Yet, in Figure 11, the variability of the EEG is less than with EMG, a result that is inconsistent with the idea of eye movement artifacts contaminating the record.

(3) Eye movement artifacts, when they occur, take place when the light stimulus first goes on and the S attends to the stimulus screen as in Figure 14A (over 1 sec before the actual response of the S). Therefore, if eye movement artifacts are present in our templates in a consistent way, then the artifacts occurring at the onset of stimulation should be present in the averaged records; yet nothing of this sort is seen in the majority of templates (e.g., Figures 10 and 11).

(4) If eye movement artifacts are contributing significantly to correct classification of the EEG response, then a greater consistency would be expected between EEG channels in their percentage of correct classification than was found. That is, we should expect the eye movement artifacts to be consistent on a given channel if they contribute to computer classification. In this case, all EEG channels should classify equally well. However, this was not true; some EEG channels proved to be better classifiers than others (though not in any consistent way across, between, or within Ss).

In any event, in Group III experiments (see Discussion, below), we will attempt to increase response classification performance by removing as many of these errors as possible, and to assess the contributions to success or failure of those that cannot be removed.

<u>Classification by Other Statistics</u>

In addition to the average template comparisons described above, several other statistics were also calculated for Subject C, Session .

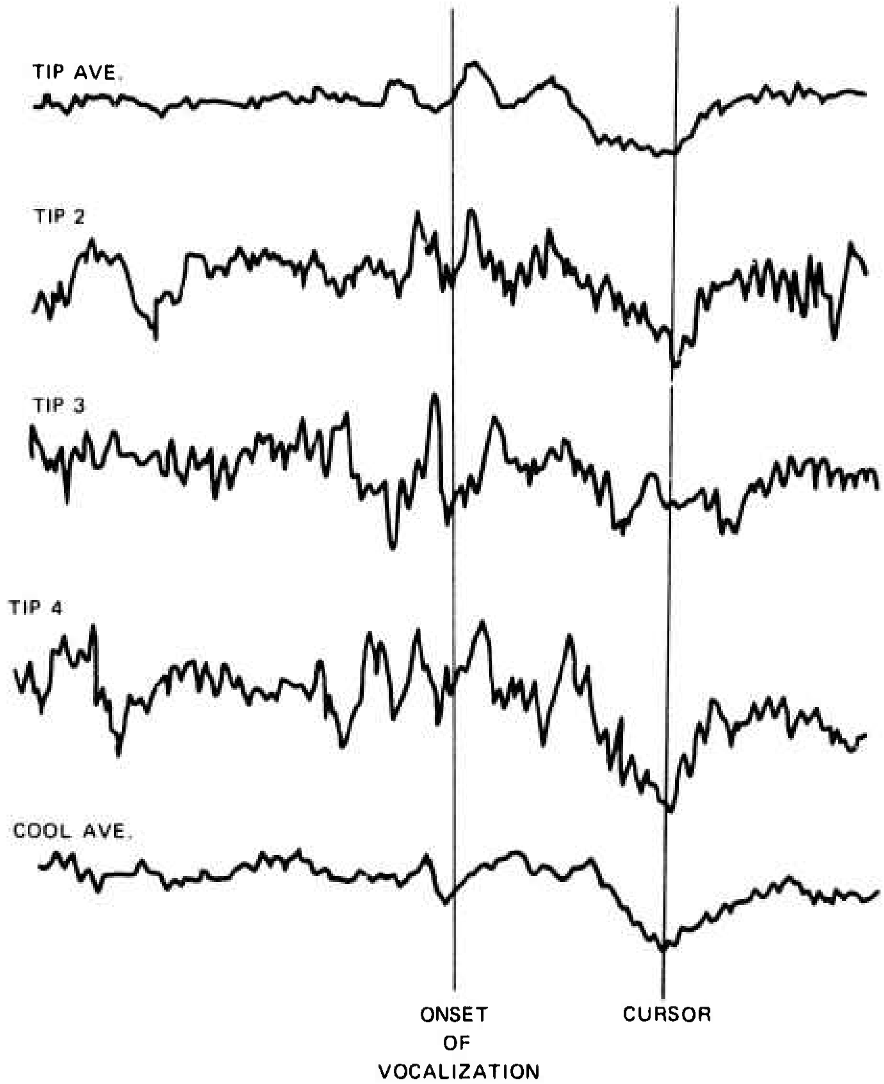


FIGURE 16 THREE EEG RESPONSES (ELECTRODE F7, SUBJECT C5) TO TIP CONFUSED WITH COOL DUE TO TIME SHIFT

including linear coherence (Coh), weighted-average coherence (Ave Coh), and spectral densities (Freq) for auto- and cross-spectra (see the Appendix for rationale and equations). The results were uniformly disappointing as follows:

