FAILURE DETECTION BY HUMAN OBSERVERS

by

THIRUVENKATASAMY GOVINDARAJ

B. Tech., Indian Institute of Technology
Madras, India
1971

M.S., Indian Institute of Technology
Madras, India
1973

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Signature of Author ______________________________
Department of Aeronautics and Astronautics
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Certified by ______________________________
Thesis Supervisor

Accepted by ______________________________
Chairman, Departmental Graduate Committee

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ABSTRACT

Two important issues in failure detection by human monitors are considered: the threshold change which can be consistently detected, and the process by which the human detects a change. The observed process is modelled by a second order shaping filter with white noise input. Changes in frequency and the displayed process variance are considered for increases and decreases from the nominal values. The results reveal that the thresholds for increases and decreases are not significantly different from each other. Also thresholds are higher for changes in variance than for changes in frequency.

The results obtained from detection time experiments suggest that the human may be using changes in rms velocity as a means of detecting failures. Detecting changes in variance takes a longer time than corresponding changes in frequency. Models are formulated for predicting the observed detection times. A Kalman filter followed by a decision mechanism which operates on the measurement residuals to perform a Sequential Probability Ratio Test matches the experimental results for changes in frequency and variance. A simpler model using the velocity magnitude is also found to explain the detection time results for changes in frequency. The model which tests the residuals for a variance change seems better since it can handle both changes in frequency and in variance of the displayed process.

Thesis Supervisor: Dr. Renwick E. Curry
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The random ordering used above was generated on the PDP-11/34 of the Man Vehicle Laboratory.

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CHAPTER I

INTRODUCTION

1.1 Background and Motivation

Traditionally, man has functioned as a controller in tasks involving a human. Since controlling a plant or a system requires continuous monitoring, the tasks of controlling and monitoring cannot be separated. However, in recent years, there is a trend for the human to function as a supervisor or a monitor since most of the control tasks have been relegated to automatic control systems. Hence, failure detection and isolation by human monitors is of interest. The ability of the human monitor to detect failures as they occur and take corrective action is vitally important for the success of the mission or even for the safety of the individual and the people for whose safety he is responsible. Failures of large magnitude in any system are usually easy to detect. Also, a failure in one particular subsystem may be more critical than in others, in that some are more crucial to the success of overall system operation. In such a system, small failures should be detected as quickly as possible so that corrective action can be taken in time. The quickness with which a failure can be detected is extremely important in aircraft terminal area operations, rendezvous of aerospace vehicles, nuclear reactor control, high speed ground transportation systems, and chemical process control, among other things. There are two important issues common to these failure detection situations. One is the threshold size of a change in a system parameter which can be detected consistently by a human, and the other is the process by which a human detects such a change. These are important for better system design, since one of the basic requirements for failure detection is to be able to define the most sensitive factors. An attempt is made in the present work to study some specific aspects of human failure detection.

Failure detection by humans has been the subject of research for a number of years by various researchers. In most of the previous work done, this was studied in the context of detecting plant failures while a human acted as a controller, and his adaptive characteristics to function normally in the changed situations were explored. Miller and Elkind (1967), Phatak and Bekey (1969), Niemela and Krendel (1975), and Young (1964, 1969) examined the various models for adaptive characteristics of the human controller for a step change or a polarity reversal in the gain of the controlled process.

Good models using classical as well as modern control theory exist for the human as a controller in a variety of tasks. However, not much work has been done in modelling the human when he is a pure monitor. Smallwood (1967) proposed models of the environment (internal to the human operator) of first and second order systems, to explain the sampling behavior while a human is monitoring a number of instruments. He used the distribution function of the current state conditioned on all the previous states as the decision function for shifting of attention between various instruments. He found that the second order shaping filters were better able to predict the operator's sampling behavior in terms of the bandwidth of the instrument being observed and the precision required of the readout in a multidegree of freedom system.

Levison and Tanner (1971) proposed a control theoretic model for human decision making. Following their optimal control model of the human operator, they suggested a Kalman filter model for the estimator and a decision mechanism using the instantaneous likelihood ratio as a decision function. Phatak and Kleinman (1972) emphasized the roles of the internal model and the optimal estimator, suggesting that the observation errors are the inputs to the decision mechanisms.

