MASSACHUSETTS INSTITUTE OF TECHNOLOGY

INVESTIGATION OF PILOT'S ROLE AND DISPLAY REQUIREMENTS IN AUTOMATIC LANDINGS

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PROGRESS REPORT

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Renwick E. Curry

Principal Investigator

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PART I

I. INTRODUCTION

This part of the progress report describes the work done under the grant by the principal investigator while in residence at the Man Machine Integration Branch, NASA-Ames Research Center. It can only be described as a most successful year and by all measures fulfills the intent of the exchange agreement. The exposure to new ideas, different approaches, and the many and varied projects was an enriching experience.

Two experimental capabilities were developed on the PDP-12 computers located in the MMIB at NASA because of the uncertainty as to the status of the SEL 840/E&S Graphics systems throughout the year. The first of these was an experimental monitor to perform experiments in the psychophysics of visual target motion prediction, discrimination, etc., and exercises the (limited) graphical capabilities of the PDP-12. The original monitor (programmed by PMI) was modified by Professor Curry and Dr. Nagel to include the capability of handling more than 64 stimuli without reinitializing the program, and is being used in the experiment described in Section II. The second experimental monitor was programmed entirely by the principal investigator and was used to investigate pilot decisions in low visibility approaches. The details of this experimental capability, which has great potential for exploring decisions and behavior, is described in detail in Section III.

Other accomplishments during the residence at Ames consisted of new analytical results in the modelling of choice behavior, results concerning uniqueness of parameter estimates in psychophysical models, the development of two computer programs (one with applicability in behavioral research, the other a general parameter optimization algorithm specifically designed for small computer applications e.g. the MMIB PDP-12).

II. MONITOR FOR THE PDP-12 CRT DISPLAY

Midway through the year of residence at Ames, preparations were initiated to perform an experimental investigation of trajectory perception and prediction, with the dual purpose of developing dynamic perceptual models and determining the essential elements in traffic situation displays. Because of the unreliability of the SEL 840 at that time, the decision was made to perform these experiments on the PDP-12. The programming staff of PMI was given the task of developing an experimental monitor to meet these criteria, and work was begun in January. This was the first use of the automatic priority interupt capability on the PDP-12, and progress was slow; the monitor was not finished until April. By this time our original experimental goal had to be modified because of the schedule slippage and the results we had developed for the decision behavior with multiple signal strengths (see Section IV below). The experimental monitor developed by PMI is quite flexible, and the complex stimulus control and response logic have been debugged by PMI. The principal investigator and Dr. Nagel subsequently modified the monitor (to provide for more than 64 stimuli and to allow a wait interval between each stimulus presentation) to perform the experiments described below.

The data in our paper are very well described by a model which assumes that subjects make decisions based on a subjective

Neyman Pearson criterion. An alternative explanation was that decisions are made on the basis of maximizing expected value and that the utilities were changing with distance from the collision point (in violation of the subjectively expected utility (SEU) model). In the paper, we gave several arguments in favor of the subjective Neyman Pearson model as opposed to the break down of the SEU model, but there have been no experiments performed on the SEU model in a similar setting to our knowledge. In fact, although choice behavior has been modified by manipulating the payoffs in the two by two stimulus response matrix of the conventional signal detection paradigm, no one has actually measured the utilities making up the decisions in such a setting.

To examine this and other display related aspects of the experimental situation (a target approaching one's own aircraft on a near collision course), we set the following objectives for the experiments

- To measure utilities in a signal detection situation
- To determine if utility varies with distance from collision (positive results will support the breakdown of the SEU model in our previous experiments - negative results will support the subjective Neyman-Pearson criterion)
- Evaluate the influence of instruction on utilities
- Gain experience in the measurement of utilities

From our previous experiments with this type of display, we know that the sensitivity (signal-to noise ratio, or d') varies as d_0/L, where d_0 is the miss distance on the display, and L is the target distance from one's own aircraft symbol on the display. We have arranged a set of stimuli to vary distance and d' in a factorial manner, and will thus be able to ascertain whether or not there is an interaction between subjective probabilities and untilities (distance). We plan to evaluate the effect of instructions of utilities by dividing the subjects into two groups: one group (control group) will be instructed that the experiments are basic research in psychology; they will be asked to extrapolate a line between two points. The second group (experimental group) will be informed that the experiment is related to traffic situation displays and anti-collision displays for pilots, and that they are to place themselves in the position of a pilot who must determine whether the intruding aircraft will pass to the left or the right.

The last objective is to gain experience in the measurement of utilities. In the current experiments, we are using the method of selling lotteries (i.e., how much will the subject be willing to accept instead of having to play the gamble of whether he was right or wrong in his guess); this is a non-trivial concept to transfer to the subject. In the experiments described in the next section (decisions in low visibility approaches) we are attempting to measure utilities by behavioral response; the relative merits of the two methods will be compared at the termination of the experiments.

In addition to the experimental monitor written by PMI, the principal investigator wrote auxilliary computer programs to provide a rapid evaluation of each subject's performance. One program is used to generate the pseudorandom stimuli upon which all subjects will be tested. Immediately after the session, the subject's responses (previously stored by the experimental monitor) are read by a program which sifts through the responses to retain only those which are appropriate. At the same time, these responses and the subject's "bets" are printed out so that they may be used in the latter stages of the experiment when the subject must either play his bet or accept the offering price. With the help of Dr. Nagel, a third program was written to generate an immediate indication of the subject's sensitivity (d') on each of the stimulus classes, and simultaneously calculate the criterion level used by the subjects (in log likelihood ratio units).

At the time this report is being written, the pilot subjects are being run to insure a smooth running experiment. The subjects for the data runs will be started within a week or two.

III. DECISION MAKING IN LOW VISIBILITY APPROACHES

In an effort which is complimentary to that of Dr. Billings and Dr. Lauber of the MMIB, the principal investigator developed and programmed a simulation which abstracts the essential elements in a decision making task during a low visibility approach. The purpose of this experimental monitor was to develop the capability to examine the effects of various parameters on decision making with a system that would be flexible and responsive to changing needs. This facility allows the preliminary examination of experimental protocols and other techniques before committing expensive simulator time, especially that of the airlines. In addition, it allows us to examine and explore methods of applying psychological stress, a major goal in our first set of experiments.

A schematic of the apparatus as seen by the pilot-subject is shown in Figure 1. The buttons available to the subject are RVR (to request an RVR reading), turn rate buttons (left, 0, or right) and GA, the go around button to initiate a missed approach.

In the central portion of the CRT is a plan view of the approach. In the lower part of the screen are three dots corresponding to the position of the approaching aircraft (present position, position one second ago, and position 5 seconds ago). In the center of the screen are two pairs of dots corresponding to the middle marker location, equivalent to the 200 foot decision height for a category I approach. Farther up the screen are the runway outline,threshold, and three pairs of approach lights or lead-in lights. Above that are scores posted for the results of any one trial: on this approach the subject would receive 100 points for a safe landing, and -40 points for a missed approach. On the left of the screen is a RVR scale with two indices corresponding to 0 RVR and that for the legal minimum (2400 feet). On the right side of the screen is an altimeter which has a dynamic range of 0 to 220 feet. The pointer indicating altitude is pegged at the upper right until the aircraft nears the middle marker; as the aircraft passes through the middle marker, the indicated altitude passes through 200 feet.

A random wind disturbance from the side (correlation time of 50 seconds) is introduced to provide a moderately-easy control task for the pilot. Control is maintained by pushing one of the three turn-rate buttons. The aircraft has the capability of being in either the 0 turn rate (constant heading) or a standard turn rate to the left or the right. The pilot's task in

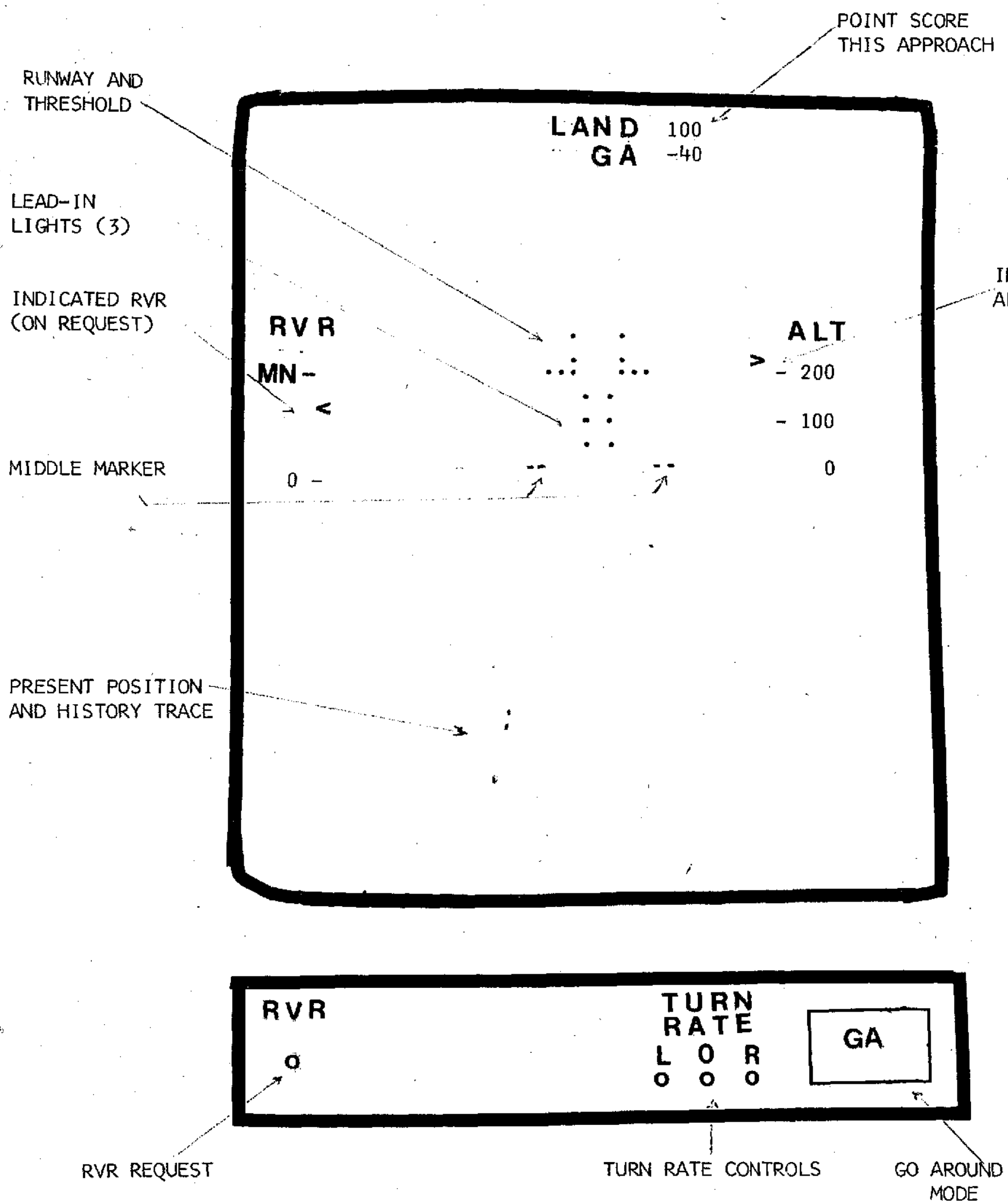


FIGURE 1. SCHEMATIC OF LOW VISIBILITY APPROACH DISPLAY AND CONTROLS

these approaches is to "fly" the aircraft through the middle marker, over the approach lights, and on to the runway. (The aircraft's position shown in Figure 1 is close to the initial condition point.) Only lateral position is important, for if the pilot crosses the extended threshold line but is not over the runway a crash is recorded. If at any time before the aircraft crosses the extended threshold line, the pilot hits the go-around button, a standard rate left turn is initiated until the heading reaches 60° from "North" at which time the computer program assumes that a missed approach was made.

The runway and approach lights may appear either to the right or left of the middle marker center line, and may be closer or farther away than the nominal position to represent electronic guidance errors. This is the appropriate aircraft-centered view, and simulates the case when one is flying the ILS with needles exactly centered but finds the runway to the left (or right) when break-out occurs, and the case when one is either high (or low) of the indicated altitude.

The slant range "visibility" is included in the program, even though the intensity in the CRT has only two values (off, on). There are 5 "characters" drawn by the PDP-12 graphic system which are under visibility control: the three pairs of lead-in lights, and the right and left halves of the runway/threshold lights. Should the center of any of these five characters be within a square (centered at the aircraft position) whose half-width is the slant range visibility, then this character will be turned "on" and will be visible. The approach lights are turned off as one gets close to each pair, to simulate their passing underneath the nose of the airplane; this also prevents the subject from obtaining additional unrealistic lateral guidance information.