Channels	Coh	Ave Coh	Freq
	Correct Responses per 150		
	Statistic		
Both EMG	31	14	34
All EEG	17	10	8
All Electrodes	25	17	16

Because of these results on Subject C, these statistics were not calculated for the other two Ss.

Since all three statistics are based on frequency analysis, we suspect that these low correct classification scores are due, partly at least, to differences in phase which were not taken into account in calculating these statistics. We will correct for phase differences in analyzing the Group III data (see Discussion).

One finding in the spectral density plots, at least for Subject C, was that more alpha activity occurred in the nondominant right hemisphere (EEG T6) than in the homologous electrode (EEG T5) over the dominant (speech) hemisphere. Since, in this S, T6 (nondominant) responses were the poorest EEG classifiers and T5 responses were the best EEG classifiers, then this alpha difference may be related to the variability in the two templates for response classification. This will be further examined during collection and analysis of Group III data.

DISCUSSION AND CONCLUSIONS

Significance of Results

(1) For all three Ss tested, a high percentage of individual word utterances were correctly classified, based only on machine recognition of biological signals. There was some variability in this capacity. Within each S, the second session had a higher rate of correct classifications than the first, indicating a learning or habituation effect that probably reduced the response variability. There were also differences among Ss, due to differences in the variability among them, with the responses of Subject C classifying more correctly than either B or D. Nevertheless, for all three Ss, variability in their individual templates was relatively low, and the rate of correct classifications was high--generally over 50%. The numbers correctly classified were significant with a probability well below .001 that this occurred by chance.

(2) The greatest variability within Ss was between types of biological recordings. EMG responses were almost twice as good as classifiers as were FEG responses, although the two taken together were better than either group (or individual electrodes within a group) alone. This finding suggests that more than one electrode should be used in a biocybernetic communication system. It is supported by the result that there was no evidence in any of the Ss that a given electrode of either the EMG or EEG groups was consistently better as a classifier than any other electrode in the group. One exception to this, however, is that in homologous EEG electrodes T5 and T6, in Subjects C and D, T5 was a predominantly better classifier than was T6, while in Subject B the opposite was true. This finding is possibly related to the results from the spectral analysis in Subject C, that T6 contained consistently higher amplitudes of alpha frequencies than T5.

(3) Another source of variability, shown by the F-ratios, was the part of the biological response analyzed. It is evident that if only that portion of the biological response associated with the actual verbal response is used, then the rate of correct classification increases. This may actually be easier to do with continuous speech (or thought) than single words, since variability with single words is greatest between words.

(4) As expected from Group I results, each S's biological responses associated with speech are unique to him, as confirmed by the Between Subjects results. It is of scientific interest that a fair number of EMG responses were significantly classified correctly between Ss, indicating that muscle activity for verbal expression may be more invariant between individuals than has been supposed (MacNeilage and MacNeilage, 1971).

This result also means, however, that unique templates must be built for each individual using a biocybernetic communication system.

(5) A surprising result from the confusion matrices was the finding that emphasis on different parts of the bisyllabic words did not materially effect biological responses. This should reduce possible future problems, since the library of templates in a biocybernetic communication system may be reduced to tolerable dimensions if emphasis on all accented words can be ignored.

(6) One additional source of error identified in our results may be eliminated by additional computer processing, while two others may not be eliminated at all. The first is the time shift in a biological response with respect to the onset of vocalization (or verbal thinking) from one response to another. We do not know how many errors occurred due to this shifting, but the error can be removed by time justification using a minimum difference criteria between two responses before combining them to make a template, and before calculating an RMS difference for classification. This will be done on Group III data.

(7) The other two errors we may have to accept--namely, amplitude and movement artifacts. The first of these may possibly be corrected for by an automatic gain-change feature in biocybernetic amplifiers, or by identification through context, or both. The second of these, and especially eye movement artifacts, may be reduced when speech (or thought) is continuous, by time shifting or by closing the eyes. We are confident from the results of our control study that eye movements did not overly contaminate our records to <u>reduce</u> classification rate, and certainly were not the major EEG parameter that contributed to correct classification (despite the fact that parts of some of the EEG averages <u>look</u> like artifact).

