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This research investigates the feasibility of utilizing pattern recognition procedures for automatic classification of evoked brain potentials according to their stimulus characteristics. A variety of visual stimuli were employed and a quadratic classifier was found most effective. Correct classification rate exceeded 80% in the cases tested.

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SUMMARY

The purpose of this exploratory research program was to demonstrate the feasibility of on-line classifications of brain waves associated with specific visual stimulus events. A number of classification and discrimination techniques were tested and compared.

It was found that by utilizing 4 electrodes placed on the scalp and measuring the voltage amplitude at no more than six time points, a classification accuracy of over 90% was achieved for choosing between the four stimuli: blank field; full field checkerboard; upper half field checkerboard; and lower half field checkerboard.

Other types of visual stimuli were utilized and their brain responses classified using techniques developed for the earlier set of tests. Visual stimuli investigated included: stimulation of the upper and lower half visual fields and the right and left visual fields with a checkerboard pattern. Stimulation of the four visual quadrants and the full visual field with a checkerboard pattern. In addition, the effects of focusing or defocusing a letter on the brain potentials were examined. Also, an edge matching experiment was conducted. During this test, the subject was shown, side by side, two slides of a photographic image. One of the slides, always shown on the left, was known to be ground-truth slide. Once this decision process terminated, both sides were flashed, the EEG recorded at this time, and the subject asked whether these 2 slides were the same ones he had previously observed.

Classification results obtained with these experiments were always in the high 80% category or low 90%. The results obtained were very encouraging and suggest that these techniques may be suitable for practical application.

PREFACE

This research was performed by the School of Electrical Engineering, Purdue University, West Lafayette, Indiana under AF Contract No. F33615-77-R-0511. Principal Co-investigators were Dr. Clare D. McGillem and Dr. Jorge I. Aunon. Research Monitors for the Department of the Air Force were Capt. Frank Gomer and Capt. Arthur Ginsburg, Visual Displays Branch, Human Engineering Division, Aerospace Medical Laboratory, Wright Patterson Air Force Base, Dayton, Ohio.

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INTRODUCTION

The purpose of this exploratory research program was to demonstrate the feasibility of on-line classification of evoked cortical potentials associated with specific stimulus events. A number of stimuli were selected after consultation with personnel at the Visual Display Systems Branch (AMRL) and a preliminary pilot study conducted utilizing the selected stimuli.

A number of classification and discrimination techniques were tested and compared. A combination of data preprocessing for dimensionality reduction and use of a quadratic discriminant function yielded relatively high classification accuracies.

Following the completion of the pilot study, a number of other experimental tests were performed at AMRL and the previously developed classification techniques employed on the new data. A significant further improvement in performance was obtained by prefiltering the data with a powerful minimum mean square error (MMSE) filter designed on the basis of a smooth signal shape determined from the latency corrected averages of the experimental data.

Specific Reports on Technical Requirements

Task 4.1

"Conduct a literature review and pilot studies for the appropriate selection of chromatic stimuli. Variables to be addressed include the intensity, duration, and wavelength of the stimuli, as well as the intensity and special composition of the adaptation field. Foveal viewing shall be employed and all preliminary testing will be conducted at the contractor's laboratory."

Literature Search and Selection of Stimuli

Averaging is the most common signal processing technique used to enhance the signal to noise ratio so that the various components of the evoked potential can be discerned and studied. Unless preceded by the words single or individual, the terms evoked potential or evoked response refer to the average or summation of cortical activity recorded from scalp electrodes. Evoked potentials are related to a number of variables involving the subject and the stimulus.

Since much data concerning the average evoked response to various vareual stimuli is available in the literature, and since this study deals with single responses, an assumption had to be made before the information in the literature could be used to select the visual stimuli parameters. The assumption is that the features present in the average evoked response which enable pattern detection and classification will be present to some degree in the corresponding single evoked responses. In order to simplify the initial classification scheme and to offset the difficulties that differences between single responses to the same stimulus will present, a set of visual stimuli that show large differences in their average responses will be chosen.

There is a wide variety of visual stimuli to choose from. Color and intensity are changeable characteristics of light itself; all transient stimuli will have changeable shape, size and duration; one can also consider patterns of varying degrees of discernability, moving patterns, and stimuli presented to different areas of the visual field.

THE EFFECT OF ACHROMATIC STIMULI

The average evoked response to flashes of white light of varying intensity and duration presented to both eyes is well known and documented [Regan, 1972; MacKay, 1973; Riggs, 1972; Perry, 1969]. Basically, the amplitude of the early components increases with increasing intensity (up to a saturation point) and the latency of the peaks decreases with increasing intensity. This relationship is illustrated in Figure 1. Variation of both latency and amplitude with stimulus parameters is important to this study because of ease of classification. As an example, variation in only the amplitude of the average evoked response would make classification difficult because it does not necessarily mean that the corresponding single evoked responses will likewise vary in amplitude. This, for instance, can be due to a large but narrow peak with a different latency in each single response, resulting in a wide peak with a small amplitude in the average response. This can also be due to the background EEG activity or "noise", resulting in amplitude distortion in the single evoked responses, but true amplitude representation in the average evoked response.

Frequency of stimulation is restricted by the latency of the particular components in the evoked response that the investigator wishes to study. It is possible to study early components with a higher stimulus repetition rate than with late components, but empirical evidence supports the assumption that the tail of one response overlaps and adds in to the beginning of the next response at frequencies above three flashes per second [Perry, 1969]. The amplitude of the individual responses is also dependent on stimulus repetition rate, being largest at stimulus frequencies of between 8 and 10 Hz [Regan, 1972; Perry, 1969].

Stimulus duration is also important because it is possible to discern both "on" and "off" responses to stepwise modulated homogeneous fields of white light [Regan, 1972; MacKay, 1973; Perry, 1969]. A very brief homogeneous flash produces a response similar to the "on" response described above [MacKay, 1973].

THE EFFECT OF MONOCHROMATIC STIMULI

When the dimension of color is added to the above parameters, the results are controversial and analysis is rather complex [Regan, 1972; Riggs, 1972; Perry, 1969; MacKay, 1969; White, 1969]. Care must be taken that any evoked potential changes that occur are truly due to color effects and not to changes in luminance. This must be done by including a sufficiently wide range of intensities to make sure that any change in the evoked potential is a spectral rather than an intensity induced change. The problem is complicated further by many definitions of what the spectral changes are. Figure 2 shows the evoked potentials of two color normal subjects to 16 colors of matched intensities. Difficulty in precisely describing these apparently spectral dependent changes has hampered work in this area. Also,

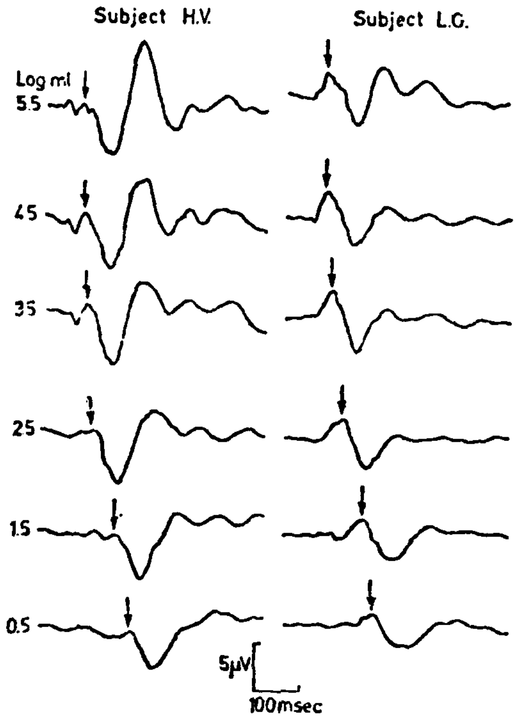

Figure 1. Evoked responses recorded over a 5 log unit luminance range for two subjects. The arrows indicate the peak of the wave for which latencies were measured.
(From Riggs, L. A.; Wooten, B. R., "Electrical Measures and Psychophysical Data on Human Vision," Handbook of Sensory Physiology, Vol. 7, Part 4, 1972).

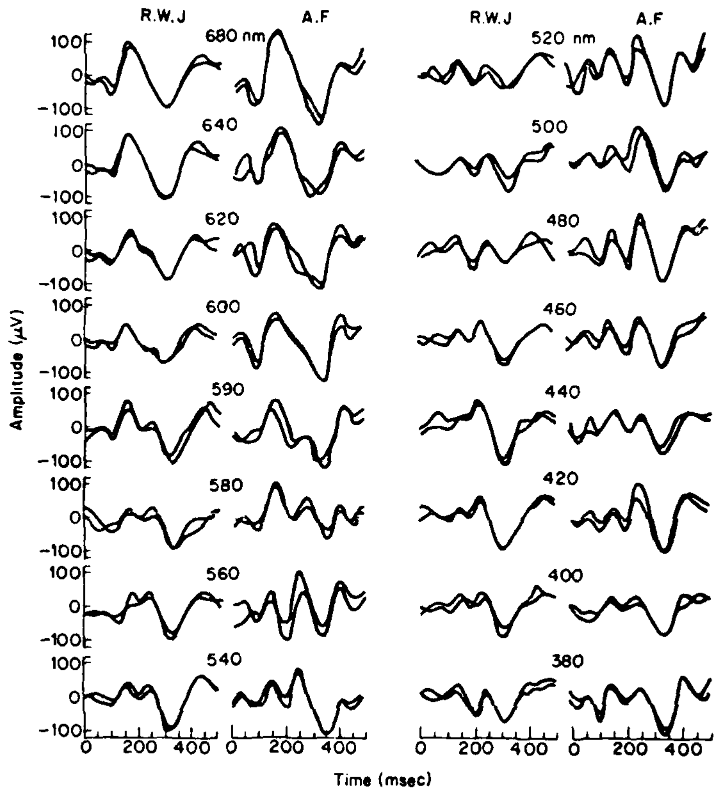

Figure 2. Evoked potentials for 16 colors for two color normal subjects. (From Regan, D., Evoked Potentials in Psychology, Sensory Physiology, and Clinical Medicine, London, Chapman and Hall, 1972.)

subjectively matching intensities to different colors is of dubious quality since there is no experimental evidence indicating correlation between spectral sensitivities measured subjectively and spectral sensitivities measured by evoked potential features [Regan, 1972].

It has also been reported that color dependent evoked potentials can be elicited by abruptly changing colors while keeping the subjective luminance the same. The results again are dubious because of the subjective luminance matching and because of color adaptation effects. Color adaptation effects have been studied by using backgrounds of different colors and intensities [Regan, 1972; MacKay, 1969, White, 1969]. Changes in amplitude of the evoked potential seem to be related to the difference in wavelengths of the background and stimulus [Riggs, 1972]. White, et al, differentiated three responses to red, green, and blue stimuli respectively in this manner [White, 1969]. Evoked potential correlates with stimulus duration and frequency have also been noted [Regan, 1972; Riggs, 1972], as well as changes in the evoked potentials elicited by monocular and binocular color stimulation [White, 1969].

Even though many of the discrepancies reported in the literature can be ascribed to differences in stimulus conditions, the results normally show only small changes in later components (150-300 msec) as shown in Figure 3 [Riggs, 1972; MacKay, 1969]. One possible source of artifacts is that of unintentional patterns in the stimulus field. Patterns seem to produce a large response which can obscure the color effects [Regan, 1972; White, 1969]. In general, the discrepancies and complications involved with color related evoked potentials and the small and hard to define changes in the responses make transient homogeneous color changes alone unsuitable for stimuli in this study.

THE EFFECT OF PATTERNED STIMULI

Presenting the element of contrast to the subject seems to produce much more consistent and interesting results, especially if the stimulus contains only a change in contrast and not in mean luminance [MacKay, 1973].

Figure 4 shows typical patterned stimuli along with their average evoked responses. The responses to the stripes and to the blank flash are rather similar whereas the response to the checkerboard pattern is larger than the rest and has different components in the first 200 milli-seconds. Although these responses were produced to stimuli with changes in both contrast and mean luminance, the large difference in the response to the checkerboard pattern shown here gave it consideration to be used as a stimulus for this study.

Much work has been done with checkerboard pattern stimuli. Changes in responses to variations in check size, contrast, visual field, etc. have been documented in the literature [Eason, 1970; Harter, 1968; Harter, 1970; John, 1967; Moskowitz, 1974; Siegfried, 1975; Nash, 1970; White, 1969]. One of the most striking effects is that of check size. Check size seems to affect the amplitude of the average evoked potential rather than the latency of its components [Harter, 1968; Siegfried, 1975]. Figure 5 shows the effect of check size on the amplitude of the average evoked response. The largest amplitude is obtained when the unit check subtends about 10 minutes

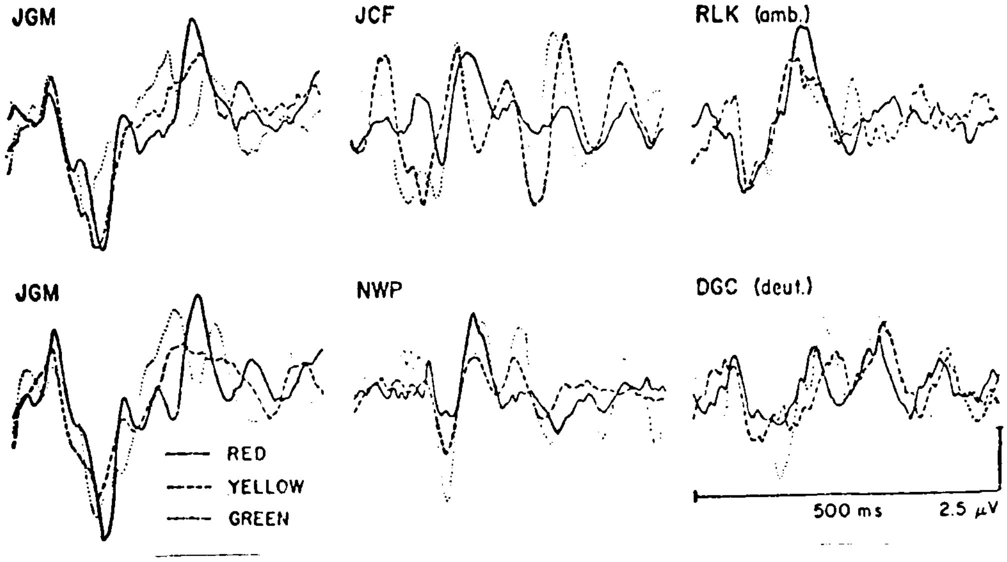

Figure 3. Binocular responses to 630, 577, and 520 nm stimuli for four subjects. Each trace is the mean of two replications. The two sets for subject JGM were obtained approximately one month apart. Subject DGC is affected with deuteranopia while subject RLK is affected with amblyopia.
(From Perry, N. W.; Childers, D. G.; Dawson, W. W., "Human Cortical Correlates of Color with Monocular, Binocular and Dichoptic Vision," Vision Research, Vol. 9, 1969).