A computer program was written to generate files of approach trajectories and currently has a catalog of nine approach trajectories. Five of these trajectories have constant (but different) slant range visibilities leading to the following effect: when the middle marker is passed, nothing is in view; soon the first approach light appears, followed by the second and then the third; as the first approach light is neared, it disappears (passes underneath), and then the runway/threshold lights suddenly appear and a safe landing can be accomplished. The decreasing slant range visibility in this group of five trajectories is such that one must proceed farther and farther beyond the middle marker (or below decision height) before the first approach light is sighted. The fifth of these five trajectories is zero-zero visibility, so the approach lights and runway/threshold lights never appear. The other four trajectories correspond to

(1) a high visibility approach (runway and approach lights are visible as shown in Figure 1 at all times)

(2) an extremely optimistic RVR reading, but very low slant range visibility

(3) passing through a fog bank after initial acquisition of the approach lights: the approach lights and runway lights "drop out", only to reappear after three to four seconds

(4) fog bank as in (3), but the approach and runway lights do not reappear.

First Experiment

In the first set of experiments, performed with the help of Dr. John Lauber, we had the following objectives:

1. To structure the experimental setting to make the pilot as aversive to a crash in the simulator as he would be in real life.
2. To alter the decision strategies by manipulating the relative values of a landing and a missed approach.

The first objective was desirable to make the decisions as meaningful as possible. After "sacrificing" several pilots, we finally arrived at the following procedure.

As the subject is led into the experimental chamber he is shown a poster-sized list on the wall of people who have previously been subjects in the experiment. Each subject is listed by name, organization, and score (the total number of points accumulated over the 50 data trials). The first subject on the list was a fictitious one (in this case), and in place of his point score was the word CRASHED in bright red letters. The experimenter writes in the subject's name and organization (e.g. Joe Jones, TWA) and leaves the score column blank. The subject is told at that time that should he crash during the data trials, even if on the first data trial, his services are no longer required. That is, in terms of the experiment, he is "dead".

It was obvious to the subject at this point that he was committed to follow through the experiment, and the idea that he might crash and have that event recorded for all to see had a very noticeable effect on almost all subjects.

Preliminary Results

This is a preliminary report on the results of the experiment, a summary of the responses to the questionaire. A detailed examination of the decisions in the trials themselves will be reported on at a later date.

Thirteen pilot subjects participated in the test and completed a questionnaire, but as the simulation was changed after the first three pilots, they were not included in the data regarding the simulation itself. Of the remaining 10 subjects, 6 are airline pilots and 2 are IFR rated NASA employees.

The questionaire consisted of 3 major parts: recent experience in low visibility approaches and missed approaches; fidelity of the decision simulation; and stress ratings for actual low visibility approaches and the simulation. The questionaire is shown in Table I.

Recent Experience - Of the 11 pilots completing the questionaire, 7 had made a total of 37 category I approaches within the last 12 months (six of these 37 approaches were military approaches). Only 2 missed approaches were made by these 7 pilots. When asked what were the most common causes for executing a missed approach, (based on their experience), the 3 most frequently mentioned items were

runway alighment/crosswinds	7 times
visibility	5 times
other traffic	3 times

Simulation Fidelity - The subjects were asked to comment via the questionaire about the simulator fidelity only with respect to the decision of whether or not to continue an approach. This was

Name: ______________________ Date: ______________

Position: Capt. / F.O. / S.O. ______ Cat. II Qualified? Yes / No

Equipment Currnetly Flying: ______________ Company: ______________

During the last 12 months, how many approaches have you flown when reported visibility was at or very near Cat. I minimums?

As Pilot: ________ Date of most recent: ________

As Copilot: ________ Date of most recent: ________

During the last 12 months, how many missed approaches have you flown?

As Pilot: ________ Date of most recent: ________

As Copilot: ________ Date of most recent: ________

Judging from your own experience, what is the most likely reason for executing a missed approach?

Considering only the task of deciding whether to continue an approach or to go around, how similar is the experimental task you just flew to an actual approach? Mark the line below to indicate your best estimate.

Totally Unlike										Completely Identical
0	1	2	3	4	5	6	7	8	9	10

Still considering only the task of deciding whether to continue an approach or to go around, what in your opinion are the major similarities or dissimilarities between the experimental task and an actual low visibility approach?

How stressful do you find actual low visibility approaches to be?

Not at all Stressful										Extremely Stressful
0	1	2	3	4	5	6	7	8	9	10

How stressful did you find the experimental task to be?

Not at all Stressful										Extremely Stressful
0	1	2	3	4	5	6	7	8	9	10

Table I. Pilot Questionnaire for Low Visibility Decision Simulation done both on a semantic differential scale (Totally Unlike - Completely Identical) and by soliciting comments on the similarities and dissimilarities of the simulation to an actual low visibility approach. The ratings of the subjects are shown in Table II where it is seen that the mean fidelity rating is 5.2 with a standard deviation of 1.87, indicating the usual dispersion in intersubject ratings.

Comments on the similarities of the simulation to a low visibility approach detailed the assimilation of information through different sources (RVR, altitude, and runway alignment). When commenting on the dissimilarities, 3 pilots mentioned the lack of danger ("one will not die if you miss", "...lacks the element of danger"). Two of the pilots mentioned that in a real approach more reliance would be placed on decision height, i.e., that is a cut and dried decision (a go, no-go situation). Another commented that he felt the reward structure was not correct because in actual flight the rewards for going below minima may be the loss of job, etc, whereas reward here is a higher point count.

There were other comments made about dissimilarites of the simulator and the actual approach: three pilots mentioned that the visual cues were different, and one pilot mentioned the fixed turn rate characteristics of the simulator. These were offered even though the question asked specifically about the similarities of decision making; either the questions were misunderstood or these factors really do influence the decision. In either case we feel that these latter two factors are of secondary importance in

Subject/ Organiza-tion	Simulator Fidelity Rating	Stress Rating -Actual Approach	Stess Rating Simulator	$S_{SIM}-S_{ACT}$	$\frac{S_{SIM}}{S_{ACT}}$
1/A	7	3	2	-1	.67
2/B	7	4	6	2	1.50
3/C	3	7	3	-4	.43
4/B	3	8	5	-3	.62
5/B	7	8	6*	-2	.75
6/A	4	7	2	-5	.28
7/A	7	6	6	0	1.00
8/C	6.5	5.5	5.5	0	1.00
9/D	2.8	7	4	-3	.57
10/D	5	8	6.5	-1.5	.81
Mean	5.23	6.35	4.60	-1.75	.763
S.D.	1.87	1.73	1.73	2.01	.344

*Indicated a change to 2 later in the trials

TABLE II Semantic Differential Ratings of Simulator Fidelity and Stress the light of the other dissimilarities mentioned by the pilots.

Stress Ratings - The pilots were asked to rate the stress of the experimental task and an actual low visibility approach on a semantic differential scale (Not At All Stressful - Extremely Stressful); the results are shown in the other columns of Table II. We have added columns showing the difference in stress rating, and the simulator stress (rating) as a fraction of the actual stress (rating). Of these 10 subjects, three felt that the simulator was at least as stressful as an actual low visibility approach. At the other extreme, is subject number 6 who reported the simulator "lacks the element of danger".

Discussion

We are very encouraged by our first attempt at inducing stress analogous to actual flight results, although improvements can be made. It is apparent that some people are not as influenced by the potential embarassment or "failure" as we had hoped, and another stressor will be required.

One unexpected factor emerging from these experiments is the possible existence of airline differences. Subject no. 2 felt that an actual low visibility approach is a cut and dried decision because of the reliance on decision height. He also indicated higher stress in the simulator than in the actual low visibility approach, presumably because of the lack of a well-defined, externally imposed decision criterion. Subject 5 who talked about the different reward structure in an actual approach (loss of job, etc) flies for the same airline (Airline B). Discussions with these individuals indicated that the policy of that particular airline was to observe decision height as a hard and fast rule; descent below decision height was to be done under only the most extreme circumstances. In conversation with pilots from other airlines we found the interpretation of the decision height to be less strict.

Although these behavioral data are not sufficient to infer the existence of differences in airline operating criteria, or differences in an interpretation by the airline's pilots, they suggest that such differences may exist, differences (real or imagined) which are perceived by some pilots.

IV. DECISION BEHAVIOR WITH RANDOMLY VARYING SIGNAL STRENGTHS

One of the major thrusts of the research under this grant has been the description and modelling of decision behavior with time varying psychophysical stimuli. Our approach has been the extension of sensory-continuum models from random variables (eg. auditory detection) to random processes. The results of these investigations will have applications not only to information and display interpretation, but to simulator evaluation as well. Interestingly enough, this topic has received very little attention in the literature, and we feel that our results are of major importance in these areas of application. The principal investigator developed a model for the description of some of our earlier data, and in collaboration with Dr. David Nagel of the MMIB and Mr. Gai of MIT, wrote a paper on our findings. The abstract of this paper, (submitted to the Journal of Mathematical Psychology), is reprinted below.

DECISION BEHAVIOR WITH CHANGING SIGNAL STRENGTH

Abstract

The Theory of Signal Detectability (TSD) has nearly replaced classical notions of the threshold because of its ability to separate sensory and decision processes in weak signal detection and recognition paradigms. The primary emphasis of recent work has concentrated on the sensory rather than the decision aspects and almost all work has been exclusively at one signal strength. We propose a model to describe behavior at different signal strengths based on subjective rather than objective distributions. The model predicts ensemble performance at a constant objective likelihood ratio (LR) criterion (even though subjective distributions are the basis for determining cutoff criteria) unless the observer adopts a subjective Neyman-Pearson objective. Results from an experiment in visual discrimination show that some observers in fact operate at a constant objective LR's as signal strength is varied randomly over a wide range. The objective LR's of the other subjects changed dramatically with signal strength, but this behavior is consistent with the use of a subjective Neyman-Pearson decision rule and the linear relation between subjective and objective log LR's found in studies of subjective probability.

V. MUNOML - A MULTINOMIAL MAXIMUM LIKELIHOOD PROGRAM FOR BEHAVIORAL RESEARCH

Much of the data taken in behavioral research is grouped data, that is, responses are grouped into categories (e.g., the familiar stimulus-response matrix). When developing models to explain these data, one must develop analytical expressions which are theoretical predictions for these probabilities. During the tenure at NASA Ames, the principal investigator developed a very general "executive" program to perform maximum likelihood estimation of the parameters imbedded in the theoretical probabilities. The program derives its generality from the fact that only the theoretical probabilities $P_{ij}(x)$ and the partial derivatives $\partial P_{ij}/\partial x_k$ are required for the iteration process, and these are provided by a user-supplied subroutine. The introduction and summary of a paper prepared for publication (and NASA CR) which describes the program in detail is provided below.

MUNOML: A MULTINOMIAL MAXIMUM LIKELIHOOD PROGRAM FOR BEHAVIORAL RESEARCH

Introduction and Summary

In our research on modelling sensory and decision phenomena we were soon confronted with the task of evaluating both old and new models using both old and new data. Rather than design an ad hoc estimation program for each new model, as is typically done, we developed an "executive" program which provides a general method for estimating parameters and simultaneously provides flexibility for accomodating new models with a minimum amount of programming. Our experience with canned computer programs has been equivocal, so we decided to provide only the general framework and let the user accomplish the objectives of estimating parameters for his particular model by writing a new subroutine within the constraints of the executive program. In this paper we report on the method of and our experience with MUNOML, an executive program for Multinomial Maximum Likelihood Estimation.

The most common class of distributions for which parameters must be extracted are multinomial distributions resulting from a stimulus-response classificiation, e.g. binary responses (YES-NO or two alternative forced choice methods), the method of successive categories (rating scales) or transition probabilities in a Markov chain. Although a number of methods exist for estimating such parameters (Restle, 1971) we have chosen the Maximum Likelihood method and have implemented the scoring of Rao to adjust the parameters from one iteration to the next. We have chosen the Maximum Likelihood (ML) method because (1) it is a member of the class of consistent asymptotically normal estimators (CAN); (2) it will easily handle situations in which all the responses fall into one category; (3) there are many situations in which the Maximum Likelihood estimator can be shown to yield unique estimates for parameters (but, see Curry, 1974a, where it is shown that other estimation techniques may have this property as well); and (4) it is the only one exhibiting first order efficiency (Rao, 1973).

