Evaluation of Three Digital EMG Processors

by

Mark Morley McKenzie

A thesis
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DEDICATION

To my mother, my brother, and my father.

For everything you have done.

ABSTRACT

Three five-state digital electromyographic processors were evaluated in the course of two experiments. The first experiment used modified fixed contraction signals to simulate user input with varying amounts of operator error. The processors evaluated were a Bayes fixed sample size and a Bayes sequential. Both processors showed a similar degradation in performance in response to an increase in operator error. The Sequential receiver required approximately 25% fewer samples to attain a given error rate.

In the second experiment, the above mentioned processors along with a third, developed on the basis of composite hypotheses, were evaluated through the use of a tracking study in which ten healthy subjects and four amputees participated. The processors were compared on the basis of response of error rate and average number of required samples (ANS) to the abrupt changes in signal variance as a subject attempts to track a moving target.

Once again little difference was found in the receivers' relative error performances. The Sequential receiver was found to be superior in regard to average number of samples required with an approximate 20% savings over the number required by the Bayes fixed receiver and about 50% savings

over the number required by the Composite Hypothesis receiv-
er.

ACKNOWLEDGEMENTS

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Mark McKenzie

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Chapter I

INTRODUCTION

Myoelectric control of prosthetic limbs has a long and varied history. In general, control of a device is accomplished by extracting some parameter of the myo-electric signal and assigning limb functions to different ranges of parameter values. As an example, in two-state control, the possible range of the control parameter is divided into two regions and the limb function executed is determined by the region into which the generated parameter value falls. The amount of control, or number of control states, is dependent on the control parameter chosen.

Several factors are taken into consideration in the selection of a suitable signal parameter. An important consideration is that the user have a high degree of control over the chosen parameter over a wide range of values. The parameter must also be easily extractable from the EMG signal. The need for the second consideration is seen in view of the fact that the response time of the system should be small (< 200 ms) and that the space available in a prosthetic limb limits the processing capability of the system.

Reiter (1948) developed a two-state hand which opened and closed according to power levels in the myoelectric signal.

This method of using power levels has proven to be the basis of many of the developments in the field of myo-electric control. Further experiments and advances in technology have allowed improvements to be made on Reiter's design.

Miniaturization of electronic components has allowed more processing power to be placed in a limb. Improvements in amplifier technology have provided more efficient processing, thereby prolonging battery life. All these improvements have led to the development of other types of myo-control based on pattern recognition and auto-regressive modelling, etc. However, power level control has remained the predominant method due to the amount of control it provides and the simplicity of the processing it requires.

Parker (1977), in an extensive survey of the physiology of EMG signal generation and the statistics of the signal, found that the signal power directly reflects the contraction level of the muscle. He also found that the EMG signal can be accurately modelled as a zero-mean Gaussian process with controllable variance. Parker's findings coupled with the long history of successful use indicate that signal variance is the logical parameter to provide maximum control.

With an increase in the number of control states, the problem arises as to where to define the boundaries between states in order to maximize performance. Solutions in this area have been provided by Parker (1977) and Fleisher (1979) who determined the optimum signal set and corresponding optimum boundaries based on a Gaussian signal model. These solutions resulted from the application of communication theory, treating the user as a transmitter of messages and the controlled device as a receiver.

Further advances in technology improved the accuracy of signal variance estimation and the sophistication of the decision making algorithms. More recently, advances in integrated circuit technologies have provided for even more flexibility in algorithm design and the possibility of increased performance. However, some difficulty lies in the determination of the performance of these receivers. Analytical calculation of error rates is possible but complicated by operator error. That is, the power in the signal presented to the receiver will vary around the optimum due to the fact that although a user has a general feeling for the contraction level of the muscle, he does not have the feedback necessary to generate exact values from trial to trial. This limits the performance of a processor in that, no matter how accurately a receiver can determine variance, there will always be an error introduced by the operator. Paciga (1980) suggests that, "in practice it will probably be the operator which determines the performance of a prosthesis." Therefore any evaluation of EMG processors must incorporate some sort of operator error, either simulated or actual.

This thesis is concerned with the evaluation and comparison of three digital EMG receivers. This comparison is carried out primarily on the basis of two statistics; error rate and average number of samples required to make a decision. Some comparison is also made on the basis of the receiver's ability to perform under the error introduced by the operator.

EMG data for the comparison was acquired in two ways. The first was the constant contraction run, in which EMG was recorded while the subject supported a stationary weight. The second method was a tracking study, in which a subject attempted to follow a moving target with a marker whose position is determined by the RMS power in the subject's EMG signal. A complete description of these methods and the way in which each set of data was used is described later in the text.

Chapter 2 is concerned with an in-depth description of EMG receivers, concentrating on digital methods and the three particular algorithms involved. The different algorithms are described along with their theoretical and experimental performance characteristics. Methods of measuring a receiver's performance and its ability to handle operator error are also discussed.

Chapter 3 describes the experimental setup used to collect and process the EMG records. A full description of hardware, software, and experimental procedures are given.

In Chapter 4 a more complete explanation of the data collected, the statistics produced, and the methods of producing them are given. The receivers are compared on the basis of error rate and average number of samples. Some conclusions are made regarding the relative capabilities of the receivers in handling operator error.

Chapter 5 presents the conclusions of the investigation and suggests further work indicated by the results of the experiment.

Chapter II

EMG PROCESSORS

2.1 INTRODUCTION

Studies have shown that the myoelectric signal can be modelled as a zero-mean Gaussian process with controllable variance and hence this parameter has been used as the differentiating feature since the earliest attempts at myoelectric control. Earlier, more heuristic, processors recognized that the variance or power of the EMG signal corresponded directly to muscle contraction level and was the most controllable characteristic of the signal. Today, the majority of processors still use signal variance as the control parameter although the actual design of the processor varies greatly.

Early processors, limited by the available technology, made decisions based on an estimate of RMS power in the signal. Typically, this estimate was made by rectifying the raw EMG signal and passing the result through a single pole low-pass filter to obtain a DC voltage proportional to signal power. There have been improvements of these systems through the application of communication theory and the subsequent derivation of optimum signal sets and decision boundaries.

In the pursuit of a greater number of states and lower error rate, and as a result of the application of communication theory, sophisticated algorithms have been developed which make use of sampled data. These types of algorithms have been difficult to implement but, with the recent advances in semi-conductor technology, the possibility exists for having a prosthetic limb with an on board microprocessor, analog to digital converters and other devices necessary for the implementation of systems using sampled data processors. These receivers can make variance estimates more quickly and accurately than the analog processors now in use. One of the simplest processors is the fixed sample size Bayes receiver.

2.2 THE BAYES RECEIVER

Consider an EMG processor designed to decide between 2 hypotheses with each hypothesis corresponding to an operator producing one of two discrete variance values, σ_0 and σ_1. If the signal is modelled as a zero-mean Gaussian process then the probability of receiving the set of statistically independent samples x_i; i=1,N given hypothesis H_0 is,

$$p(x_i/H_o) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi}\sigma_o} e^{-1/2(x_i/\sigma_o)^2} = \frac{1}{(2\pi)^{N/2}\sigma_o^N} e^{-z/2\sigma_o^2} \qquad (1)$$

where $z=\Sigma x_i^{\ 2}$. A similar expression holds for H_1 with σ_0 being replaced by σ_1.

To decide which hypothesis produced the set of samples, both probabilities are calculated and the larger chosen as correct, i.e.

$$\frac{1}{(2\pi)^{N/2}\sigma_1^N} e^{-z/2\sigma_1^2} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{1}{(2\pi)^{N/2}\sigma_0^N} e^{-z/2\sigma_0^2} \qquad (2)$$

However, assume that H_0 is more likely to happen or the consequences of choosing H_1 when H_0 is correct are greater than the consequences of choosing H_0 when H_1 is correct. In these cases H_1 should be made more difficult to chose. One therefore introduces a constant A, whose value is determined by the a priori probabilities of each hypothesis and the costs assigned to each error. The decision rule of (2) becomes;

$$\frac{1}{(2\pi)^{N/2}\sigma_1^N} e^{-z/2\sigma_1^2} \underset{H_0}{\overset{H_1}{\gtrless}} A \frac{1}{(2\pi)^{N/2}\sigma_0^N} e^{-z/2\sigma_0^2} \qquad (3)$$

or equivalently

$$\lambda = \frac{(2\pi)^{N/2}\sigma_0^N}{(2\pi)^{N/2}\sigma_1^N} \frac{e^{-z/2\sigma_1^2}}{e^{-z/2\sigma_0^2}} \mathop{\gtrless}_{H_0}^{H_1} A \qquad (4)$$

For the purposes of testing the receivers discussed it will be assumed that all hypotheses are equally likely and the costs attributed to each error are equal. Under these conditions, A becomes unity and the decision rule is;

$$\lambda = \frac{\sigma_0^N}{\sigma_1^N} \frac{e^{-z/2\sigma_1^2}}{e^{-z/2\sigma_0^2}} \mathop{\gtrless}_{H_0}^{H_1} 1 \qquad (5)$$

A simplification of the test can be made by taking logarithms and rearranging, i.e.;

$$\frac{1}{2}\left(\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}\right)z + N \ln \frac{\sigma_0}{\sigma_1} \mathop{\gtrless}_{H_0}^{H_1} \ln(1) = 0 \qquad (6)$$

Parker (1977) and Fleisher (1979) have shown that the optimum signal set for Gaussian, controllable variance signals is achieved if the variances are arranged exponentially, that is;

$$\frac{\sigma_1^2}{\sigma_0^2} \equiv C \tag{7}$$

This constraint provides a further simplification of the decision test,

$$z \underset{H_0}{\overset{H_1}{\gtrless}} \sigma_1^2 \frac{N \ln(C)}{C-1} \tag{8}$$

The value $z=\Sigma x_i^2$ is known as the sufficient statistic. The test therefore simply calculates z and determines whether it is greater than or less than the right-hand side of (8), which is a constant for given σ's and sample size. This logic is easily extended to m hypotheses, resulting in a decision space as shown in figure 2.1. Operation of the m hypotheses receiver consists of calculating the value of z and

$$K_i = \sigma_i^2 \frac{N \ln(C)}{C-1}$$

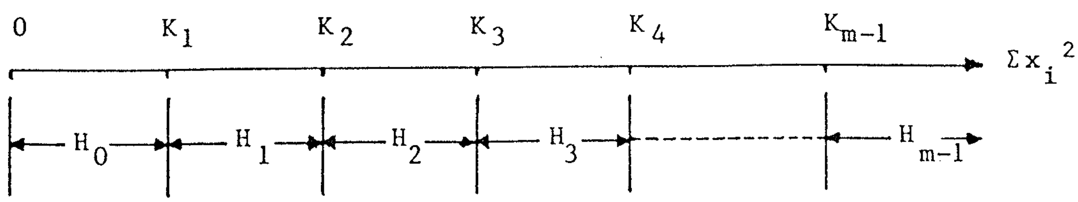

Figure 2.1: Decision Spaces for m Hypothesis Receiver

determining into which range it falls. More precisely if

$$\sigma_{j+1}^{2} \frac{N \ln(C)}{C-1} > z > \sigma_{j}^{2} \frac{N \ln(C)}{C-1} \qquad (9)$$

then H_j is chosen as the true hypothesis.

Although this processor is simple to implement it may be inefficient in its use of samples. A slight change in approach brings us to the more sample efficient sequential algorithms.

2.3 SEQUENTIAL ALGORITHMS

A sequential algorithm is one in which a decision is attempted after every sample rather than after a fixed number of samples have been taken. A sequential algorithm accounts for the trade-off between error and number of samples taken by taking samples sequentially and making a decision only when a prescribed certainty has been reached. In order to understand the operation of the sequential receiver, recall that the two-state processor made its decision based on the rule

$$\frac{p(\hat{x}/H_1)}{p(\hat{x}/H_0)} = \lambda_n \underset{H_0}{\overset{H_1}{\gtrless}} A \qquad (10)$$

A sequential receiver makes use of two thresholds, A and B, one for each hypothesis. The receiver then keeps taking samples as long as

$$A > \lambda_n > B \qquad (11)$$

(where λ_n is the ratio of probabilities after the nth sample), and to choose H_1 if

$$\lambda_n \geqslant A \qquad (12)$$

and H_0 if

$$\lambda_n < B \tag{13}$$

The values of A and B will determine the performance of the receivers. It is apparent that raising A will decrease the probability of choosing H_1 when H_0 is true and similarily for B.

At any point in the test λ_n will be equal to

$$\lambda_n = \frac{(2\pi)^{n/2}\sigma_0^n}{(2\pi)^{n/2}\sigma_1^n} \frac{e^{-z/2\sigma_1^2}}{e^{-z/2\sigma_0^2}} \tag{14}$$

Following arguements similar to that used in the reduction of the Bayes receiver boundaries, the decision rule of equation (10) results in decision boundaries;

$$a = \frac{2\sigma_1^2\sigma_0^2}{(\sigma_1^2 - \sigma_0^2)} \left(\ln(A) + n \ln \frac{\sigma_1}{\sigma_0}\right)$$

$$b = \frac{2\sigma_1^2\sigma_0^2}{(\sigma_1^2 - \sigma_0^2)} \left(\ln(B) + n \ln \frac{\sigma_1}{\sigma_0}\right) \tag{15}$$

In contrast to the fixed size sample test, the decision boundaries here change with n. As before the ratio of decision levels σ_{j+1}/σ_j is set equal to a constant, C, and the decision regions become,

$$a = \frac{\sigma_1^2}{C-1} \{2 \ln(A) + n \ln(C)\}$$
$$b = \frac{\sigma_1^2}{C-1} \{2 \ln(B) + n \ln(C)\} \tag{16}$$

Once again the decision regions can be extended to m hypotheses giving;

$$a_j = \sigma_{j+1}^2 \frac{1}{C-1} \{2 \ln(A) + n \ln(C)\}$$
$$b_j = \sigma_{j+1}^2 \frac{1}{C-1} \{2 \ln(B) + n \ln(C)\} \tag{17}$$

The boundary regions for a five state receiver are shown in figure 2.2.

The operation of the sequential processor is straightforward. A sample of EMG signal is obtained and used to update the values of z, a_j, and b_j. If z satisfies any of the inequalities

$$a_{j-1} < z < b_j \tag{18}$$

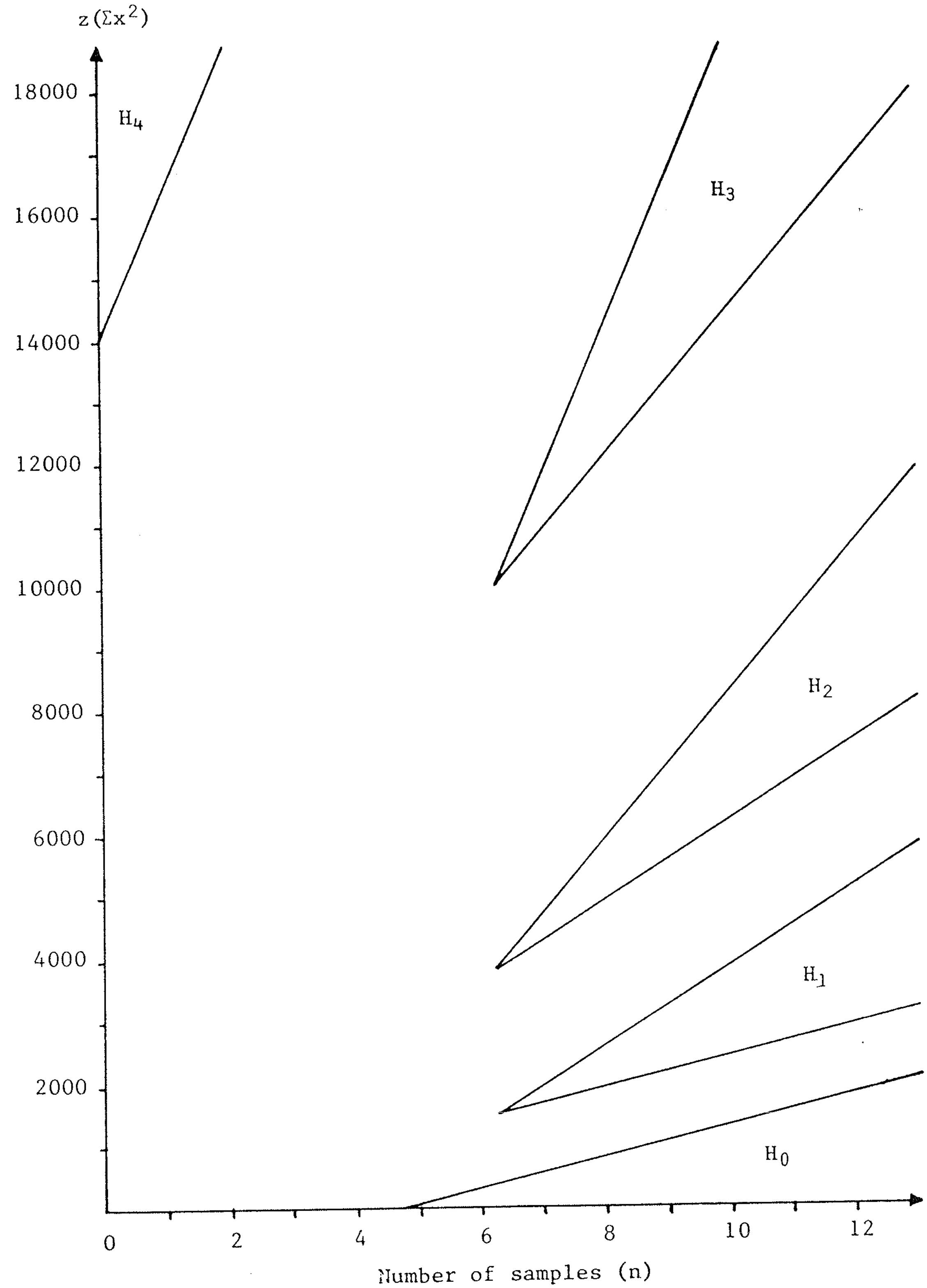

Figure 2.2: Boundary Regions for a Five-State Sequential Receiver

then H_j is accepted. If none of the inequalities are satisfied then no decision can be made, another sample is taken, and the process continues.