Gai and Curry (1976) reported experiments on the detection of failures in the mean of a random process, which consisted of the output of a second order shaping filter driven by white Gaussian noise. An estimator consisting of a Kalman filter and a decision mechanism based on the observation residuals (i.e., the difference between observations and their estimates) was found to match the failure detection behavior of the human monitor. In a random process, there are many parameters subject to change when a failure occurs, for instance: the variance, bandwidth or the damping ratio of the process (Anyakora and Lees, 1972).

Since no previous data could be found on the ability of the human to detect such failures, preliminary experiments were conducted to obtain an estimate of the various thresholds and detection response characteristics. For a basic study of how these failures are detected, a simple, yet adequate, system is a second order shaping filter driven by random input. Even for higher order systems, it is reasonable to assume that the human is sensitive to the dominant modes of the system, and hence a second order approximation for system dynamics is usually sufficient; hence, the observers were expected to detect failures in a second order shaping filter driven by white noise. The results of this study were reported in Curry and Govindaraj (1976). Based on the information inferred from the data collected, it was decided to explore some aspects of the changes more thoroughly. Better experimental procedures were designed using well-proven psychophysical procedures for measuring thresholds and for evaluating detection response characteristics.

From the preliminary series of experiments, it was obvious that a change in damping ratio could not be handled in a consistent manner. Some subjects tended to perceive the decreases in damping as increases in damping, and vice versa. Also the detection times had no apparent relation with the magnitude of the stimuli presented. Hence, only changes in variance and frequency were taken for careful and detailed investigation. As the first step, thresholds were determined for changes in frequency and variance for all combinations of two frequencies and two damping ratios. The frequencies were chosen (corresponding to periods of one and three seconds) on the basis of being representative of the passband characteristics of the instruments encountered in aircraft monitoring situations. Damping ratios of 0.707 and

0.2 were used, which correspond to a moderately damped system and an underdamped system respectively.

Another series of experiments was conducted to study the detection behavior as the stimulus strength was varied. Detection times were measured for various levels of change in the parameter values from nominal, for changes in frequency and variance. Finally, the data obtained from these experiments have been used to formulate a model for the detection process.

1.2 Organization of the Thesis

Chapter II contains a detailed description of the experiment for threshold estimation and detection time studies. Various methods of estimating thresholds are compared. The staircase method, which is used in this work, is described in detail. Its advantages over other methods are pointed out. Modifications in the threshold experiments to perform detection time studies are indicated.

Chapter III concerns the results of the threshold measurements. Effects of different nominal parameters, i.e., frequency, and damping ratio, on thresholds for changes in frequency and input variance are analyzed.

In Chapter IV, the detection time results are given. Increases and decreases in the parameter values from nominal are compared for frequency and variance in terms of the detection times. An attempt is made to explain the results in terms of physical conditions and variables.

Models for the detection of the failures are proposed in Chapter V. The models consist of two stages: (1) an estimator, and (2) a decision mechanism. Brief summaries of estimation theory and sequential analysis pertaining to the current work are given. The results of application of these models are compared with the experimental results.

In Chapter VI, the work is summarized, and possible directions for further investigation are suggested.

Appendices A and B include details for implementing the shaping filter digitally (using Z-transforms), and a copy of the "Instructions for the Subjects" used in the threshold experiment respectively. The schedules used for all the experiments are given in Appendix C. In Appendix D, the thresholds for each subject are tabulated, while Appendix E contains the detection times for individual subjects.

CHAPTER II

DETAILS OF THE EXPERIMENTS

In the previous chapter, the failure detection problem was introduced, and its relevance in control and monitoring systems was pointed out. A brief summary of previous work was given. In this chapter, the experiments conducted for specific failure detection situations will be described in detail. The process being monitored by the observer is a second order shaping filter driven by white noise. A general description of the procedure and the experimental setup will be given. Then the threshold experiment will be described, where comparison of various methods is followed by a detailed description of the staircase method. The detection time experiments will be described after this, with the changes clearly pointed out.