The remainder of this paper is organized as follows: in the next section, we present the theoretical basis for the program, i.e. the most general functions that can be performed by MUNOML, the executive program. In Section III, we develop the expressions for some specific behavioral models in Signal Detection/Recognition, and in Section IV we briefly describe MUNOML and the method of operation. Section V discusses some conclusions based on our experience with MUNOML and addresses the problem of storage-limited applications. The Appendices contain a FORTRAN IV listing of MUNOML, a listing of the subroutine to obtain parameter estimates for the method of successive categories, and an index of program variables for MUNOML.

VI. A RANDOM SEARCH PROGRAM FOR LABORATORY COMPUTERS

Another program developed under the grant has wide application to small laboratory computers such as the PDP-12, in the MMIB. The algorithm takes advantage of the assets of the small computer: data compatibility, low operating costs, computer availability, and is an easy-to-use program for parameter estimation, model fitting, curve fitting, generalized least squares, etc. It should find wide usage among investigators using small computers. The abstract of a paper describing the algorithm is presented below.

A RANDOM SEARCH ALGORITHM FOR LABORATORY COMPUTERS

Abstract

The small laboratory computer is ideal for experimental control and data acquisition. Post experimental data processing is many times performed on large computers because of the availability of sophisticated programs, but costs and data compatibility are negative factors. Parameter optimization, which subsumes curve fitting, model fitting, parameter estimation, least squares, etc., can be accomplished on the small computer and offers ease of programming, data compatibility and low cost as attractive features. A previously proposed random search algorithm ("random creep") was found to be very slow in convergence. We present a new method (the "random leap" algorithm) which starts in a global search mode and automatically adjusts step size to speed convergence. A FORTRAN executive program for the random leap algorithm is presented which calls a user-supplied function subroutine. An example of a function subroutine is given which calculates Maximum Likelihood Estimates of Receiver Operating Characteristics parameters from binary-response data. Other applications in parameter estimation, generalized least squares, and matrix inversion are discussed.

VII. SUFFICIENT CONDITIONS FOR THE UNIQUENESS OF PARAMETER ESTIMATES IN BEHAVIORAL MODELS

The estimation of parameters in behavioral models (or any model) to fit experimental data is done by the minimization or maximization of statistically meaningful criterion function.

Constituents of this function are the experimental data; assumptions concerning the underlying distributions; the form of the model; and the form of the criterion function (Maximum Likelihood, etc.). When minimizing (or maximizing) a function of parameters, one must always be concerned with the global aspects of the solution, i.e., has one found a set of parameters which yields the global extremum? There have been many instances where one has found a "molehill" without realizing that a "mountain" is nearby. We have examined a very wide range of behavioral models and parameter estimation criteria and have determined a practical set of sufficient conditions which will insure the resulting parameter estimates are unique regardless of the observations i.e., that there are no other values to the parameters which yield a local extremum of the criterion function, hence the local extremum is a global extremum. The abstract of the paper describing these results is presented below.

SUFFICIENT CONDITIONS FOR THE UNIQUENESS OF PARAMETER ESTIMATES FROM BINARY-RESPONSE DATA

Abstract

The proceedure of fitting parameterized models to experimental data is that of extrematizing a statistically meaningful scalar-valued vector function. The existence of multiple local extrema can greatly complicate the search for the global solution. Sufficient conditions for uniqueness of the parameter estimate are usually determined from the convexity of the criterion surface: the convexity properties are determined by the statistical criterion, the structure of the model, the underlying distribution, and the observations (data). In this paper we seek the combinations of criteria, models and distributions which yield sufficient conditions for unique parameter estimates regardless of the observed binary-response data values.

Under mild sufficient conditions usually satisfied in practice, the Maximum Likelihood, Minimum Chi Square, and Minimum Transform Chi Square criteria are convex functions when the parameters appear linearly. These results are applied to equal-variance models of signal detection/recognition, sequential response, and additive learning models with implications on the experimental design. Unequal-variance models and models of discrete-sensory processing (rectilinear ROC Curves) lead to nonconvex criteria for some observations (saddle-points are demonstrated). Although convexity cannot be assured for these cases, the results suggest an efficient search procedure in a lower dimensional subspace to find global extrema. The extension of these results to more than two response levels is discussed.

PART II

This portion of the report describes the work accomplished at MIT during the reporting period.

VIII. PSYCHOPHYSICAL MODELS OF SIGNAL DETECTION WITH TIME VARYING UNCERTAINTY

Introduction

Signal detection theory has been extensively used in the last two decades by psychophysicists for the study of perception and cognition (Swets 1973). The principal appeal of the theory is its ability to separate the detection process into its two components, namely the sensory process and the decision strategy. However these two processes have not received equal attention, since most of the published work concentrates on the analysis of the sensory processes, (Green and Swets 1966). There are, though, many detection processes in which the decision strategy is at least as important as the sensory process e.g. when determining percent correct. In those cases, the most important question to be answered concerns the way in which the decision maker changes his criteria when the signal strength changes. Therefore in order to analyze decision strategies one has to contend with detection processes in which the signal strength (detectability, signal to noise ratio, uncertainty) is time varying.

Two examples of such detection problems will be discussed. The first one is a pilot using a traffic situation display to avoid collisions with intruders in his airspace. The second deals with pilot monitoring of an automatic landing system. In both these cases the detection task becomes easier as the distance to the target decreases, thus the signal strength can be considered as time varying.

Since little prior work had been done in this class of detection problems, some preliminary experiments were necessary. A visual discrimination experiment was designed in which the signal strength was changed randomly to avoid correlation between succesive decisions (Curry 1973). The main conclusion that was drawn from these results is that the decision maker changed his threshold with the change in the signal strength. This conclusion could not be predicted on the basis of classical SDT results, although similar results were reported (but not discussed) by Kinchla and Smyzer (1967). Several decision rules that might explain the relationship between the threshold and the detectability were suggested. These include the Neyman Pearson (N.P.) decision strategy, and the linear relation between threshold and detectability (Gai and Curry 1973) as well as the modified N.P. strategy with subjective rather than objective probabilities (Curry et al 1974).

After obtaining ideas about the decision strategies that might be used by human observers, we applied our concepts to more realistic situations. Two types of such situations were considered: in the first, we studied the effect of correlation between successive discrete decisions when the signal strength was changed in a sequential (not random) manner, in the second, we dealt with the detection of a change in the mean of a stationary continuous stochastic process. The work on these two problems, which will be described in more detail in the next sections, was the main effort during the last year.

<u>Sequential change of signal strength in signal detection tasks</u>

In our basic experiments one of the experimental design goals was to change the signal strength so that the subject's decisions in successive decision intervals would tend toward statistical independence. However, in many real-life situations the signal strength does not change in a random way, so that a correlation between successive decisions is almost inevitable. This raises the question as to whether the correlation in signal strength changes the performance of the subjects, and if so, in which direction? The use of SDT is particularly helpful because it can separate the effect of the correlation on the sensory process and the decision strategy, and thereby simplify the analysis.

There are many possible ways of changing the signal strength in a correlated manner. The method that we chose (referred to as a "sequential" change) is related to the problem of avoiding collisions. If two airplanes are flying in linear motion with constant velocity, the distance between them changes linearly with time. If in addition one of the pilots is using a Traffic Situation Display, which is updated by radar (once per 4 seconds), then the position of the intruder changes linearly on the display, and the state of the world (closest approach, either inside or outside the miss-distance circle) is the same for all decision intervals. Therefore we define "sequential" presentation as follows: The input data is presented to the subjects in blocks, each one of these blocks contains a fixed number of decision intervals, with the following characteristics:

1. The true state of the world is the same for all the decision intervals within the same block.
2. The signal strength in each interval in the block is constant, but is increasing from one interval to the next.

3. There are no blanking periods between intervals.

By letting the subjects make decisions in two similar tasks, one in which the signal strength is correlated, and one in which the signal strength is random, we analyzed the effect of the signal correlation alone. The results showed that there was a significant difference in the overall behavior of the subjects. However, the statistical test showed that there was no significant difference in the sensory sensitivity, i.e. the hypothesis that the detectability d' was the same for both presentations could not be rejected. This means that almost all differences in behavior are due to changes in the decision strategy.

In order to analyze these changes in the decision strategy, we used a Markov model, in which we assumed that the current decision is dependent only on the previous decision (but not on the state of the world, or the signal strength). The transition probability matrices based on this model, showed a strong tendency of the subjects to repeat their previous decisions even in those cases in which their decisions were incorrect in the previous interval. Therefore the Decision Rule (DR) curves for the random and sequential signals were totally different as can be seen in Figures 2 and 3. In the framework of classical SDT these results show an over confident behavior, in which the subject moves his criterion in such a way as to increase his probability of hit and therefore increases his probability of false alarm. The manner in which he does this depends on the decision rule that he is using. If he is using a constant likelihood ratio decision rule, he increases the apriori probability of that state of the

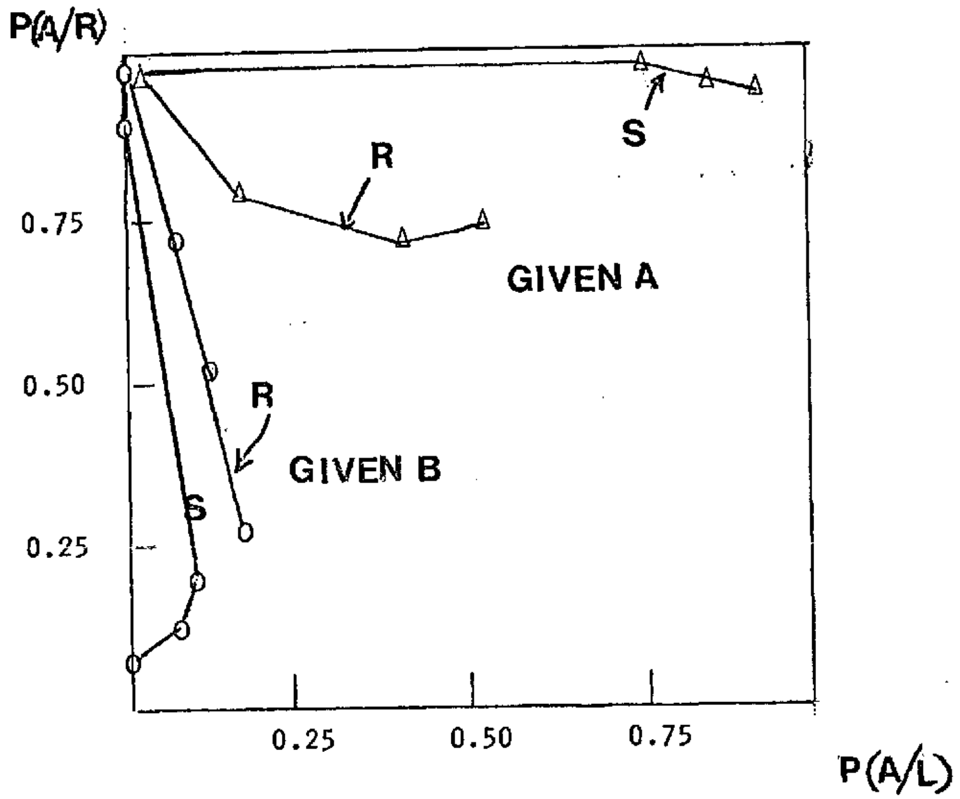


FIGURE 2. CONDITIONAL DR CURVES FOR SEQUENTIAL AND RANDOM PRESENTATION.
SUBJECT A.C.
(STIMULUS: R=RANDOM, S=SEQUENTIAL)

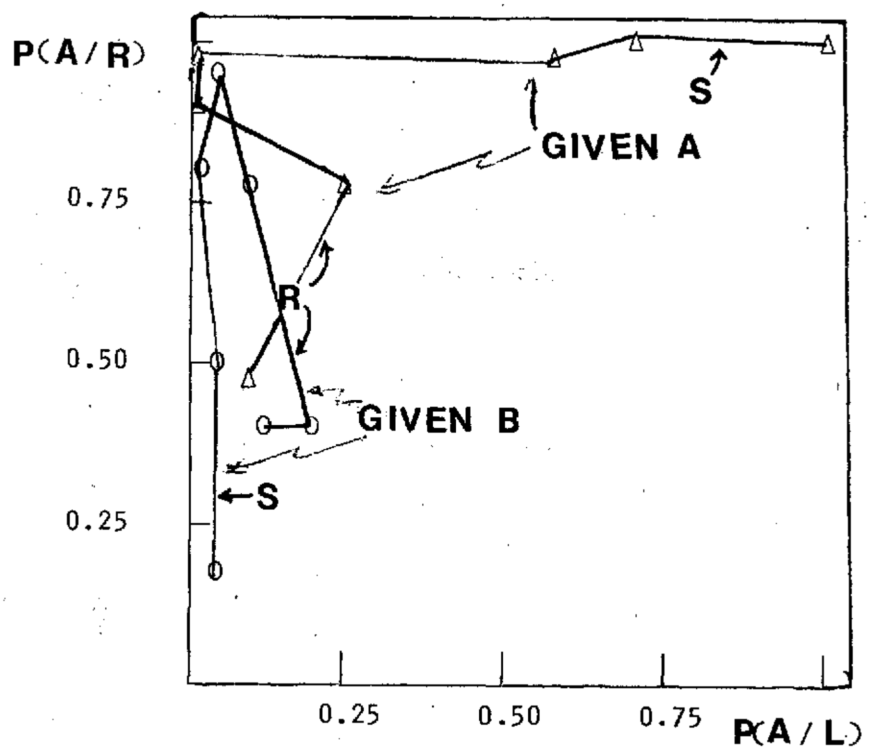


FIGURE 3. CONDITIONAL DR CURVES FOR SEQUENTIAL AND RANDOM PRESENTATION
SUBJECT A.T.
(STIMULUS: R=RANDOM, S=SEQUENTIAL)

world on which he had decided before. If he is using a N.P. strategy, he decreases the probability of a false alarm. (See Fig 2,3).