2.4 COMPOSITE HYPOTHESIS RECEIVER

As shown, myoelectric control is based on the EMG signal being modelled as a Gaussian distributed variable with hypotheses corresponding to different variance levels, σ_i ;i=1...m-1. However, the exact value of σ generated by the operator will vary according to a variety of factors, chiefly the operator's inability to know exactly what value he is generating. Although an operator may have a general feeling for the degree to which his muscle is contracted, he does not posses the feedback necessary to produce exact values. Thus, the problem becomes complicated in that the variable which characterizes each hypothesis is an unknown random quantity. These types of problems are known as composite hypothesis.

Operator error will cause the generated value of σ to vary around the optimum with a conditional probability distribution, $p(\sigma/H_j)$. The theoretical approach to the problem is to average out $p(\sigma/H_j)$, i.e.

$$p(x/H_j) = \int p(x/\sigma,H_j)\, p(\sigma/H_j)\, d\sigma \qquad (19)$$

This reduces the problem to one of simple hypotheses which is more easily solved. Unfortunately, the distribution of σ is not known and a different strategy must be adopted. Consider the representation of figure 2.3. Instead of testing the optimum values of each hypothesis, μ_j, against each other, two values $\sigma_{j,u}$ (upper) and $\sigma_{j,l}$ (lower) are chosen to represent the endpoints of the ranges of σ_j. These values are tested against each other by forming two probability ratio tests

$$\Lambda_{j-1} = \frac{p(x_i/\sigma_j,l)}{p(x_i/\sigma_{j-1},u)} \underset{H_{j-1}}{\overset{H_j}{\gtrless}} \begin{matrix} A \\ B \end{matrix}$$

$$\Lambda_j = \frac{p(x_i/\sigma_{j+1},l)}{p(x_i/\sigma_j,u)} \underset{H_j}{\overset{H_{j+1}}{\gtrless}} \begin{matrix} A \\ B \end{matrix} \qquad (20)$$

and choose H_j if $\Lambda_j < B$ and $\Lambda_{j-1} > A$. Each hypothesis now

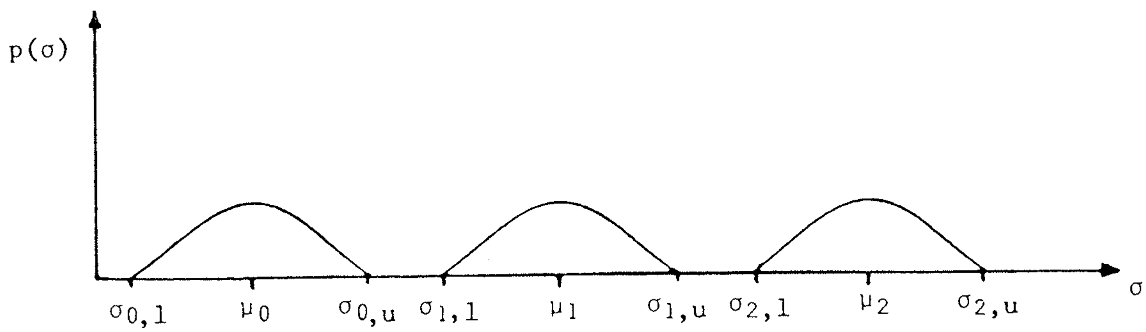

Figure 2.3: Composite Hypotheses Representation

consists of two sub-hypotheses ($\sigma=\sigma_{j,u}$ and $\sigma_{j,l}$) which are tested against their neighbouring sub-hypotheses ($\sigma=\sigma_{j+1,l}$ and $\sigma_{j-1,u}$), in effect, turning one composite hypothesis test into two simple hypothesis tests. The decision regions for this type of receiver are of the same form as the previously discussed sequential receiver as can be seen from figure 2.4. Intuitively, this type of receiver should give better error performance at the expense of larger number of samples. This is due to the fact that the hypothesis means in each of the probability ratio tests are closer together than before. However, it is hoped that the decrease in error rate will outweigh the increase in average sample number.

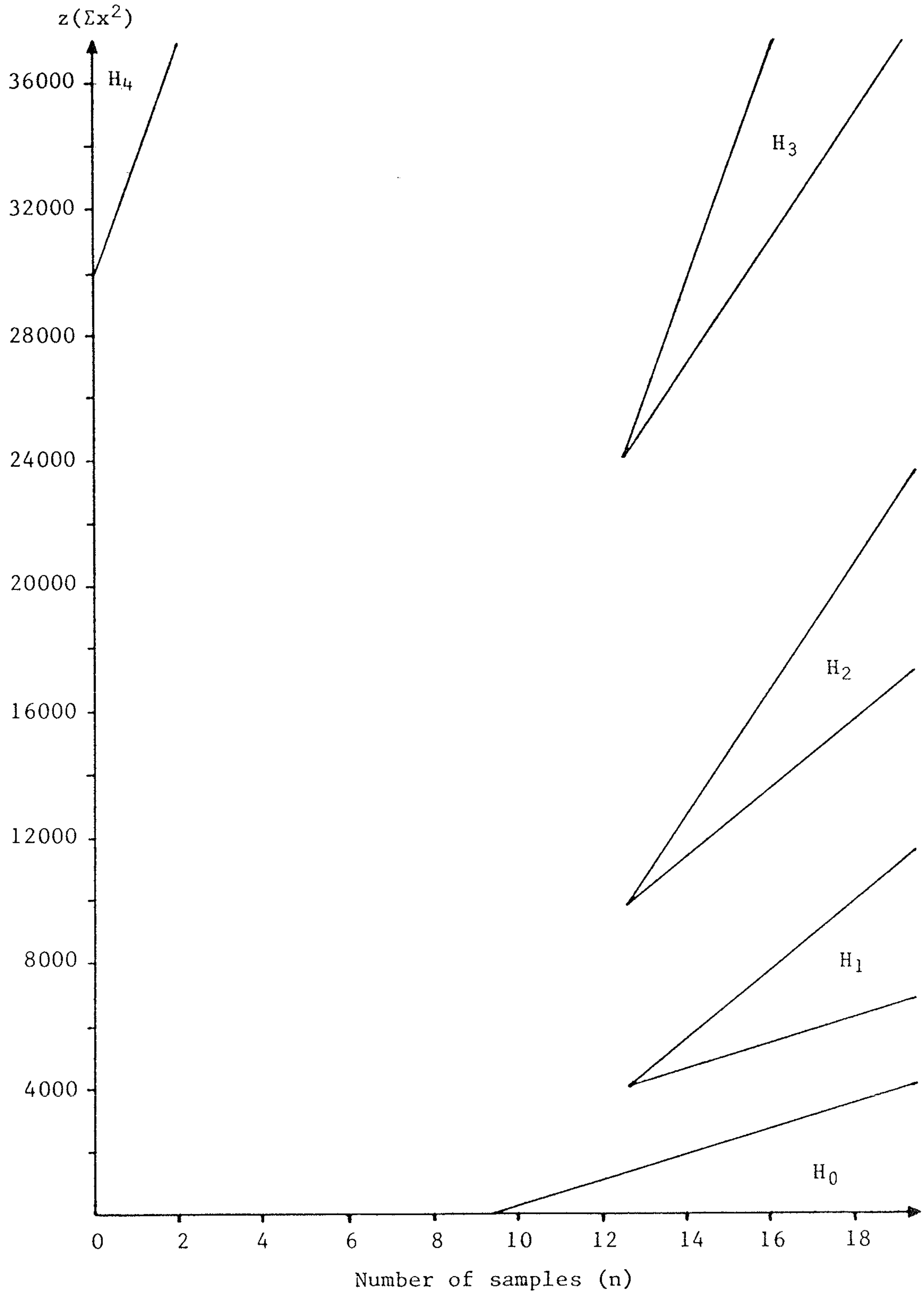

Figure 2.4: Boundary Regions for the Composite Hypothesis Receiver

2.5 RECEIVER PERFORMANCE

Two statistics are most important when evaluating the performance of an EMG receiver; error rate, and time required to make a decision. A tradeoff between these two is inherent since variance estimate accuracy increases with sample size.

Analytical solutions for error rate and average sample number (ASN) can be found for limited cases of the three receivers previously discussed. These solutions indicate that for exact inputs (perfect operator) the sequential receiver requires fewer samples, on average, to make decisions given comparable specified error rates. However, these solutions are derived for special cases which are not easily generalized to the case of non-ideal operators. In order to get meaningful performance statistics, the solutions for error rate and ANS must be averaged over the probability distribution of σ. The nature of this distribution is unknown with the factors affecting the variation of σ around the optimum difficult to model. The analytical calculation of overall ASN and overall error rate is thus impossible. Therefore, since performance of a receiver cannot be accurately predicted analytically, error rate and ASN must be determined experimentally. Studies by Fleisher and Shwedyk (1979) have shown that the sequential receiver requires about 60% of the number of samples required by the Bayes receiver. What remains to be seen is if this saving is maintained when operator error is present and whether or not one processor proves superior in regard to error rate. The experimental determination of a receiver's performance when subjected to operator error is discussed in the next chapter.

Chapter III

EXPERIMENTAL PROCEDURE

In order to compare the performance characteristics of the three EMG receivers (Bayes fixed, Sequential, and Composite Hypothesis) two experiments were performed. One was a computer simulation using fixed contraction EMG recordings, the other a tracking study.

All experiments were carried out using five level receivers. A five level EMG receiver is the logical step from three levels and will allow the control of two powered devices from one muscle site. That is, five states provides each device with two control states along with the necessary rest or "no-action" state. The lowest level was chosen to be $2\mu v$ (at the electrodes) to allow for noise produced by the amplifiers, 60 Hz sources, etc. The highest level was $100\mu v$ which corresponds to a comfortably strong contraction of the biceps brachii. The middle three levels were then chosen according to the optimum exponential distribution discussed previously.

3.1 COMPUTER SIMULATION

The computer simulation involved digitizing an EMG signal during a fixed contraction and modifying it to simulate the five input hypotheses. This was done by first determining the actual variance of each individual signal (which will be constant over the period of the signal) and then scaling by an appropriate multiplier according to the hypothesis being simulated. In this way any desired variance could be created for use as input to the receivers. The acquisition of the fixed contraction records was straightforward. Electrodes were placed over the biceps brachii and the EMG signal fed to an instrumentation amplifier. While a subject maintained a 3 pound weight in a standard, fixed position, samples of the amplified EMG were taken at 1 kHz and stored on hard disk for later processing. The computer used to acquire and process the signal was a Digital Equipment PDP-11.

3.2 TRACKING STUDY

While the computer simulation described in the previous section gives some indication of the performance of the receivers, it does not reveal anything about the receivers' dynamic performance, that is, the performance of the receivers during the period when the user changes variance from one level to another. The manner is which the signal variance changes as the transition is made is unknown and therefore hard to simulate using fixed contraction EMG records.

A more complete evaluation of receiver performance was obtained through the use of a tracking study. In this particular study a subject controls the position of a band on a television screen by contracting and relaxing his biceps brachii muscle. The subject attempts to maintain the center of the band over a target line. The target line moves among five possible levels and changes position once every second. This method enabled the study of the receiver's performance during the transition period.

3.3 HARDWARE

The apparatus used in the tracking study is illustrated in schematic form in figure 3.1. The subject's tracking band was produced by feeding back the rms value of the EMG signal. This was accomplished by amplifying and rectifying the raw EMG and passing this result through a low-pass filter having a time constant of 100ms. Then, in order to linearize the exponentially spaced target levels, the filter output is passed through a logarithmic amplifier (see Appendix A for schematics of all amplifiers and filters). The target levels are thereby converted to a more easily interpreted equally spaced configuration. The output of the log amp was routed to a dual trace oscilloscope which was in turn viewed by a video camera for final display on a standard television screen. Target levels were displayed using the other channel of the oscilloscope. A computer program

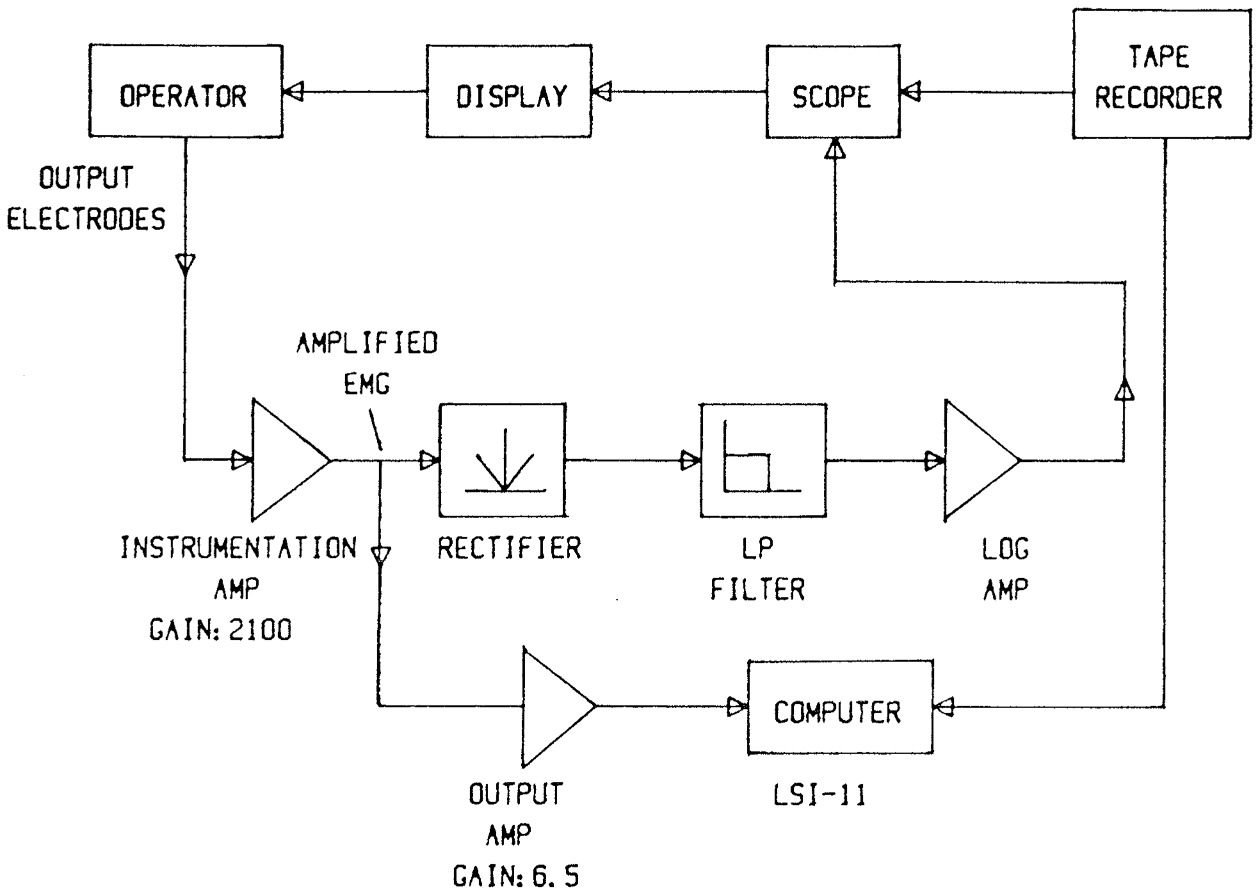

Figure 3.1: Block Diagram of System

was written to generate a sequence of random numbers and store it in a disk file. Another program then converted each number, via a digital to analog converter, to a corresponding voltage to be recorded on an instrumentation tape-recorder, with -10v representing the lowest hypothesis and +10v representing the highest (see Appendix A for software listings). Each level was maintained for 1 second. A typical display, as seen by the subject, is shown in figure 3.2. The subject controlled the wider band.

The correct functioning of the system was verified in a variety of ways. Each component of the system (instrumentation amplifier, rectifier, etc.) was adjusted separately to have the correct parameter values (gain, time constant etc.). After the individual components were calibrated, the system as a whole was further tested in two ways. First, a Gaussian noise generator was used to input a 250 Hz bandwidth, Gaussian signal to the input of the output amplifier. This was done for each of the five input hypotheses. This signal was then sampled and processed. Based on 340 trials, the error rates obtained for each hypothesis were as follows: H_0- 1.6%, H_1-2.2%, H_2-2.4%, H_3-1.8%, H_4-1.3%. These error rates varied through a .4% range but were consistent throughout the duration of the record as can be expected from the nature of the input signal.

A similar test was performed with signal records obtained as a subject maintained the tracking band at one target level. Once again these signals were sampled and processed. Error rates obtained in the second test, again based on 340 trials, were somewhat higher, viz: H_0-5.4%, H_1-8.6%, H_2-7.6%, H_3- 7.8%, H_4-4.9%. Fluctuations in this second test were higher (2%) which can be attributed to operator error.

The results of these two test indicate that the system functions as desired. The higher error rates obtained with the human subject are due to a human operator being unable to generate and maintain exact signal variance values.

Figure 3.2: Typical Display as Seen by Subject


ELECTROHOME
educator

3.4 TRACKING RUNS

Each tracking run consisted of 80 level transitions at 1 transition per second. Before a tracking run was begun, paste-coupled electrodes spaced approximately 5 cm apart were placed over the belly of the biceps brachii. In the case of the amputees, the electrodes were placed over the site used to control their present myo-electric limb. The proper functioning of the amplifiers was then assured. Noise levels were minimized by making small adjustments to the subjects' basic position. Although the subject was always seated about 2m from the display, small changes were allowed.