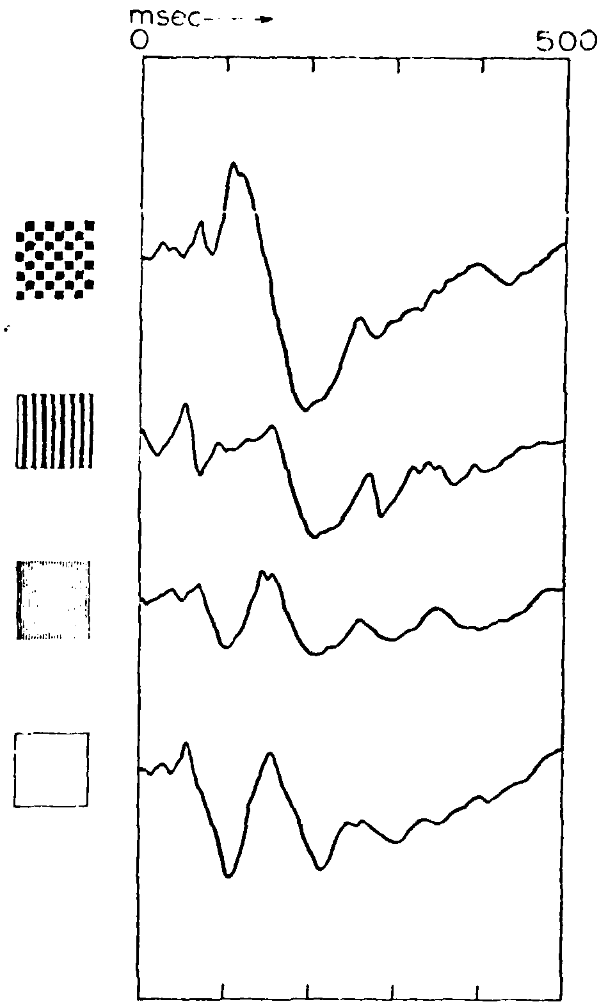

Figure 4. Responses to checkerboard pattern, stripe patterns, and to blank flash.
(From Rietveld, W. J.; Tordoir, E. M.; Hagenouw, J. R. B.; Lubbers, J. A.; Spoor, A. C., "Visual Evoked Responses to Blank and to Checkerboard Patterned Flashes," Acta. Physiol. Pharmacol. Neerl., Vol. 14, 1967.)

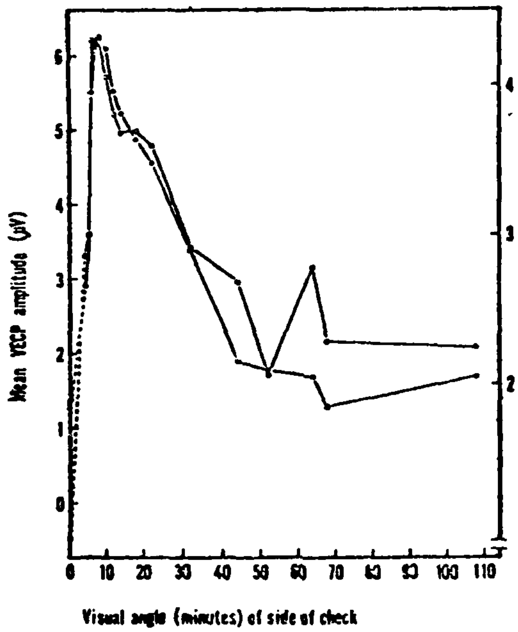

Figure 5. The effect of unit check size on the visual evoked potential. Mean amplitudes for two subjects (right and left scale). Zero unit check size is a blank flash of one-half the space average luminance for other check sizes.
(From Siegfried, J. B., "The Effects of Checkerboard Pattern Check Size on the VECP," Bulletin of the Psychonomic Society, Vol. 6(3), 1975.)

of visual angle [Harter, 1968; Harter, 1970; Siegfried, 1975; White, 1969]. The data here also involve presentation of the pattern by changes in luminance level.

It has been suggested that when the presentation of the pattern involves changes in mean luminance, two different mechanisms are responsible for the visual evoked response: one for the change in luminance and the other for the change in contrast present in the pattern [Spekreijse, 1973; Jeffreys, 1972]. As a result, some researchers have subtracted the response to a change in luminance, or have used more sophisticated stimulus presentation schemes that can present a pattern to the subject without changing the mean luminance [MacKay, 1973; Nash, 1970; Spekreijse, 1973; Jeffreys, 1972; Jeffreys, 1971].

The effect of stimulation of various quadrants and octants of the visual field by a pattern without changing mean luminance is shown in Figure 6. The columns of evoked potentials correspond to the active electrode positions shown at the bottom of the figure. Looking down the middle column, part (a) shows small amplitude and latency changes between the responses to stimuli in the upper right octants and quadrant. Similarly part (b) shows small changes between the responses to stimuli in the lower right octants and quadrant. The midline electrode does, however, show a more noticeable difference between parts (a) and (b), that is, the responses to the stimulus of octants and quadrants in the upper and lower right visual field. The early components (less than 100 milliseconds) of the responses to stimuli in the lower right visual field show positive peaks, whereas the same components of the responses to stimuli in the upper right visual field show a negative peak. This suggests that responses to half-field stimuli should be investigated for large differences.

Left or right half-field stimulation is supposed to produce a large response in the contralateral hemisphere [MacKay, 1973; Jeffreys, 1972], but there is some controversy about this [MacKay, 1973]. Jeffreys and Axford reported more consistency between subjects in the responses to upper and lower half-field stimulation rather than left or right half-field stimulation [Jeffreys, 1972].

Figure 7 shows the responses of six subjects to patterned stimulation of the upper and lower halves of the visual field (dashed and continuous lines, respectively). Polarity reversals, especially in the early peaks, appear to be common differences between average responses to stimuli of the upper and lower visual fields [Jeffreys, 1972]. Notice that although the responses for subjects J.F. and C.M. bear some similarities, they are much different from the responses for subjects C.J.W. or D.A.J. This suggests that the differences produced by patterned stimulation of the upper and lower half fields may not be consistent enough for different subjects.

The relationship between responses to full-field stimulation and half-field stimulation for various electrode positions is shown in Figure 8. The first, second, and fourth columns show responses to upper, lower, and full visual field stimulation for the electrode positions shown. The third column is the sum of the previous two columns. In the light of the previously shown polarity reversals, the remarkable similarity between the third and fourth columns suggests that the full field response may be flat where

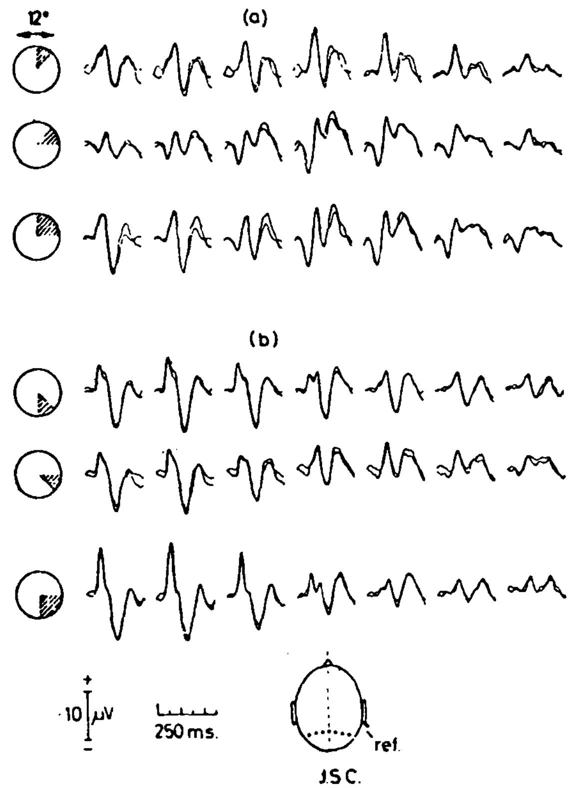

Figure 6. Visual evoked potentials to quadrant and octant stimulation. (From Jeffreys, D. A.; Axford, J. G., "Source Locations of Pattern-Specific Components of Human Visual Evoked Potentials. I. Component of Striate Cortical Origin," Experimental Brain Research, Vol. 16, 1972.)

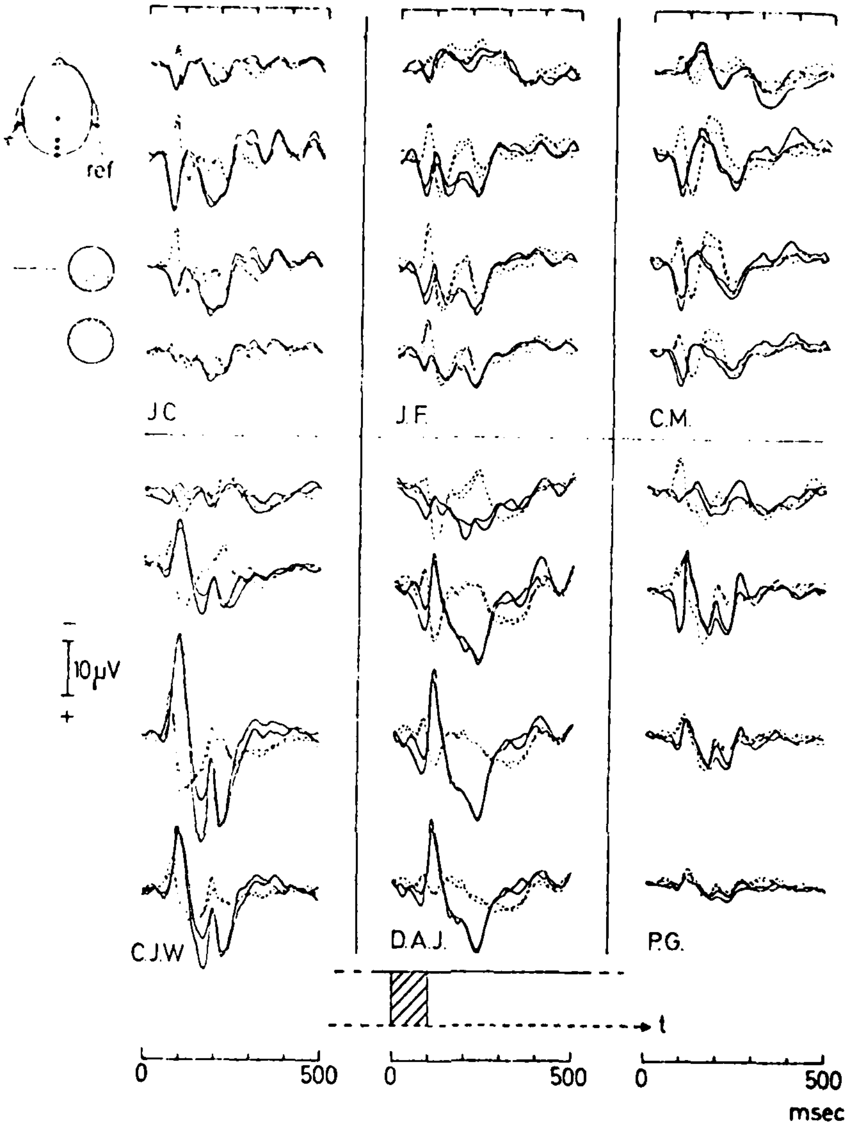

Figure 7. Visual evoked potentials to pattern stimulation of the upper and lower visual half fields for six subjects. The responses for two identical runs of 100 averages are superimposed in each case. Field size is 7° and pattern duration is 100 msec. (From MacKay, D.; Jeffreys, D. A. "Visually Evoked Potentials and Visual Perception in Man," Handbook of Sensory Physiology, Vol. 7(3), Part B, 1973.)

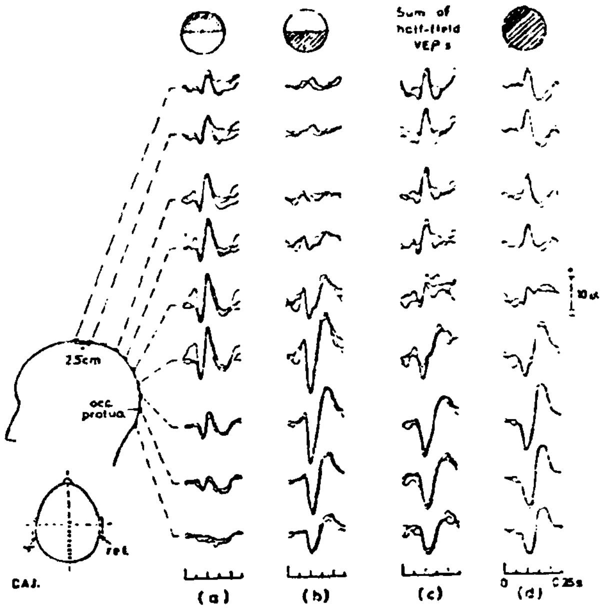

Figure 8. Visual evoked responses for one subject (D. A. J.) to patterned stimulation of (a) the upper half of the 6^{o} stimulus field, (b) the lower half of the stimulus field, and (d) the full stimulus field. The sum of the waveforms for the upper and lower half field stimuli is shown in (c).
(From Jeffreys, D. A., "Cortical Source Locations of Pattern-Related Visual Evoked Potentials Recorded from the Human Scalp," Nature, Vol. 229, 12 February 1971.)

the half field responses show peaks of their respective polarities. This is most evident in the middle row of Figure 8 where the half field responses are of approximately the same magnitude. Figure 8 shows yet another property that would aid in classification of full and half field patterned responses: the upper half field response is almost flat at the lower extreme electrode position (below the inion), whereas the lower half field response is almost flat at the upper extreme electrode position (near C_z) making the sum of the two (and the very similar full field response) non flat everywhere along the electrode positions shown.

Since recognizing a checkerboard pattern composed of small checks requires high visual acuity, it is intuitive to assume that foveal vision plays an important role in the patterned evoked response [Jeffreys, 1972; Rietveld, 1967]. Figure 9 illustrates the importance of the foveal area to the checkerboard pattern response. The top row in this figure is the response to full-field stimulation. The next three rows show the responses to the same pattern with 2^{o}, $2^{o}5'$, and $4^{o}4'$ of the central visual area covered by a black disc. Since the foveal area plays such an important role in the response to checkerboard pattern stimulation, it would seem important that the subject's gaze be fixed on a precise point in the stimulus field, particularly for upper or lower half field stimulation [Jeffreys, 1972; John, 1967].

Some work has been done with both color and pattern, but the results again contain the color controversy [MacKay, 1973; White, 1969], and it has been suggested that the two mechanisms are separate and produce the sum of both types of response when color and pattern are combined [MacKay, 1973]. White and others [White, 1969] abandoned an investigation using both color and a checkerboard pattern because the pattern response seemed to obscure any color effects. Regan and Spekreijse confirmed these results and used them to their advantage in work with normal and color blind subjects [Regan, 1974].

THE EFFECT OF MOTION

Evoked potentials have been elicited by the deflection of a pattern on the retina. As a result, either movement of the pattern or movement of the eye (including saccadic movement) can elicit evoked potentials [MacKay, 1973; Clarke, 1972; Clarke, 1973a]. Clarke has found that evoked potentials elicited by motion (motion onset, motion offset, or motion reversal) were almost invariant to intensity, direction of motion, and sharpness of boundaries [Clarke, 1973b].

Motion onset evoked potentials are much smaller than motion offset or motion reversal evoked potentials. For velocities below 15^{o}/sec, the motion reversal potential is very similar to the sum of the motion onset and motion offset potentials suggesting that the motion reversal evoked potential is produced by independent motion onset and motion offset mechanisms (Figure 10) [Clarke, 1973a].