To conclude, we believe that the results of this year's research, and particularly the results reported herein, have demonstrated beyond our expectations that a biocybernetic communication system using biological information related to speech is definitely feasible. During the next year, we expect to find out if it is also feasible for verbal thinking.

Future Research--Group III Data

Details of the work to be conducted in the second contract year are in SRI Proposal No. LSU 72-133, dated October 30, 1972. In the light of the present results, it would be useful to list the specific objectives.

(1) Biologic response measurements will be made over shorter intervals of time to correspond with verbal (overt and covert) responses.

(2) Instrumentation will be used to monitor all types of artifacts. Samples containing artifacts of any sort will be divided into subgroups according to type, and classified separately to assess the contribution of artifact-rich relative to artifact-poor measures.

(3) All other sources of error described above will be eliminated as nearly as possible.

(4) Attempts will be made to identify the smallest unit of speech that can be correctly classified with a minimum template vocabulary or library.

(5) An effort will be made to assess the contributions of the EEG from dominant and nondominant speech areas of the brain to correct classification.

(6) An attempt will be made to identify the various components of a biological response related to overt and covert speech, including mechanical, semantic, contextual, and affective components.

(7) Finally, and most important, we will primarily attempt to classify covert verbal behavior, or thinking, with biological signals alone.

Appendix

DISCUSSION OF STATISTICS USED FOR MACHINE RECOGNITION

To classify the words in the test vocabulary automatically, it is necessary to have both a procedure of combining the data from the measurements and a statistic whose numerical value determines the final classification. Several statistics have been tried in this project, and the formal mathematical definitions for each are given below.

Introduction and Terminology

We believe that it is helpful to clarify some basic facts about the recognition process in general, before describing our particular recognition application using bioelectric potentials. The purpose of all our statistics is to enable accurate recognition so that the signals can be used for biocybernetic communication purposes. The two main approaches used are template matching based, first, on the pattern of the signal over time, and second, on the pattern over frequency of the power spectral density function of the signal. Recognition allows us great economy in biocybernetic communication because we may substitute the label or recognition category for the signal itself.

"Recognition" means the labeling of some measurement data according to pre-established criteria or boundaries. In our case, we use the names of the words themselves--e.g., HAD, PUT, and so on--as the labels for groups of measurements that were taken when the subject was saying these words. Recognition requires such labels to be supplied, whereas clustering does not. "Clustering" means the partitioning of all the measurements into self-consistent or homogeneous groups, without reference to any preconceived labels. Clustering handles the measurements as they are, whereas recognition fits the measurements to external labels. A clustering method finds an appropriate number of valid groups so that the clustering is an accurate but abbreviated description (summary or template) of the data. Clustering facilitates recognition usually by providing a rational objective method of labeling the measurements. The recognition labels may be rather arbitrary and not logically related to the measurements, except by convention, established practice, or preference.

"Spectral Analysis" is a method of decomposing any time waveform into a set of sinusoidal waves that can be combined to reconstruct the original waveform. There are two kinds of spectral analysis: the usual kind, which we have used, which ignores the phase of the frequency components, and a more sophisticated kind, called complex spectral analysis, which gives phase information as well. We will discuss only the first kind here. In future work, we will apply a spectral analysis program that will take phase into account (Singleton, 1967). The purpose of spectral analysis is to transform the waveform or time description of a signal into a frequency description in the hope that recognition of the signal can be made, assuming the frequency description corresponds more closely to the recognition requirements than does the time description.

Clustering Approach to Recognition

It had been our original intention to apply the clustering program ISODATA to the data. The computation time for one iteration through the data for this program is given approximately by the following formula:

$$T = NCOLS \times NROWS \times NPATS \times M \text{ seconds}$$

where

NCOLS = the number of variables (columns)

NROWS = the number of clusters (rows)

NPATS = the number of patterns

M = a factor depending on the basic cycle-time of the computer.