Every effort was made to minimize subject distraction during tracking runs. These measures included ear muffs and turning the lights off. A few subjects found viewing the display screen in the darkened room irritating to their eyes and were therefore allowed to make the tracking runs with the lights on.

After the subject was comfortable and system noise minimized, tracking runs were begun.

To begin, each subject was allowed 2 or 3 trial runs to become familiar with the task. These were shorter sequences of approximately 50 transitions. Following this, recorded runs were made.

After the subject was relaxed, the tape recorder was turned on to begin the random sequence of target levels. This started the target line moving among the 5 levels in a random manner. EMG and target level samples were then recorded as the subject followed the target across the screen. After 80 seconds had elapsed the computer stopped sampling and the tape recorder was turned off. Each subject made 6 runs which were spread over at least 2 days in order to avoid fatigue and boredom.

3.5 DATA COLLECTION

During each tracking run, data were collected from two sources; the amplified EMG and the target level. After the EMG signal was amplified 13650 times it was sampled at 250 Hz and stored on floppy disk for later use in evaluation of the processors. Samples of the target level were taken at one quarter the EMG sampling frequency and were also stored on disk. Target level data was used to determine the true hypothesis for comparison with the processor's choice.

3.6 SUBJECTS

Ten subjects were chosen from the university population and four subjects were referred by the Rehabilitation Centre for Children. These last four were amputees and were used as subjects to examine the ability of a prospective user to control a 5-state device of the type projected.

Chapter IV

DATA PROCESSING AND RESULTS

The simulation of the different receivers and the way in which the EMG data was processed was carried out in a variety of ways. In the first experiment, using fixed contraction records, the processing is straightforward while the second experiment required more complex processing. Both are explained in the following sections.

4.1 COMPUTER SIMULATED ERROR

In the computer simulation, constant contraction records, that is, records with the same power level throughout, were scaled up or down to simulate the five different hypotheses. The order in which the hypotheses were presented to the receiver was determined by a random sequence of uniformly distributed numbers. After selecting a number from this sequence, the appropriate scaling factor was calculated to modify the sampled EMG data. Processing then proceeded according to the receiver being simulated. In the case of the Bayes fixed receiver, the designated number of samples were taken, squared and summed, and assigned to a hypothesis according to the decision boundaries calculated previously. This choice is then compared to the correct hypothesis as chosen from the random input sequence. If an error is found it is catalogued according to the correct hypothesis and the incorrectly identified hypothesis. The next trial then begins at the point in the signal record where the previous trial ended. This process continues until the end of the record is reached.

Processing is similar in the case of the sequential algorithms, except that records are also kept regarding the number of samples required for each decision since this will vary from trial to trial.

The introduction of simulated error is accomplished by altering the scaling factor according to a second random number chosen from a continuous uniform distribution of width K (see figure 4.1a).

Once the input hypothesis is chosen, the corresponding scaling factor is altered by multiplying it by a number chosen from the above distribution. The variance of the signal actually presented to the receiver now varies over a range for each hypothesis, in essence, simulating an operator having a uniform error distribution as in figure 4.1b.

To examine the receivers' response to increasing amounts of input error, trials were made with K values of 0 (no error), 0.1, 0.2, and 0.5. As K increases the possible range of input variance increases thereby raising the possibility of error. When K=0.5 the ranges of input variance actually

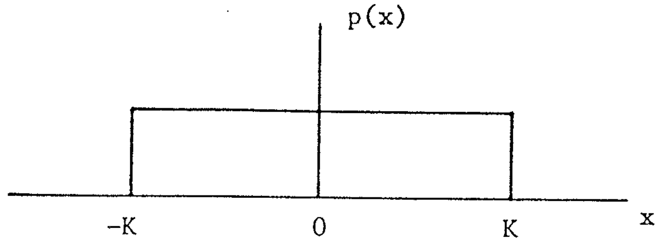

Figure 4.1a: Probability Distribution of Multiplier Used to Generate Operator Error

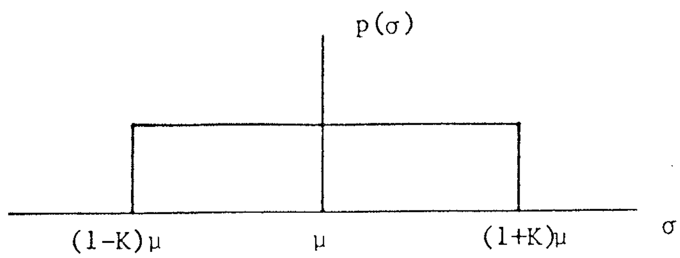

Figure 4.1b: Resultant Probability Distribution of Signal Variance

Figure 4.1: Distribution of Error

overlap, producing a somewhat artificial condition where the input variance should correctly be classified as coming from the adjacent hypothesis but will be recorded as an error. This will produce an increase in the each processor's error rate.

Programs to carry out the computer simulation were written in BASIC on a Digital Equipment PDP-11 computer. The programs SEQRAN and BAYRAN (see Appendix A) were run for each different value of K. A sample of the output of the processing program for a value of K=0.2 is shown in table 4.1.

TABLE 4.1

Sample of Computer Simulation Output

		Identified Hypothesis 1	2	3	4	5
TRUE	1	183	3	0	0	0
	2	5	156	1	0	0
HYPO-	3	0	3	188	2	0
	4	0	0	4	193	1
THESIS	5	0	0	0	1	193

4.2 TRACKING RUN DATA

The processing of the signal acquired during the tracking study is more complex since the signals themselves are more complicated and the time response is more difficult to extract. Two basic modes of processing were used in this experiment; continuous and synchronous. The programs that performed both methods of processing the tracking run data were written in Fortran and run on a Digital Equipment LSI-11 computer (see Appendix A for program listings). Two programs, one for each processing mode, were required for each of the three processors for a total of six programs.

The continuous mode is similar to the processing method discussed for the computer simulated error data. Trials are made with no regard to the occurrence of transitions. This simulates the way a receiver would function in actual use, continuously sampling the signal and making decisions. The statistics obtained in this way will not, however, give any clue as to where, in relation to the transitions, the errors are made. It is during the transition from one power level to another that the interesting features of the processor's time characteristics will be seen.

A synchronous mode of processing was used to extract the dynamic characteristics of the algorithms. Synchronous here means that processing takes place with the knowledge of where the transitions occurred. The basics of this method

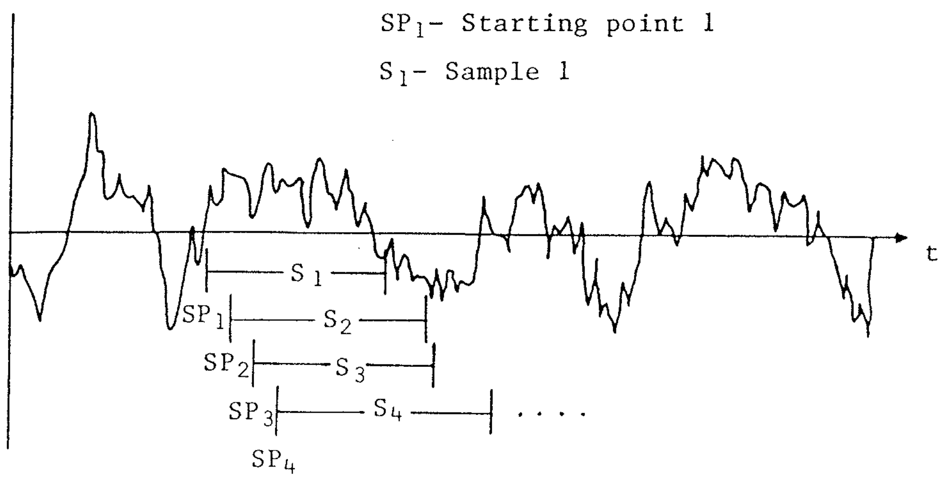

Figure 4.2: Synchronous Processing

are illustrated in figure 4.2. Essentially, a "window" is moved along the record and a decision is obtained for each position of the window. In the case of the sequential receivers, the window length varies and it is therefore the starting point of the window that is moved.

As the window progresses, statistics regarding error rate and average sample number are recorded as a function of time from transition. The statistics produced in this way can be combined in a variety of ways to reveal characteristics of the receivers' time response. For example, as well as an overall average, the average of all transitions to level 5, or all transitions originating from level 3 etc., can be isolated.

The two classes of curves which are the main points of comparison between the receivers are shown in figure 4.3 and 4.4. While both curves give an average error rate as a function of time from transition, they differ in one aspect. Figure 4.3 is generated under the assumption that the destination level, that is, the level present immediately after transition, corresponds to the correct hypothesis. Consequently, the error rate at the beginning of the plot will be near 100% since the subject has not yet reacted to the change in target levels.

On the other hand, figure 4.4 assumes that the hypothesis indicated by the level preceding transition is correct until

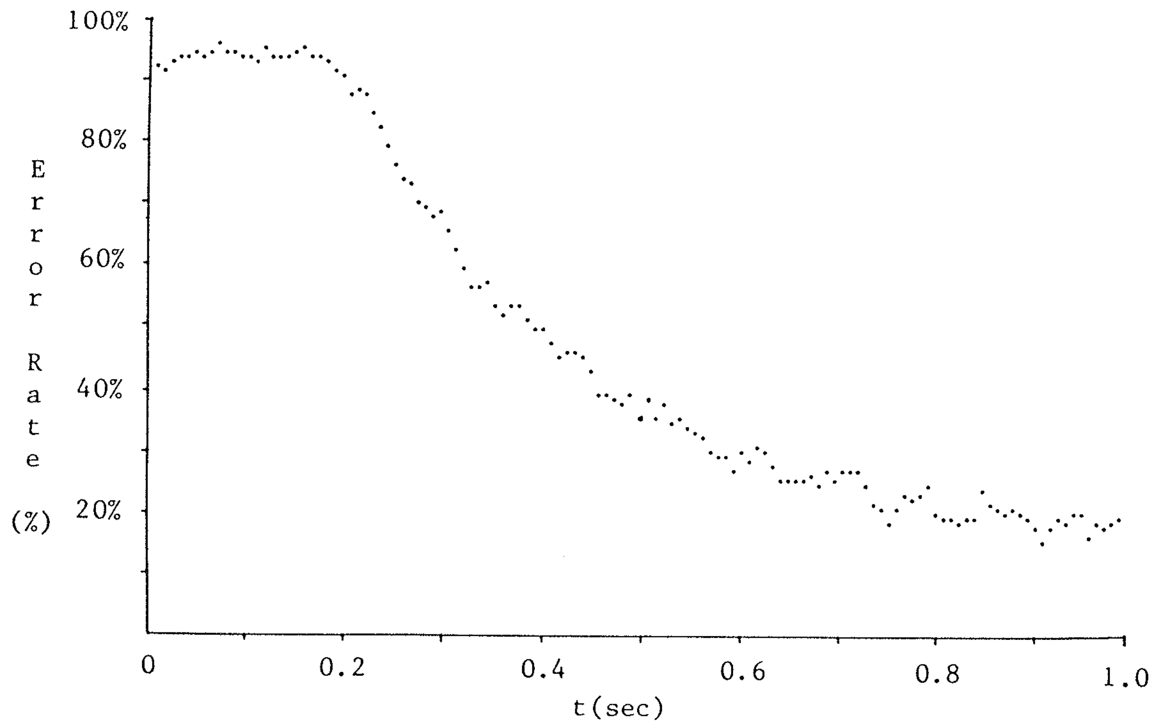

Figure 4.3: Example of Type I curve

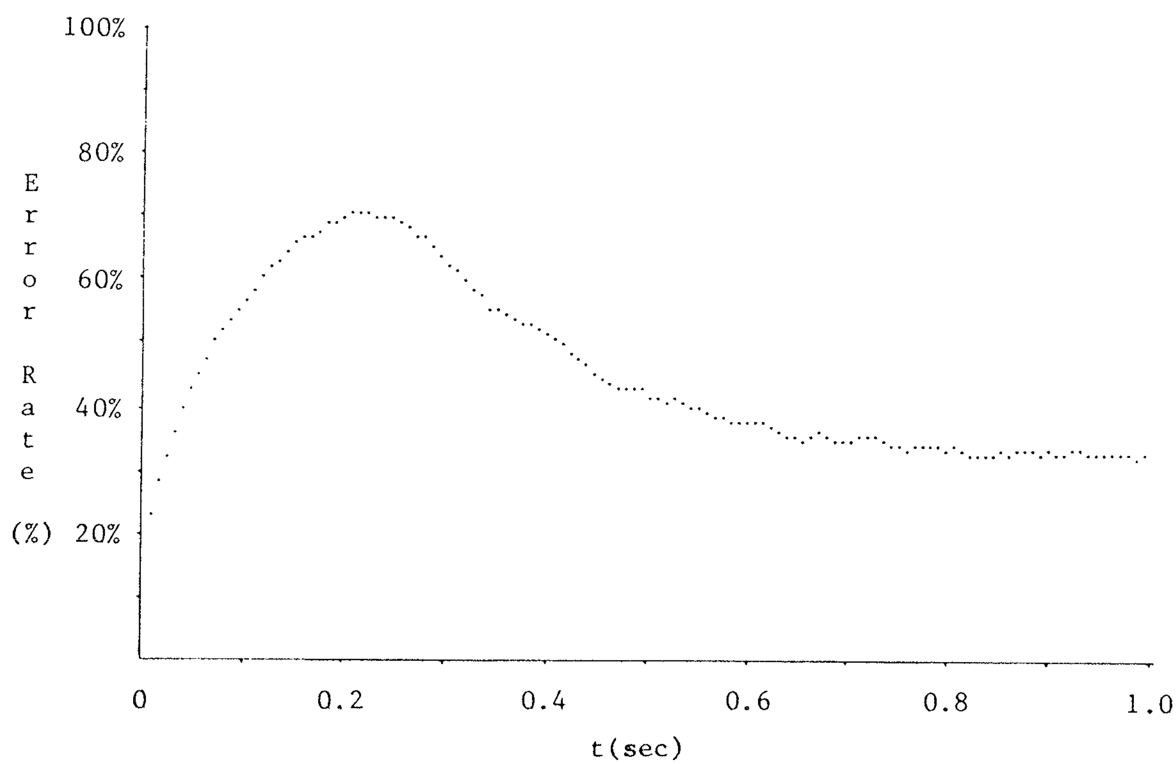

Figure 4.4: Example of Type II curve

a different decision is made. For instance, consider a transition from level 5 to level 3. The processor would consider H_5 to be correct until a decision other than 5 is made. After this, H_3 will be considered correct. Figure 4.4 therefore has a low error rate initially since the processor is still being presented with a variance corresponding to the previous hypothesis. The error rate rises as the subject reacts to the change and then decreases as the new target level is approached. This method of processing accounts for subject reaction time and also gives more realistic results since the processor is allowed to make the correct decision based on the signal it is presented with. As well, this sort of error does not diminish the performance of the processor significantly since maintaining the previous decision merely reflects as a delay in the activation of a new function.

The two types of curves obtained in the above described manner provide the information necessary to compare the three receivers. In a general sense, the smaller the area under either curve the better the processor, since this area is a measure of the product of error and time. Any decrease in this quantity indicates an improvement in performance. Also, certain elements of the curves correspond to specific performance characteristics. For instance, a processor more tolerant of operator error will demonstrate an earlier decline in error rate on both the Type I and Type II curves and will achieve a lower steady-state error level. To see why the earlier decline would occur, consider that a more error tolerant receiver would produce a given error rate at a value of σ further away from the optimum than would a less tolerant receiver. Therefore, as the user approached the optimum variance level, the more tolerant receiver would make more correct decisions earlier. The lower steady-state error results from the more tolerant processor being less sensitive to fluctuations around the optimum. This tolerance will also appear on the Type II curves as a less steep rise in error rate. A more robust receiver will keep making correct decisions for a longer time as the user's signal variance moves away from the present target level.

A third type of curve used to compare the receivers is a plot of the product of error rate and Average Number of Samples (ANS) versus time. This allows the examination of the contribution of both of the performance indicators from a single plot.

4.3 COMPARISON OF RECEIVERS

COMPUTER SIMULATION

Figure 4.5 shows the results obtained in the first experiment. Error rate increases with increasing error distribution width for both the Bayes fixed and Sequential receivers. The degeneration of performance is similar in both cases, giving a preliminary indication that neither processor performs better when input error is present. The sequential receiver maintains its saving in number of samples required to approximately 60% of the number that the Bayes receiver requires. The difference in absolute error is due to differences in specified error. While error can be specified to any value in the Sequential processor, the fixed Bayes processor has discrete levels of error and therefore the two can only be approximately equal.

TRACKING RUN

Processing the EMG records obtained in the tracking runs in the continuous mode produced error rates on the order of 40%. Errors this high are due to the time averaging effect of the continuous processing mode. The high error rates present immediately after transition force the overall time average high. There was no discernible difference in the receivers' performance but this is not surprising since time averaging can obscure differences in dynamic performance.