The visual evoked potential elicited by motion reversal, motion offset, and stationary pattern appearance seem to have very similar components and scalp distributions, and all three show polarity reversals between upper and lower half-field stimulation. Motion onset and stationary pattern disap-

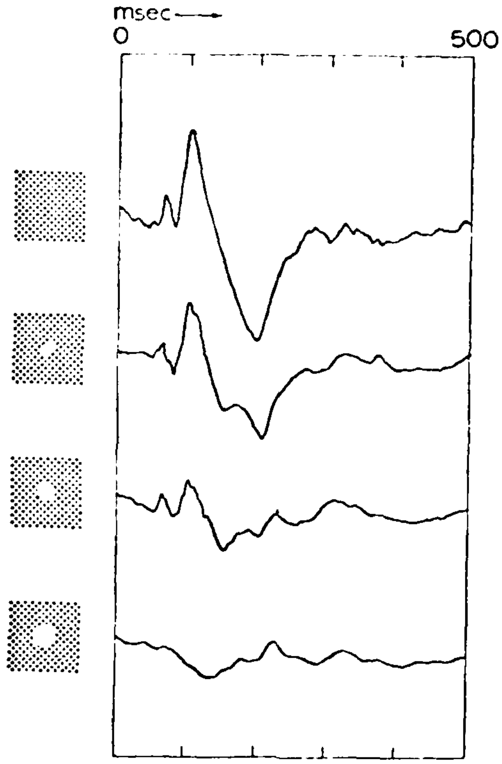

Figure 9. The effect of foveal area on the patterned response. (From Rietveld, W. J.; Tordoir, E. M.; Hagenouw, J. R. B.; Lubbers, J. A.; Spoor, A. C., "Visual Evoked Responses to Blank and to Checkerboard Patterned Flashes," Acta. Physiol. Pharmacol. Neerl., Vol. 14, 1967.)

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The visual evoked potential elicited by motion reversal, motion offset, and stationary pattern appearance seem to have very similar components and scalp distributions, and all three show polarity reversals between upper and lower half-field stimulation. Motion onset and stationary pattern disappearance responses also seemed to be very similar, but did not show polarity reversals between upper and lower half-field stimulation [Clarke, 1973b].

When pattern appearance/disappearance and motion are combined, the evoked potentials are velocity dependent as shown in Figure 11. The

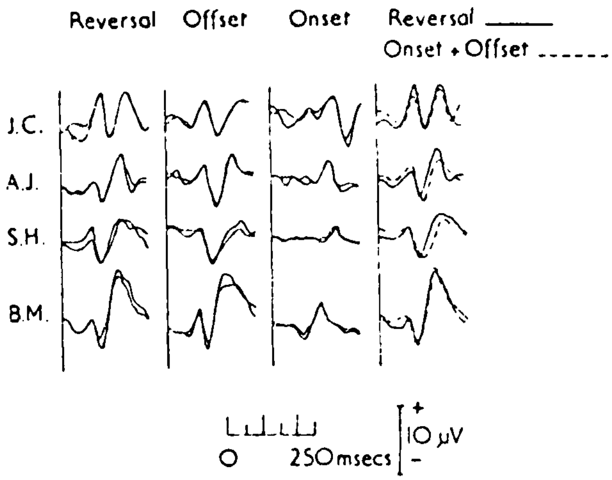

Figure 10. Visual evoked potentials to offset, onset, and reversal of a patterned field. Velocities are 10^{o}/sec (J.C.), 8^{o}/sec (A.J.) and 5^{o}/sec (S.H. and B.M.).
(From Clarke, P. G. H., "Visual Evoked Potentials to Changes in the Motion of a Patterned Field," Experimental Brain Research, Vol. 18, 1973.)

pearance responses also seemed to be very similar, but did not show polarity reversals between upper and lower half-field stimulation [Clarke, 1973b].

When pattern appearance/disappearance and motion are combined, the evoked potentials are velocity dependent as shown in Figure 11. The responses to pattern appearance or disappearance are largest for stationary patterns and all the components are reduced as the velocity increased [Clarke, 1972].

BASIS FOR SELECTION

As mentioned earlier, variations in both amplitude and latency of evoked response components are important to this study because of ease of detection and classification. However, some of the largest changes in average evoked potentials seemed to be the polarity reversals in certain peaks elicited by changes in the stimulus. The polarity reversal in the 100 msec component of the responses to a white blank field and to a checkerboard pattern (Figure 4) makes the responses easily distinguishable. Likewise, the polarity reversals shown in Figure 7 are large enough to make the response distinguishable.

As mentioned previously, the use of color was ruled out because of the complicated stimulus conditions necessary, the controversial nature of the results, and small and hard to define changes in the responses. The use of motion was also ruled out mainly because of the great similarity between responses to moving and to stationary objects. Also, it seems more likely that motion would tend to elicit more eye movement artifacts, as the eyes tend to follow a moving object.

The response to the appearance of a checkerboard pattern without change in mean luminance was chosen because cortical cells are known to respond to straight edges in the visual field, and because of the large response it elicits which is easy to distinguish from the response to the appearance of a white blank field. It has also been suggested that these two types of stimuli represent two independent mechanisms for encoding visual information. The large amplitudes of the responses are also advantageous to this study because they are indicative of either large signal to noise ratios or consistency of single evoked responses to the same stimulus, which are both desirable effects.

The responses to the appearance of a checkerboard pattern in the upper and the lower visual half fields without a change in mean luminance in these fields also show polarity reversals. These two stimuli were also chosen because they represent two different locations in the primary visual cortex and because of the large differences in their average evoked responses. These responses will also lend themselves to detection based on information from multiple electrodes because different areas of the cortex are involved and because of the difference in the responses depending on electrode position as shown in Figure 7.

Task 4.2

"Following the selection of the stimulus events, the preferred electrode array will be specified and ensemble average templates will be gen-

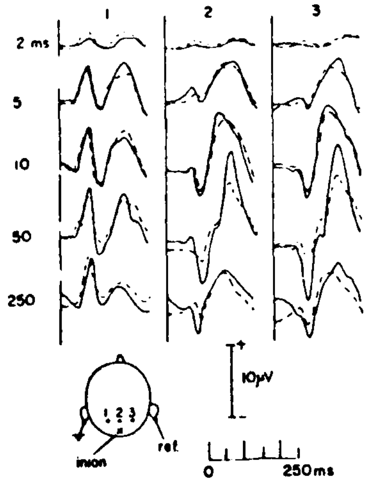

Figure 11. Average visual evoked potentials (N=100) to stationary (continuous lines) and moving (dashed lines) patterns. Velocity is 8^{o}/sec.
(From Clarke, P. G. H., "Visual Evoked Potentials to Sudden Reversal of the Motion of a Pattern," Brain Research, Vol. 36, 1972.)

erated. Initially, the following configuration will be utilized: O_1, O_2, O_z (according to the 10-20 System) and two other electrodes placed on midline 2 cms above and below O_z. The ensemble averaged data will be used to develop minimum mean square error filters. The outputs of these processors should characterize the individual evoked potentials in terms of component amplitudes and latencies, as well as overall morphology. Several iterative procedures should be instituted to derive better estimates of the true signals and hence more accurate filters."

EXPERIMENTAL CONDITIONS

The subjects sat in a dark and quiet room binocularly viewing a cathode ray tube screen from 45 inches which subtended $14^{\circ}38'$ by $12^{\circ}25'$ of visual angle. The subject viewed 128 stimuli from each of four stimulus conditions:

(1) A step change in luminance of the blank screen from 0 to 15 foot Lamberts.

(2) An abrupt presentation of a full screen checkerboard pattern of checksize 10' and contrast 24/8 from a blank field. Space average luminance remained constant throughout at 15 foot Lamberts.

(3) The same as (2) above, but with a black opaque piece of cardboard covering to lower half of the screen.

(4) The same as (3) above, but with a black opaque piece of cardboard covering the upper half of the screen.

A small cross in the center of the screen provided a steady central fixation point. The stimulus duration was 766 milliseconds and the interstimulus interval was 3 seconds.

The electrodes used were Beckman miniature biopotential silver/silverchloride electrodes. Four simultaneous channels were recorded from the monopolar electrodes at C_z, P_z, O_z, and the inion (International 10-20 electrode configuration). The right earlobe was used as a reference, and the left earlobe was grounded. Electrodes were also placed on the brow and cheek so that eye blinks and eye movement artifacts could be detected. A 100 μV amplitude 10 Hz sine wave was fed to all four channels as a calibration both before and after the data taking session. The data from the four channels were then amplified by Grass 7P511 amplifiers and recorded on a Honeywell FM tape recorder. Two of the five channels (from the Cz and Oz electrodes) were low pass filtered and averaged online. The data were then sampled at 250 samples/second and stored digitally on magnetic tape in 1 second epochs starting 1/2 second prior to the stimulus and continuing 1/2 second after the stimulus. For the preliminary work it was decided that two subjects (numbers 409 and 410) be tested according to the procedure outlined above.

PRELIMINARY RESULTS

From the online filtering and averaging mentioned earlier, it was found that the data from subjects 409 and 410 contained a rather large amount of 60 Hz noise from sources which could not be eliminated at the time the data were taken. Therefore, it was decided to filter the data before doing any other processing.

The data, originally sampled at 250 samples/sec, were digitally filtered with a low pass filter whose transfer function was zero for frequencies above 60 Hz. The frequency spectrum of the digital low pass filter appears in Figure 12. The phase characteristic of the filter is zero for all frequencies concerned so that it could not alter the phase information in the data that might prove valuable to this study. Each single response from the stimulus onset to 1/2 second after the stimulus onset was then represented by 125 samples of data.

After filtering, the averages of the first 100 responses for both subjects were computed for each electrode position and stimulus condition. These averages are shown in Figures 13 and 14. As can be seen, there are polarity reversals of the early components for the upper and lower field checkerboard stimulus conditions. Also, the checkerboard top half response is almost flat at the inion electrode and the checkerboard bottom half response is almost flat at C_z: c.f. Figure 8.

CLASSIFICATION RESULTS

a) Correlation Classifier

One of the more basic and easy to implement classifiers is the correlation classifier or matched filter [Fukunaga, 1972]. Consider M signals $s_1(t),\ldots,s_M(t)$ with a priori occurrence probabilities $P_1,\ldots,P_M$. Assume that each signal lasts for T seconds and that the observed signal $v(t) = s(t) + n(t)$ is contaminated by additive white noise with one-sided spectral density N_o. The problem is to decide which of the M signals was transmitted, that is, to classify v(t) into one of M classes. The correlation classifier computes M correlations and compares them after adding M biases:

$$\int_o^T v(t)\ s_j(t)\ dt + b_j \qquad (j = 1,\ldots,M)$$

where b_j is a constant bias given by

$$b_j = \frac{N_o}{2} \ln P_j - \frac{1}{2}\int_o^T s_j^2(t)\ dt \qquad (j = 1,\ldots,M)$$

The correlation classifier then assigns v(t) to the class whose correlation plus bias is largest. The correlation can be implemented as the convolution of impulse response $h_j(t) = s_j(T-t)$ with v(t) where the impulse response $h_j(t)$ is matched to the signal $s_j(t)$ hence the name matched filter.

For discrete time signals the signal to be classified, X, is a vector having N components $x_1,\ldots,x_N$ corresponding to N samples of v(t), $0 \leq t \leq T$ above. Similarly, consider S_j^N to be the discrete vector of $s_j(t)$ above. Then the cross-correlation of v(t) and $s_j(t)$ above can be written as $S_j^T X$, and the correlation plus bias can be written as

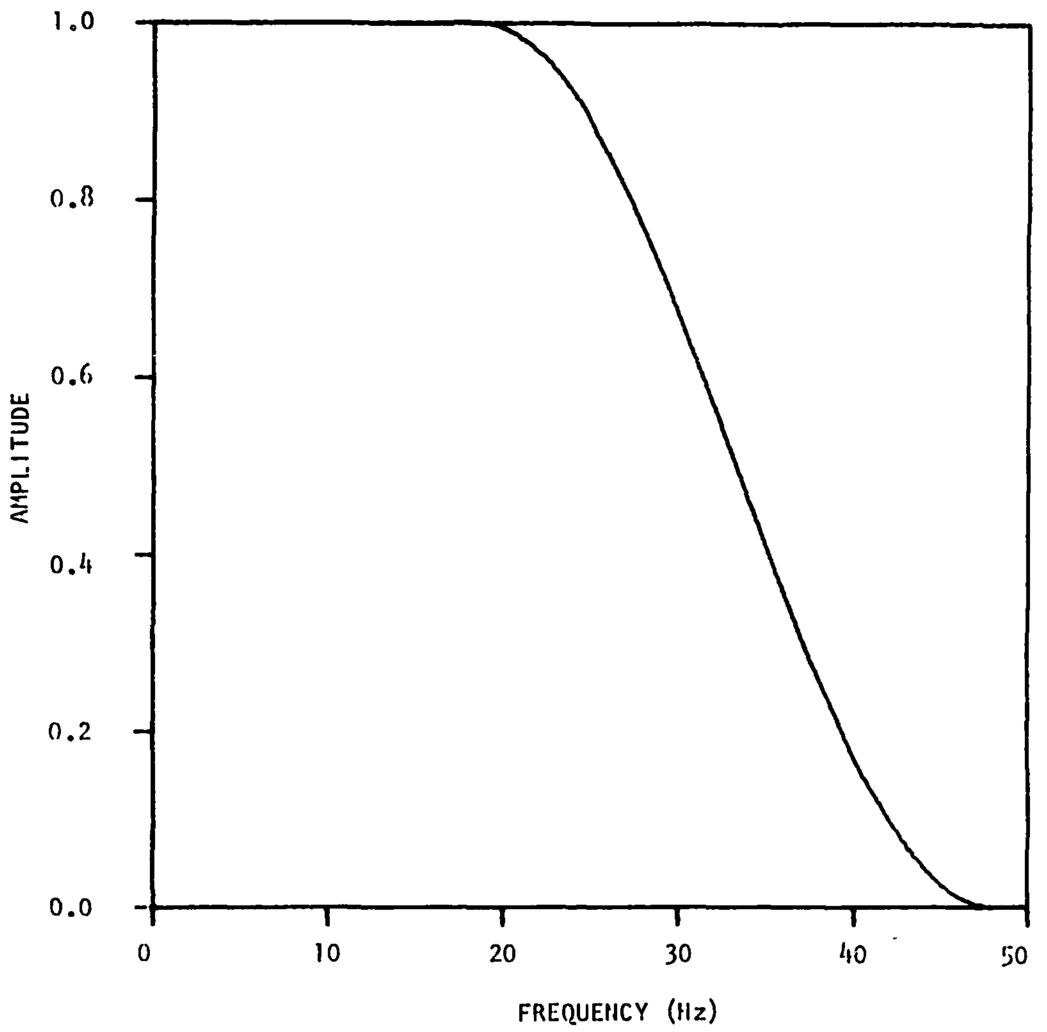

Figure 12. Digital Filter Amplitude Spectrum.