In the case of Group II data, there are 15 words, so we can hopefully find 15 clusters--one cluster for each word. By evaluating NCOLS, NROWS, and NPATS and estimating a value for M, it was found that the computation time and the computer memory size required were rather large for this project. Thus, to save computation time necessary for the iterative searching procedure of ISODATA, and because we would have had to modify the program to expand its memory requirements to accommodate the large number of data samples, we economized on computation expenses by writing a noniterative, special-purpose "clustering" program for this particular application. Because the data are sufficiently well-clustered, this approach is satisfactory at the 15-cluster level, so the usual iterative search procedure was not necessary, and templates formed from averages of the data in each category were used as the cluster cente-.

Let ${}_{st}X_{ijk\ell}$ be a basic data value for

subject s, s = B, C, or D

session t, t = 1 or 2

time i, $1 \leq i \leq 255$

channel j, $1 \leq j \leq 6$

word category k, $1 \leq k \leq 15$

repetition ℓ, $1 \leq \ell \leq 10$.

The data were digitized to 9 bits accuracy, so $-255 \leq {}_{st}X_{ijk\ell} \leq 255$ for all i, j, k, ℓ, s, and t as above.

The template or average value is computed by averaging (Clynes et al., 1967) each point in the ten responses (i.e., repetitions) within a known word category (k). Thus, for any word category k,

$$ {}_{st}A_{ijk} = \frac{1}{10} \sum_{\ell=1}^{10} {}_{st}X_{ijk\ell} \quad . $$

The RMS difference (${}_{c}R_{k\ell m}$) between the ℓth utterance of word k and the template for word category m ($1 \leq m \leq 15$), where c denotes the combination of time samples and channels, is given by:

$$ {}_{c}R_{k\ell m} = \sqrt{\frac{1}{N_c} \sum_{i\varepsilon c} \sum_{j\varepsilon c} \left({}_{s_1 t_1}X_{ijk\ell} - {}_{s_2 t_2}A^{*}_{ijm} \right)^2} $$

where N_c is the number of data points in combination c and

$$ {}_{s_2 t_2}A^{*}_{ijm} = \begin{cases} {}_{s_2 t_2}A_{ijm} \text{ if } s_1 \neq s_2 \text{ or } t_1 \neq t_2 \text{ or } m \neq k \\ \text{or} \\ \dfrac{10\,{}_{s_1 t_1}A_{ijk} - {}_{s_1 t_1}X_{ijk\ell}}{9} \text{ if } s_1 = s_2 \text{ and } t_1 = t_2 \text{ and } m = k \end{cases} \quad . $$

<u>F-Ratio Test for Significance of Variance Between and Within Templates</u>

An F-statistic was calculated for each point in time for each channel and for each session, and a plot was made of each F-value versus time.

Let ${}_{st}F_{ij}$ be a F value at

time i, $1 \leq i \leq 255$

channel j, $1 \leq j \leq 6$

subject s, s = B, C, or D

session t, t = 1 or 2

then

$$ {}_{st}F_{ij} = \frac{{}_{st}SSB_{ij}/(15 - 1)}{{}_{st}SSW_{ij}/[15(10 - 1)]} $$

where

${}_{st}SSB_{ij}$ = sum of squares between templates

${}_{st}SSW_{ij}$ = sum of squares within templates

15 - 1 = 14 = degrees of freedom in numerator

15(10 - 1) = 135 = degrees of freedom in denominator.

$$ {}_{st}SSB_{ij} = \frac{1}{10}\left\{\sum_{k=1}^{15}\left(\sum_{\ell=1}^{10} {}_{st}X_{ijk\ell}\right)^2 - \frac{1}{15}\left[\sum_{k=1}^{15}\left(\sum_{\ell=1}^{10} {}_{st}X_{ijk\ell}\right)\right]^2\right\} $$

$$ {}_{st}SSW_{ij} = \sum_{k=1}^{15}\left[\left(\sum_{\ell=1}^{10} {}_{st}X_{ijk\ell}\right)^2 - \frac{1}{10}\left(\sum_{\ell=1}^{10} {}_{st}X_{ijk\ell}\right)^2\right] $$

where ${}_{st}X_{ijk\ell}$ is the same as previously defined.

From a table of the F-statistic (Selby, 1971), values greater than 1.77 are significant at the .05 level, and values above 2.23 are significant at the .01 level. In most cases, the F-statistic showed that the time segment over which the classification was significant was from the middle subgroup samples 101-200.