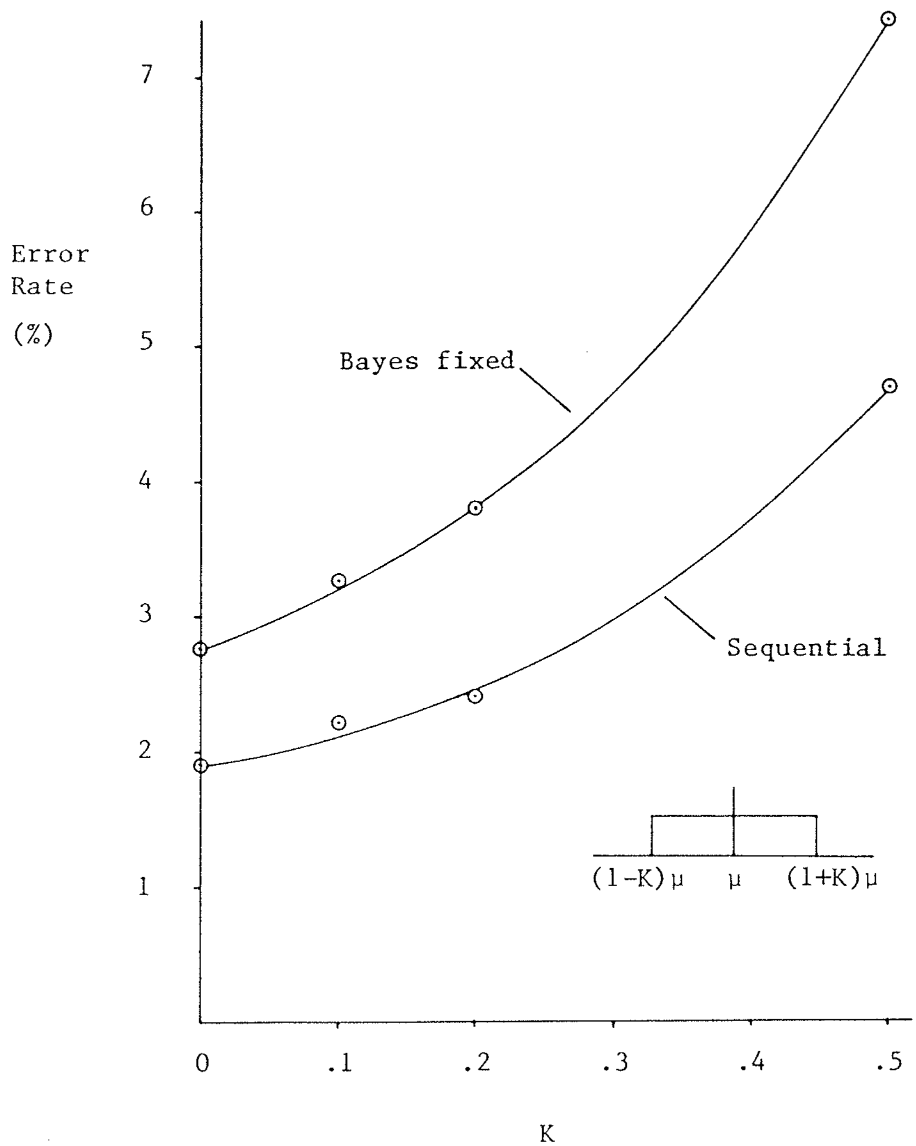

Figure 4.5: Error rate vs error distribution width

Any such differences should appear in the results from the synchronous processing mode.

Figures 4.6, 4.7, and 4.8 are the Type I error rate curves for the Bayes fixed,Sequential, and Composite Hypothesis receivers respectively, averaged over all ten healthy subjects and all transitions. Comparison of these curves shows that there is little difference in overall shape. The sequential receiver demonstrates a lower error rate in some parts of the curve but the difference is not great enough to indicate a superior ability to cope with operator error. The Composite Hypothesis receiver shows a lower error rate in all portions of the curve but this is nullified by the large number of samples required for each decision. The superiority of the Sequential receiver can be seen on the plots of error*ANS of figures 4.9, 4.10, and 4.11. Although the Composite Hypothesis receiver may have a lower error rate, its high ANS makes it unusable. A similar error performance can be achieved by the Sequential receiver with a lower number of required samples.

The Sequential receiver maintains its ANS to approximately 80% of the number required by the Bayes receiver. Comparison of the Type II curves yielded similar results, with no significant differences in error performance appearing.

In order to examine differences in individual performances, results averaged over all transitions were plotted for