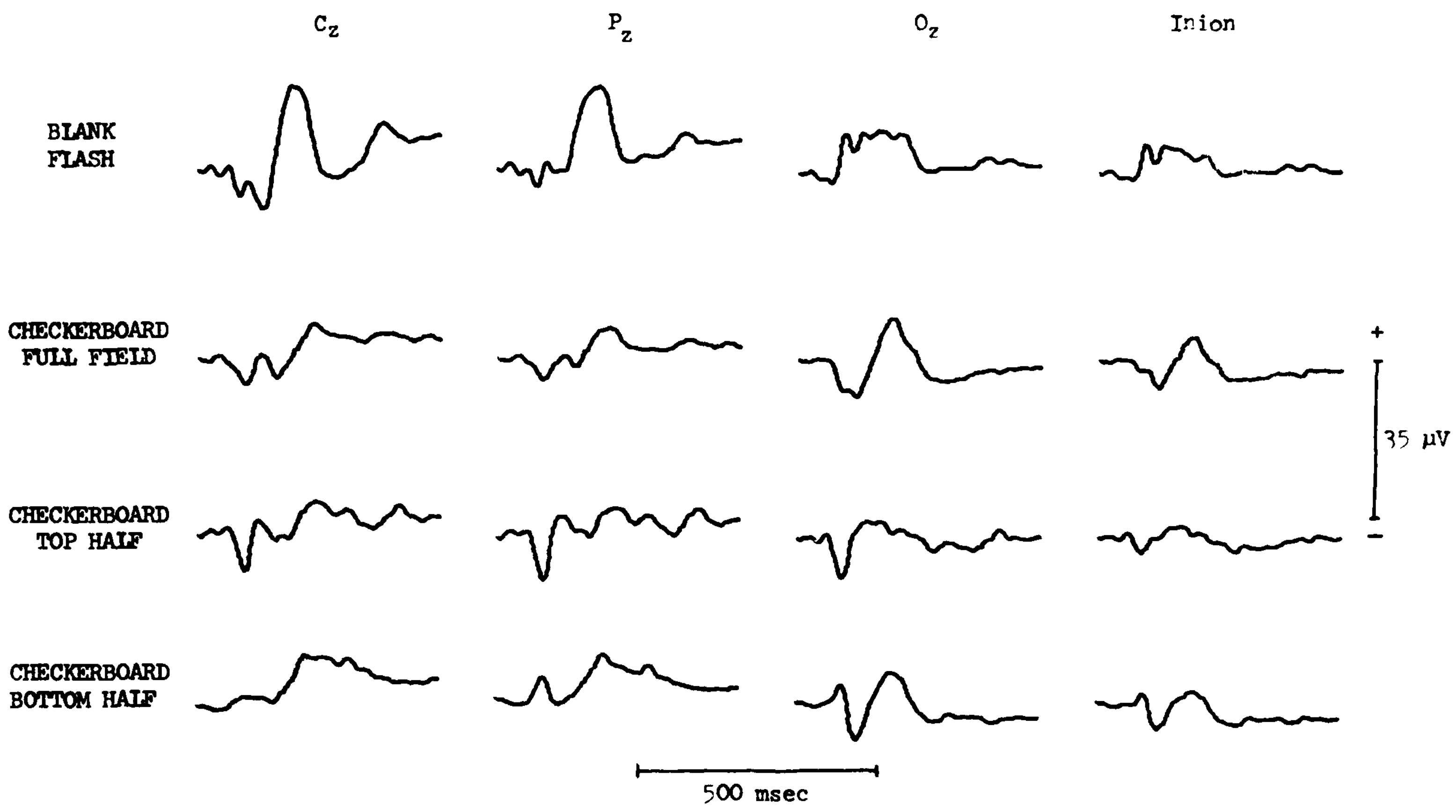

Figure 13. Average Evoked Responses for Subject 409, N=100.

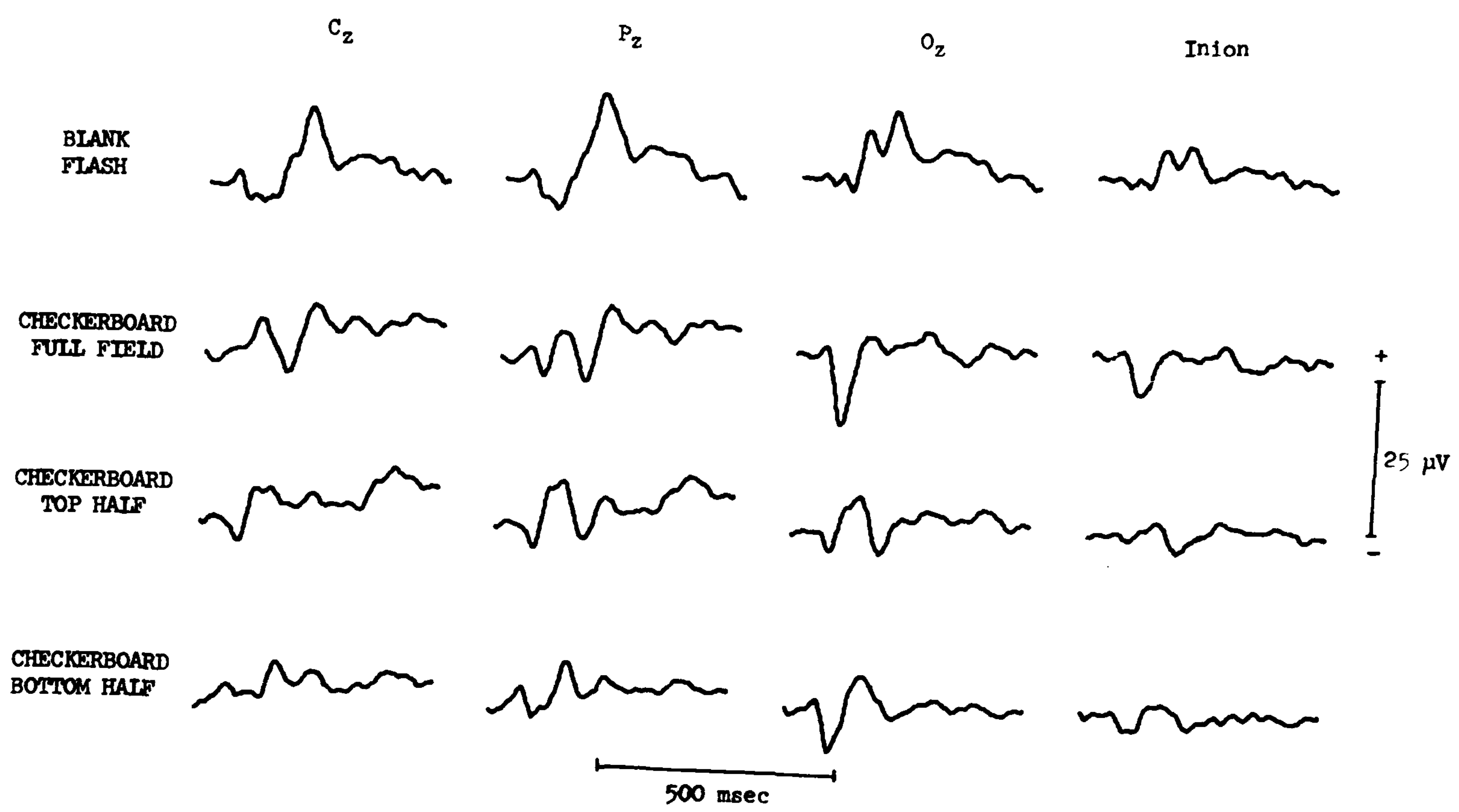

Figure 14. Average Evoked Responses for Subject 410, N=100.

$$S_j^T X + \frac{N_o}{2} \ln P_j - \frac{1}{2} S_j^T S_j \qquad (j = 1,\ldots,M)$$

In implementing this classifier, M = 4 and the a priori probabilities $P_1,\ldots,P_4$ were assumed to all equal 0.25. This makes the $\frac{N_o}{2} \ln P_j$ term a constant for all classes and it drops out of the equation when the correlation plus bias terms are compared. The S_j's are the signal templates or approximations to the signals so $S_1,\ldots,S_4$ were initially chosen as the digitized average evoked responses corresponding to a certain electrode position and the four stimulus conditions.

The average response for each stimulus condition and each electrode position was then examined for both subjects, and it was decided to eliminate the last 240 msec of data (keeping the first 260 msec) because it conveyed very little information to the correlation classifier. Each single response was then represented by 65 data samples. This number was still too large to make any but a linear classifier practical, so it was decided to reduce the data further without destroying features necessary for classification.

For each single response, the autocorrelation function was computed and these autocorrelations were averaged to obtain an average autocorrelation functions. The Fourier transform of this average autocorrelation function was computed and examined for each stimulus condition and each electrode location for both subjects. It was found that these average frequency spectra contained very little energy at frequencies above 25 Hz. The data were then digitally filtered with a low pass filter that admitted no energy above 25 Hz. Since the highest frequency present in the filtered data was below 25 Hz, every 5th sample was selected from the filtered data so that the sampling rate was artificially lowered from 250 to 50 samples/sec. Each single response was then represented by 14 data samples.

The averages of the 25 Hz low pass filtered data and the 60 Hz low pass filtered data were then compared. The filtering operation was evident for only certain stimulus conditions and electrode positions. In order to determine if the 25 Hz filtering destroyed information critical to the classification procedure, a criterion similar to the Fisher criterion was computed. The criterion was the ratio of the average of the 6 between-class Euclidean distances of the 4 mean vectors in N-space to the average within-class distance of each sample vector from the mean vector. This ratio was computed for each electrode position of both subjects for the 25 Hz and 60 Hz low pass filtered data and no significant differences were found.

The correlation classifier, as implemented, correlates the first quarter second of a single evoked response with each of the four average evoked responses, adds a class dependent bias value equal to one half the energy of the signal, and classifies each single evoked response according to the largest correlation plus bias value obtained.

As would be expected from Figures 13 and 14, this classifier gave the best results for the O_z and P_z electrode positions for both subjects. The results of the correlation classifier using 400 single evoked responses (100 for each stimulus condition) for the Oz electrode position are shown in Table I.

One of the assumptions of the correlation classifier is that the additive noise is Gaussian and white with the same spectral density for all the classes involved. This assumption probably does not hold very well for the data shown above because the data are time series data and the sampling rate is over two times larger than the highest frequency present in the data. This means that adjacent time samples of the data and of the noise are highly correlated and therefore the noise is not white.

Table 1: Decision Matrix for the Correlation Classifier Using the O_z Electrode Position.

Subject 409

		Chosen Class			
		BF	CF	CT	CB
True Class	BF	85	2	8	5
	CF	10	54	8	28
	CT	22	5	67	6
	CB	16	23	2	59

Subject 410

		Chosen Class			
		BF	CF	CT	CB
True Class	BF	75	7	10	8
	CF	17	58	10	15
	CT	12	7	69	12
	CB	12	21	17	50

The symbols BF, CF, CT, and CB refer to the classes or stimulus conditions: "Blank Flash," "Checkerboard Full Field," "Checkerboard Top Half," and "Checkerboard Bottom Half."

A prewhitening filter can be used to whiten the noise before it is presented to the correlation classifier, but if the statistics of the noise are different for the different stimulus conditions, the correlation classifier may still not give a satisfactory performance.

b) Linear Classifiers

The correlation classifier is a special case of the linear classifier. Linear classifiers are easy to implement and are related to techniques such as correlations and Euclidean distances. Although they give suboptimum results for many types of data, the ease of implementation and the simplicity often make up for the suboptimum performance [Fukunaga, 1972].

The general linear classifier makes use of M vectors $V_1,\ldots,V_M$ and M scalar biases $b_1,\ldots,b_M$. The decision rule assigns each data vector X, to the class which has the largest discriminant function:

$$h(X) = V_j^T X + b_j \qquad (j = 1,\ldots,M)$$

The objective is to choose the coefficients of V_j and the bias b_j such that the discriminant function will have a large value when the data vector

X is a member of class j, and a small value when X is a member of any other class.

c) Quadratic Classifier

The Bayes classifier uses a decision rule based on a posteriori probabilities which is designed to give a minimum of error or risk. If X is a data vector which can belong to any one of M classes with known a priori probabilities $P_1,\dots,P_M$. the a posteriori probabilities can be calculated from the a priori probabilities and the conditional density functions $p(X|1),\dots,p(X|M)$. When the costs of all the different types of errors are the same, the Bayes decision rule to minimize the error becomes choosing the class which has the largest a posteriori probability or discriminant function:

$$h(X) = p(X|j)P_j \qquad (j = 1,\dots,M)$$

Thus the Bayes classifier requires either a knowledge or an estimate of the conditional probability density functions $p(X|1),\dots,p(X|M)$. In the case where these density functions are normal with expected vectors M_j and covariance matrices Σ_j, the discriminant functions can be written as quadratic functions of X:

$$h(X) = \ln[P(X|j)P_j] \qquad (j = 1,\dots,M)$$

$$h(X) = \ln P_j - \frac{1}{2}\ln|\Sigma_j| - \frac{1}{2}(X-M_j)^T\Sigma_j^{-1}(X-M_j) \qquad (j = 1,\dots,M)$$

When $\Sigma_1 = \Sigma_2 = \Sigma$, these quadratic functions reduce to linear functions of X:

$$h(X) = \ln P_j + M_j^T\Sigma^{-1}X - \frac{1}{2}M_j^T\Sigma^{-1}M_j \qquad (j = 1,\dots,M)$$

When $\Sigma = I$ the identity matrix, the Bayes classifier becomes the correlation classifier mentioned earlier:

$$h(X) = \ln P_j + M_j^TX - \frac{1}{2}M_j^TM_j \qquad (j = 1,\dots,M)$$

Remembering that the Bayes classifier is optimum in the sense that it minimizes the error, one can see that the linear classifier will always give suboptimum performance unless $p(X|1),\dots,p(X|M)$ are normal with equal covariance matrices. Thus, the linear classifier is an optimum classifier when the additive noise is Gaussian with the same covariance for the different classes; and the correlation classifier is an optimum classifier when, in addition, the additive noise is white.

In implementing the maximum likelihood classifier for the present data set, two assumptions are made. First, all of the a priori probabilities P_j are assumed to be equal. Second, the conditional density functions are assumed to be normal with mean vectors approximated by the average evoked potential vectors $M_1,\ldots,M_4$ and covariance matrices approximated by the sample covariance matrices $K_1,\ldots,K_4$. Although the assumption of normality may not be entirely valid, the maximum likelihood classifier is known to give favorable results in many such practical cases (Glaser, 1976). Under the assumption of normality, the discriminant functions which are the negative logarithm of the a posteriori probabilities can be written as (Fukunaga, 1972):

$$h_j(X) = (X - M_j)^T K_j^{-1} (X - M_j) + \ln|K_j| \qquad j = 1,\ldots,4$$

which are seen to be quadratic functions of X. The waveform X is assigned to the class which yields the minimum discriminant function. Notice that in the case where the covariance matrices for each class are equal to the identity matrix (white noise for each stimulus condition), the maximum likelihood classifier becomes the correlation classifier described above.

Initially, training and testing were done using all data points for each stimulus condition. Table 2 shows the classification accuracy obtained with a maximum likelihood classifier using data from C_Z, P_Z, O_Z, and I_N electrodes in all possible combinations. The performance is seen to be exceptionally good for two or more electrodes in all possible combinations and reasonably good (94% accuracy) for the single O_Z electrode. Similar tests were carried out for the other test subject with a somewhat lower classification accuracy obtained.

Classification tests were carried out using half the data for training and half the data for testing. Only a very slight reduction in accuracy occurred for this combination.

Methods of reducing the number of features (i.e., the number of data points) used for classification were investigated. The technique employed is called forward sequential feature selection. In this technique, time samples (or features) were chosen from the set of 56 (4 electrodes and 14 samples per electrode) by a forward sequential feature selection procedure. Six features were chosen because they will provide a more statistically significant estimation of the probability density functions. This technique first chooses the single sample from among the 56 that gives the best discrimination using a one-dimensional maximum likelihood classifier.