Combinations of Data Points and Channels

Based on the results with the F-ratio test, various combinations of points in time and various channels (electrode placements) were used to explore time segments and electrode placements to determine which combinations would give the highest correct identification of the words. The samples in time were divided into subgroups--i.e., samples 1-100 being the first subgroup, samples 101-200 the second subgroup (where the F-ratios were significant), and 201-255 the final subgroup. In addition, all samples (1-255) were used, giving four groups of time points.

All six channels were treated individually. In addition, EMG channels (1 and 2) were grouped together, EEG channels (3, 4, 5, and 6) were grouped together, and finally all channels were grouped together, giving nine different channel combinations.

Thus, with the four time segments there were 36 different channel-time combinations. Typical values of N_c (used in calculating the RMS difference) are:

Combination	N_c
Channel 1, samples 101-200	100
EMG (Channels 1 and 2), all samples	510
All channels, all samples	1530

Closest-Match Recognition and Confusion Matrix

The recognition or classification of each test word was accomplished by matching it to the set of all templates. The best match is word w where

$$ {}_{c}^{R}{}_{k\ell w} = \min_{m=1}^{m=15} \left\{ {}_{c}^{R}{}_{k\ell 1},\ {}_{c}^{R}{}_{k\ell 2}, \ldots {}_{c}^{R}{}_{k\ell m}, \ldots {}_{c}^{R}{}_{k\ell 15} \right\} \text{ occurs.} $$

If $w = k$ for the minimum value, this is considered a correct match; if $w \neq k$, an incorrect match was found.

A confusion matrix (C_{kw}) was computed as the table for the number of times word k was classified as being word w. Matrices were formed for each combination of time samples and channels. The main diagonal (where $k = w$) gives a tally of the number of correct matches for each word. A chi-square statistic was calculated based on these correct matches to test for significance (nonrandomness).

The Chi-Square Test of Significance

As there are 15 different words, the probability of picking a particular word correctly by chance is 1/15. There are ten repetitions of each word, giving 10/15 as the expected number of correct responses assuming random data.

Two chi-square statistics were computed: (1) a chi-square with 15 degrees of freedom, which tests significance of recognition of the 15 words; and (2) a chi-square with 1 degree of freedom, which tests the significance of the total number of responses correctly classified, summed over all words.

Let C_{kw} be the general element of the confusion matrix, as defined earlier--i.e., C_{kw} is the number of times word k gets classified as if it were word w. Let χ_1^2 be the chi-square statistic with 1 degree of freedom, and χ_{15}^2 be the chi-square statistic with 15 degrees of freedom. Then, for one session,

$$\chi^2_1 = \frac{\left(\sum_{\ell=1}^{15} c_{ii} - \frac{150}{15}\right)^2}{\frac{(15 - 1)}{15 \cdot 15}(150)}$$

$$\chi^2_{15} = \frac{\sum_{\ell=1}^{15} \left(c_{ii} - \frac{10}{15}\right)^2}{\frac{(15 - 1)}{15 \cdot 15}(10)} .$$

Critical values for rejection of the hypothesis of no significant difference between the observed sample and a random population were 6.64, $p \leq .01$, for 1 degree of freedom, and 30.58, $p \leq .01$, for 15 degrees of freedom.

Spectral Analysis Using the Fast Fourier Transform

The method of transforming a waveform in the time domain to a mathematically equivalent representation in the frequency domain is known as a "Fourier transformation." The computational implementation of this transform on a computer is called a "fast" transform, because a particular algorithm is required to make such computations efficient. For this project, we used a computer program supplied to us by one of our project consultants, Dr. Gary Galbraith. This program came from the Biomedical Data (BMD) series developed at UCLA, was adapted by Galbraith for his computer, and then readapted by Wolf for the SRI CDC-6400. Galbraith first used a spectral analysis program that is documented (Dixon, 1970) as BMD02T "Autocovariance and Power Spectral Analysis." After gaining experience with this particular program, Galbraith updated his approach to the newer version in the same series, which is cataloged as 91 v FF.

Although the mathematics of Fourier transformation is readily available from many sources, an outline of the mathematical fundamentals is presented below because we wish to develop an exposition of this approach for comparison to the clustering approach that we find more effective in this application. A single frequency, or a pure spectral line, is given by

$$s_n(t) = A_n \cos \left(2\pi \frac{nt}{T} - \phi_n\right)$$

and is represented in Figure **17**. The peak amplitude is A_n, and the phase angle with respect to the origin is ϕ_n. It is important to note that the time variable is assumed to extend from $-\infty$ to $+\infty$; although this is unrealistic for actual signals, it is convenient mathematically. Actual biological signals, such as the EMG and EEG waveforms measured in this project, may be considered to be mathematically composed of a summation of such sinusoidal signals. By using enough harmonics, any limited bandwidth periodic signal can be represented by the composition of a number of sinusoidal (i.e., purely periodic) signals only.