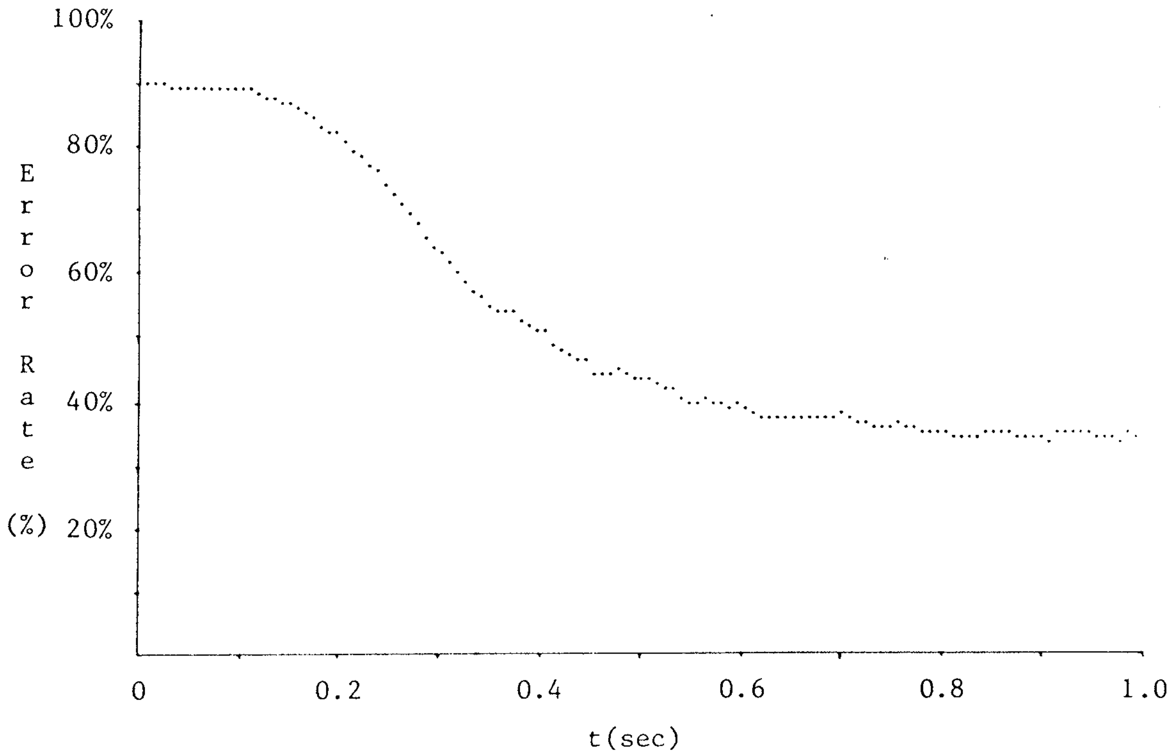

Figure 4.6: Error vs Time for Bayes Receiver

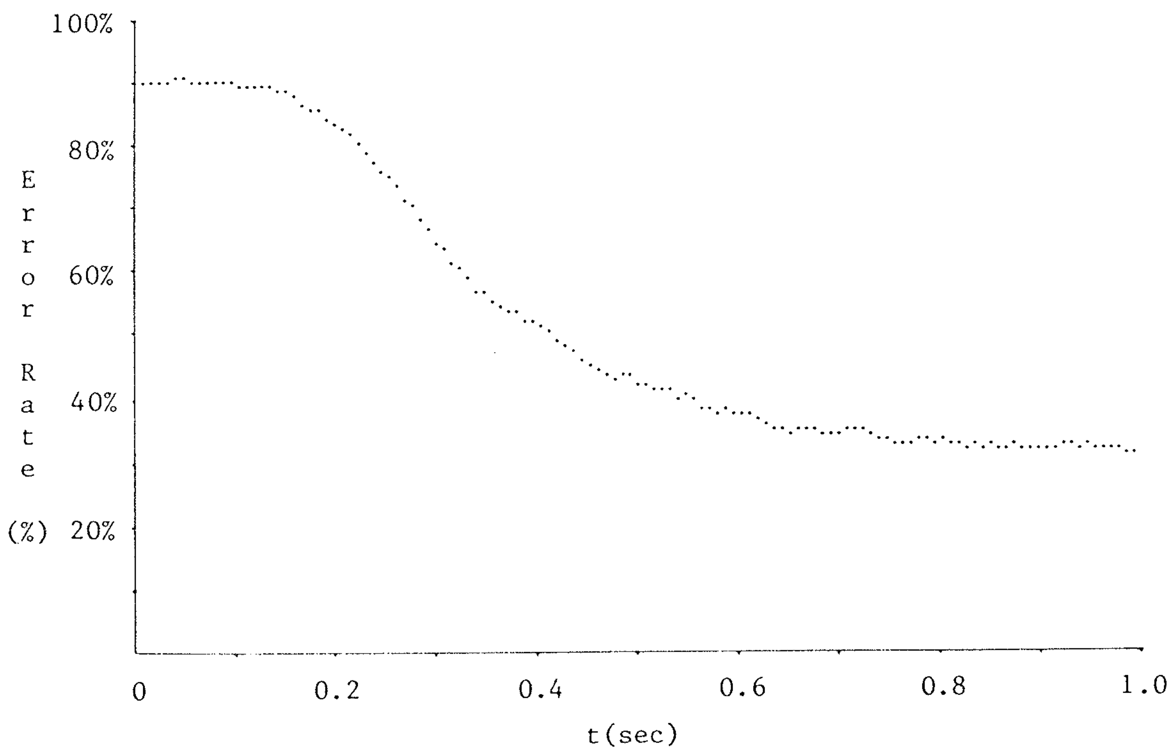

Figure 4.7: Error vs Time for Sequential Receiver

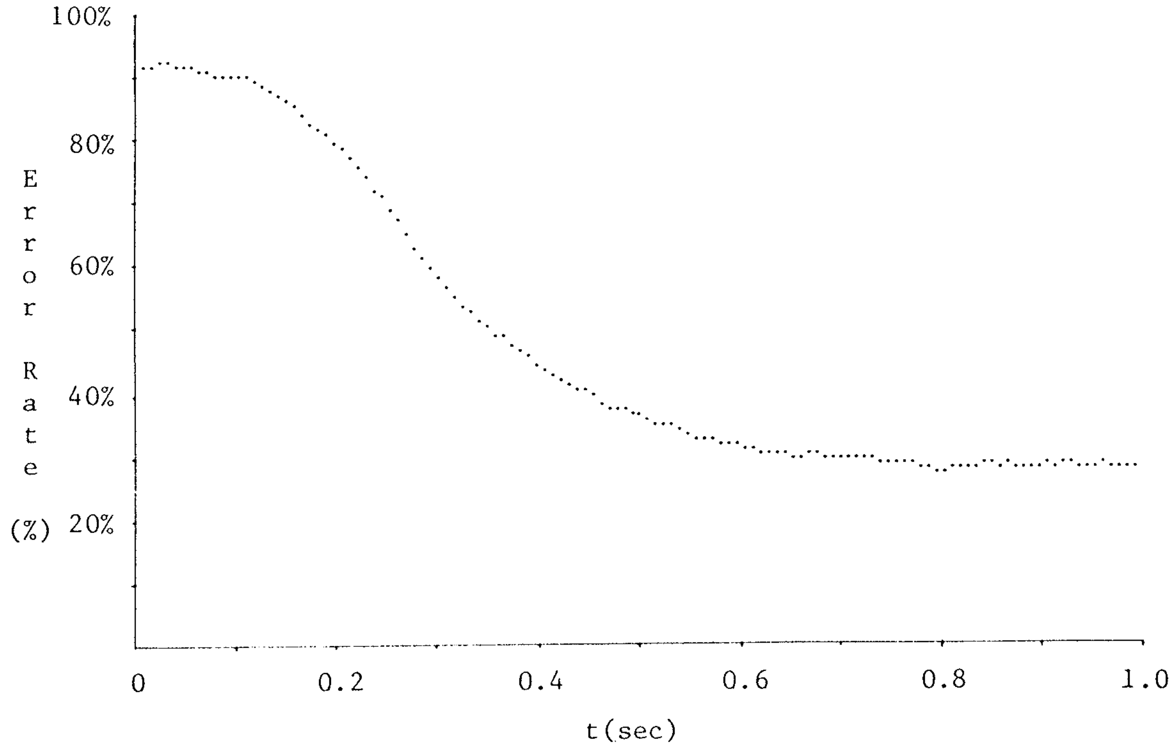

Figure 4.8: Error vs Time for Composite Hypothesis Receiver

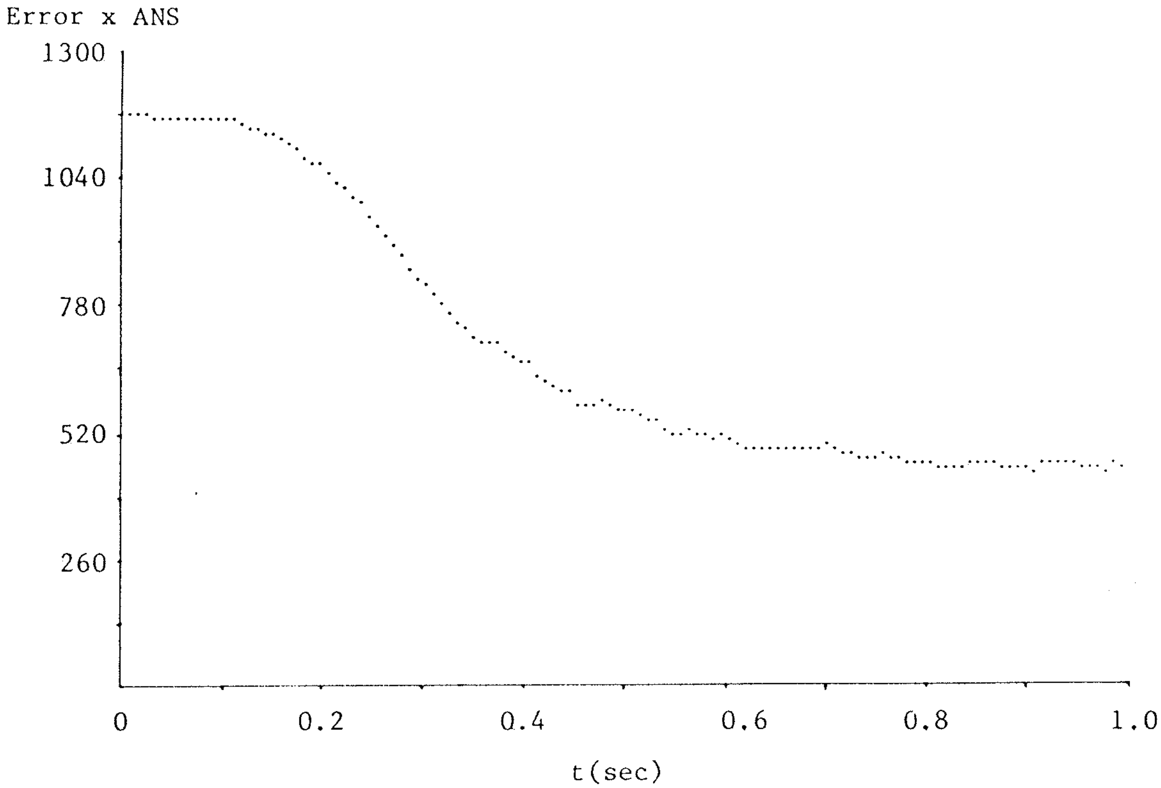

Figure 4.9: Error*ANS for Bayes receiver

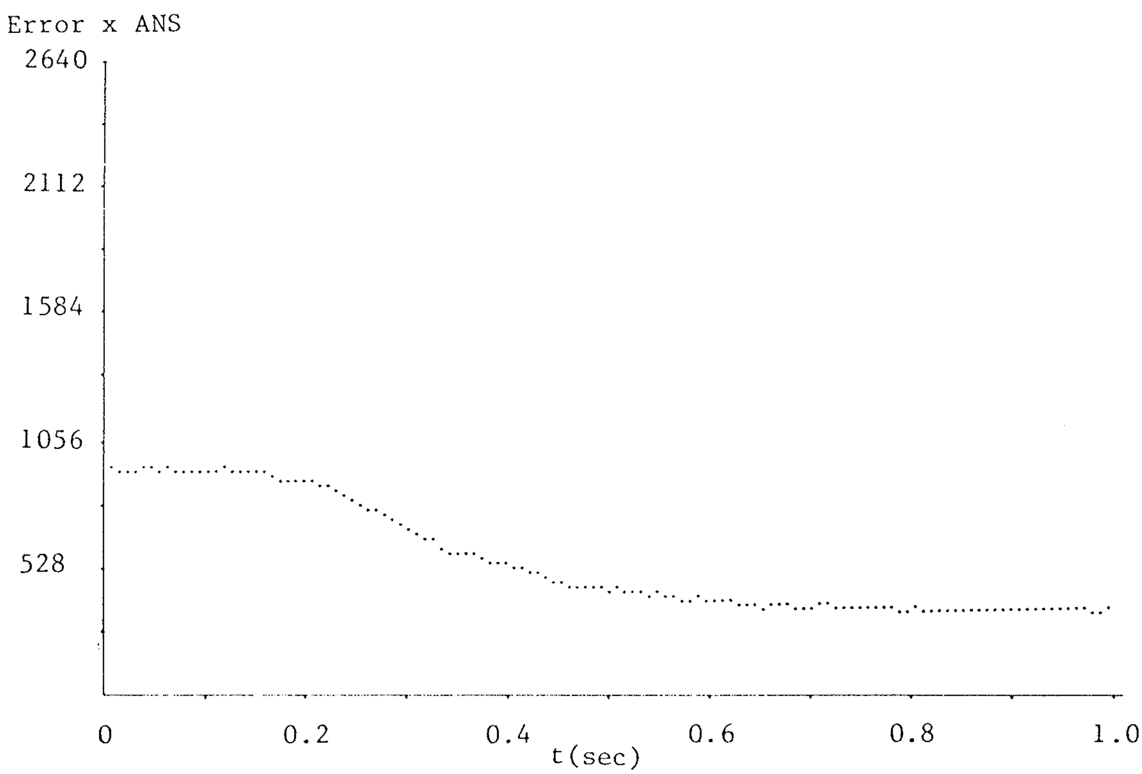

Figure 4.10: Error*ANS for Sequential receiver

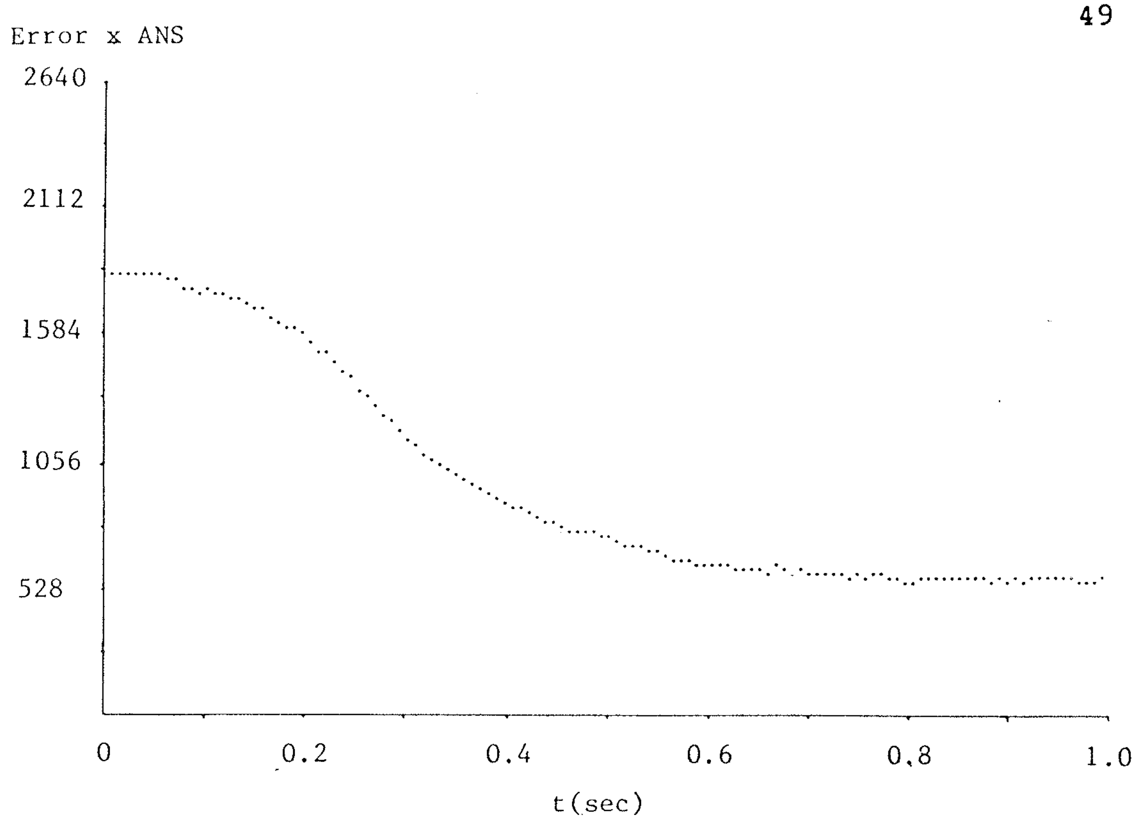

Figure 4.11: Error*ANS for Composite Hyp. Receiver

each subject. Although all curves were of the same basic shape, the steady-state error varied from 18% to 45% (see figure 4.2). It was conjectured that this wide range was probably due to the fact that the subjects had very little training. That is, some subjects had a natural ability to control their EMG signals while others did not.

Table 4.2 also lists the steady-state errors for each of the amputees. As can be seen, while the amputees' error rates were above average, 3 of the 4 had steady-state errors within the range of the healthy subjects and the general shape of the error rate versus time curves were not significantly different between the two groups. The amputees' poor performance is partly due to difficulty in reaching the highest target level. This difficulty can be attributed to the small muscle mass of the amputees control site which limits the maximum signal power available. and leads to an increase in error rate.

To ascertain whether training would improve performance, 3 subjects were re-run once a day for 5 days (see table 4.3). The subject that had already produced a low error rate maintained it. Subject NA showed considerable improvement while little change occured in the performance of subject KL. Thus, training seems to have an effect and it is possible that all subjects could attain the same performance level given sufficient training.

TABLE 4.2

Individual Steady State Error

STEADY STATE ERROR

		PROCESSOR			
	SUBJECT	SEQUENTIAL ERROR	SEQUENTIAL ANS	BAYES (N = 13) ERROR	T
UNIVERSITY SUBJECTS	EB	18%	9.9	22%	355
	RM	21%	10.1	24%	408
	WB	22%	10.9	25%	350
	ES	33%	10.7	37%	406
	WT	34%	11.1	38%	342
	LP	37%	10.1	38%	407
	NA	38%	9.4	37%	407
	KL	38%	9.9	40%	408
	LO	39%	10.1	40%	347
	EW	47%	10.1	50%	348
SUBJECTS REFERRED BY REHAB. CENTRE	CR	34%	11.2	35%	400
	TG	38%	10.3	37%	408
	JR	47%	10.9	49%	413
	JP	55%	10.7	60%	363

ANS - Average number of samples.
T - Number of trials used for error calculations. Only level changes were considered for the error calculations.

TABLE 4.3

Learning Table

ERROR RATE (BY DAY)

	SUBJECT		
DAY	KL	EB	NA
1	25%	20%	40%
2	20%	20%	35%
3	25%	18%	25%
4	25%	20%	25%
5	20%	20%	24%

Chapter V

SUMMARY AND DISCUSSIONS

5.1 SUMMARY

The first experiment, which used fixed contraction electromyographic signals to simulate the different input hypotheses, compared the performance of the Bayes fixed and Sequential receivers. The results of this experiment showed that both processors responded similarly to an increase in operator error. Neither processor demonstrated any marked superiority in handling operator error (see figure 4.5). The sequential receiver demonstrated a savings in average number of samples required (ANS) to about 80% of the number required by the fixed Bayes receiver. This was higher than predicted by analytical solutions and previous studies (Fleisher(1979)) which indicated a savings closer to 60%. The difference is probably due to the fact that the analytical solutions were calculated for optimum inputs, that is, no operator error. The input of non-optimum signal variances produces a higher average number of required samples.

The second experiment, the tracking study, provided for a more detailed examination of the receivers' performance. Error rates as a function of time from transition were calculated and plotted for each of the three processors. Once again, little difference was found in the receivers' relative error performances. Each receiver produced curves of similar shape with only small differences visible. The differences were not large enough to indicate any receiver's superiority in handling operator error. Although the Composite Hypothesis receiver did have an approximately 5% lower error rate throughout, it required almost twice as many samples as the Sequential receiver. A similar increase in performance can be obtained from the Sequential receiver with a smaller increase in ANS. Therefore, while the CH receiver appears to perform better with regard to error rate this is misleading as can be seen from an examination of the plots of error*ANS versus time. While none of the receivers proved superior with regard to operator error, the Sequential receiver remains superior to the other two since it requires the fewest samples to attain a given error rate.

5.2 DISCUSSIONS AND RECOMMENDATIONS

The steady-state errors obtained in this tracking study were higher than expected and higher than results obtained by other experimenters, particularly Paciga (1980) who attained error rates under 5%. These very low error rates were attained by subjects who had up to three months of extensive training while the subjects in this study had only enough training to familiarize them the task. It is therefore not surprising that higher error rates were obtained. However, it remains doubtful that levels as low as 5% could be obtained even after extensive training. The amount of control demonstrated by the subjects does not seem sufficient to allow the achievement of these low error levels. A longer-term study in which the subjects received extensive training would answer the question of whether or not training would account for such a large difference in the two study's error rates.

Also regarding further studies, it is possible that one of the three processors examined demonstrates some performance superiority when only small amounts of operator error are present. Any such superiority would not be visible in results from the present experiment since lower levels of steady-state error are never reached. It is recommended that a subsequent experiment should attempt to achieve lower error rates to examine possible performance differences at these lower levels. This can be accomplished in two ways. First, the training of the subjects can be extended, which will require a longer period in which to perform the study, or the period between level changes can be lengthened. It is believed that 1 second is not sufficient time for a subject to achieve a steady-state signal variance. Lengthening the interval between level changes to 2 seconds would allow subjects to achieve lower steady-state error rates and thereby reveal any hidden differences in receiver performance.

Finally, a comment on the viability of 5-state control. While this study was meant to compare the relative performance of three processors and cannot be said to be an exhaustive evaluation of the potential receiver performances, a preliminary observation can be made. The high error rates obtained in this study indicate that a limb incorporating a five-state receiver of the type discussed in this study will not be very reliable and would only be usable after extensive training. From the results of the experiments and from observation of the subjects during tracking runs, it is believed that, given the dynamic range of EMG signal power and the amount of control a user has over the signal, reliable 5-state control will be difficult to achieve.

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Appendix A

PROGRAM LISTINGS

A.1 SEQUENTIAL PROCESSOR WITH RANDOM ERROR (SEQRAN)

This program processes fixed contraction records through a Sequential processor with variable amounts of operator error width, K. Program written in BASIC on a DEC PDP-11.

```
10 DIM V(4),E(4,4),D(4),T3(4)
11 RANDOMIZE
12 '
13 'OPEN THE FILE FROM WHICH EMG DATE IS TO BE TAKEN.
14 '
20 OPEN "RK0:SH1" FOR INPUT AS FILE VF1%(10000)
21 '
22 'OPEN A FILE TO RECEIVE THE RANDOM INPUT SEQUENCE TO BE CREATED BELOW
23 '
30 OPEN "RK0:VCH" FOR OUTPUT AS FILE VF2%(500)
31 '
32 'OPEN A FILE TO RECEIVE THE INPUT ERROR
33 'VF3 WILL CONTAIN NUMBERS CHOSEN FROM A CONTINOUS UNIFORM DISTRIBUTION
34 '
40 OPEN "RK0:OPER" FOR OUTPUT AS FILE VF3(500)
41 '
42 'CREATE THE RANDOM SEQUENCE THAT DETERMINES THE TRUE INPUT HYPOTHESIS
43 '
50 FOR I=0 TO 500
60 VF2(I)=INT(5*RND(0))
70 NEXT I
80 CLOSE VF2
90 OPEN "RK0:VCH" FOR INPUT AS FILE VF2%(500)
91 '
92 'CREATE THE INPUT ERROR
93 '
100 FOR I=0 TO 500
110 VF3(I)=RND
120 NEXT I
130 CLOSE VF3
135 OPEN "RK0:OPER" FOR INPUT AS FILE VF3(500)
136 '
137 'SET UP TARGET LEVELS AND INITIALIZE OTHER VARIABLES.
138 '
140 V(0)=4\V(1)=24.49\V(2)=150\V(3)=918.56\V(4)=5625
150 M=0\R=0\T=0\X=0
155 C=6.124
160 N2=10000
170 S1=0
180 N5=10000
190 A=2*LOG(99)
200 B=-A
210 C1=LOG(C)\C2=1/(C-1)
220 V0=V(0)*C2\V1=V(1)*C2\V2=V(2)*C2\V3=V(3)*C2\V4=V(4)*C2
221 '
222 'CALCULATE AVERAGE VALUE FOR UPCOMING VARIANCE CALCULATION
223 '
230 FOR I=0 TO N2
240 M=M+(VF1(I)-2047)/2048
250 NEXT I
260 M=M/(N2+1)
261 '
262 'CALCULATE ACTUAL VARIANCE OF SIGNAL RECORD.
263 '
270 FOR I=S1 TO N5
280 R1=(VF1(I)-2047)/2048\R1=R1-M
```

```
290 R=R+R1*R1
300 NEXT I
310 R=R/(N5-S1+1)
311 '
312 'CHOOSE THE TRUE INPUT HYPOTHESIS AND DETERMINE THE CORRESPONDING
313 'TARGET LEVEL.
314 '
330 H=VF2(T)
340 V5=V(H)
345 K=.1
346 '
347 'Y-IS THE MODIFYING MULTIPLIER WHICH INTRODUCES THE RANDOM ERROR
348 'CONTAINED IN VF3(T).
349 '
350 Y=K*(2*VF3(T)-1)
351 '
352 'V6-IS NOW THE VALUE OF THE VARIANCE TO BE INPUT TO THE PROCESSOR
353 '
360 V6=V5*(1+Y)
361 '
362 'S-IS THE RATIO OF DESIRED INPUT VARIANCE TO ACTUAL SIGNAL VARIANCE.
363 '
370 S=SQR(V6/R)
390 FOR J=S1 TO N2 STEP 4
391 '
392 'THE VALUE OF N (THE NUMBER OF SAMPLES TAKEN) IS INCREMENTED AND
393 'USED IN THE CALCULATION OF THE BOUNDARY LEVELS.
393 '
400 N=N+1\N1=A+N*C1\N9=C*(B+N*C1)
410 B0=V0*N9\B1=V1*N9\B2=V2*N9\B3=V3*N9\B4=V4*N9
420 A0=V1*N1\A1=V2*N1\A2=V3*N1\A3=V4*N1
421 '
422 'THE SAMPLE IS MODIFIED TO CREATE THE DESIRED VARIANCE
423 '
430 X1=(VF1(J)-2047)/2048
431 '
432 'THE VALUE OF THE SUM OF THE SQUARES IS UPDATED.
433 '
440 X=X+(S*(X1-M))^2
441 '
442 '450-520 DETERMINE WHERE IN THE DECISION REGION THE SUM OF THE
443 'SQUARES FALLS.
445 '
450 IF X<=B0 THEN 550
460 IF X<=A0 THEN 690
470 IF X<=B1 THEN 570
480 IF X<=A1 THEN 690
490 IF X<=B2 THEN 590
500 IF X<=A2 THEN 690
510 IF X<=B3 THEN 610
520 IF X<=A3 THEN 690
521 '
522 'THE DECISION MADE BY THE PROCESSOR IS THEN COMPARED WITH THE
523 'ACTUAL INPUT HYPOTHESIS AND ERROR STATISTICS UPDATED ACCORDINGLY.
524 '
530 IF H=4 THEN 630
540 E(H,4)=E(H,4)+1\GO TO 630
550 IF H=0 THEN 630
560 E(H,0)=E(H,0)+1\GO TO 630
570 IF H=1 THEN 630
580 E(H,1)=E(H,1)+1\GO TO 630
590 IF H=2 THEN 630
600 E(H,2)=E(H,2)+1\GO TO 630
610 IF H=3 THEN 630
620 E(H,3)=E(H,3)+1\GO TO 630
621 '
622 'PREPARATIONS ARE THEN MADE FOR A NEW TRIAL AND TO DETERMINE
623 'WHETHER OR NOT THE END OF THE SIGNAL RECORD HAS BEEN REACHED.
624 '
630 N3(H)=N3(H)+N\D(H)=D(H)+1\S1=S1+N+1\X=0\N=0
640 IF N5-S1>100 THEN 680
660 IF N5>10000 THEN 750\R=0
670 GO TO 270
680 T=T+1
681 IF T<=500 THEN 330
682 T=0\GO TO 330
```

```
683 '
684 'RETURN TO START A NEW TRIAL
685 '
690 NEXT J
691 '
692 'PRINT OUT ERROR RESULTS
693 '
750 FOR W=0 TO 4
760 T3(W)=E(W,0)+E(W,1)+E(W,3)+E(W,2)+E(W,4)
770 N3(W)=N3(W)/D(W)
780 PRINT "TRUE HYPOTHESIS IS H=";W
790 PRINT "TOTAL NUMBER OF TRIALS=";D(W)
800 PRINT "AVERAGE NUMBER OF SAMPLES=;N3(W)
810 PRINT "TOTAL NUMBER OF ERRORS=";T3(W)
820 PRINT E(W,0),E(W,1),E(W,2),E(W,3),E(W,4)
830 NEXT W
840 END
```

A.2 BAYES PROCESSOR WITH RANDOM ERROR (BAYRAN)