The conclusion from the above discussion is that the effect of correlated decisions is manifested in the criterion level for the experiments described here.

Detection of a change in random processes

In the previous section we discussed a detection problem in which decisions were of a discrete-time routine, i,e. at the end of each decision interval. This was possible because the information updating was discrete (radar sweep) and as a result the (displayed) signal strength remained fixed for 4 seconds. In other cases the changes may occur continuously, as for example in the case when an ILS system is used for updating an automatic landing system. In these cases the signal strength is a continuous stochastic process, and the detection problem is usually a problem of failure detection, e.g., a detection of a change in the steady state (s.s.) mean of the process.

In order to analyze the behavior of the decision maker in such a situation we designed an experiment in which the subject's task was to detect a change in the s.s. mean of a Gaussian process. The stimulus was a horizontal line (on a CRT display) whose displacement was determined by the output of a second order, time invariant system driven by white Gaussian noise. The steady state mean value of the output was zero for the non-failure mode. After the subject was trained and familiarized with the nominal process, a change in the mean was made at an arbitrary time, and the subject had to decide whether the change in mean was up or down.

There were four levels of changes of the means with sizes $\pm 1/2\sigma$, $\pm\sigma$, $\pm 2\sigma$, and $\pm 3\sigma$, where σ was the standard deviation of the displayed process.

Two observation intervals (limited and unlimited) were used. When the subject had an unlimited observation interval, results showed that the product of the size of the change and the average time to detection was constant, suggesting an integrative process. However when the length of the decision interval was fixed and the subject was told that the change always occurred in each interval, the above relation was not kept and the average detection time for the smaller changes in mean value was much smaller.

The model which was suggested by the data for the description of the behavior is based on optimal estimation theory (Kailath 1974) and sequential hypothesis testing (Wald, 1947). A block diagram of this model is shown in Figure 4. The displayed output is the input to the decision mechanism. Based on these outputs, the optimal estimates for the states of the shaping filter are found by the use of the Kalman filter. However for the detection process the subject uses the filter residual to obtain uncorrelated measurements rather then the estimates of the state. Since we assume that the subject is familiar with the "non failure" mode, the filter is the correct filter for this mode, and is in the steady state. Therefore the residual is a zero mean Gaussian process. When a failure happens, the mean of the displayed input is changed, and this will cause the mean of the residual to change. The detection is therefore done by a discrimination of two Gaussian random variables with equal variances but different means.

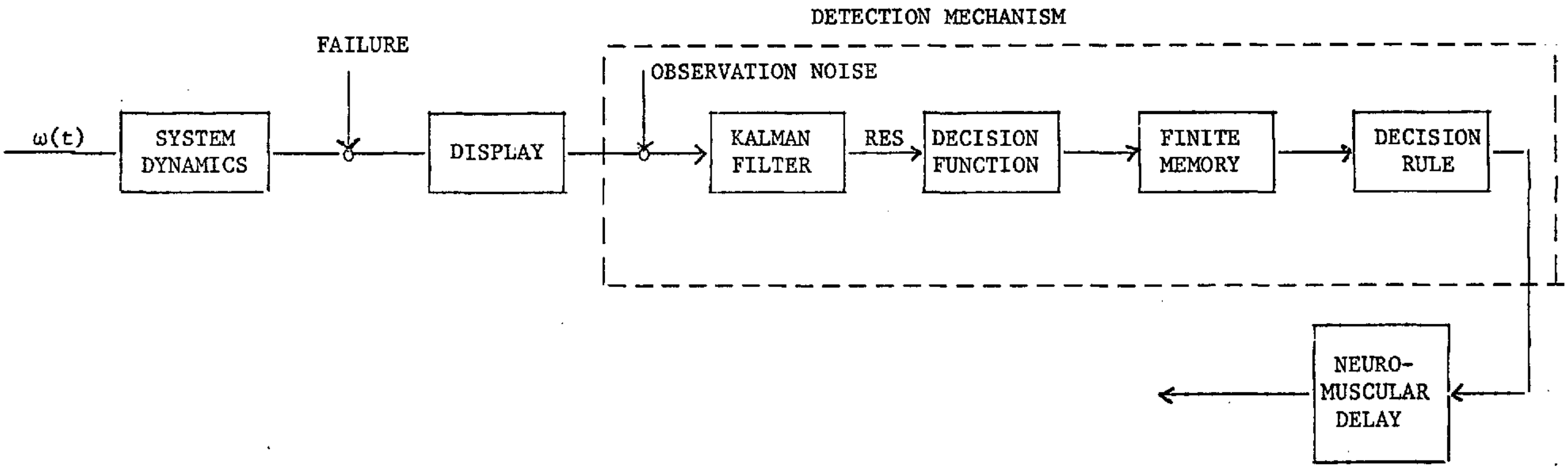


FIGURE 4. A MODEL FOR DETECTION OF A CHANGE IN THE MEAN OF A RANDOM PROCESS

This discrimination is done by using Wald's sequential probability ratio test (Wald 1947). The decision function is the sum of the successive likelihood ratio of the residuals. However because of the finite memory of the human subject he does not use the entire residual history and we have included an exponential smoothing operator (Schweppe 1973).

The decision mechanism is somewhat different from the decision mechanism that is used in classical SDT. In sequential observations the subject chooses two thresholds A and B and decides:

<u>Up</u>, if the decision function is greater then A

<u>Down</u>, if the decision function is smaller then B

<u>Take another measurement</u>, if the decision mechanism is between A and B

The values of A and B are determined by the values which the subject assigns to the two types of error. For a free length interval the values for the two types of error are fixed during the whole decision interval. However when the length is fixed and because the subject knows that a change must occur, he tends to let the type I error grow with time.

The average detection times for two subjects as a function of the change in the mean for a unlimited decision interval are shown in Figures 5 and 6. The results predicted by the model (disregarding the finite memory) are also shown in those figures. Figures 7 and 8 show the same results for the same subjects in a limited decision interval experiment. The predicted results of the model, in which the size of the error of type I is changed exponentially with time are also shown on these figures.

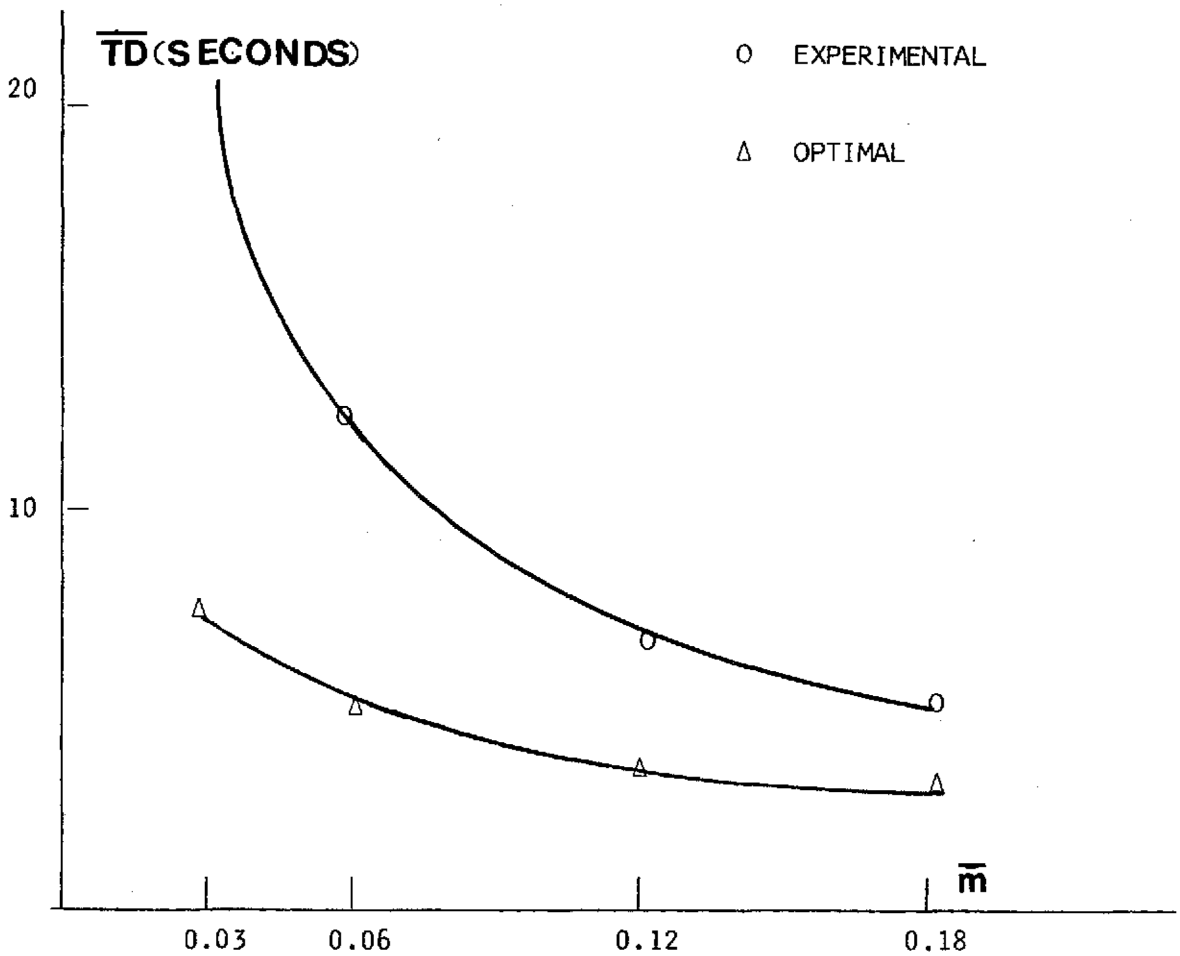


FIGURE 5. EXPERIMENTAL AND OPTIMAL DETECTION TIME
SUBJECT B.C.