Table 2: Results of Maximum Likelihood Classifier (Training on All Data and Testing All Features).
Subject 409

Electrodes Used	% Correct Classification
C_Z	78
P_Z	79
O_Z	94
I_N	85
C_ZP_Z	97
C_ZO_Z	99
C_ZI_N	98
P_ZO_Z	99
P_ZI_N	97
O_ZI_N	100
$C_ZP_ZO_Z$	100
$C_ZP_ZI_N$	100
$C_ZO_ZI_N$	100
$P_ZO_ZI_N$	100
$C_ZP_ZO_ZI_N$	100

The next sample is chosen to provide the best discrimination for a two-dimensional classifier using the previously selected feature as one of the two. This step of adding a selected sample to the existing set continues until 6 features are chosen. This procedure does not guarantee optimality, but it is a feasible solution to the problem of feature selection when the original dimensionality is large. The optimum solution would be to try all possible combinations of 6 features and would involve testing 32,468,436 six-dimensional classifiers which is obviously impractical. The maximum likelihood classifier was designed using the selected samples from the first 65 potentials in an experiment. Then 60 subsequent potentials from the same experiment were classified to determine the recognition. The results are shown in Table 3.

Table 3

Feature	Electrode	Latency (ms)	Recognition
1	O_z	100	51.67%
2	O_z	120	75.00%
3	P_z	120	85.42%
4	Inion	100	87.92%
5	Inion	120	91.67%
6	C_z	100	92.92%

From these results one can see that the maximum likelihood classifier will yield a higher performance using less data than the linear correlation classifier. In most cases the linear classifiers have the advantages of being easier to implement and requiring less calculations than the quadratic classifiers. However in the case where the first three features and the inverse of the covariance matrix are known, the quadratic classifier not only performs better, but also is simplified so that it poses no problems in implementation. For this case, it also uses less multiplications than the linear classifier which required the entire data set to achieve a comparable performance.

The features that were selected by this procedure generally correspond to the components in the averages which show polarity reversals for some of the stimulus conditions. These polarity reversals and latencies are to be expected when one considers the results of the studies done by Jeffreys et al (Jeffreys and Axford, 1972, I and II) involving pattern-appearance stimuli. As Donchin et al. (Donchin, 1969) have pointed out, features selected by any procedure must bear some connection to the underlying process before any relationship between the discriminant functions and the evoked potentials for the different stimulus conditions is to be inferred.

The forward sequential feature selection procedure was then performed on the combinations of three class data obtained by eliminating one class. These results are shown in Table 4. The first few features selected in Table 4 are again at 100 and 120 ms in electrodes O_z and P_z. But now other latencies are evident especially when the CF stimulus condition is eliminated.

Table 4

Class Eliminated: BF

Feature	Electrode	Latency (ms)	Recognition
1	O_z	100	62.22%
2	O_z	120	81.11%
3	Inion	100	81.11%
4	P_z	220	88.89%
5	Inion	140	89.44%
6	Inion	140	90.00%

Class Eliminated: CF

Feature	Electrode	Latency (ms)	Recognition
1	P_z	100	62.22%
2	O_z	100	76.67%
3	O_z	140	88.33%
4	C_z	140	92.78%
5	C_z	180	95.56%
6	Inion	180	96.67%

Table 4 (Continued)

Class Eliminated: CT

Feature	Electrode	Latency (ms)	Recognition
1	O_z	100	63.33%
2	O_z	120	77.22%
3	P_z	120	86.11%
4	Inion	100	88.89%
5	Inion	120	93.33%
6	C_z	100	93.89%

Class Eliminated: CB

Feature	Electrode	Latency (ms)	Recognition
1	O_z	100	66.67%
2	O_z	120	85.00%
3	P_z	120	92.22%
4	P_z	160	95.00%
5	C_z	200	95.00%
6	C_z	160	95.56%

Since the averages shown in Figure 13 are the summation of many evoked potentials, one cannot ascertain much about the components in a single potential from the average alone. In order to obtain more information bout the single evoked potentials, these components were located by a procedure outlined by McGillem and Aunon (McGillem and Aunon, 1977), and a histogram of the number of peaks detected at each latency was constructed. Figure 15 shows the matrix of histograms for each electrode and stimulus condition.

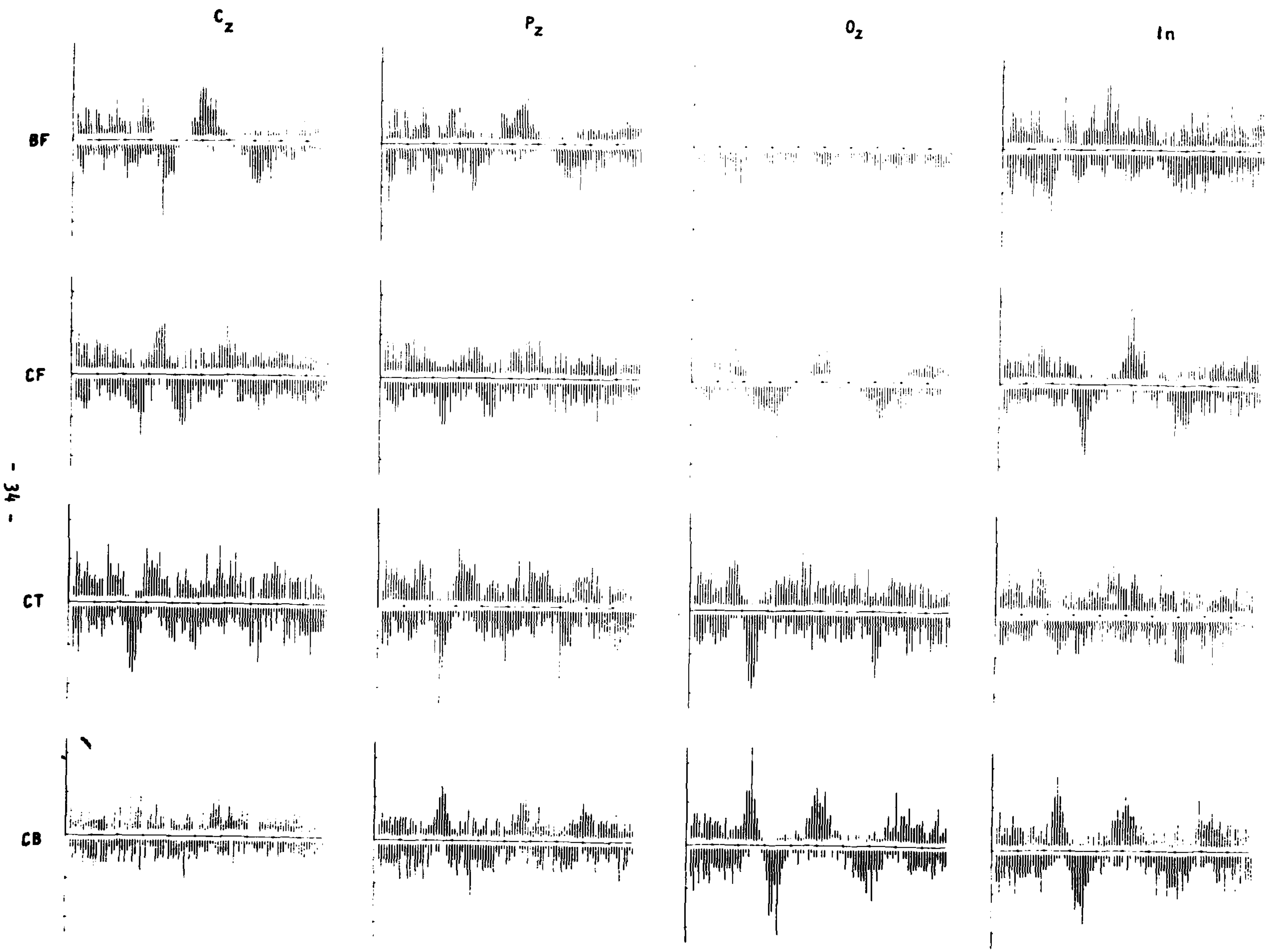

Figure 15. Matrix of Histograms for each Electrode and Stimulus Conditions.

In many cases the general shape of the histogram bears some relation to the average evoked potential. Notice that the histograms for the C_z electrode and CF or CB stimulus condition are generally flat in shape. The corresponding averages shown in Figure 13 also tend to have less sharply defined peaks. From Table 4 one can see that when the CF or CB stimulus condition is eliminated, two of the features selected are from C_z compared with one or none in the other two cases.

The components with polarity reversals evident in Figure 3 are also present in Figure 14. Thus the peaks which show polarity reversals between the stimulus conditions are present in the single potentials as well as in the averages. These peaks correspond to the features chosen by forward sequential feature selection correspond to components having the largest frequency of occurrence in the single potentials.

Note that the recognition values in Table 3 correspond not only to the single feature given but also to all the features preceding it. So two selected features from 100 and 120 ms in O_z gave discrimination comparable to the entire set of time points in O_z. This is understandable from Figure 2 in that many latencies show an approximately equal number of potentials having both positive and negative peaks. The amplitudes at these latencies will present little, if any, discriminant information to the classifiers.

Task 4.3

"Subsequent to the preliminary investigations, data acquisition for the latter phases of this contract is to be completed at the Visual Display Systems Branch of AMRL. This will require that a controlled interface be established between the recording systems at the contractor's laboratory and those at AMRL. Consequently, at least two trips by the contractor to AMRL (two investigators) and two trips by AMRL personnel to the contractor's laboratory (two investigators) will be necessary to ensure complete compatibility of hardware. Specifications will be agreed upon for: (a) type of digitization procedure; (b) data encoding; (c) data calibration; and (d) EEG amplification settings."

This task was completed as the data were transferred between AMRL and the contractor's laboratory. Specifications concerning data recording, coding, calibration and digitization were completed.

Tasks 4.4, 4.5 and 4.6

4.4 "The initial tests to be performed at AMRL will utilize the stimulus events and electrode placements determined in sections 4.1 and 4.2 above. Digital tapes will be submitted to the contractor and signal processing studies will commence at this point. Data processing techniques developed in section 4.2 above will be improved with the highly controlled evoked potential activity recorded at AMRL. Other single event evoked potential procedures are to be considered, such as the use of a latency corrected average which takes into account time related fluctuations of individual components of the single response. Further, the use of selected segments of the latency corrected average (100-250 msec after stimulus onset) as a matched filter for the detection of corresponding components in the single response should be investigated. Following the completion of these tasks, the single responses associated with the different chromatic stimulus events will be accurately characterized."

4.5 "The "features" of the single responses elucidated in section 4.4 above will form the basis for classification according to stimulus type. Some of the techniques to be utilized in the study of this relationship are the linear least squares multidimensional classifier and the maximum likelihood classifier. These techniques and the software developed for their implementation will be tested in the remaining subjects of this initial testing session. The possibilities of utilizing a filter "common" to all subjects will also be explored. The existence of such a filter would imply that no *a priori* information concerning a specific subject would be needed in order to specify (within some statistical bound) the color of the stimulus. This would be advantageous because then no initial testing for a specific subject would be required prior to the actual experiment."

4.6 "A new set of experiments will be conducted at AMRL utilizing subjects not used in the first set of experiments. The theories and hypotheses developed earlier will be tested with this new set of data and changes or alterations will be made at this time in the software to optimize the performance of the data processing algorithms. The digital tapes submitted by AMRL to the contractor (in section 4.4 above) will remain at that facility until the completion of this contract. The attached program schedule indicates the phasing of tasks to be completed under this contract."

A new set of tests were performed at AMRL in order to verify the usefulness of the previously developed classification procedures to different and more complex situations. First, the tests performed earlier were expanded to include quadrants and right and left visual fields. The number of electrodes used was also increased to incorporate electrodes off the midline. Electrodes were positioned in the right and left parietal cortex and the right and left occipital cortex. Stimulus parameters were as follows:

(1) The entire CRT screen abruptly becomes a checkerboard of checksize 10' for a duration of 0.5 seconds. The screen then returns to the quiescent state for 1.5 seconds. Space average luminance remains constant throughout the 2 seconds.

(2) Same as (1) except left half of screen becomes a checkerboard, right half stays blank (quiescent).

(3) Same as (1) except right half of screen becomes a checkerboard, left half stays blank (quiescent).

(4) Same as (1) except upper half of screen becomes a checkerboard, lower half stays blank (quiescent).

(5) Same as (1) except lower half of screen becomes a checkerboard, upper half stays blank (quiescent).

(6) Same as (1) except upper left quadrant of screen becomes a checkerboard, the other quadrants stay blank (quiescent).

(7) Same as (1) except upper right quadrant of screen becomes a checkerboard, the other quadrants stay blank (quiescent).

(8) Same as (1) except lower left quadrant of screen becomes a checkerboard, the other quadrants stay blank (quiescent).

(9) Same as (1) except lower right quadrant of screen becomes a checkerboard, the other quadrants stay blank (quiescent).

A minimum of 200 repetitions of each stimulus were presented to each of 5 subjects. Time between the onset of stimulus repetitions equaled 2 seconds.

The above tests are expected to provide a more detailed experimental evaluation of the techniques developed earlier by increasing to nine the choices available to the classifier. The electrodes positioned off the mid-line are expected to provide the extra features needed for accurate classification.

In addition to the above tests, the following tests involving underlying psychological factors were also performed.

(10) <u>V Inverted V</u>

In this test, the subject views the alphabet letter V and occasionally the same letter inverted. Interstimulus intervals were uniformly distributed between 2 and 5 seconds in order to negate build up of the contingent negative variation (CNV). Probability of occurrence for the inverted letter was 20% and for the normal letter 80%. "On-time" for each letter was 0.5 seconds and recording of the EEG was coincident with the presentation of each letter.

(11) <u>Sternberg Paradigm Test</u>

During this test, the subject was given two letters to memorize (such as T and F). These were called relevant letters (RL), the rest of the alphabet comprising the nonrelevant letters (NRL). The subject was then shown a letter and asked to make a decision as to whether it was an RL or an NRL, the decision involving pushing one of two provided buttons. The interstimulus interval was approximately 5 seconds. The RL had a 50% probability of occurrence and NRL a 50% chance of occurring. Recording of the EEG was coincident with the presentation of each letter.

(12) <u>Focused and Defocused Letters</u>

During this test, the subject was shown five letters of the alphabet, one at a time, 200 times each. The letters (I, R, B, O, C) were shown first as sharply defined and then as defocused letters. Recording of the EEG was coincident with the presentation of each letter.

(13) <u>Edge Matching</u>

During this test, the subject was shown, side by side, two slides of a photographic image. One of the slides, always shown on the left, was known to be ground-truth level. The subject was then asked to make a subjective judgment as to whether the test slide was more or less sharply defined than the ground-truth slide. Once this decision process terminated, both sides were flashed, the EEG recorded at this time, and the subject asked whether these 2 slides were the same ones he had previously observed.

RESULTS

Checkerboard Stimulation

Conditions 1 through 9 were digitized and filtered following the procedure outlined earlier. The results of applying the quadratic classifier to the data are summarized in the Appendix. These results were not as dramatic as those reported earlier, but no further data processing was performed on the data in order to allow time to analyze data from the other modalities of stimulation. Out of the four conditions left, namely 10 through 13, most of the effort was concentrated on the Edge Matching experiment.

Due to poor data (V inverted V) and lack of time (Sternberg test), it was not possible to analyze the data from experiments 10 and 11.

Focused and Defocused Letters Classification Results

The tests performed attempted to classify blurred against focused letters presented to the subject. A quadratic classifier was used as the classification algorithm and the results achieved are shown in Table 5.