This program is similar to the previous one, except that it simulates a Bayes processor rather than a Sequential. Program written in BASIC on a DEC PDP-11.

```
10 DIM V(4),E(4,4),D(4),T3(4)
11 RANDOMIZE
12 '
13 'OPEN THE FILE FROM WHICH EMG DATA IS TO BE TAKEN.
14 '
20 OPEN "RK0:SH1" FOR INPUT AS FILE VF1%(10000)
21 '
22 'OPEN A FILE TO RECEIVE THE RANDOM INPUT SEQUENCE TO BE CREATED
23 'BELOW.
24 '
30 OPEN "RK0:VCH" FOR OUTPUT AS FILE VF2%(500)
31 '
32 'OPEN A FILE TO RECEIVE INPUT ERROR
33 'VF3 WILL CONTAIN NUMBERSCHOSEN FROM A CONTINUOUS DISTRIBUTION
34 '
40 OPEN "RK0:OPER" FOR OUTPUT AS FILE VF3(500)
41 '
42 'CREATE THE RANDOM SEQUENCE THAT DETERMINES THE TRUE INPUT
43 'HYPOTHESIS.
44 '
50 FOR I=0 TO 500
60 VF2(I)=INT(5*RND(0))
70 NEXT I
80 CLOSE VF2
90 OPEN "RK0:VCH" FOR INPUT AS FILE VF2%(500)
91 '
92 'CREATE THE INPUT ERROR
93 '
100 FOR I=0 TO 500
110 VF3(I)=RND
120 NEXT I
130 CLOSE VF3
135 OPEN "RK0:OPER" FOR INPUT AS FILE VF3(500)
136 '
137 'SET UP TARGET LEVELS AND INITIALIZE OTHER VARIABLES.
138 '
140 V(0)=4\V(1)=24.49\V(2)=150\V(3)=918.56\V(4)=5625
150 M=0\R=0\T=0\X=0\S2=0
160 C=6.124
170 N2=10000
180 S1=0
190 C1=LOG(C)\C2=1/(C-1)
191 '
192 'DETERMINE SAMPLE SIZE
193 '
195 N=18
196 '
197 'CALCULATE BOUNDARY LEVELS
198 '
200 C3=C1*C2
210 K0=V(1)*N*C3\K1=V(2)*N*C3\K2=V(3)*N*C3\K3=V(4)*N*C3
211 '
212 'CALCULATE AVERAGE VALUE FOR UPCOMING VARIANCE CALCULATION
213 '
220 FOR I=0 TO N2
230 M=M+(VF1(I)-2047)/2048
240 NEXT I
241 M=M/(N2+1)
242 S1=0
243 N5=10000
244 F=4
245 '
246 'CALCULATE ACTUAL VARIANCE OF SIGNAL RECORD.
247 '
250 FOR I=S1 TO N5
260 R1=(VF1(I)-2047)/2048\R1=R1-M
270 R=R+R1*R1
```

```
280 NEXT I
285 R=R/(N5-S1+1)
286 '
287 'CHOOSE THE TRUE INPUT HYPOTHESIS AND DETERMINE THE CORRESPONDING
288 'TARGET LEVEL.
289 '
290 H=VF2(T)
300 V5=V(H)
310 K=.5
311 '
312 'Y-IS THE MODIFYING MULTIPLIER WHICH INTRODUCES THE RANDOM ERROR
313 'CONTAINED IN VF3(T).
314 '
320 Y=K*(2*VF3(T)-1)
321 '
322 'V6-IS NOW THE VALUE OF THE VARIANCE TO INPUT TO THE PROCESSOR
323 '
330 V6=V5*(1+Y)
331 'S-IS THE RATIO OF DESIRED INPUT VARIANCE TO ACTUAL SIGNAL VARIANCE.
332 'THIS WILL BE USED TO MODIFY THE SAMPLES TO CREATE THE DESIRED VALUE.
333 '
340 S=SQR(V6/R)
345 N3=S1+F*(N-1)
346 X=0
347 '
348 'SAMPLES ARE TAKEN, SQUARED AND SUMMED.
349 '
350 FOR J=S1 TO N3 STEP F
360 X1=(VF1(J)-2047)/2048
370 X=X+(S*(X1-M))^2
380 NEXT J
381 '
382 'THE NEXT 4 LINES DETERMINE THE REGION INTO WHICH THE SUFFICIENT
383 'STATISTIC FALLS.
384 '
390 IF X<=K0 THEN 450
400 IF X<=K1 THEN 470
410 IF X<=K2 THEN 490
420 IF X<=K3 THEN 510
421 '
422 'THE DECISION MADE BY THE PROCESSOR IS THEN COMPARED WITH THE ACTUAL
423 'INPUT HYPOTHESIS AND ERROR STATISTICS ARE UPDATED ACCORDINGLY.
424 '
430 IF H=4 THEN 530
440 E(H,4)=E(H,4)+1\GO TO 530
450 IF H=0 THEN 530
460 E(H,0)=E(H,0)+1\GO TO 530
470 IF H=1 THEN 530
480 E(H,1)=E(H,1)+1\GO TO 530
490 IF H=2 THEN 530
500 E(H,2)=E(H,2)+1\GO TO 530
510 IF H=3 THEN 530
520 E(H,3)=E(H,3)+1\GO TO 530
521 '
522 'PREPARATIONS ARE THEN MADE FOR A NEW TRIAL AND TO DETERMINE WHETHER
523 'OR NOT THE END OF THE SIGNAL HAS BEEN REACHED.
524 '
530 T=T+1\D(H)=D(H)+1\S1=S1+N
535 IF T<=500 THEN 540
536 T=0
540 N3=S1+F*(N-1)
570 R=0
571 '
572 'RETURN TO START A NEW TRIAL
573 '
580 GO TO 250
581 '
582 'PRINT OUT ERROR RESULTS
583 '
620 FOR W=0 TO 4
630 T3(W)=E(W,0)+E(W,1)+E(W,3)+E(W,2)+E(W,4)
640 PRINT "TRUE HYPOTHESIS IS H=";W
650 PRINT "TOTAL NUMBER OF TRIALS=";D(W)
660 PRINT "TOTAL NUMBER OF ERRORS=";T3(W)
670 PRINT E(W,0),E(W,1),E(W,2),E(W,3),E(W,4)
680 PRINT T3(W)/D(W)
```

```
690 NEXT W
700 END
```

A.3 ONE STEP SEQUENTIAL PROCESSOR (OSTEP)

OSTEP processes the signals acquired in the tracking study through a Sequential processor in the synchronous manner described in Section 4.2. The programs used to simulate the Bayes and Composite Hypothesis receivers, in the synchronous mode, are not included here since the are essentially the same, with the only difference being the way in which the decision boundaries are calculated. This program generates the results plotted in the Type I curves. Program written in FORTRAN on a DEC LSI-11.

```
        REAL V(5),A,N1,N9,X,C,C1,C2,V0,V1,V2,V3,V4,XN,X1,B0,B1,
     *  B2,B3,B4,A0,A1,A2,A3,STAT(20,125,2),DIF
        INTEGER I,J,K,TR(20),N,LN,LEVARR(4),ABDIF,SUM,T,LL,
     *  NR,TC,SP,CP,ARRAY(5),Q,B,SPC,L,FL,HET,MARK,D,FLNUM,RLNUM
        LOGICAL*1 FLNM1(14),FLNM2(14),FLNM3(14),FLNM4(14)
C
        DATA NUL/"0/
        OPEN(UNIT=3,NAME='DY1:FLFL.DAT',TYPE='UNKNOWN'
     *  ,ACCESS='DIRECT',RECORDSIZE=4)
C    ***FLFL.DAT IS THE FILE CONTAINING THE NAMES OF THE FILES TO BE
C    ***PROCESSED.
C    ***INITIALIZE NECESSARY ARRAYS
        DO 3,K=1,125
        DO 4,J=1,20
        STAT(J,K,1)=0.0
        STAT(J,K,2)=0.0
4       CONTINUE
3       CONTINUE
C
C
C
        DO 5,I=1,20
        TR(I)=0
5       CONTINUE
C    ***SET UP OF VARIOUS CONSTANTS TO BE USED LATER IN THE
C    ***PROGRAM.
C    ***TARGET LEVELS.
C
        V(1)=122.94
        V(2)=869.34
        V(3)=6147.19
        V(4)=43467.18
        V(5)=307359.36
C   ***RATIO OF TARGET LEVELS
        C=7.071068
C
        A=2*ALOG(99.0)
        C1=ALOG(C)
        C2=1/(C-1)
C
C
C
        V0=V(1)*C2
        V1=V(2)*C2
        V2=V(3)*C2
        V3=V(4)*C2
        V4=V(5)*C2
C
C    ***ENTER THE NUMBER OF FILES TO BE PROCESSED
C
        WRITE(7,2)
2       FORMAT(' ENTER # OF FILES')
        READ(7,1) FLNUM
1       FORMAT(I3)
        RLNUM=2*FLNUM-1

C    ***THE NAMES OF THE FILES TO BE PROCESSED ARE READ IN.
C    ***EACH FILE CONSISTS OF 2 SUBFILES; A FILE CONTAINING THE EMG
C    ***DATA AND, A FILE CONTAINING THE TARGET LEVEL DATA.
        DO 701,FL=1,RLNUM,2
        READ(3'FL) (FLNM1(L),L=1,14)
        FLNM1(14)=NUL
```

```
      READ(3'FL+1) (FLNM2(L),L=1,14)
      FLNM2(14)=NUL
      PRINT 6,FLNM1
      PRINT 6,FLNM2
C   ***THE FILES CORRESPONDING TO THE NAMES ARE OPENED IN
C   ***PREPARATION FOR PROCESSING.
      OPEN(UNIT=1,NAME=FLNM1,TYPE='UNKNOWN'
     * ,ACCESS='DIRECT',RECORDSIZE=1)
      OPEN(UNIT=2,NAME=FLNM2,TYPE='UNKNOWN'
     * ,ACCESS='DIRECT',RECORDSIZE=1)
C
C
C
6     FORMAT(15A1)
C
C
C
      N=0
      X=0.0
      LN=1
C   ***N KEEPS TRACK OF THE NUMBER OF SAMPLES USED IN
C   ***MAKING A DECISION. LN IS THE POSITION IN THE
C   ***LEVEL DATA FILE.
10    IF(LN .GT. 2500)GO TO 700
C   ***FOUR TARGET LEVELS ARE READ IN.
11    READ(2'LN) (LEVARR(L),L=1,2)
      LN=LN+1
      READ(2'LN) (LEVARR(L),L=3,4)
C
C   ***THE FOLLOWING SECTION FINDS THE CHANGES IN THE TARGET
C   ***LEVEL AND IDENTIFIES WHAT TYPE OF TRANSITION OCCURED;
C   ***1 TO 2,3 TO 4,3 TO 2,ETC.
C   ***IT ALSO IDENTIFIES THE HYPOTHESIS CORRESPONDING TO THE
C   ***LEVEL PRESENT AFTER THE TRANSITION.
      DIF=LEVARR(2)-LEVARR(1)
      ABDIF=ABS(DIF)
C
      IF(ABDIF .GT. 500) GO TO 100
C
      DIF=LEVARR(3)-LEVARR(2)
      ABDIF=ABS(DIF)
      IF(ABDIF .GT. 500) GO TO 110
C
C
C
      GO TO 10
C
C
C
100   LN=LN-1
      SUM=LEVARR(2)+LEVARR(1)
      GO TO 120
110   SUM=LEVARR(3)+LEVARR(2)
C
120   IF(ABDIF .LT. 1200) GO TO 300
C
200   IF(ABDIF .LT. 2000) GO TO 310
C
210   IF(ABDIF .GT. 2800) GO TO 330
      GO TO 320
C
C
C
300   IF(SUM .GT. 2480) GO TO 301
      T=1
      H=2
      GO TO 400
301   IF(SUM .GT. 4057) GO TO 302
      T=6
      H=3
      GO TO 400
302   IF(SUM .GT. 5640) GO TO 303
      T=11
      H=4
      GO TO 400
C
```

```
C
C
303     T=16
        H=5
C
C
C
400     IF (DIF .GT. 0) GO TO 500
        T=T+4
        H=H-1
        GO TO 500
C
C
C
310     IF(SUM .GT. 3270) GO TO 311
        T=2
        H=3
        GO TO 420
C
C
C
311     IF(SUM .GT. 4850) GO TO 312
        T=7
        H=4
        GO TO 420
C
C
C
312     T=12
        H=5
C
420     IF(DIF .GT. 0) GO TO 500
        T=T+7
        H=H-2
        GO TO 500
C
C
C
320     IF(SUM .GT. 4063) GO TO 321
        T=3
        H=4
        GO TO 440
C
321     T=8
        H=5
C
C
C
440     IF(DIF .GT. 0) GO TO 500
        T=T+10
        H=H-3
        GO TO 500
C
C
C
330     T=4
        H=5
        IF(DIF .GT. 0) GO TO 500
        T=17
        H=1
C    ***THIS IS THE END OF TRANSITION DETECTION.
C    ***KNOWING WHERE THE TRANSITION OCCURS IN THE LEVEL DATA
C    ***THE POSITION OF THE CORRESPONDING EMG DATA IS CALCULATED.
C    ***THIS IS SIMPLE SINCE ONE LEVEL SAMPLE IS TAKEN FOR EVERY
C    ***FOUR EMG SAMPLES. SO,NR=4 X LL, WHERE LL=LEVEL LOCATION
C    ***AND NR=RECORD NUMBER(OF EMG)
500     LL=LN
        TR(T)=TR(T)+1
        PRINT*,'T',T
        NR=4*LL
        TC=1
        SP=NR-3
        SPC=1
510     CP=SP
C    ***PROCESSING IS THEN INITIATED BEGINNING WITH THE THIRD RECORD
C    ***BEFORE THE LEVEL TRANSITION. PROCESSING CONTINUES UNTIL
```

```
C    ***122 RECORD AFTER TRANSITION(3 RECORDS BEFORE NEXT TRANSITION)
C
        IF(SP .GE. (NR+122)) GO TO 600
520     IF(CP .GT. 10000) GO TO 700
521     READ(1'CP) (ARRAY(B),B=1,2)
C
C   ***INCREMENT N AND CALCULATE BOUNDARY LEVELS.
C
530     XN=ARRAY(TC)
        X1=XN-2047
        N=N+1
        TC=TC+1
        N1=A+N*C1
        N9=C*(N*C1-A)
C
C
C
        B0=V0*N9
        B1=V1*N9
        B2=V2*N9
        B3=V3*N9
        B4=V4*N9
C
C
C
        A0=V1*N1
        A1=V2*N1
        A2=V3*N1
        A3=V4*N1
C
C    ***UPDATE THE SUM OF THE SQUARES
        X=X+X1**2
C
C    ***THE NEXT SECTION DETERMINES IF THE SUM OF THE SQUARES FALLS
C    ***INTO ANY OF THE DECISION REGIONS.
C    ***IF IT DOES THE HYPOTHESIS IS IDENTIFIED AND IF IT DOESN'T,
C    ***THE PROGRAM RETURNS TO TAKE ANOTHER SAMPLE.
C
        IF(X .GT. B0) GO TO 540
        I=1
        GO TO 590
C
C
C
540     IF(X .LE. A0) GO TO 580
        IF(X .GT. B1) GO TO 550
        I=2
        GO TO 590
C
C
C
550     IF(X .LE. A1) GO TO 580
        IF(X .GT. B2) GO TO 560
        I=3
        GO TO 590
C
C
C
560     IF(X .LE. A2) GO TO 580
        IF(X .GT. B3) GO TO 570
        I=4
        GO TO 590
C
C
C
570     IF(X .LE. A3) GO TO 580
        I=5
        GO TO 590
C
C
C
580     IF(TC .LE. 2) GO TO 530
        CP=CP+1
        TC=1
        GO TO 520
C    ***AT THIS POINT THE PROCESSOR HAS MADE A DECISION AND IT
```

```
C     ***WILL BE COMPARED TO THE PRESENTED HYPOTHESIS AND THE
C     ***ERROR STATISTICS UPDATED ACCORDINGLY.
C
590       STAT(T,SPC,1)=STAT(T,SPC,1)+N
          IF(I .EQ. H)GO TO 591
          STAT(T,SPC,2)=STAT(T,SPC,2)+1
C
C     ***NOW THE PROCESSOR MOVES ON TO THE NEXT STARTING POINT.
C
591       X=0.0
          N=0
          SP=SP+1
          SPC=SPC+1
C
          TC=1
          GO TO 510
C
C     ***AT LINE 600 THE CURRENT TRANSITION HAS BEEN COMPLETED AND
C     ***VARIABLES ARE RESET IN PREPARATION TO FIND THE NEXT TRANSITION.
C
600       NR=NR+100
          LN=INT(NR/4.0)
          X=0.0
          N=0
          GO TO 10
C
C     ***AT 700 THE CURRENT FILE IS FINISHED AND PREPARATIONS ARE MADE
C     ***TO BEGIN PROCESSING A NEW FILE.
700       CLOSE(UNIT=1)
          CLOSE(UNIT=2)
C     ***AT 701 ALL THE FILES HAVE BEEN PROCESSED AND OUTPUT FOLLOWS
701       CONTINUE
          CLOSE(UNIT=3)
C
C     ***FILENAMES ARE CREATED FOR THE FILES THAT WILL CONTAIN THE
C     ***RESULTS.
          DO 704,D=1,14
          FLNM3(D)=FLNM1(D)
          FLNM4(D)=FLNM1(D)
704       CONTINUE
          FLNM3(9)='S'
          FLNM4(9)='T'
C
C     ***RESULTS ARE WRITTEN ONTO DISK.
C
          OPEN(UNIT=4,NAME=FLNM3,TYPE='UNKNOWN'
     *    ,ACCESS='DIRECT',RECORDSIZE=5000)
          WRITE(4'1) (((STAT(J,K,L),K=1,125),J=1,20),L=1,2)
          CLOSE(UNIT=4)
C
C
C
          OPEN(UNIT=5,NAME=FLNM4,TYPE='UNKNOWN'
     *    ,ACCESS='DIRECT',RECORDSIZE=10)
          WRITE(5'1) (TR(J),J=1,20)
          CLOSE(UNIT=5)
          STOP
          END
```

A.4 ONE STEP PREVIOUS HYPOTHESIS CORRECT (OPRE)