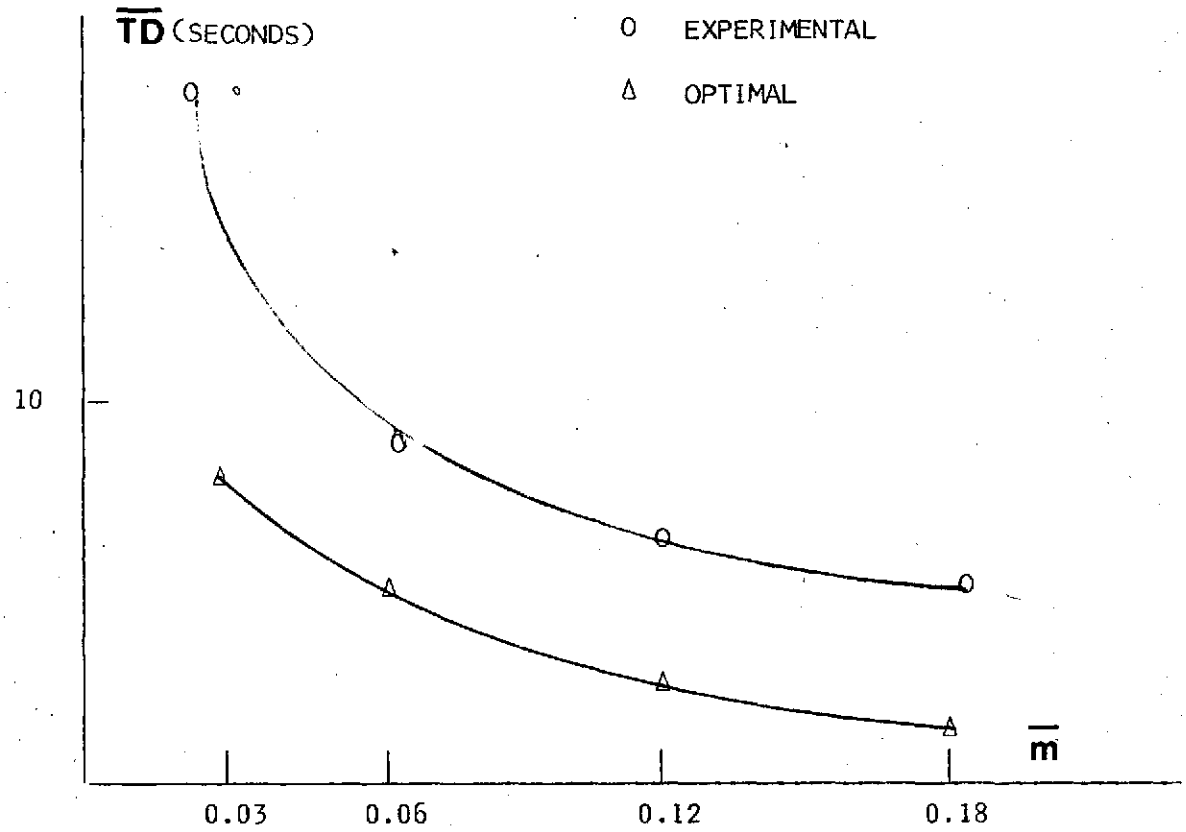


FIGURE 6. EXPERIMENTAL AND OPTIMAL AVERACE DETECTION TIME
SUBJECT A.C.

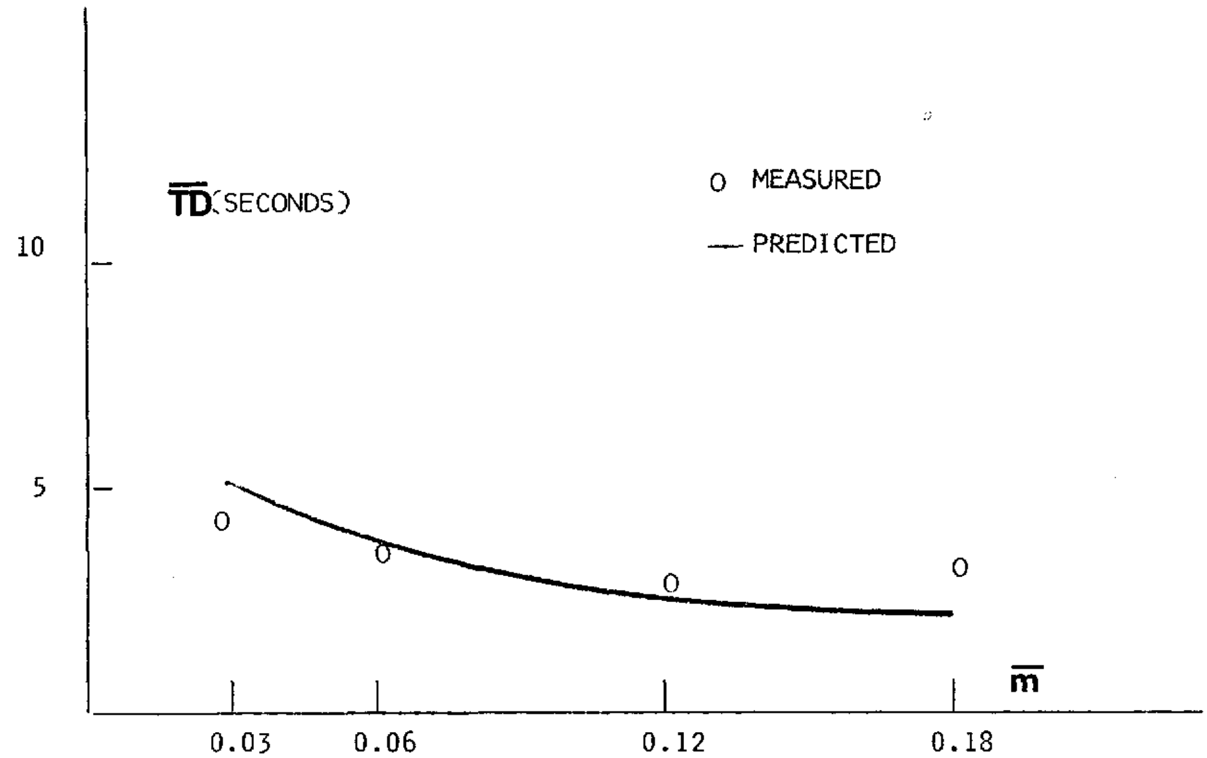


FIGURE 7. PREDICTED AND MEASURED AVERAGE DETECTION TIME FOR CLOSED INTERVAL SUBJECT B.C.

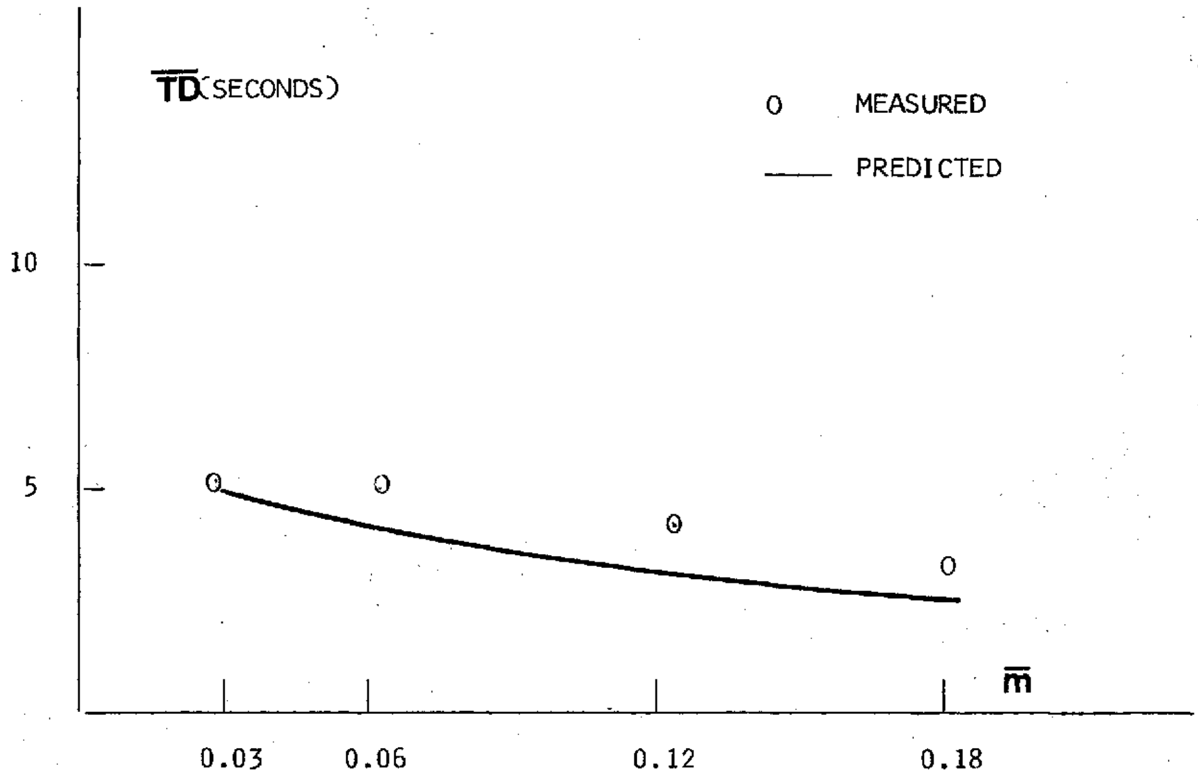


FIGURE 8. PREDICTED AND MEASURED AVERAGE DETECTION TIME FOR CLOSED INTERVAL SUBJECT A.C.

IX. FAILURE DETECTION BY PILOTS IN MULTI-AXIS TASKS

Background

This study of failure detection or the decision of proper system operation by the pilot concerns itself with the situation of an aircraft in an automatic Category III landing approach. The pilot monitors the progress of the approach and the operation of the equipment and provides a (hopefully) failsoft capability: should the automatic landing system (ALS) fail, the pilot will detect the failure, identify it and take corrective actions as dictated by the type and time of the failure.

It is axiomatic that the pilot should be capable of detecting and identifying failures of the ALS accurately, reliably, and with minimal time delay. We hypothesize that the factors with significant effect on the pilot's failure detection capability are the following

a. Participation--ranging from passive monitoring of the displays to actively controlling in one or more axes. This appears to be important because Young (1969) found that monitors have poorer detection performance then controllers; Vreuls et al (1968), on the other hand, found monitors to be better failure detectors.

b. "Workload"--induced by the primary task(s) and the associated disturbances, by secondary tasks, and by variations in control dynamics.

Work to date

Simulation facility--During the past months, a simulation capability including the ADAGE AGT/30 digital graphics computer and a fixed-base cockpit simulator have been developed.

a. Simulator dynamics--A mathematical model has been developed of a large transport aircraft. The actual flight data of a DC-8 were used in the equations of motion (Teper 1969) and the various parameters were later refined following a series of flight tests by an American Airlines senior captain. The flight envelope of the simulator ranges from landing approach to cruise at up to 400 kts., at altitudes from 0 to 6000 feet. Non-linear phenomena such as ground effect and stall characteristics have also been included. The simulator has been flown by ex-fighter pilots and airline captains and all feel it is more than adequate for the experimental program to follow. As an illustration: a non-experienced pilot tried to align the aircraft with the runway center line on short final by skidding at a high angle of bank; the simulator reacted by entering an over-the-top flat spin.

An integrated cue flight director system has been designed for this simulator, providing the capability to land it manually in zero-zero conditions in a satisfactory manner. Also, a two-axis autopilot has been incorporated into the simulation which is capable of flying ILS-coupled approaches, in either axis or in both axes, to touchdown. The autopilots and the flight director system have been tested extensively.

We also have the capability to add wind disturbances to the simulation. The current wind modes are:

a. No wind.

b. Steady 10 kt. wind from 260° (i.e., at 135° to the runway heading. Runway 4R at Logan Airport, whose heading is 35°, is our active runway).

c. 5 kt. wind, gusting to 10 kt., from 260°.

d. 10 kt. wind, gusting to 20 kt., from 260°.

The gusts are modelled as filtered white noise with a cutoff frequency of $\pi/6$ rad/sec. (See Appendix A, "Disturbances")

b. Displays--A CRT mounted on the captain's instrument panel is used to present flight information in the format of conventional instruments: airspeed, attitude and flight director, DME, vertical speed, HSI, RMI, altitude and localizer/glide slope deviations. We also have the capability to incorporate a flight director mode annunciator, if desired.

c. Support software--Support programs have been written to input analog data (control column, rudder pedals, etc.), discretes (e.g., gear), output (CRT, marker beacon indicators, etc.) to operate the side task and to store trajectory data in real time (see Appendix B, "Sample of Trajectory Data").

The side-task is of the warning light type: two small red lights are mounted close to each other in the pilot's peripheral vision field. Either one of the lights turns on at random times, uniformly distributed between 0.5 and 5 sec., and stays on for 2.0 secs. at most. The pilot is required to turn the light off with a three-position, spring-loaded rocker thumb switch which is mounted on the left horn of the control wheel. The program records a correct response if the switch is activated in the correct direction within the 2.0 seconds; it also stores the response-time and the spatial coordinates of the aircraft at the time of the response and turns the light off. An incorrect response is recorded, and the spatial coordinates stored if the switch is activated in the wrong direction or if the light has not been turned off within the 2.0 seconds.

This side task is similar to the one used by Spyker et al (NASA CR-1888 1971). It is especially suitable for our purposes because it reportedly does not require the pilot's entire reserve capacity and therefore does not result in a significant degradation of primary task performance (5% loading was reported); at the same time the performance on this side task is highly sensitive to attention on the primary task, making it a good workload measuring device.