Table 5
Training and Classification on Same Samples

Class 1: R focused — Class 2: R blurred

Feature	Electrode - Latency	% Correctly Classified
1	O_z - 200 MS	66
2	IN - 500 MS	70
3	O_z - 300 MS	74
4	C_z - 200 MS	76
5	C_z - 160 MS	77
6	O_z - 380 MS	78

Class 1: B focused		Class 2: B blurred
Feature	Electrode - Latency	% Correctly Classified
1	C_z - 240 MS	65
2	O_z - 500 MS	72
3	C_z - 300 MS	74
4	C_z = 220 MS	76
5	C_z - 180 MS	77
6	INION - 540 MS	77

Class 1: O Focused		Class 2: O Blurred
Feature	Electrode - Latency	% Correctly Classified
1	O_z - 260 MS	61
2	INION - 340 MS	62
3	INION - 140 MS	67
4	O_z - 80 MS	70
5	O_z - 120 MS	71
6	O_z - 0 MS	70

Class 1: R focused		Class 2: O focused
Feature	Electrode - Latency	% Correctly Classified
1	P_z - 260 MS	59
2	O_z - 480 MS	65
3	C_z - 220 MS	66
4	O_z - 600 MS	68
5	INION - 40 MS	69
6	P_z - 360 MS	70

The first three tests attempted to separate the same focused and blurred letters. The last test attempted to separate two letters that were focused. The classification accuracy obtained in these tests was approximately 70 percent. This indicates that some type of data preprocessing similar to the one used to be described in the edge-matching experiments should be investigated.

Edge Matching Classification Results

There were five possible gradations of sharpness numbered 1, 7, 11, 17 and 22. The ground-truth slide, which always appeared on the left, corresponded to number eleven. Number 1 slide was the sharpest and 22 the least focused. Therefore, the subject was shown slide 11 on the left and one of the other five on the right. Throughout the test, the average luminance level observed by the subject was kept constant to minimize any intensity changes in the evoked potential caused by defocusing of a slide. Using the quadratic classifier, it was then attempted to discriminate among the test images using the evoked potentials. A class was made up of combinations of slides such as: Class 1 made up by showing slides 11 and 11 and Class 2 from slides 11 and 22, etc... The first approach was to classify the individual evoked potentials produced by the two extreme slides. These two slides corresponded to the sharpest and the least sharply defined images (slide 11 was always shown on the left), i.e. Class 1 = 11/1, Class 2 = 11/22. The results are shown on Table 6.

Table 6

Training and classification on same samples

	Feature	% Correctly Classified
1	C_z (300 msec)	71.4
2	P_z (280 msec)	76.4
3	I_n (100 msec)	79.3
4	C_z (240 msec)	82.1
5	C_z (60 msec)	84.3
6	I_N (360 msec)	85.7
7	P_z (500 msec)	89.3
8	P_z (100 msec)	90.0
9	I_N (460 msec)	91.4
10	C_z (320 msec)	92.7

As it may be observed with 8 features, the percent correct classification is on the order of 90%. It is also interesting to observe that if only the first feature is considered, i.e., C_z @ 300 msec, the classification accuracy is 71%. In this procedure training and testing were carried out using all samples.

Training on half of the samples - Testing on half of the samples. Class 1 - 11/1, Class 2 - 11/22 when only the first half of the data set is used for training the classifier and then testing is carried out over the second half of the data set there is a reduction in performance as shown in Table 7.

Table 7
Training and classification on different samples

	Feature	% Correctly Classified
1	C_z (300 msec)	67.1
2	I_n (100 msec)	75.7
3	P_z (120 msec)	82.9
4	O_z (160 msec)	85.7
5	O_z (240 msec)	87.1

The next test attempted to classify between the sharpest slide (1) and the standard slide (11), i.e. Class 1 = 11/11 and Class 2 = 11/1. The results are shown on Table 8.

Table 9
Training and classification on different samples

	Feature	% Correctly Classified
1	C_z (280 msec)	62.9
2	C_z (0 msec)	65.7
3	C_z (200 msec)	70.0
4	O_z (580 msec)	72.9
5	O_z (83 msec)	78.6
6	C_z (340 msec)	78.6
7	I_n (120 msec)	81.4
8	O_z (20 msec)	81.4
9	P_z (340 msec)	82.8
10	P_z (540 msec)	84.3

It is difficult to interpret the second feature selected by the classifier, except that this is one out of three possible choices (alternate trees) at this level. It apparently represents a stable point in the response by which changes at other points can be measured.

The next test attempted to classify between the standard and the least sharp slides, Class 1 = 11/11 and Class 2 = 11/22. The results are shown on Table 9.

Table 9
Training and classification on different samples

	Feature	% Correctly Classified
1	C_z (280 ms)	71
2	I_n (80 ms)	77
3	O_z (200 ms)	81
4	P_z (40 ms)	84
5	C_z (60 ms)	83

Although the results were adequate, they did not have the degree of correct classification that was desired, so several techniques of data processing were explored.

Acceptance or Rejection of Single Responses According to Their Euclidean Distance from the Ensemble Mean

After the mean and standard deviation of the Euclidean distances between each single response and the ensemble mean were calculated, those single responses whose distances exceeded 1 standard deviation were rejected. Results of the classification on the remaining responses (10% of the responses were rejected) are shown in Table 10.

Table 10
Training and classification on different samples
(Class 1 = 11/1, Class 2 = 11/22)

	Feature	% Correctly Classified
1	O_z (440 ms)	70
2	P_z (120 ms)	75
3	C_z (300 ms)	78
4	I_N (100 ms)	83
5	O_z (40 ms)	85

The increase in correctly classified responses was not very significant.

Improved MMSE Filtering Procedure

By employing a more powerful filtering technique designed to separate the evoked potential from the ongoing EEG it should be possible to obtain performance comparable to that which would be obtained for higher SNR. One filter that has been designed for this purpose is the minimum mean square error filter (MMSE) which makes use of the autocorrelation matrix of the data and an estimate of the autocorrelation function of the signal waveform [McGillem, 1977]. In previous experiments with the MMSE filter the autocorrelation function of the signal waveform was approximated by the autocorrelation function of the average evoked potential. This led to the design of useful MMSE filters but not too high performance filters because much of the detail of the signal waveform is lost in the averaging process.

As a means of improving the performance of the MMSE filter a new procedure for estimating the autocorrelation function of the evoked potential waveform was developed. This method made use of the latency corrected average (LCA) which is obtained in the following manner. Each individual response in an ensemble of MMSE filtered evoked potentials is searched by computer to locate the individual peaks. The peaks are then clustered by a statistical procedure into groups corresponding to the same portion of the response waveform. Within each group the mean latency is determined and the corresponding segments of the original waveforms are aligned to that latency and averaged giving the LCA for that component. This is repeated for each cluster giving the complete LCA. When computed in this manner the LCA is a set of disjoint waveform segments corresponding to the components in the evoked potential. Figure 16 shows a superposition of the conventional averages and the LCAs for four electrode positions for the image comparison evoked potentials. Prior to processing, the data shown were filtered with a 30 Hz low pass filter.

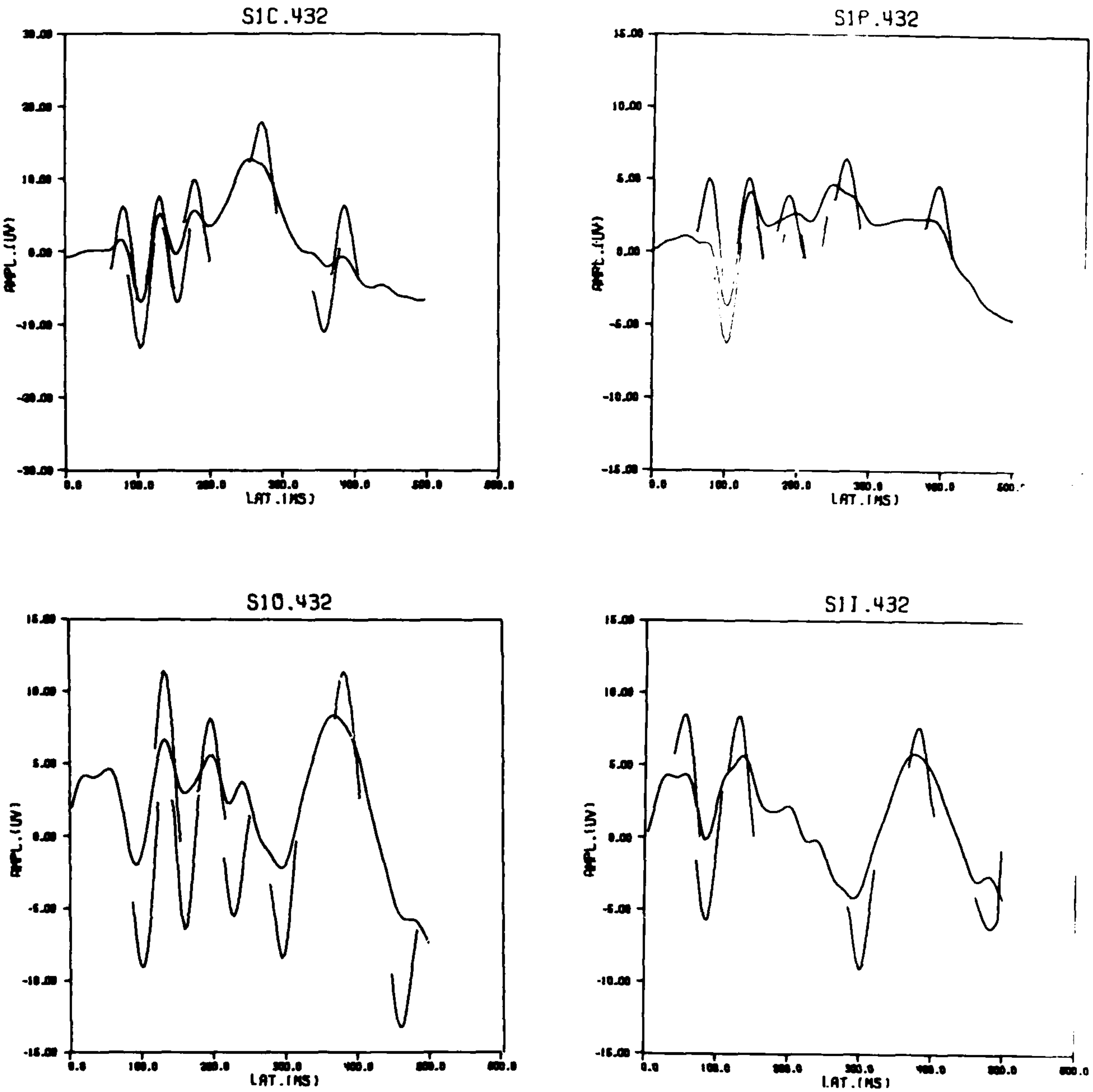

Figure 16. Superposition of the Conventional Averages of the Low Pass Filtered [30 Hz] Data and their corresponding LCA's.

In order to be useful in the design of an improved MMSE filter, it is necessary to convert the disjoint LCA into a continuous waveform so that its autocorrelation function can be computed. Several methods of accomplishing this were tried, and it was found that excellent fits in the immediate vicinity of the LCA segments could be obtained. However, when one or more components were missing the approximating function behaved erratically. This is illustrated in Figure 17 where the LCA of Figure 16 was fitted with a sum of sinusoids. The large peaks in Figures 17A and 17B occur where there are no components of the LCA present and are obviously not a valid approximation in that region. Also, Figure 17D looks unnatural because of the presence of only low frequency components. This latter effect was the result of there being only a limited number of components that can be unambiguously computed due to the relatively few components present in the LCA. In the weighted least squares fitting procedure used the frequencies of the components are selected first (the number of different frequencies possible is determined by the amount of data available) and then the amplitude determined. By eliminating those components that have very small coefficients and adding new components not previously used, an improved fit can be obtained by several iterations. At the same time by setting the values of the data in the vicinity of missing components to a small value (typically zero), but using a greatly reduced weighting factor (1/10) in this region relative to the rest of the data set, the generation of spurious peaks can be eliminated. The results of four iterations of the fitting procedure gave the continuous LCA waveforms shown in Figure 18. Comparison of the continuous LCA waveforms with the disjoint LCA waveforms of Figure 16 shows excellent agreement.

As an illustration of the increased filtering action that resulted from redesigning the MMSE filter using the autocorrelation function, of the continuous LCA to represent the signal autocorrelation function the first individual response for the four electrodes are shown in their original (30 Hz low pass filtered) form in Figure 19 and as filtered by the improved MMSE filter in Figure 20. It is seen that the overall trends are retained with a substantial enhancement of the individual components. It is this signal enhancement that is expected to lead to improved classification performance.

Classification of Improved MMSE Filtered Data

In order to investigate the effect of improved filtering on classification accuracy the previous tests relating to image comparison were repeated after filtering the data with the improved MMSE filter. The classification procedure was as follows. The MMSE filter was computed for data corresponding to one of the classes (Class 1: sharpest image) and used to filter the data of both Class 1 and Class 2 (least sharp image). The first half of the data was then used to train the quadratic classifier and the second half used to determine the classification accuracy. The results are shown in Table . Comparing these results with those given in Table 11 shows that the error rate has been reduced by more than 50%. It seems likely that by refining this procedure even further improvements in performance should be possible.

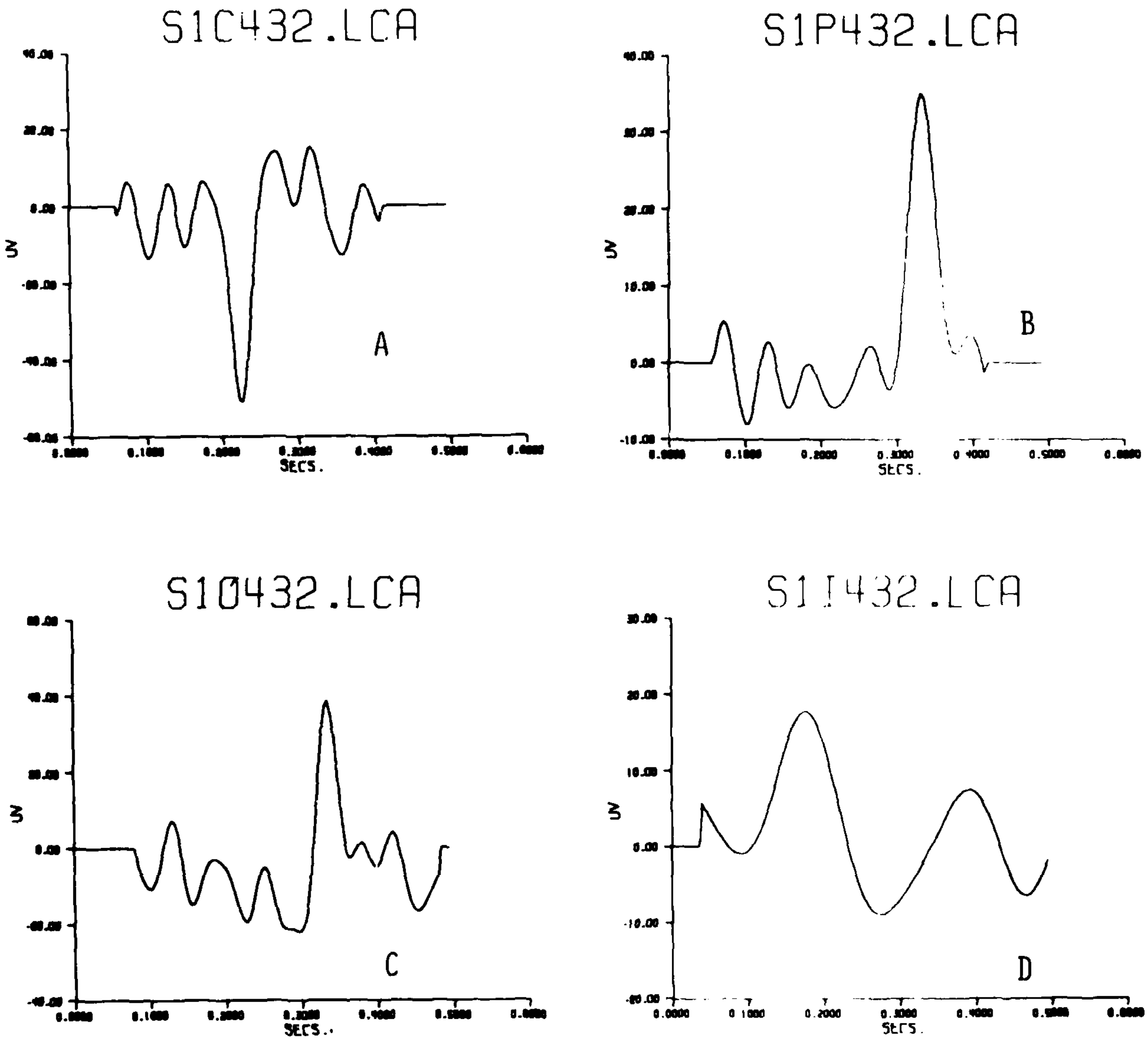

Figure 17. Representation of the LCA's with a sum of sinusoids.