OPRE is the program which generates the results for the Type II curves. This particular listing is for the Sequential processor as with OSTEP. Program written in FORTRAN on a DEC LSI-11.

```
      REAL V(5),A,N1,N9,X,C,C1,C2,V0,V1,V2,V3,V4,XN,X1,B0,B1,
     * B2,B3,B4,A0,A1,A2,A3,STAT(20,125,2),DIF
      INTEGER I,J,K,TR(20),N,LN,LEVARR(4),ABDIF,SUM,T,LL,
     * NR,TC,SP,CP,ARRAY(5),Q,B,SPC,L,FL,HET,MARK,D,FLNUM,RLNUM,HP,BFR
      LOGICAL*1 FLNM1(14),FLNM2(14),FLNM3(14),FLNM4(14)
C
      DATA NUL/"0/
      OPEN(UNIT=3,NAME='DY1:FLFL.DAT',TYPE='UNKNOWN'
     * ,ACCESS='DIRECT',RECORDSIZE=4)
C   ***FLFL.DAT IS THE FILE CONTAINING THE NAMES OF THE FILES TO BE
C   ***PROCESSED.
C   ***INITIALIZE ARRAYS.
      DO 3,K=1,125
      DO 4,J=1,20
      STAT(J,K,1)=0.0
      STAT(J,K,2)=0.0
4     CONTINUE
3     CONTINUE
C
C
C
      DO 5,I=1,20
      TR(I)=0
5     CONTINUE
C   ***SET UP OF VARIOUS CONSTANTS TO BE USED LATER IN THE
C   ***PROGRAM.
C
C   ***TARGET LEVELS.
      V(1)=122.94
      V(2)=869.34
      V(3)=6147.19
      V(4)=43467.18
      V(5)=307359.36
C   ***RATIO OF TARGET LEVELS.
      C=7.071068
C
      A=2*ALOG(99.0)
      C1=ALOG(C)
      C2=1/(C-1)
C
C
C
      V0=V(1)*C2
      V1=V(2)*C2
      V2=V(3)*C2
      V3=V(4)*C2
      V4=V(5)*C2
C
C
C   ***ENTER THE NUMBER OF DATA FILES TO BE PROCESSED.
      WRITE(7,2)
2     FORMAT(' ENTER # OF FILES')
      READ(7,1) FLNUM
1     FORMAT(I3)
      RLNUM=2*FLNUM-1

C   ***THE NAMES OF THE FILES TO BE PROCESSED ARE READ IN.
C   ***EACH FILE CONSISTS OF 2 SUBFILES;A FILE CONTAINING THE EMG DATA
C   ***AND A FILE CONTAINING THE TARGET LEVEL DATA.
      DO 701,FL=1,RLNUM,2
      READ(3'FL) (FLNM1(L),L=1,14)
      FLNM1(14)=NUL
      READ(3'FL+1) (FLNM2(L),L=1,14)
      FLNM2(14)=NUL
      PRINT 6,FLNM1
      PRINT 6,FLNM2
```

```
C    ***THE FILES CORRESPONDING TO THE NAMES ARE OPENED IN PREPARATION
C    ***FOR PROCESSING.
        OPEN(UNIT=1,NAME=FLNM1,TYPE='UNKNOWN'
     *  ,ACCESS='DIRECT',RECORDSIZE=1)
        OPEN(UNIT=2,NAME=FLNM2,TYPE='UNKNOWN'
     *  ,ACCESS='DIRECT',RECORDSIZE=1)
C
C
C
6       FORMAT(15A1)
C
C
C
        N=0
        X=0.0
        LN=1
C    ***N KEEPS TRACK OF THE NUMBER OF SAMPLES USED IN
C    ***MAKING A DECISION. LN IS THE POSITION IN THE
C    ***LEVEL DATA FILE.
10      IF(LN .GT. 2500)GO TO 700
C    ***FOUR TARGET LEVEL SAMPLES ARE READ IN.
11      READ(2'LN) (LEVARR(L),L=1,2)
        LN=LN+1
        READ(2'LN) (LEVARR(L),L=3,4)
C
C    ***THE FOLLOWING SECTION FINDS THE CHANGES IN THE TARGET
C    ***LEVEL AND IDENTIFIES WHAT TYPE OF TRANSITION OCCURED;
C    ***1 TO 2,3 TO 4,3 TO 2,ETC.
C    ***IT ALSO IDENTIFIES WHICH HYPOTHESES CORRESPOND TO THE
C    ***LEVELS PRESENT BEFORE AND AFTER THE TRANSITION.
        DIF=LEVARR(2)-LEVARR(1)
        ABDIF=ABS(DIF)
C
        IF(ABDIF .GT. 500) GO TO 100
C
        DIF=LEVARR(3)-LEVARR(2)
        ABDIF=ABS(DIF)
        IF(ABDIF .GT. 500) GO TO 110
C
C
C
        GO TO 10
C
C
C
100     LN=LN-1
        SUM=LEVARR(2)+LEVARR(1)
        GO TO 120
110     SUM=LEVARR(3)+LEVARR(2)
C
120     IF(ABDIF .LT. 1200) GO TO 300
C
200     IF(ABDIF .LT. 2000) GO TO 310
C
210     IF(ABDIF .GT. 2800) GO TO 330
        GO TO 320
C
C
C
300     IF(SUM .GT. 2480) GO TO 301
        T=1
        H=2
        HP=1
        GO TO 400
301     IF(SUM .GT. 4057) GO TO 302
        T=6
        H=3
        HP=2
        GO TO 400
302     IF(SUM .GT. 5640) GO TO 303
        T=11
        H=4
        HP=3
        GO TO 400
C
C
```

```
C
303     T=16
        H=5
        HP=4
C
C
C
400     IF (DIF .GT. 0) GO TO 500
        T=T+4
        HP=H
        H=H-1
        GO TO 500
C
C
C
310     IF(SUM .GT. 3270) GO TO 311
        T=2
        H=3
        HP=1
        GO TO 420
C
C
C
311     IF(SUM .GT. 4850) GO TO 312
        T=7
        H=4
        HP=2
        GO TO 420
C
C
C
312     T=12
        H=5
        HP=3
C
420     IF(DIF .GT. 0) GO TO 500
        T=T+7
        HP=H
        H=H-2
        GO TO 500
C
C
C
320     IF(SUM .GT. 4063) GO TO 321
        T=3
        H=4
        HP=1
        GO TO 440
C
321     T=8
        H=5
        HP=2
C
C
C
440     IF(DIF .GT. 0) GO TO 500
        T=T+10
        HP=H
        H=H-3
        GO TO 500
C
C
C
330     T=4
        H=5
        HP=1
        IF(DIF .GT. 0) GO TO 500
        T=17
        H=1
        HP=5
C    ***THIS IS THE END OF TRANSITION DETECTION.
C    ***KNOWING WHERE THE TRANSITION OCCURS IN THE LEVEL DATA
C    ***THE POSITION OF THE CORRESPONDING EMG DATA IS CALCULATED.
C    ***THIS IS SIMPLE SINCE ONE LEVEL SAMPLE IS TAKEN FOR EVERY
C    ***FOUR EMG SAMPLES. SO,NR=4 X LL, WHERE LL=LEVEL LOCATION
C    ***AND NR=RECORD NUMBER(OF EMG)
```

```
500     LL=LN
        TR(T)=TR(T)+1
        PRINT*,'T',T
        NR=4*LL
        TC=1
        BFR=1
        SP=NR-3
        SPC=1
510     CP=SP
C    ***PROCESSING IS THEN INITIATED BEGINNING WITH THE THIRD RECORD
C    ***BEFORE THE LEVEL TRANSITION. PROCESSING CONTINUES UNTIL
C    ***122 RECORD AFTER TRANSITION(3 RECORDS BEFORE NEXT TRANSITION)
C
        IF(SP .GE. (NR+122)) GO TO 600
520     IF(CP .GT. 10000) GO TO 700
521     READ(1'CP) (ARRAY(B),B=1,2)
C
C
C
530     XN=ARRAY(TC)
        X1=XN-2047
C    ***INCREMENT N AND CALCULATE BOUNDARY LEVELS.
        N=N+1
        TC=TC+1
        N1=A+N*C1
        N9=C*(N*C1-A)
C
C
C
        B0=V0*N9
        B1=V1*N9
        B2=V2*N9
        B3=V3*N9
        B4=V4*N9
C
C
C
        A0=V1*N1
        A1=V2*N1
        A2=V3*N1
        A3=V4*N1
C
C    ***UPDATE THE SUM OF THE SQUARES.
        X=X+X1**2
C
C    ***THE NEXT SECTION DETERMINES IF THE SUM OF THE SQUARES FALLS INTO
C    ***ANY OF THE DECISION REGIONS.  IF IT DOES HYPOTHESIS IS IDENTIFIED
C    ***AND IF IT DOESN'T THE PROGRAM RETURNS TO TAKE ANOTHER SAMPLE.
C
        IF(X .GT. B0) GO TO 540
        I=1
        GO TO 590
C
C
C
540     IF(X .LE. A0) GO TO 580
        IF(X .GT. B1) GO TO 550
        I=2
        GO TO 590
C
C
C
550     IF(X .LE. A1) GO TO 580
        IF(X .GT. B2) GO TO 560
        I=3
        GO TO 590
C
C
C
560     IF(X .LE. A2) GO TO 580
        IF(X .GT. B3) GO TO 570
        I=4
        GO TO 590
C
C
C
```

```
570     IF(X .LE. A3) GO TO 580
        I=5
        GO TO 590
C
C
C
580     IF(TC .LE. 2) GO TO 530
        CP=CP+1
        TC=1
        GO TO 520
C    ***AT THIS POINT THE PROCESSOR HAS MADE A DECISION AND IT
C    ***WILL BE COMPARED TO THE PRESENTED HYPOTHESIS AND THE
C    ***ERROR STATISTICS UPDATED ACCORDINGLY.
C    ***THE DECISION WILL CALLED CORRECT IF THE IDENTIFIED HYPOTHESIS IS
C    ***THE SAME AS THE PREVIOUS HYPOTHESIS (PROVIDING A DIFFERENT
C    ***HYPOTHESIS HAS NOT BEEN IDENTIFIED) OR IF THE IDENTIFIED
C    ***HYPOTHESIS CORRESPONDS TO TARGET LEVEL PRESENT AFTER TRANSITION.
C
590     STAT(T,SPC,1)=STAT(T,SPC,1)+N
        IF(BFR .EQ. 0) GO TO 592
        IF(I .EQ. HP) GO TO 591
        BFR=0
592     IF(I .EQ. H)GO TO 591
        STAT(T,SPC,2)=STAT(T,SPC,2)+1
C
C    ***NOW THE PROCESSOR MOVES ON TO THE NEXT STARTING POINT.
C
591     X=0.0
        N=0
        SP=SP+1
        SPC=SPC+1
C
        TC=1
        GO TO 510
C
C    ***AT LINE 600 THE CURRENT TRANSITION HAS BEEN COMPLETED AND
C    ***VARIABLES ARE RESET IN PREPARATION TO FIND THE NEXT TRANSITION.
C
600     NR=NR+100
        LN=INT(NR/4.0)
        X=0.0
        N=0
        GO TO 10
C
C    ***AT 700 THE CURRENT FILE IS FINISHED AND PREPARATIONS ARE MADE
C    ***TO BEGIN PROCESSING A NEW FILE.
700     CLOSE(UNIT=1)
        CLOSE(UNIT=2)
C    ***AT 701 ALL THE FILES HAVE BEEN PROCESSED AND OUTPUT FOLLOWS
701     CONTINUE
        CLOSE(UNIT=3)
C
C    ***FILENAMES ARE CREATED FOR THE FILES THAT WILL CONTAIN THE RESULTS.
C
        DO 704,D=1,14
        FLNM3(D)=FLNM1(D)
        FLNM4(D)=FLNM1(D)
704     CONTINUE
        FLNM3(9)='R'
        FLNM4(9)='E'
C
C    ***RESULTS ARE WRITTEN ONTO DISK.
C
        OPEN(UNIT=4,NAME=FLNM3,TYPE='UNKNOWN'
     *  ,ACCESS='DIRECT',RECORDSIZE=5000)
        WRITE(4'1) (((STAT(J,K,L),K=1,125),J=1,20),L=1,2)
        CLOSE(UNIT=4)
C
C
C
        OPEN(UNIT=5,NAME=FLNM4,TYPE='UNKNOWN'
     *  ,ACCESS='DIRECT',RECORDSIZE=10)
        WRITE(5'1) (TR(J),J=1,20)
        CLOSE(UNIT=5)
        STOP
        END
```

A.5 AVERAGER OF FILE RESULTS (AVER)

This program averages the results obtained from processing seperate data files and then plots graphs as chosen fom a menu. Program written in FORTRAN on a DEC LSI-11.

```
      LOGICAL*1 FLNM1(14),FLNM2(14),FLNM4(14),BAY,ANS,ERR,PROD,
     * OTAR(132),CAL(132),OAE,OAS,OAP
      REAL STASUM(125),STAT(125),OAESUM(125),OASSUM(125)
      INTEGER J,K,L,FLNUM,REALNUM,TR(20),TRSUM(20),FL,BC,MARK,T,RFL,
     * S,Q,M,P,U,B,OATSUM
      WRITE(7,2)
2     FORMAT(' ENTER NUMBER OF FILES')
      READ(7,1) FLNUM
1     FORMAT(I3)
      BC=1
4     FORMAT (A1)
      WRITE(7,3)
3     FORMAT(' PROCESSING FIXED NUMBER BAYES FILES?(Y/N)')
      READ(7,4) BAY
      WRITE(7,5)
5     FORMAT(' 1. NUMBER OF SAMPLES')
      WRITE(7,6)
6     FORMAT(' 2. ERROR RATE')
      WRITE(7,7)
7     FORMAT(' 3. ANS*ERROR RATE')
      WRITE(7,25)
25    FORMAT(' 4. OVER ALL ERROR')
      WRITE(7,26)
26    FORMAT(' 5. OVER ALL SAMPLE')
      WRITE(7,27)
27    FORMAT(' 6. OVER ALL PRODUCT')
C
C  ***CHOOSE AMONG THE AVIALABLE PLOTS.
C
      WRITE(7,8)
8     FORMAT(' DO YOU WANT TO PLOT 1. ?')
      READ(7,4) ANS
      WRITE(7,9)
9     FORMAT(' DO YOU WANT TO PLOT 2. ?')
      READ(7,4) ERR
      WRITE (7,11)
11    FORMAT(' DO YOU WANT TO PLOT 3. ?')
      READ(7,4) PROD
      WRITE(7,28)
28    FORMAT(' DO YOU WANT TO PLOT 4. ?')
      READ(7,4) OAE
      WRITE(7,29)
29    FORMAT(' DO YOU WANT TO PLOT 5. ?')
      READ(7,4) OAS
      WRITE(7,30)
30    FORMAT(' DO YOU WANT TO PLOT 6. ?')
      READ(7,4) OAP
C
C
      DO 31,U=1,132
      CAL(U)=' '
31    CONTINUE
C  ***PRINT OUT THE VERTICAL AXIS MARKERS.
      CAL(1)='+'
      CAL(14)='+'
      CAL(27)='+'
      CAL(40)='+'
      CAL(53)='+'
      CAL(67)='+'
      CAL(80)='+'
      CAL(93)='+'
      CAL(106)='+'
      CAL(119)='+'
      CAL(132)='+'
C
C
```

```
C
          B=1
          IF(BAY .NE.'Y')GOTO 20
          B=0
C
C
20        DO 35,J=1,20
          TRSUM(J)=0
35        CONTINUE
C
C     ***OPEN THE FILE (STAFL.DAT) THAT CONTAINS THE NAMES OF THE FILES
C     ***TO BE AVERAGED.
C
          OPEN(UNIT=1,NAME='DY1:STAFL.DAT',TYPE='UNKNOWN'
     *    ,ACCESS='DIRECT',RECORDSIZE=4)
          READ(1'1) (FLNM4(M),M=1,14)
          CLOSE(UNIT=1)
          FLNM4(8)='A'
          FLNM4(9)='V'
C
C     ***OPEN THE FILE INTO WHICH THE AVERAGED DATE WILL BE WRITTEN.
C
          OPEN(UNIT=4,NAME=FLNM4,TYPE='UNKNOWN'
     *    ,ACCESS='DIRECT',RECORDSIZE=125)
          IF (BAY .EQ. 'Y') GOTO 12
          BC=2
12        REALNUM=2*FLNUM-1
C
C
C
          DO 40,L=1,BC
          DO 50,J=1,20
C
          DO 10,K=1,125
          STASUM(K)=0.0
10        CONTINUE
C
C     ***AVERAGING OF THE FILE BEGINS.
C
          DO 80,FL=1,REALNUM,2
          OPEN(UNIT=1,NAME='DY1:STAFL.DAT',TYPE='UNKNOWN'
     *    ,ACCESS='DIRECT',RECORDSIZE=4)
C
C     ***THE NAME OF THE CURRENT FILE TO BE PROCESSED IS READ IN.
C
          READ(1'FL) (FLNM1(M),M=1,14)
          READ(1'FL+1) (FLNM2(M),M=1,14)
          CLOSE(UNIT=1)
C
C     ***DATA REGARDING THE NUMBER OF TRIALS IS READ IN FROM THE FILE.
C
C
          OPEN(UNIT=2,NAME=FLNM1,TYPE='UNKNOWN'
     *    ,ACCESS='DIRECT',RECORDSIZE=125)
          RFL=J+(L-1)*20
          READ(2'RFL) (STAT(K),K=1,125)
          CLOSE(UNIT=2)
          DO 60,K=1,125
          STASUM(K)=STASUM(K)+STAT(K)
60        CONTINUE
C
C
C
          IF((L.NE.1).OR.(J.NE.1)) GOTO 80
          OPEN(UNIT=3,NAME=FLNM2,TYPE='UNKNOWN'
     *    ,ACCESS='DIRECT',RECORDSIZE=10)
          READ(3'1) (TR(S),S=1,20)
          CLOSE(UNIT=3)
C
C     ***THE NUMBER OF TRIALS IN THE CURRENT FILE IS ADDED TO RUNNING SUM.
C
          DO 70,S=1,20
          TRSUM(S)=TRSUM(S)+TR(S)
70        CONTINUE
C
C
```

```
C
80      CONTINUE
C
C
C
C
C
C
        WRITE(4'RFL) (STASUM(K),K=1,125)
C
C
50      CONTINUE
40      CONTINUE
        CLOSE(UNIT=4)
C
C
        DO 110,J=1,20
        IF(TRSUM(J).NE.0) GOTO 110
        TRSUM(J)=-1
110     CONTINUE
C
C
        DO 111,U=1,132
        OTAR(U)=' '
111     CONTINUE
C
C
C
        DO 119,K=1,125
        OAESUM(K)=0.0
        OASSUM(K)=0.0
119     CONTINUE
C
C
        OATSUM=0
        DO 120,J=1,20
        OATSUM=OATSUM+TRSUM(J)
120     CONTINUE
C
C
        OPEN(UNIT=1,NAME=FLNM4,TYPE='UNKNOWN'
     *  ,ACCESS='DIRECT',RECORDSIZE=125)
161     FORMAT(A1)
160     FORMAT(132A1)
C
C    ***THE NUMBER OF SAMPLES REQUIRED PER DECISION IS READ IN (FOR THE
C    ***SEQUENTIAL TYPE OF PROCESSORS) AND ADDED TO THE RUNNING SUM.
C
        DO 230,J=1,20
        READ(1'J)(STASUM(K),K=1,125)
        DO 231,K=1,125
        OASSUM(K)=OASSUM(K)+STASUM(K)
231     CONTINUE
230     CONTINUE
C
C    ***THE NUMBER OF ERRORS FOR EACH POINT IS READ IN AND ADDED TO THE
C    ***RUNNING SUM.
        DO 232,J=1,20
        P=J+B*20
        READ(1'P) (STASUM(K),K=1,125)
        DO 233,K=1,125
        OAESUM(K)=OAESUM(K)+STASUM(K)
233     CONTINUE
232     CONTINUE
C
C    ***THE NEXT SECTION OUTPUTS THE PLOTS CHOSEN IN THE FIRST SECTION.
C
C    ***PLOTS THE AVERAGE NUMBER OF SAMPLES VS TIME FOR EACH OF THE 20
C    ***TRANSITIONS.
        IF((BAY.EQ.'Y').OR.(ANS .NE. 'Y')) GOTO 130
        DO 140,J=1,20
        PRINT*,' J',J,'# OF TRIALS=',TRSUM(J)
        PRINT 160,(CAL(T),T=1,132)
        READ(1'J)(STASUM(K),K=1,125)
        DO 150,K=1,125
        MARK=INT(5*STASUM(K)/TRSUM(J))+1
```

```
      OTAR(MARK)='*'
      PRINT 160,(OTAR(T),T=1,MARK)
      OTAR(MARK)=' '
150   CONTINUE
140   CONTINUE
C
C   ***PLOTS ERROR VS TIME CURVES FOR EACH OF THE 20 TRANSITIONS.
C
130   IF(ERR .NE. 'Y') GOTO 170
      DO 180,J=1,20
      P=J+B*20
      READ(1'P) (STASUM(K),K=1,125)
      PRINT*,' P=',P,'# OF TRIALS=',TRSUM(J)
      PRINT 160,(CAL(T),T=1,132)
      DO 181,K=1,125
      MARK=INT(132*STASUM(K)/TRSUM(J))
      OTAR(MARK)='*'
      PRINT 160,(OTAR(T),T=1,MARK)
      OTAR(MARK)=' '
181   CONTINUE
180   CONTINUE
C
C   ***PLOTS ERROR*ANS VS TIME CURVES FOR EACH OF THE 20 TRANSITIONS.
C
170   IF(PROD .NE. 'Y')GOTO 190
      DO 191,J=1,20
      PRINT*,' J',J,'# OF TRIALS',TRSUM(J)
      READ(1'J) (STASUM(K),K=1,125)
      P=J+20
      READ(1'P) (STAT(K),K=1,125)
      PRINT 160,(CAL(T),T=1,132)
      DO 192,K=1,125
      MARK=INT(5*(STASUM(K)/TRSUM(J))*(STAT(K)/TRSUM(J)))
      OTAR(MARK)='*'
      PRINT 160,(OTAR(T),T=1,MARK)
      OTAR(MARK)=' '
192   CONTINUE
191   CONTINUE
C
C
190   CLOSE(UNIT=1)
C
C   ***PLOTS ERROR VS TIME CURVES AVERAGED OVER ALL 20 TRANSITIONS.
      IF(OAE .NE. 'Y') GOTO 200
      PRINT 160,(CAL(T),T=1,132)
      DO 205,K=1,125
      MARK=INT(132*(OAESUM(K)/OATSUM))
      OTAR(MARK)='*'
      PRINT 160,(OTAR(T),T=1,MARK)
      OTAR(MARK)=' '
205   CONTINUE
C
C
C   ***PLOTS ANS VS TIME CURVES AVERAGED OVER ALL 20 TRANSITIONS.
200   IF (OAS .NE. 'Y') GOTO 210
      PRINT 160,(CAL(T),T=1,132)
      DO 215,K=1,125
      MARK=INT(5*(OASSUM(K)/OATSUM))
      OTAR(MARK)='*'
      PRINT 160,(OTAR(T),T=1,MARK)
      OTAR(MARK)=' '
215   CONTINUE
C
C
C   ***PLOTS ANS*ERROR VS TIME CURVES AVERAGED ALL 20 TRANSITIONS.
210   IF (OAP .NE. 'Y') GOTO 220
      PRINT 160,(CAL(T),T=1,132)
      DO 225,K=1,125
      MARK=INT(5*(OASSUM(K)/OATSUM)*(OAESUM(K)/OATSUM))
      OTAR(MARK)='*'
      PRINT 160,(OTAR(T),T=1,MARK)
      OTAR(MARK)=' '
225   CONTINUE
C
C
C
```

```
220     PRINT*,'OVER ALL NUMBER OF TRIALS=',OATSUM
        STOP
        END
```