Future Work

The purpose of this research is the study of the pilot's short term decisions regarding performance assessment and failure monitoring. We wish to investigate the relationship between the pilot's ability to detect failures, his degree of participation in the control task, and his overall workload level. To this end, the following three phases of work will be undertaken:

a. Completion of the simulation--As we already have a good simulator incorporating autoland capability, several levels of wind disturbances and workload measuring side task, we only need to add pre-programmed failures in the lateral and longitudinal axes. During the development of the simulator we had many unplanned failures which we may now incorporate into the programs deliberately.

b. Experimentation--In this phase, scheduled to last for four to six months, airline pilots who are type-rated in either B-707, DC-8 or B-747 will be asked to fly approaches with different degrees of automation and with different levels of wind disturbance; the pilot's ability to detect failures, to correctly identify them and to provide a reliable manual back-up capability will be monitored.

c. Analysis--The data recorded in the second phase will be analyzed, to identify statistically significant relationships among the experimental treatments, to wit, participation, workload and failure detection. An optimum point will be sought, i.e., the participation mode and workload level which produce the optimal failure detection performance. Equally important is the sensitivity of failure detection to these independent variables.

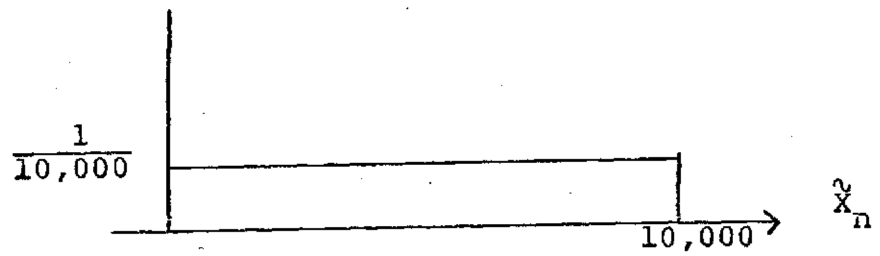
APPENDIX A

Disturbances

Both horizontal and vertical disturbances are modelled as random wind gusts. A random numbers generator is therefore incorporated in the program, as follows:

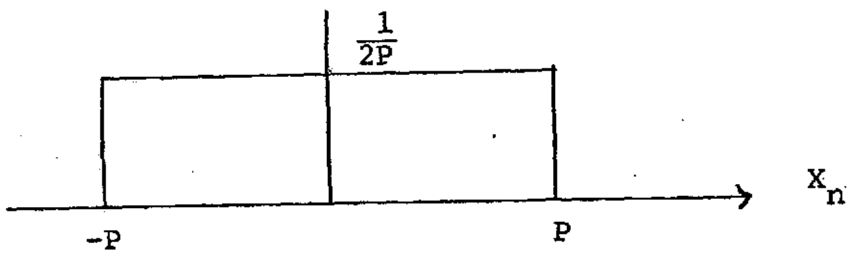
Define $\tilde{X}_{n+1} = (7701 \cdot \tilde{X}_n + 3927) \bmod 10{,}000 \qquad \tilde{X}_0 = 7129$

$\tilde{X}_n$ is then a random number in the range $0 \leq \tilde{X}_n < 10{,}000$, with the probability distribution



Define $\quad X_n = \left(\frac{\tilde{X}_n}{10{,}000} - \frac{1}{2}\right) \cdot 2P \qquad P \ll 10{,}000$

to obtain X_n, a random number in the range $-P \leq X_n < P$ with the square distribution



and since for a square distribution $\sigma_x^2 = \frac{(2P)^2}{12}$

$$P = \frac{\sqrt{12}}{2} \; \sigma_x$$

The gust sequence y_n was obtained from the random sequence X_n by passing it through a first order filter $G(s)$

$$G(s) = \frac{1}{s+\omega_i}$$

The output of the filter was sampled by the program at intervals of T seconds (the program's update rate), to obtain the gust sequence

$$y_{n+1} = e^{-\omega_i T} y_n + T \cdot X_{n+1} \qquad y_0 = 0$$

The gust sequence has the following statistics:

$$\bar{y}_n = T \cdot \bar{X}_n \quad \text{but} \quad \bar{X} = 0 \quad \Rightarrow \quad \bar{y} = 0$$

$$\sigma_y^2 = e^{-2\omega_i T} \cdot \sigma_y^2 + T^2 \sigma_x^2$$

or

$$\frac{\sigma_x}{\sigma_y} = \frac{\sqrt{1-e^{-2\omega_i T}}}{T}$$

It is desired that the gusts y_n should not exceed some preset value V_{max} 99.75% of the time (which corresponds to $3\sigma_y$). Therefore, $\sigma_y = V_{max}/3$ and

$$\sigma_x = \frac{V_{max}}{3} \frac{\sqrt{1-e^{-2\omega_i T}}}{T}$$

$$\Rightarrow \quad P = \frac{\sqrt{12}}{2} \sigma_x = \frac{\sqrt{12}}{2} \frac{V_{max}}{3} \frac{\sqrt{1-e^{-2\omega_i T}}}{T} = \frac{V_{max}}{T} \sqrt{\frac{1-e^{-2\omega_i T}}{3}}$$

<u>To summarize:</u>

1. We generate the random numbers sequence

$$\tilde{X}_{n+1} = (7701 \cdot \tilde{X}_n + 3927)\mathrm{mod}\ 10,000 \qquad \tilde{X}_0 = 7129$$

2. Define the modified random sequence

$$X_n = \left(\frac{\tilde{X}_n}{10,000} - \frac{1}{2}\right) 2 \cdot \frac{V_{max}}{T} \sqrt{\frac{1-e^{-2\omega_i T}}{3}}$$

where: V_{max} is the desired maximum gust velocity

ω_i is the gust's cutoff frequency set at $\pi/6$ rad/sec

T is the program's update time, $\simeq 0.2$ sec

3. Pass this sequence through a first order filter G(s)

$$G(s) = \frac{1}{s + \omega_i}$$

to obtain the random wind gusts.

4. As a final step, a steady (constant) wind is superimposed on the gusts.

In a series of tests in the computer, the actual mean and standard deviation of the generated gusts were found to be within less than 1.2% of the theoretical values, even when as little as 150 sample points were used.

<u>Dynamics</u>

The aircraft is assumed to posess two separate motions:

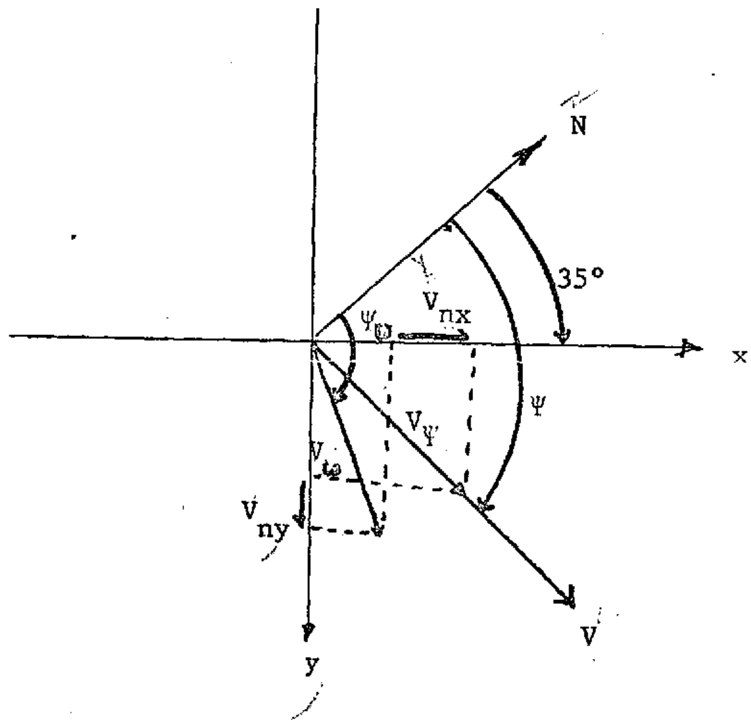
a. motion relative to the air (wind axes).

b. motion of the air relative to the ground.

The vector addition of these two motions yields the motion of the aircraft relative to the ground.

Also, if there is a component of the wind normal to the heading of the aircraft, $V_{n\omega}$, the aircraft is assumed to acquire a component of velocity, V_n, relative to the ground according to the relationship $V_n = V_{\omega n}(1-e^{-\tau/t})$ or

$$\frac{V_n(s)}{V_{\omega n}(s)} = \frac{1/t}{s + 1/t}$$



from the geometry of the problem:

$$V_{\underline{\psi}\omega} = V_\omega \cdot \cos(\underline{\psi}_\omega - \underline{\psi})$$

$$V_{n\omega} = V_\omega \cdot \sin(\underline{\psi}_\omega - \underline{\psi})$$

$$V_{nx} = -V_n \cos[90° - (\underline{\psi}-35°)] = -V_n \sin(\underline{\psi}-35°)$$

$$V_{ny} = V_n \cos(\underline{\psi}-35°)$$

where, in the ground frame of reference:

$V_{\underline{\psi}\omega}$ is the wind velocity component colinear with the aircraft heading

$V_{n\omega}$ is the wind velocity component normal to the aircraft heading

V_n is the aircraft velocity component normal to its heading induced by the wind.

V_{nx}, V_{ny} are the components of V_n along the x,y axes.

Now,

$$\frac{V_n(s)}{V_{n\omega}(s)} = \frac{1}{ts+1}$$

$$\Rightarrow \quad \dot{V}_n = \frac{1}{t}[V_{\omega n} - V_n] = \frac{1}{t}[V_\omega \sin(\underline{\psi}_\omega - \underline{\psi}) - V_n]$$

The aircraft's ground speed, V_g, is then computed from its airspeed:

$$V_g = V_a + V_\omega \cdot \cos(\underline{\psi}_\omega - \underline{\psi})$$

and the aircraft senses a side-slip angle β

$$\beta = \beta_0 + \arctan \frac{V_{n\omega} - V_n}{V_a}$$

The components of the aircraft's ground speed along the principal axes are:

$$V_x = [V_a + V_\omega \cdot \cos(\underline{\psi}_\omega - \underline{\psi})] \cdot \cos(\underline{\psi} - 35°) - V_n \cdot \sin(\underline{\psi} - 35°)$$

$$V_y = [V_a + V_\omega \cdot \cos(\underline{\psi}_\omega - \underline{\psi})] \cdot \sin(\underline{\psi} - 35°) + V_n \cdot \cos(\underline{\psi} - 35°)$$

For the purpose of the simulation, the following values are used:

$t = 1$ sec

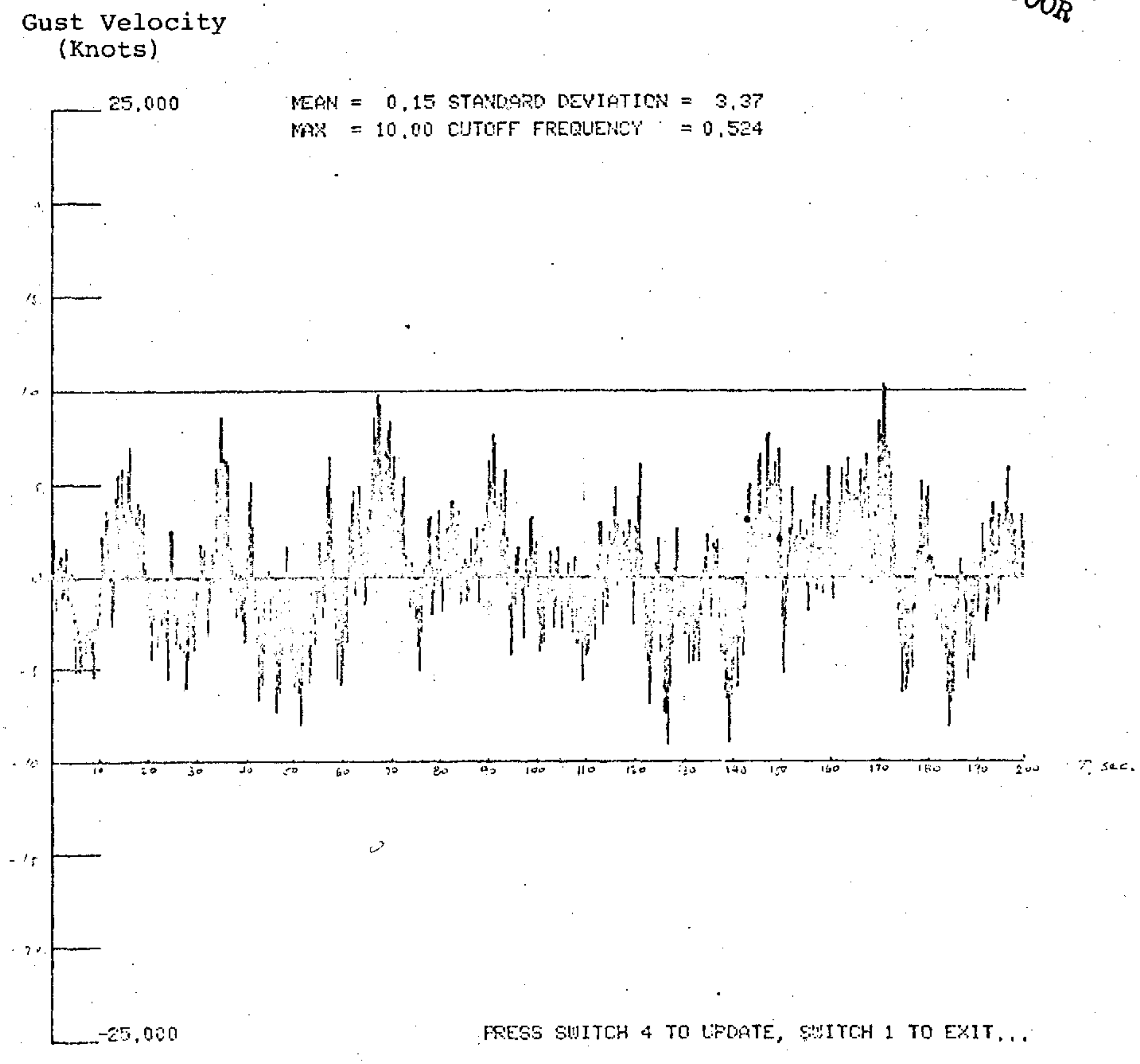
$\underline{\psi}_{\omega} = 80°$ (45° to the runway heading, which is 35°)