We may thus represent any periodic waveform by

$$s(t) = \sum_n A_n \cos \left(2\pi \frac{nt}{T} - \phi_n\right) \quad .$$

The quantities A_n are the spectra (or spectral amplitudes) and are given by the computer program output. The program has been calibrated by means of a test signal recorded by using a signal generator of known (calibrated) frequency.

The source listing of the computer program for spectral analysis consists of two pages of FORTRAN and several subroutines as listed below.

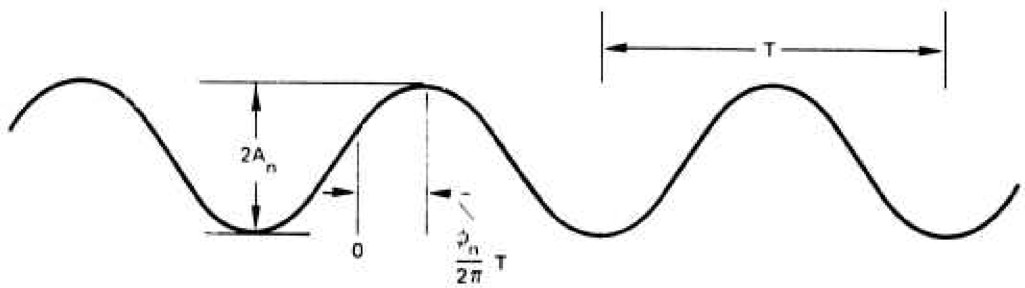


FIGURE 17 DEFINITION OF TERMS FOR FOURIER ANALYSIS

Name	Lines of FORTRAN	Purpose
GARY	97	MAIN PROGRAM, READS TAPE, APPLIES WINDOW
FAST	50	COMPUTES SPECTRA
PRT	23	PRINTS VALUES
XBAR	72	COMPUTES AVERAGE COHERENCE

The output of the program first lists the description of the data on the tape such as the subject's number and date of recording. Next, the coherence (as defined below) between all possible pairs of channels is given for each of the 33 bins of the frequency spectrum we employed (0 to 19 Hz). Since we used six channels, there are $\binom{6}{2} = 15$ different combinations of channels taken two at a time for cross-spectral amplitudes, and six auto-spectral amplitudes, making a total of 21. Similarly for the quantity $\bar{C}$, there are another 21 values for each of the bins.

The Coherence and Weighted-Average Coherence Statistics

"Linear coherence" is a statistic that provides an estimate of the degree to which a particular frequency component in the EEG of one brain region is related to an identical frequency component in the EEG of another brain region. Thus, in a cross-sectral analysis as many coherence values may be calculated as there are frequency bins (Walter, 1963). The "weighted-average coherence," on the other hand, is a statistic derived from cross-spectral frequency analysis parameters that, in a sense, summarize over the several linear coherences in a cross-spectrum to give a single number that measures the overall degree of interaction between two brain regions (Galbraith, 1967). The term "weighted" refers to the fact that the EEG of the two regions used in computation must be large in amplitude and highly coherent.

Following Galbraith (1966, 1967) we define the coherence function, at frequency f, as

$$C(f) = A_{xy}(f)/[A_x(f)\ A_y(f)]^{1/2}$$

where

A_{xy} is the cross-spectral density

A_x is the autospectral density of Channel x

A_y is the autospectral density of Channel y.

C(f) is normalized and bounded between 0.0 (Complete lack of relationship) and 1.0 (perfect linear relationship).

The weighted average coherence function is defined by

$$\bar{C} = \sum_i [A_{xy}(f_i)\ C(f_i)]/\sum_i A_{xy}(f_i)$$

where

$A_{xy}(f_i)$ is the cross-spectral density at frequencies f_i satisfying a threshold criterion that they must exceed.

$C(f_i)$ is the coherence at frequency f_i satisfying the threshold criterion.

The computer program prints out these quantities, which we later used as input to the template matching program, in place of the original time series data. The use of these spectral data or coherence statistics did not provide as good recognition results as obtained with the original waveform data.

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