A.6 OUTPUT OF TARGET LEVELS FOR RECORDING ON TAPE (OTPT)

OTPT is the program used to generate the 1 per second random level sequence. Program written in MACRO on a DEC LSI-11.

```
        .TITLE  OTPT.MAC
        .MCALL  .LOOKUP,.READW,.EXIT

OTPT::  .LOOKUP #AREA,#1,#FILE
        .READW  #AREA,#1,#RNUM,#300.,#0
        MOV     #LVLS,R0
        MOV     #0222,(R0)+                 ;SET OUTPUT LEVELS
        MOV     #1654,(R0)+                 ;WITH 0060 CORRESPONDING TO THE
        MOV     #4141,(R0)+                 ;LOWEST LEVEL AND 7720 TO THE
        MOV     #5574,(R0)+                 ;HIGHEST.
        MOV     #7544,(R0)

        MOV     #RNUM,R0                    ;RNUM IS THE FIRST ADRESS OF
        MOV     #300.,R3                    ;SERIES OF RANDOM NUMBERS
LOOP:   MOV     (R0)+,R1                    ;USED TO GENERATE AN OUTPUT
                                            ;LEVEL.
        ASH     #1,R1                       ;R1 CONTAINS A # BETWEEN 0 AND
        MOV     #LVLS,R2                    ;8. THIS IS ADDED TO LVLS TO
        ADD     R1,R2                       ;CREATE THE ADDRESS OF AN
        MOV     (R2),R1                     ;OUTPUT LEVEL.
        MOV     R1,@#170440                 ;MOVE THE OUTPUT VALUE TO O/P
        MOV     #127000,R1                  ;BUFFER. DELAY.
LOOP1:  NOP
        NOP
        NOP
        NOP
        SOB     R1,LOOP1
        SOB     R3,LOOP                     ;DO IT AGAIN.

        .EXIT
AREA:   .BLKW   5                           ;SCRATCHPAD
FILE:   .RAD50  /DK FTN11 DAT/              ;FILE CONTAINING RANDOM #'S
LVLS:   .BLKW   5                           ;OUTPUT LEVELS
RNUM:   .BLKW   300.                        ;START OF RANDOM #'S
        .END    OTPT
```

A.7 EXTERNALLY STARTED A/D SAMPLING PROGRAM (EXSTR)

EXSTR is the program that samples the EMG and target level data, converts it to digital form and writes the data onto disk under a previously entered file name. Program written in MACRO on a DEC LSI-11.

```
          .TITLE    EXSTR.MAC
          .MCALL    .ENTER,.LOOKUP,.READW,.WRITW,.CLOSE,.EXIT
EXSTR::   .LOOKUP   #AREA,#0,#FILE
          .READW    #AREA,#0,#NAME1,#8.,#0
          .ENTER    #AREA,#1,#NAME1,#80.
          .ENTER    #AREA,#2,#NAME2,#20.
          CLR       @ADSR
          MOV       #TABLE,R0          ;SET UP R0 AND R2 WITH THE
          MOV       #PAD,R2            ;LOCATIONS OF ALLOCATED SPACE
          MOV       #5000.,R1          ;LOAD R1 WITH NUMBER OF SAMPLES
LOOP:     MOV       #4,R3              ;TO BE TAKEN AND SET UP R3 SO
LOOP1:    MOV       #20,@ADSR          ;**THAT EVERY 5TH SAMPLE IS A
LOOP2:    BIT       #200,@ADSR         ;LEVEL SAMPLE.
          BEQ       LOOP2
          MOV       #400,@ADSR         ;*****
          MOV       @ADBR,(R0)+        ;MOVE SAMPLE TO SPACE TABLE
          SOB       R3,LOOP1           ;HAVE 4 SAMPLES BEEN TAKEN?
          INC       @ADSR
LOOP3:    BIT       #200,@ADSR
          BEQ       LOOP3              ;AND STORE IT IN PAD.
          MOV       @ADBR,(R2)          SOB        R1,LOOP
          .WRITW    #AREA,#1,#TABLE,#20000.,#0
          .WRITW    #AREA,#2,#PAD,#5000.,#0
          .CLOSE    #1
          .CLOSE    #2
          .CLOSE    #0
          .EXIT
ADSR:     170400
ADBR:     170402
AREA:     .BLKW     5
FILE:     .RAD50    /DK FTN32 DAT/     ;FILE CONTAINING THE FILE NAMES
NAME1:    .BLKW     4
NAME2:    .BLKW     4
TABLE:    .BLKW     20000.             ;SPACE FOR EMG SAMPLES.
PAD:      .BLKW     5000.              ;SPACE FOR LEVEL SAMPLES.
          .END      EXSTR
```

A.8 FILE NAME ACQUIRING PROGRAM (FLNAME)

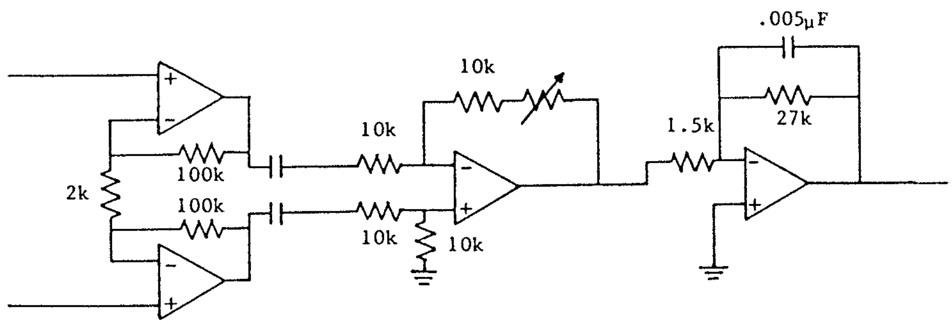
FLNAME acquires a file name for each subject and each tracking run and places it in a file (FTN32.DAT) where the name can be accessed by EXSTR. Program written in FORTRAN on a DEC LSI-11.

```
        INTEGER Q,V,I,J,K
        DOUBLE PRECISION SUM1,SUM2,SUM3,SUM4
        LOGICAL*1 FILE(14),RAD(14),RADL(14)
        REAL*4 NAME1,NAME2,NAME3,NAME4
C
C       DEFINE I/O CHANNELS USED
C
5       DEFINE FILE 32 (1,40,U,Q)
        DEFINE FILE 22 (1,12,U,V)
C
C       CLEAR FILE NAMES
C
        DO 110,K=1,14
        FILE(K)=' '
        RAD(K)=' '
        RADL(K)=' '
110     CONTINUE
C
C       READ IN THE FILE NAME TO WHICH THE DATA IS TO GO
C
        WRITE (7,10)
10      FORMAT (' ENTER FILE NAME')
        READ (7,20)(FILE(I),I=1,14)
20      FORMAT (14A1)
        I=1
C
C       GENERATE THE RAD50 NAME CORRESPONDING
C
30      IF(FILE(3).NE.':'.AND.FILE(4).NE.':')GO TO 5
        IF(FILE(I).EQ.':')GO TO 40
        RAD(I)=FILE(I)
        RADL(I)=FILE(I)
        I=I+1
        GO TO 30
C
40      J=4
        I=I+1
50      IF(FILE(I).EQ.'.')GO TO 70
        RAD(J)=FILE(I)
        RADL(J)=FILE(I)
        I=I+1
        J=J+1
        GO TO 50
        K=1
C
70      RADL(J-1)='L'
        DO 80,K=1,3
        RAD(9+K)=FILE(I+K)
        RADL(9+K)=FILE(I+K)
80      CONTINUE
C
        K=1
C
C       WRITE RAD TO A DISK AND READ IT BACK AS SUM1/2
C
        WRITE (22'1) (RAD(K),K=1,6)
        READ (22'1) SUM1
        WRITE (22'1) (RAD(K),K=7,12)
        READ (22'1) SUM2
        WRITE (22'1) (RADL(K),K=1,6)
        READ (22'1) SUM3
        WRITE (22'1) (RADL(K),K=7,12)
        READ (22'1) SUM4
C
C       CONVERT TO RAD50 REPRESENTATION
C
```

```
      NAME1=RAD50(SUM1)
      NAME2=RAD50(SUM2)
      NAME3=RAD50(SUM3)
      NAME4=RAD50(SUM4)
C
C     WRITE THE NAME TO A DISK AND CLOSE THE I/O CHANNELS
C
      WRITE (32'1) NAME1,NAME2,NAME3,NAME4
      CLOSE (UNIT=32)
      CLOSE (UNIT=22)
C
C
60    STOP
      END
```

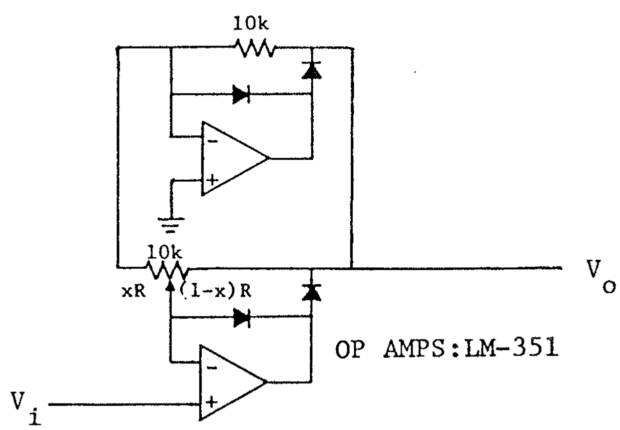
Appendix B

SCHEMATIC DIAGRAMS



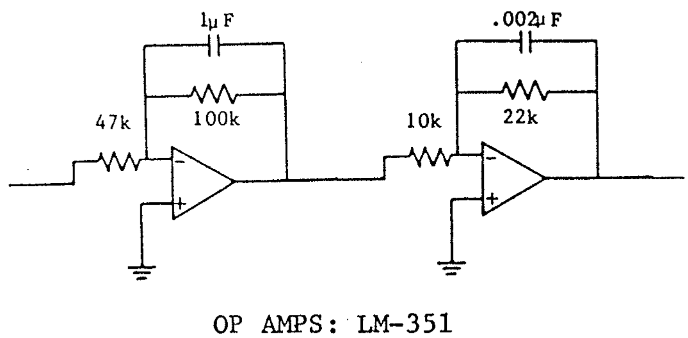
OP AMPS: PMI OP-07

Instrumentation Amplifier: Gain=2100

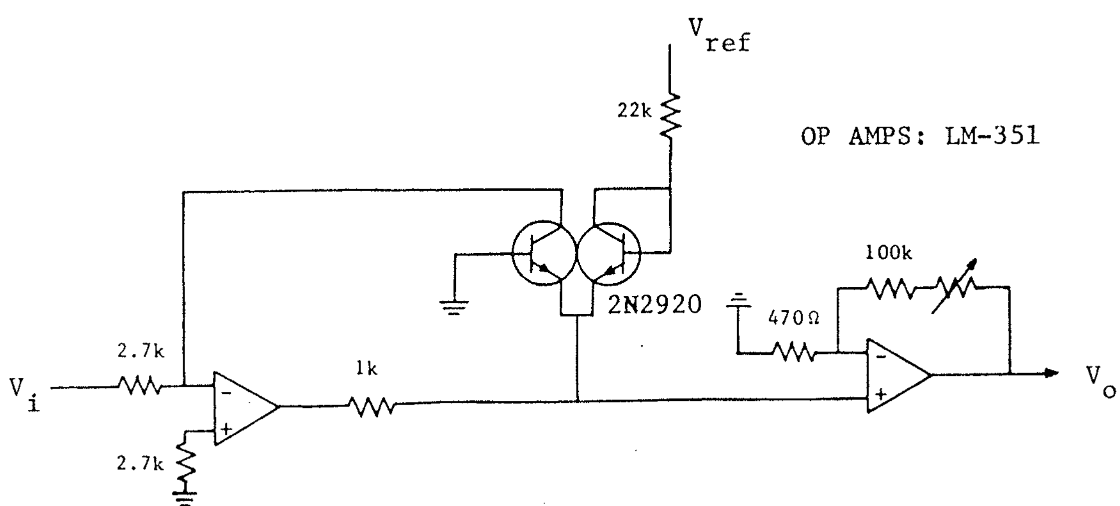


OP AMPS:LM-351

Active Rectifier: $V_o = \frac{|V_i|}{x}$

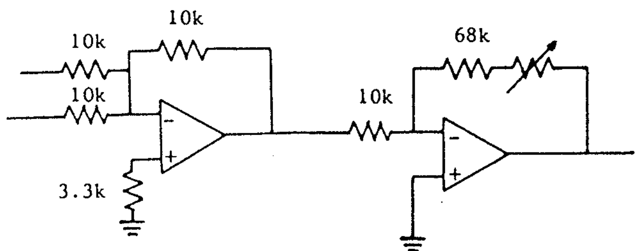


Low-pass filter: τ = 100 msec



Logarithmic Amplifier: $V_o = 5.1 \ln (V_i)$

OP AMPS: LM-351



Summing and final output amplifier: Gain = 6.5