and three values for V_{ω}:

a. $V_{\omega} = 10$ kts. steady wind

b. $V_{\omega} = 5$ kts. steady wind + gusts ranging between ± 5 kts.

c. $V_{\omega} = 10$ kts. steady wind + gusts ranging between ± 10 kts.


Gust Velocity
(Knots)
25,000
MEAN = 0,15 STANDARD DEVIATION = 3,37
MAX = 10,00 CUTOFF FREQUENCY = 0,524
-25,000
PRESS SWITCH 4 TO UPDATE, SWITCH 1 TO EXIT...

APPENDIX B

SAMPLE OF TRAJECTORY DATA

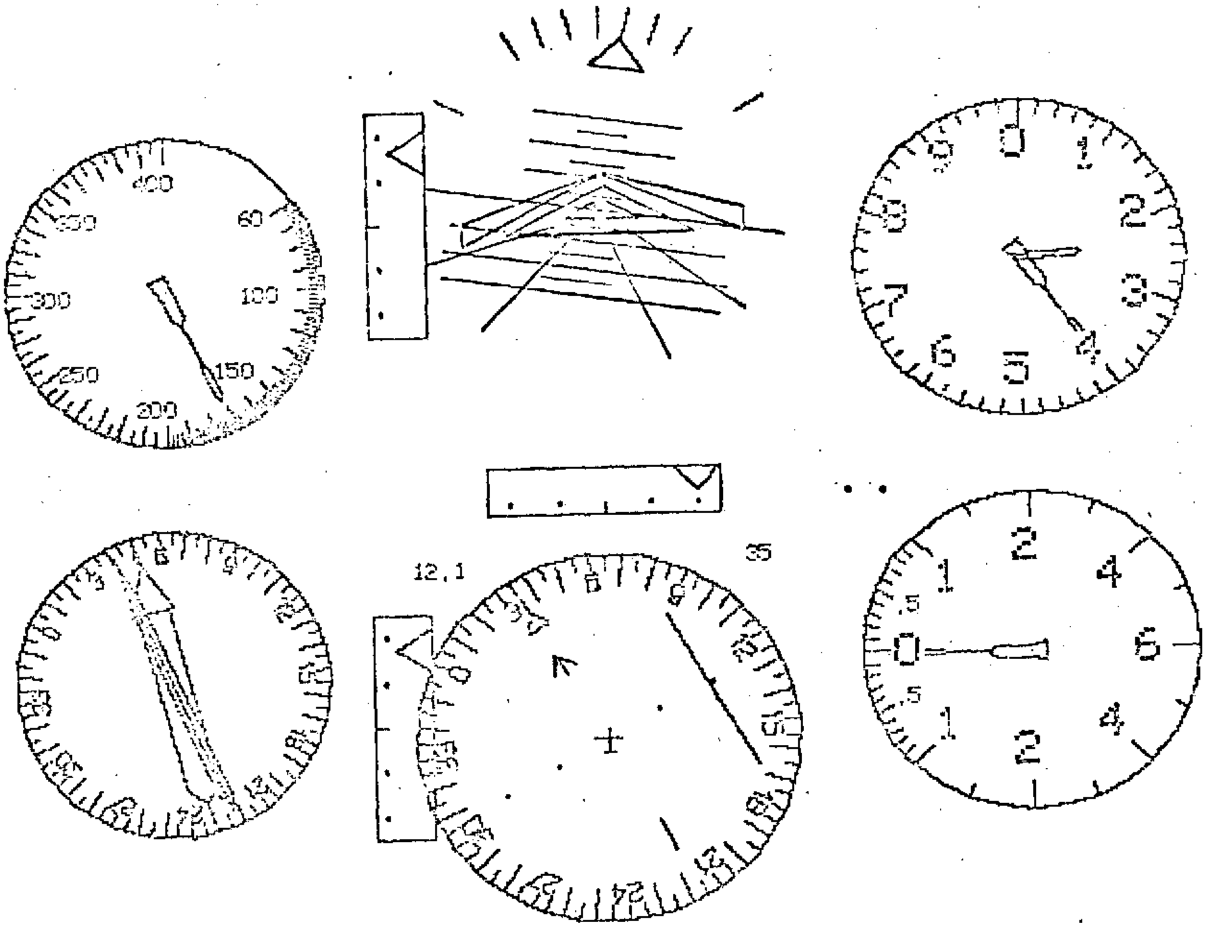


Figure 10. Instrument Panel

PARAMETERS AT TOUCHDOWN OR AT STOPACTION

DISTANCE FROM THRESHOLD	1707.	FT.
DISTANCE FROM CENTERLINE	12.	FT.
INDICATED AIRSPEED	127.	KNOTS
VERTICAL SPEED	-178.	FPM
FLARE COMMANDED AT ALT.	45.9	FT.

PITCH ANGLE	5.	DEGS.
BANK ANGLE	-1.	DEGS.
HEADING	35.	DEGS.
GROUND TRACK	36.	DEGS.
CRAB ANGLE	1.	DEGS.

DT = 0.2000
DATA UPDATE RATE = 5
LOCD= 67 HITS= 73 MISS= 12

75 SAMPLES OF SPATIAL COORDINATES FOLLOW:

ELAPSED TIME, SECS.	X, FEET	A, FEET	Y, FEET
0.000	-71087.	2500.	-6079.
5.108	-70539.	2490.	-5347.
10.058	-69360.	2489.	-4637.
15.008	-68078.	2489.	-3926.
20.058	-66822.	2489.	-3201.
25.028	-65588.	2488.	-2496.
30.108	-64288.	2486.	-1840.
35.028	-62984.	2485.	-1295.
40.108	-61682.	2484.	-810.
45.209	-60248.	2482.	-432.
50.109	-58817.	2485.	-124.
55.209	-57420.	2486.	98.
60.259	-55987.	2486.	259.
65.159	-54527.	2485.	361.
70.060	-53181.	2485.	412.
75.110	-51671.	2485.	429.
80.110	-50236.	2477.	418.
85.010	-48803.	2445.	390.
90.161	-47353.	2392.	347.
95.061	-45975.	2341.	303.
100.211	-44674.	2285.	260.
105.161	-43356.	2227.	216.
110.111	-42099.	2183.	175.
115.062	-40845.	2144.	139.
120.012	-39592.	2099.	107.
125.162	-38289.	2039.	79.
130.062	-37053.	1977.	57.
135.161	-35836.	1913.	41.
140.060	-34760.	1843.	29.
145.159	-33635.	1782.	20.
150.008	-32569.	1741.	13.
155.157	-31439.	1725.	8.
160.057	-30[illegible]	1663.	4.
165.156	-29245.	1608.	2.
170.055	-28171.	1553.	0.
175.154	-27083.	1485.	-1.
180.053	-259[illegible]	1422.	-2.
185.152	-24863.	1359.	-2.
190.052	-23727.	1309.	-2.
195.101	-2260[illegible]	1259.	-2.
[illegible]	-21572.	1204.	-2.
[illegible]	-20606.	1142.	-2.
[illegible]	-1[illegible]	1081.	-2.
[illegible]	-1[illegible]7.	1021.	-2.
[illegible]	-171[illegible]	966.	-2.
[illegible]	-161[illegible]	912.	-2.
230.144	-14996.	855.	-2.
235.193	-13809.	794.	-2.
[illegible]	-12006.	735.	-2.
[illegible]	-1170[illegible]	677.	-1.

Elapsed Time	X, feet	A, feet	Y, feet
250.090	-10623.	620.	-1.
255.109	-9526.	565.	-1.
260.138	-8419.	506.	-1.
265.137	-7323.	446.	-1.
270.237	-6249.	389.	-1.
275.206	-5142.	331.	-0.
280.235	-4046.	274.	-0.
285.234	-2917.	215.	-0.
290.233	-1954.	158.	-0.
291.132	-1623.	146.	-0.
292.103	-1393.	133.	-0.
293.033	-1207.	123.	-0.
294.082	-977.	111.	-0.
295.132	-747.	99.	-0.
296.102	-516.	87.	-0.
297.032	-302.	77.	-0.
298.082	-100.	65.	-0.
299.131	130.	54.	-0.
300.181	361.	43.	-0.
301.101	560.	33.	-0.
302.031	766.	25.	-0.
303.031	986.	16.	-0.
304.082	1216.	9.	-0.
305.082	1436.	4.	-0.
306.130	1664.	0.	-0.

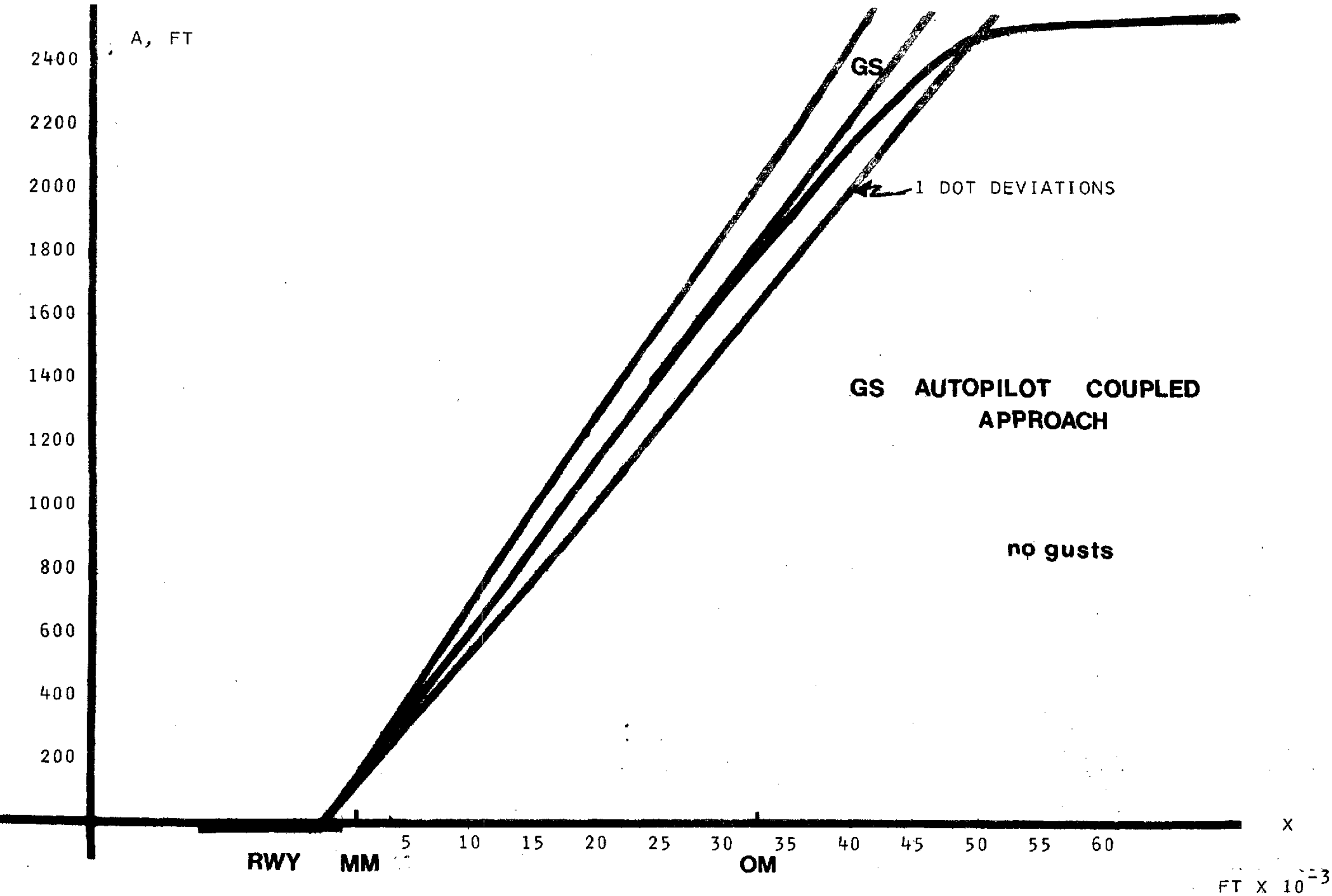
44 CORRECT RESPONSES FOLLOW:

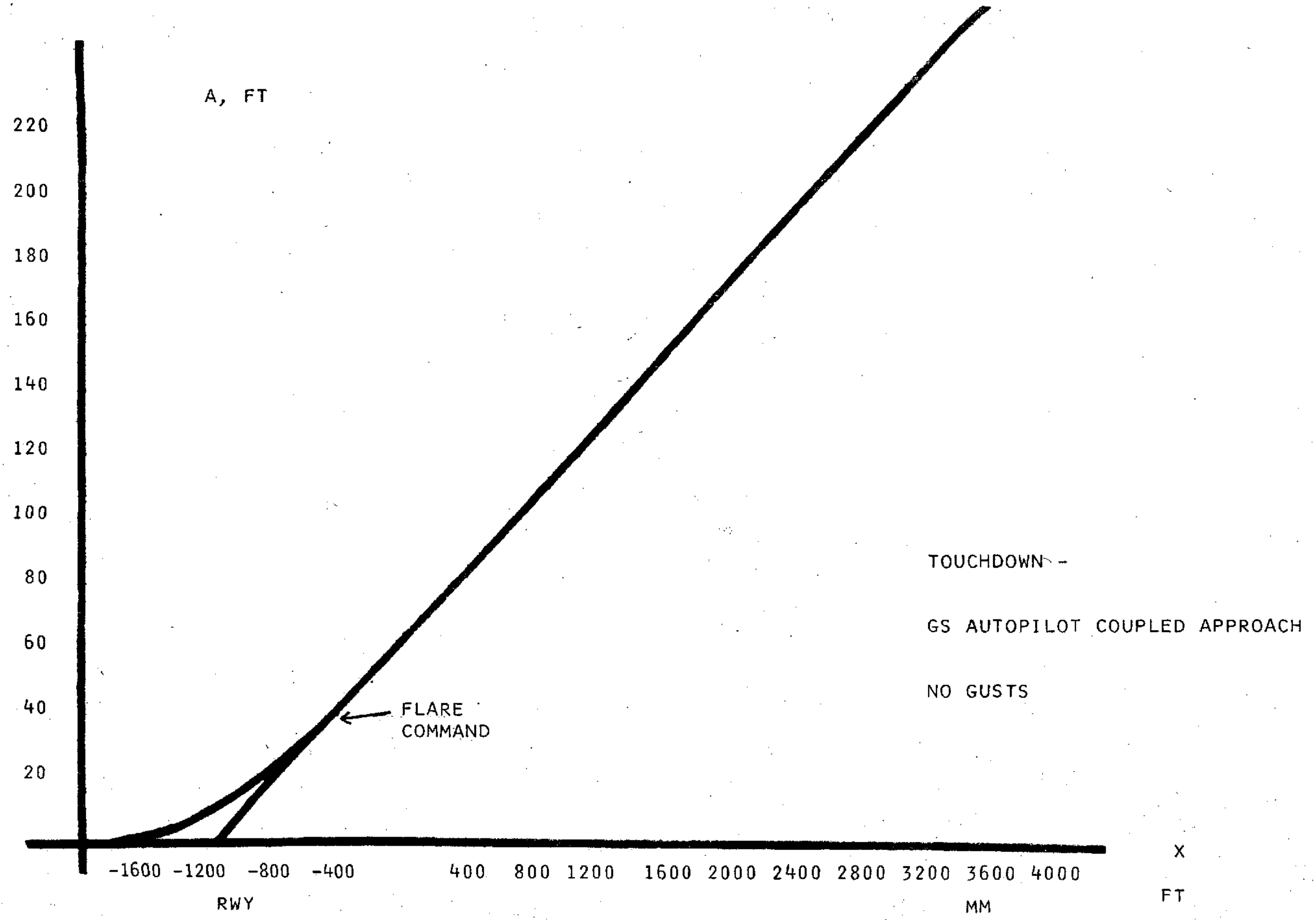
X, feet	RESPONSE T, SEC.
-70489.500	0.200
-69693.870	0.200
-68662.000	0.200
-67970.250	0.200
-62242.040	0.200
-58873.060	0.250
-58463.310	0.200
-57370.780	0.200
-56772.470	0.200
-54770.370	0.200
-53981.840	0.200
-53494.090	0.200
-52479.810	0.200
-49816.375	0.200
-44725.345	0.200
-44287.810	0.200
-42974.405	0.200
-42644.310	0.200
-40234.720	0.200
-38023.280	0.200
-33440.160	0.250
-33129.405	0.200
-31433.501	0.250
-26396.040	0.200
-26209.829	0.200
-22997.719	0.200
-19402.516	0.250
-17254.125	0.200
-16607.328	0.200
-14579.375	0.200
-14305.391	0.200
-12508.070	0.200
-11543.414	0.200
-10951.469	0.200
-9888.125	0.200
-9133.664	0.200
-8605.609	0.200
-7871.250	0.200
-7323.219	0.200
-6523.097	0.250
-4089.594	0.200
-3903.250	0.200
-3114.024	0.200
-1437.033	0.250

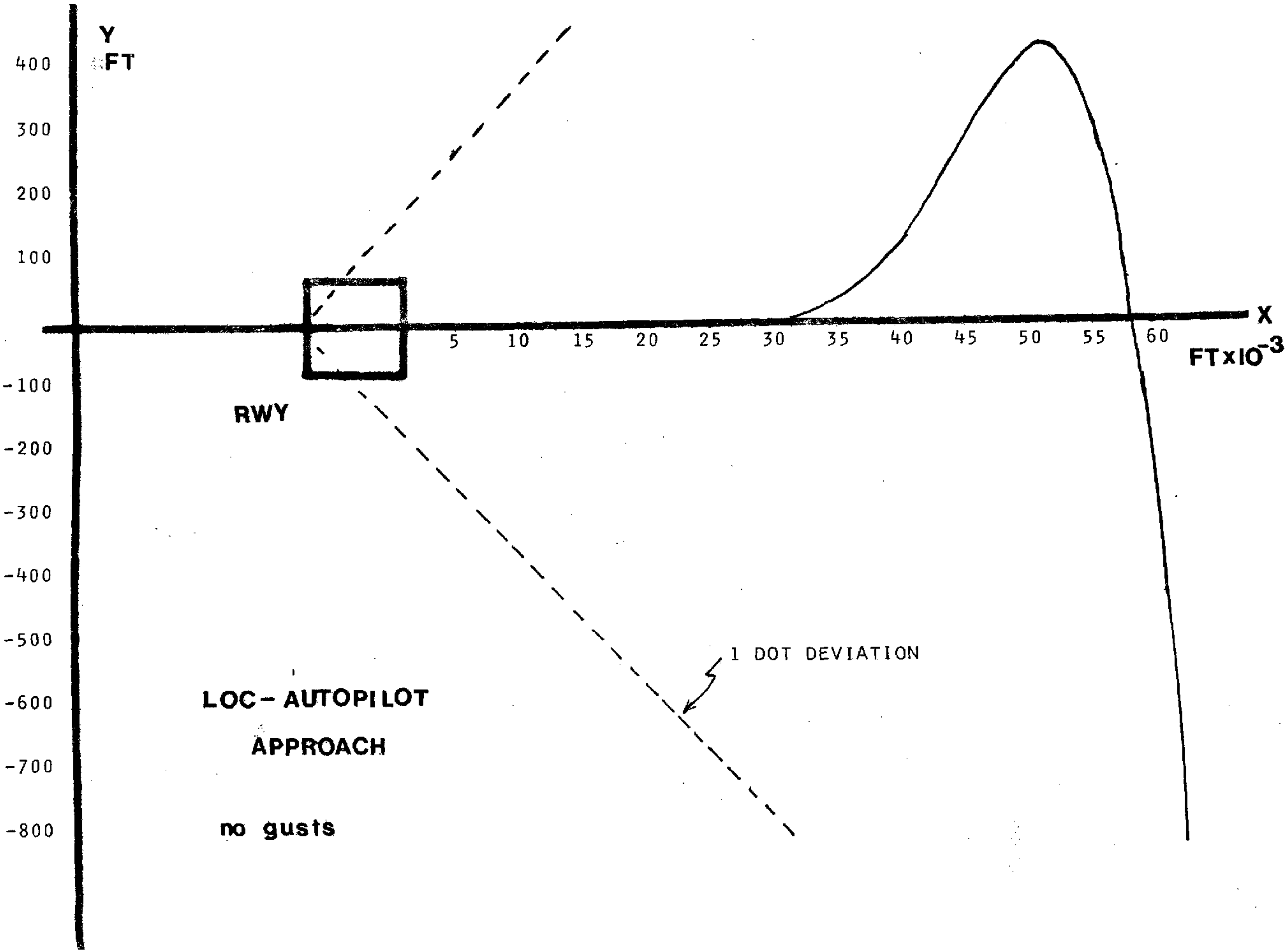
64 INCORRECT RESPONSES FOLLOW:

X, feet
-67232.3
-66772.3
-65976.4
-65487.4
-64162.1
-63661.9
-63237.0
-62526.8
-62844.9
-60303.3
-58151.8
-57612.6
-56121.4
-55558.0
-52216.9
-51671.4
-47783.2
-47238.5
-46137.7
-45627.1
-41604.8
-41123.4
-38896.0
-38402.7
-36894.0
-36442.4
-35708.9
-35282.5
-34340.0
-33921.2
-32657.0
-32239.8
-30692.5
-30275.8
-29946.8
-29530.3
-28872.4
-28455.8
-27568.2
-27141.0
-25420.8
-24993.3
-24532.9
-24105.2
-21989.0
-21572.5
-21287.5
-20882.0
-20049.1
-19632.7
-18352.3
-17933.8

X, feet
-15686.5
-15269.9
-13932.8
-13516.3
-5558.5
-5141.9
-2686.6
-2270.0
-702.7
-286.1
678.7
1073.5


A, FT
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400
200
GS
1 DOT DEVIATIONS
GS AUTOPILOT COUPLED APPROACH
no gusts
5 10 15 20 25 30 35 40 45 50 55 60
X
RWY
MM
OM
FT X 10^{-3}


A, FT
220
200
180
160
140
120
100
80
60
40
20
TOUCHDOWN -
GS AUTOPILOT COUPLED APPROACH
NO GUSTS
FLARE
COMMAND
-1600 -1200 -800 -400
400 800 1200 1600 2000 2400 2800 3200 3600 4000
X
FT
RWY
MM



Y
FT
400
300
200
100
-100
-200
-300
-400
-500
-600
-700
-800
X
5
10
15
20
25
30
35
40
45
50
55
60
FT x 10^-3
RWY
1 DOT DEVIATION
LOC - AUTOPILOT
APPROACH
no gusts

APPENDIX C

PUBLICATIONS

Curry, R.E., Nagel, D. Gai, E.G. (1974) Decision behavior with changing signal strength. To be published in the J of Mathematical Psychology. Also presented at the Tenth Annual Conference on Manual Control, 1974.

Curry, R.E. (1974) Sufficient conditions for original parameter estimates in behavioral models. In preparation.

Curry, R.E. (1974) MUNOML: A multinomial maximum likelihood program for behavioral research. In preparation.

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