2.1 Description of the Experiment

Experiments were conducted to determine the thresholds for changes in the parameters of a random process, and to study the detection behavior. A set of preliminary experiments were conducted to get an idea of the approximate values for the threshold. The process consisted of the output of a second order shaping filter with the transfer function:

$$\frac{K}{(s/\omega_n)^2 + 2\zeta(s/\omega_n) + 1} \tag{2.1}$$

and zero mean white Gaussian noise as input. The output of the shaping filter was displayed on the graphics display terminal as a horizontal line moving up and down inside a grid (see Figure 2.1). All three parameters, the natural frequency, the damping ratio, and K, the gain, could be changed.

Failure was defined as a change in one of the parameters of this shaping filter. Only variations in the natural frequency (the bandwidth) and the variance of the input noise (equivalently, the gain) were considered for the present study of failure detection. Effects of a change in damping ratio were not considered.

2.2.1 Equipment

A PDP 11/34 computer with graphics capability was used for all phases of the experiment; conducting the experiment on-line, storage of data, and for subsequent analysis and modelling. White Gaussian noise was digitally generated by summing 12 uniformly distributed random numbers. All the programming was done with discrete-time approximations using the Z-transform method. The details are given in Appendix A. The states were updated once every 10.5 milliseconds. This time was chosen since it was just sufficient for one complete cycle of operations, including the reading of the switches for subject response, when the computer was dedicated to the experiment. The subject was seated about 75 cm in front of the screen, the screen being at normal eye level. He held a small box with two switches to indicate his response (one switch to indicate an increase in parameter value, and the other for an indication of decrease), when a change was detected. In the computation cycle, the noise input was calculated, filter states were updated, and the switches were read. A 12 inch diagonal P31 fast phosphor cathode ray tube was used for all displays, and the motion of the line appeared continuous and smooth to the observer except when the frequency was about ten times the nominal during the initial familiarization phase. Then discrete jumps or flicker could be seen. The grid was 6σ high (approximately 12 cm), where σ^2 was the variance of the process, 1σ of the motion corresponding to about 0.2 radians (see Figure 2.1).

2.1.2 Procedure

The subjects for both series of experiments were recruited through advertisements in the Institute newspaper, and by advertisements posted at various places on campus. They were required to have normal vision (with or without glasses) and they were informed that they would be paid $2.50 an hour. Before anyone was started on the experimental series, he or she was told of the nature of the experiment, and that their participation in a series of experiments running into a few weeks duration was expected. A wide variety of people, both male and female, responded to the advertisements, and were recruited. About fifteen people participated for a period of about four weeks for the threshold experiment. Their backgrounds and ages ranged from sophomores at MIT and elsewhere to graduate students in