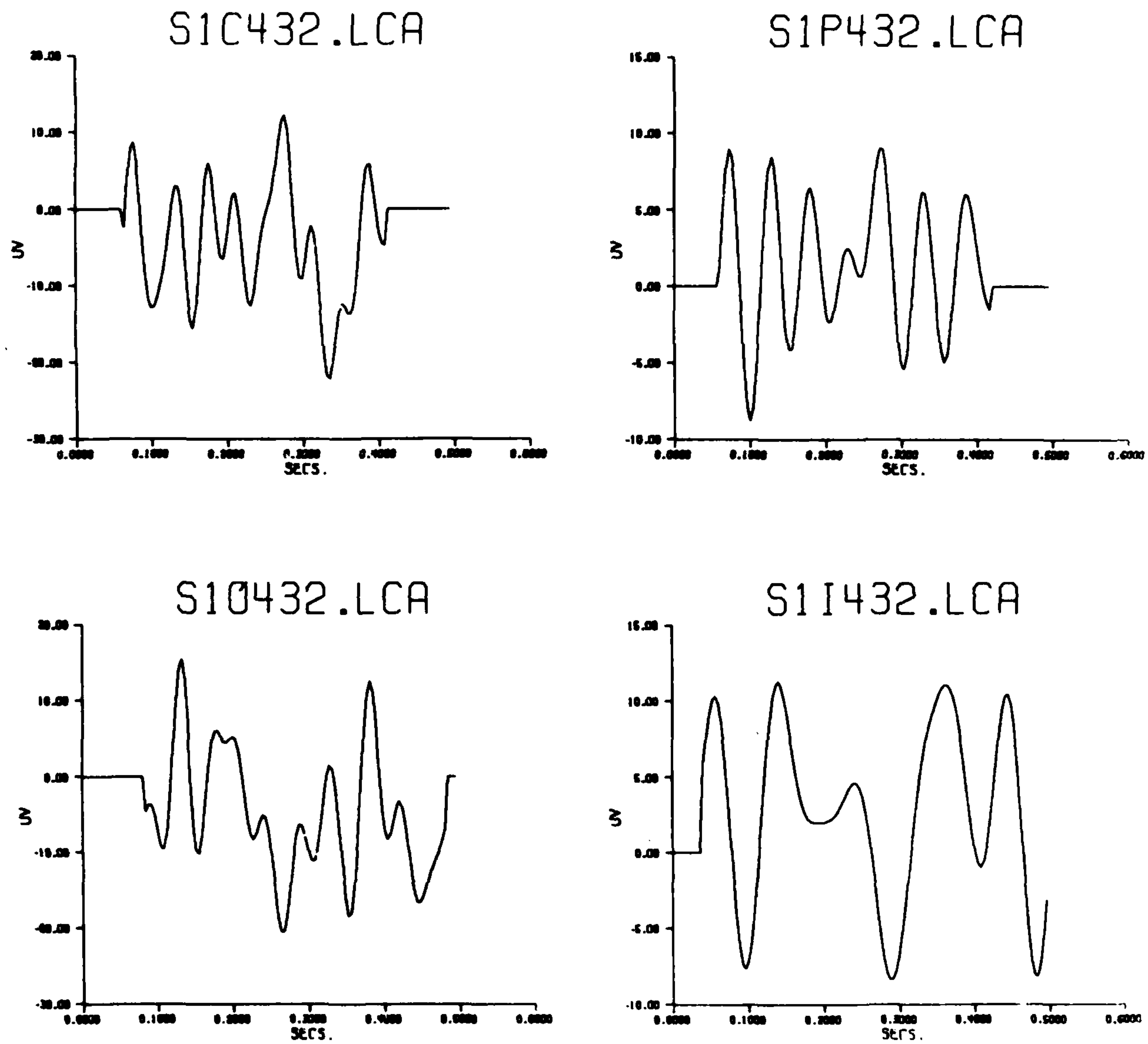

Figure 18. Continuous LCA waveforms after four iterations of the filtering procedure.

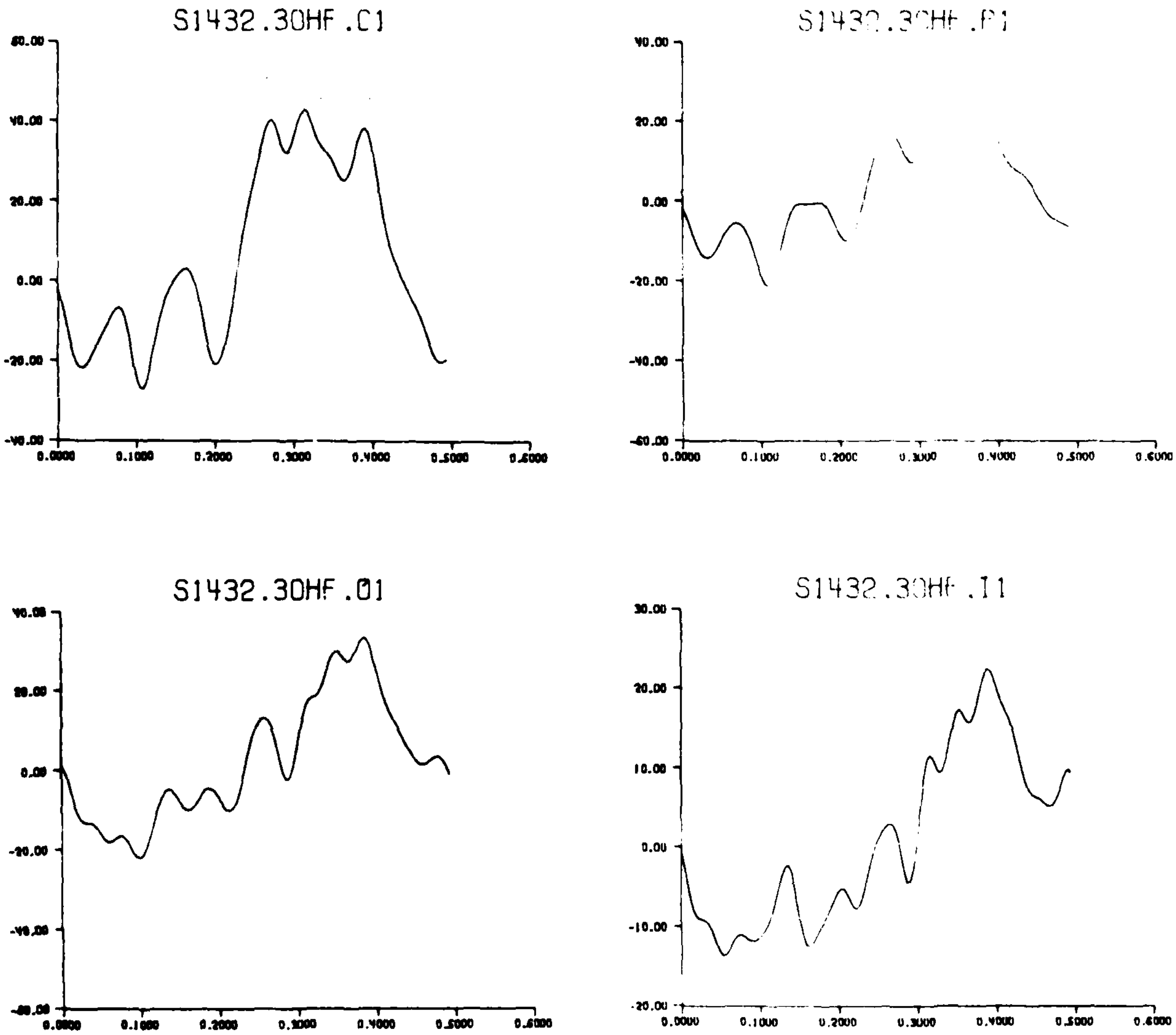

Figure 19. First individual response for the four electrodes prior to MMSE filtering.

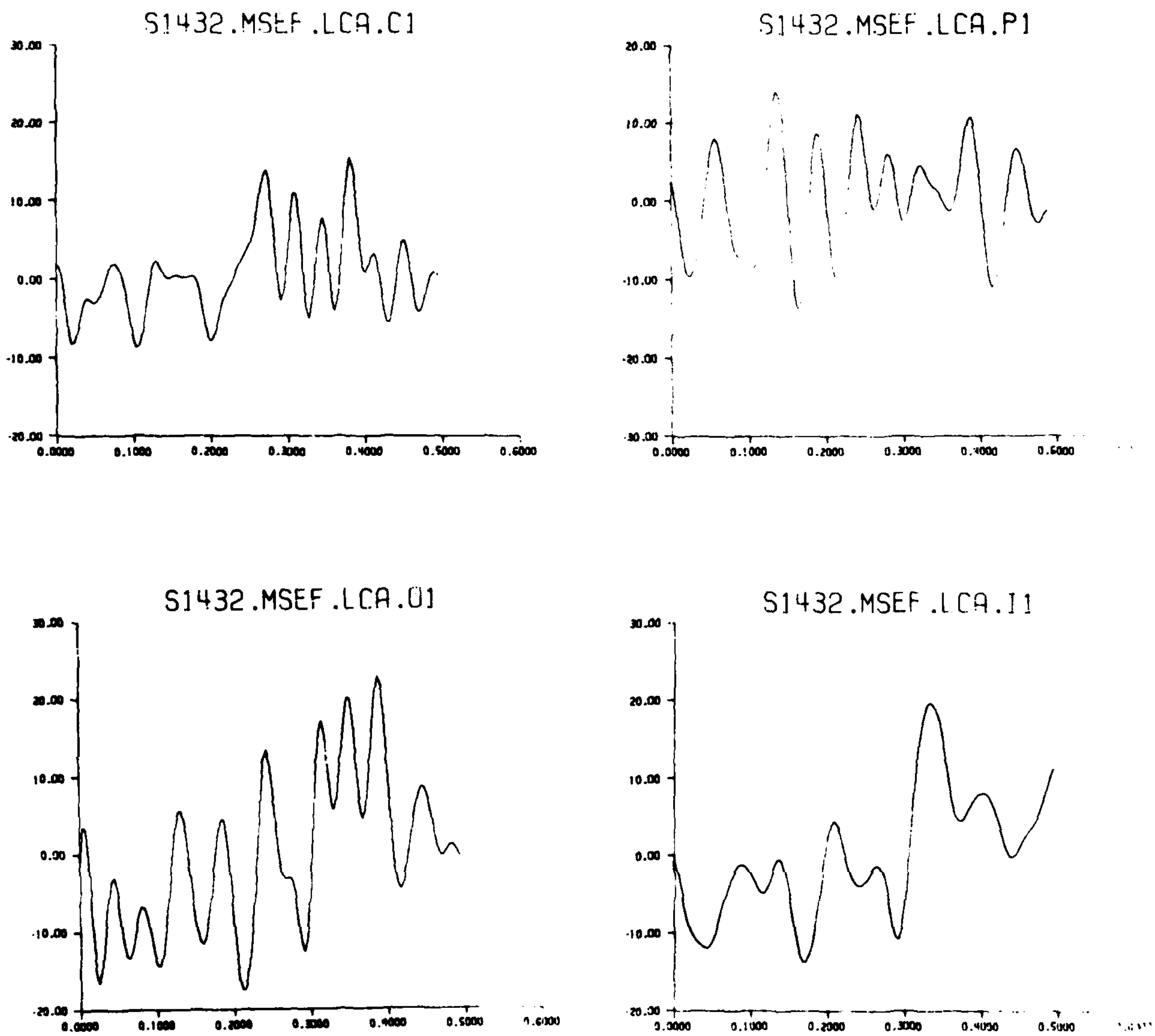

Figure 20. Same responses as in Figure 19 after MMSE filtering.

Table 11
Classification Performance on the Image Comparison Test After Processing the Data with the Improved MMSE Filter
(Class 1: Sharpest Image - Class 2: Least Sharp Image)

Feature	Electrode - Latency	% Correctly Classified
1	O_z - 160 MS	76
2	O_z - 0 MS	81
3	P_z - 0 MS	90
4	Inion - 560 MS	91
5	C_z - 140 MS	94

CONCLUSIONS

The purpose of this research program was to demonstrate the feasibility of on-line classification of evoked cortical potentials associated with specific stimulus events. For the initial experimental phase a number of stimuli (checkerboard patterns) were selected which showed pattern reversals and other noticeable feature variations in their conventional average evoked potentials. The assumption was made that the dissimilarities of the features on the average would carry to the single potentials.

Several classification techniques were investigated and tested using the single evoked potentials. A Bayes classifier utilizing a quadratic discriminant function gave the best results. Classification accuracies were on the order of 66% for a linear classifier as compared to 94% for a quadratic classifier when the optimum number of features were used.

Following these tests, the experimental measurements were extended in two directions. First, a more elaborate battery of tests involving checkerboard patterns was generated. These tests involved right and left visual fields, upper and lower visual fields and quadrants of each field. The results of these tests are included in the Appendix of this Report.

Second, a series of new experiments involving more complex experimental paradigms was generated. The aim now was to test the previously developed programs and algorithms and to investigate other techniques such as data preprocessing. Two of the new paradigms that were investigated were focus-defocused letters and edge matching.

Results obtained in the edge matching experiment, fully described in the preceding sections, were very encouraging giving classification accuracies above 80%. By using a newly developed data preprocessing technique the error rate was further reduced by more than 50%. This type of data preprocessing should be investigated further to assess its usefulness in other paradigms such as in the focus-defocused letters experiment.

Publications Resulting from this Research Contract

Sencaj, R. W., Aunon, J. I., McGillem, C. D., "Discrimination Among Visual Stimuli by Classification of Their Single Evoked Potentials," Medical and Biological Engineering and Computing, May, 1979.

Aunon, J. I., McGillem, C. D., "Detection and Processing of Individual Components in the VEP," Psychophysiology, Vol. 16, 71-79, 1979.

Aunon, J. I., "Computer Techniques for the Processing of Evoked Potentials," Computer Programs in Biomedicine, Vol. 8, pp. 243-255, 1978.

Aunon, J. I., McGillem, C. D., Sencaj, R. W., "Determination of Visual Stimuli from the Single VEP," Proceedings of the 31st ACEMB, Atlanta, Georgia, October 21-25, 1978.

APPENDIX

The following are the classification results obtained for conditions 1 through 9 as outlined in the Results section of this Report. All of the results reported below were obtained by training and classifying on different samples.

Subject 425

Subject -- 90 training/90 testing

Class 1: Bottom Left - Class 2: Top Left

Feature	Electrode	Latency (MS)	Recognition
1	O_z	80	67%
2	P_3	160	74%
3	P_3	80	77%
4	O_4	200	81%
5	O_3	160	82%
6	P_z	220	83%
7	O_3	140	84%
8	O_3	60	84%
9	P_3	20	84%

Subject 425

Subject 425 -- 90 training/90 testing

Class 1: Bottom Right - Class 2: Top Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_z	120	74
2	P_3	120	83
3	O_z	100	87
4	P_3	160	88
5	O_3	220	90
6	P_z	100	91
7	P_3	140	92
8	P_z	40	93
9	P_4	60	93

Subject 425 -- 90 training/90 testing

Class 1: Bottom Right - Class 2: Bottom Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_3	100	67
2	O_3	120	71
3	P_z	180	72
4	P_4	0	73
5	P_z	40	74
6	O_z	120	77
7	P_z	20	79
8	P_3	140	81
9	P_4	20	81

Subject 425 -- 90 training/90 testing

Class 1: Top Right - Class 2: Top Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_3	160	62
2	O_4	180	66
3	O_z	120	69
4	O_4	80	73
5	O_3	120	74
6	P_z	140	74
7	O_3	140	74
8	O_3	180	74
9	O_4	140	76

Subject 425 -- 90 training/90 testing

Class 1: Top Right - Class 2: Bottom Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_4	80	72
2	O_4	200	79
3	O_4	100	79
4	P_3	140	83
5	P_3	240	84
6	O_4	220	86
7	P_z	140	86
8	O_4	180	86
9	P_4	120	86

Subject 425 -- 90 training/90 testing

Class 1: Top Right - Class 2: Bottom Right

Feature	Electrode	Latency (MS)	Recognition (%)
1	0_z	80	77
2	P_z	80	81
3	0_z	100	82
4	0_3	140	83
5	0_z	220	86
6	P_z	140	88
7	P_z	180	90
8	P_4	120	90
9	P_3	60	91

Subject 425 -- 90 training/90 testing

Class 1: Right Half - Class 2: Top Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	0_z	120	72
2	P_3	120	88
3	0_z	100	90
4	0_z	200	92
5	0_3	120	94
6	0_4	160	94
7	P_4	220	94
8	P_4	200	93
9	P_z	120	94

Subject 425 -- 90 training/90 testing

Class 1: Right Half - Class 2: Bottom Left

Feature	Electrode	Latency	Recognition
1	O_3	80	65
2	O_4	160	74
3	O_4	80	78
4	O_z	80	79
5	O_3	180	81
6	O_z	200	82
7	O_4	200	83
8	P_4	100	85
9	O_3	200	85

Subject 425 -- 90 training/90 testing

Class 1: Right Half - Class 2: Bottom Right

Feature	Electrode	Latency	Recognition
1	O_z	80	62
2	P_3	80	72
3	P_z	160	73
4	P_z	220	74
5	O_z	220	77
6	O_4	20	77
7	O_3	20	77
8	P_z	200	77
9	O_3	120	78

Subject 425 -- 90 training/90 testing

Class 1: Right Half - Class 2: Top Right

Feature	Electrode	Latency	Recognition
1	O_z	80	73
2	O_z	120	77
3	O_z	200	80
4	P_3	120	85
5	O_z	220	88
6	P_3	140	88
7	P_3	100	88
8	O_z	40	88
9	P_3	200	88

Subject 425 -- 90 training/90 testing

Class 1: Lower Half - Class 2: Top Left

Feature	Electrode	Latency	Recognition
1	O_z	80	62
2	O_z	200	69
3	P_3	80	70
4	P_4	100	72
5	O_4	20	74
6	O_z	80	74
7	P_z	160	75
8	P_3	200	77
9	O_4	120	77

Subject 425 -- 90 training/90 testing

Class 1: Lower Half - Class 2: Bottom Left

Feature	Electrode	Latency	Recognition
1	O_4	200	63
2	O_3	220	67
3	O_4	140	70
4	O_4	0	72
5	P_3	220	72
6	O_3	0	74
7	O_z	240	76
8	P_3	60	76
9	O_3	80	76

Subject 425 -- 90 training/90 testing

Class 1: Lower Half - Class 2: Bottom Right

Feature	Electrode	Latency	Recognition
1	O_z	100	72
2	P_4	100	76
3	P_4	20	78
4	P_z	220	79
5	O_z	80	82
6	P_3	80	86
7	O_4	80	90
8	O_z	20	91
9	P_3	100	91

Subject 425 - 90 training/90 testing

Class 1: Lower Half - Class 2: Top Right

Feature	Electrode	Latency	Recognition
1	O_4	80	71
2	P_3	140	77
3	O_z	20	79
4	P_z	100	80
5	P_4	160	82
6	P_z	160	81
7	P_3	20	81
8	O_3	100	82
9	P_3	60	82

Subject 425 -- 90 training/90 testing

Class 1: Lower Half - Class 2: Right Half

Feature	Electrode	Latency	Recognition
1	P_4	200	64
2	O_3	80	69
3	O_4	80	74
4	O_4	100	78
5	O_z	100	83
6	P_z	100	86
7	P_4	0	88
8	P_z	200	89
9	P_z	240	89

Subject 425 -- 90 training/90 testing

Class 1: Bottom Half - Class 2: Top Left

Feature	Electrode	Latency	Recognition
1	O_z	120	77
2	P_3	120	91
3	O_z	100	94
4	P_3	20	96
5	O_z	60	97
6	P_3	100	97
7	O_4	60	97
8	O_z	160	96
9	P_4	100	98

Subject 425 -- 90 training/90 testing

Class 1: Bottom Half - Class 2: Bottom Left

Feature	Electrode	Latency	Recognition
1	O_z	120	66
2	O_z	100	74
3	O_z	60	78
4	P_3	120	82
5	O_z	20	82
6	P_4	20	83
7	P_z	100	84
8	O_3	220	86
9	O_z	160	88

Subject 425 -- 90 training/90 testing

Class 1: Bottom Half - Class 2: Bottom Right

Feature	Electrode	Latency	Recognition
1	P_4	100	62
2	P_4	180	63
3	O_4	180	67
4	P_4	80	73
5	P_z	20	73
6	P_z	60	73
7	O_3	40	73
8	O_4	200	73
9	O_z	20	74

Subject 425 -- 90 training/90 testing

Class 1: bottom Half - Class 2: Top Right

Feature	Electrode	Latency	Recognition
1	O_z	80	76
2	O_4	200	83
3	P_z	100	86
4	O_4	100	87
5	O_3	80	87
6	O_z	200	89
7	P_4	60	89
8	O_4	40	90
9	P_3	200	91

Subject 425 -- 90 training/90 testing

Class 1: Bottom Half - Class 2: Right Half

Feature	Electrode	Latency	Recognition
1	O_4	100	72
2	P_4	140	76
3	O_z	240	77
4	O_4	80	77
5	P_4	160	79
6	P_4	100	79
7	P_3	180	79
8	O_3	80	81
9	O_3	0	80

Subject 425 -- 90 training/90 testing

Class 1: Bottom Half - Class 2: Left Half

Feature	Electrode	Latency	Recognition
1	O_z	100	72
2	O_z	120	77
3	P_3	120	83
4	O_4	100	86
5	O_z	180	87
6	O_3	240	88
7	P_z	180	90
8	P_4	180	90
9	P_z	60	91

Subject 426

Subject 426 -- 90 training/90 testing

Class 1: Bottom Left - Class 2: Top Left

Feature	Electrode	Latency	Recognition
1	0_z	120	76
2	0_z	140	85
3	P_3	40	87
4	0_z	100	87
5	0_4	0	89
6	0_3	40	89
7	0_3	240	90
8	0_4	240	89
9	0_z	220	90

Subject 426 -- 90 training/90 testing

Class 1: Bottom Right - Class 2: Top Left

Feature	Electrode	Latency	Recognition
1	O_z	120	76
2	O_z	140	83
3	P_z	120	86
4	P_z	60	89
5	P_z	40	89
6	O_4	120	90
7	O_3	60	91
8	P_4	0	92
9	P_4	220	91

Subject 426 -- 90 training/90 testing

Class 1: Lower Half - Class 2 - Right Half

Feature	Electrode	Latency	Recognition
1	O_3	160	71
2	O_3	100	77
3	O_4	100	81
4	O_4	180	81
5	O_z	40	83
6	O_4	220	83
7	P_z	0	83
8	P_z	40	85
9	P_3	120	85

Subject 426 -- 90 training/90 testing

Class 1: Top Right - Class 2: Bottom Right

Feature	Electrode	Latency	Recognition
1	O_3	140	67
2	P_z	160	69
3	P_z	20	71
4	O_4	20	72
5	O_z	120	72
6	O_z	160	76
7	O_z	100	80
8	P_4	20	82
9	O_4	100	82

Subject 426 -- 90 training/90 testing

Class 1. Top Right - Class 2: Bottom Left

Feature	Electrode	Latency	Recognition
1	O_4	100	72
2	P_4	240	74
3	P_4	220	76
4	O_3	240	77
5	P_4	80	77
6	O_z	140	78
7	O_4	220	80
8	O_3	200	80
9	P_z	140	81

Subject 426 -- 90 training/90 testing

Class 1: Top Right - Class 2: Top Left

Feature	Electrode	Latency	Recognition
1	O_z	120	64
2	O_4	100	70
3	O_3	180	74
4	O_4	240	76
5	P_z	80	77
6	O_z	20	76
7	O_z	100	78
8	P_3	140	79
9	O_3	100	78

Subject 426 -- 90 training/90 testing

Class 1: Top Half - Class 2: Bottom Half

Feature	Electrode	Latency	Recognition
1	O_z	140	82
2	O_z	80	87
3	O_3	220	88
4	O_3	100	89
5	P_z	180	89
6	P_z	0	89
7	P_z	240	89
8	P_3	40	88
9	O_3	120	88

Subject 426 -- 90 training/90 testing

Class 1: Bottom Right - Class 2: Bottom Left

Feature	Electrode	Latency	Recognition
1	0_4	100	69
2	0_3	100	74
3	0_4	240	76
4	0_4	0	78
5	0_4	60	79
6	P_4	40	80
7	P_4	60	81
8	P_3	200	81
9	0_3	20	81

TH - Top Half

BH - Bottom Half

LH - Left Half

RH - Right Half

TR - Top Right

BR - Bottom Right

BL - Bottom Left

TL - Top Left

Subject 427

Subject 427 -- 90 training/90 testing

Class 1: Top Half - Class 2: Bottom Half

Feature	Electrode	Latency (MS)	Recognition (%)
1	P_3	120	59
2	P_4	100	60
3	O_z	60	66
4	P_3	200	68
5	P_z	180	69
6	O_4	220	69
7	P_z	60	68
8	P_4	120	68
9	P_3	160	71

Subject 427 -- 90 training/90 testing

Class 1: Left Half - Class 2: Right Half

Feature	Electrode	Latency (MS)	Recognition (%)
1	P_4	80	59
2	P_4	120	63
3	O_4	240	66
4	P_z	160	69
5	P_z	220	70
6	O_z	20	71
7	P_3	20	73
8	O_3	160	73
9	P_3	180	70

Subject 427 -- 90 training/90 testing

Class 1: Top Right - Class 2: Bottom Right

Feature	Electrode	Latency (MS)	Recognition (%)
1	P_3	220	57
2	O_z	60	62
3	O_3	120	62
4	O_4	140	64
5	P_4	180	67
6	O_z	180	71
7	O_4	180	72
8	O_z	220	73
9	O_4	0	75

Subject 427 -- 90 training/90 testing

Class 1: Top Right - Class 2: Bottom Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	0_4	140	63
2	0_4	180	68
3	0_z	180	72
4	P_4	0	75
5	P_3	120	76
6	P_3	220	76
7	P_3	100	76
8	P_3	20	74
9	P_3	80	74

Subject 427 -- 90 training/90 testing

Feature	Electrode	Latency (MS)	Recognition (%)
1	0_z	80	60
2	P_3	240	61
3	0_z	100	63
4	P_z	240	64
5	0_4	140	65
6	P_4	220	68
7	P_4	240	70
8	0_4	40	71
9	P_4	120	72

Subject 427 -- 90 training/90 testing

Class 1: Bottom Right - Class 2: Bottom Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	0_4	140	61
2	0_4	180	66
3	0_4	120	67
4	0_3	80	68
5	P_3	60	68
6	0_z	220	68
7	P_3	240	69
8	P_3	120	69
9	P_z	40	71

Subject 427 -- 90 training/90 testing

Class 1: Bottom Right - Class 2: Top Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	0_z	120	62
2	0_4	120	64
3	P_4	200	67
4	P_4	20	69
5	P_3	120	68
6	0_4	20	68
7	0_4	160	71
8	P_3	200	71
9	0_3	140	71

Subject 427 -- 90 training/90 testing

Class 1: Bottom Left - Class 2: Top Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	P_3	80	61
2	O_4	160	66
3	P_4	220	65
4	P_z	220	67
5	O_z	80	67
6	O_3	180	67
7	P_4	0	66
8	P_3	160	68
9	O_4	200	71

Subject 428

Subject 428 -- 90 training/90 testing

Class 1: Top Half - Class 2: Bottom Half

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_4	120	86
2	O_z	80	92
3	P_z	60	93
4	P_3	20	94
5	O_z	60	94
6	O_3	20	96
7	P_3	160	95
8	O_3	220	96
9	P_z	40	96

Subject 428 -- 90 training/90 testing

Class 1: Left Half - Class 2: Right Half

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_4	80	68
2	O_3	80	78
3	O_4	60	82
4	O_4	220	84
5	P_4	160	86
6	O_3	160	87
7	P_3	120	87
8	P_4	140	87
9	P_3	220	87

Subject 428 -- 90 training/90 testing

Class 1: Top Right - Class 2: Bottom Right

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_z	120	67
2	P_z	100	72
3	O_z	240	75
4	P_z	180	76
5	O_z	0	77
6	O_3	100	78
7	P_z	200	79
8	P_4	40	78
9	O_3	40	78

Subject 428 -- 90 training/90 testing

Class 1: Top Right - Class 2: Bottom Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_4	80	76
2	O_4	20	82
3	O_z	240	84
4	P_3	140	85
5	P_3	0	86
6	P_z	100	84
7	P_3	240	84
8	O_z	220	84
9	P_3	20	86

Subject 428 -- 90 training/90 testing

Class 1: Top Right - Class 2: Top Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_4	80	70
2	O_z	80	80
3	O_3	80	81
4	O_z	200	82
5	P_3	220	82
6	O_3	100	82
7	P_3	20	83
8	P_z	140	82
9	O_3	240	82

Subject 428 -- 90 training/90 testing

Class 1: Bottom Right - Class 2: Bottom Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_4	80	66
2	O_4	200	74
3	O_z	60	77
4	P_4	100	77
5	P_3	200	77
6	O_4	140	77
7	O_z	120	80
8	O_4	120	85
9	O_4	60	85

Subject 428 -- 90 training/90 testing

Class 1: Bottom Right - Class 2: Top Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_z	120	77
2	P_4	120	84
3	O_3	120	88
4	O_3	100	90
5	O_3	40	91
6	P_3	60	91
7	P_4	240	91
8	O_z	220	92
9	P_4	220	93

Subject 428 -- 90 training/90 testing

Class 1: Bottom Left - Class 2: Top Left

Feature	Electrode	Latency (MS)	Recognition (%)
1	O_z	80	71
2	O_4	120	77
3	O_4	80	82
4	P_z	100	83
5	O_4	60	84
6	P_4	100	84
7	P_4	60	83
8	P_z	200	83
9	P_4	140	83

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