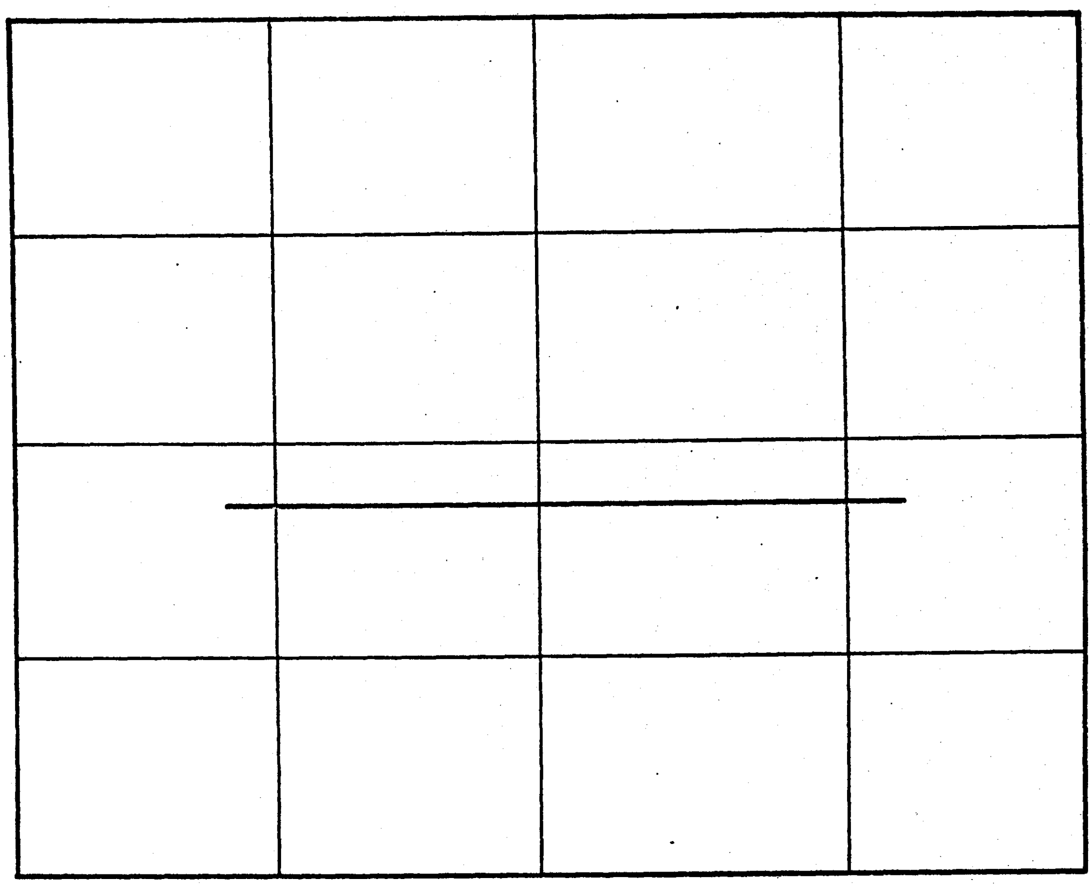


Figure 2.1 Grid (actual size).

science and engineering to a senior citizen. The experiments were conducted at various hours of the day, starting as early as 7:30 AM and running on to 11 PM on some days for some subjects. For any one subject, one session lasted for about an hour on each day. For every session, two series of experiments were conducted (one for a change in frequency and the other for a change in variance of the input). If, for any reason, it was felt that a subject was not alert in the beginning of the session or at the end of the first experiment, the remaining part was postponed. The experiments were done usually during regular working days, though some students on campus participated on weekends and holidays.

Except for one or two subjects, most were not familiar with stochastic processes or control theory, and none had any familiarity with psychophysics. Only one subject had some previous exposure to this kind of experiment, since he had participated in the earlier series of preliminary experiments. But since the (staircase) procedure used for the determination of the thresholds was completely different, and since there was a time lapse of more than three months, this did not create any problems. Hence, for our purposes all could be considered as naive subjects.

The general nature of the experiment was explained to each subject on the very first day of the experiment. A brief explanation of the observed process was given in terms of the analog of a spring-mass system, with which almost everyone was familiar. The subjects were told that there would not be any definite pattern, since the input or the excitation was random, and that they could only form an idea of "how far on either side the line moves away from the centerline" or "how fast or slow it is moving". They were told to observe the "average behavior of the line". Since the instructions were clear and simple, no uncontrolled effects were expected.

2.1.3 Learning or Familiarization Phase

After the procedure was explained, the nominal mode was shown for two minutes. After the nominal, large failures of either sign were shown, to familiarize the subject with the nature of the failures. For every trial other than the nominal, the process started with the nominal parameter values, and a failure occurred every time between 8 and 12 seconds after starting. Though it was obvious, the subjects were told about the nature of the failures (i.e., increase or decrease) during this phase. One nominal and four failure modes were sufficient for all subjects to become familiar with the changes. If, at this stage, anything was not clear, these trials were repeated and any specific questions were answered. Data from the first session was not used in the analysis.

2.1.4 Response and Feedback

The subject held the switch box used to indicate his response in his lap, or on a table nearby, depending on whichever was convenient for quick response. The subject was told to press the appropriate switch as soon as he was certain of the nature of the change. The grid on the screen appeared only when the line was in motion, and it was blanked out at the end of each trial. The screen was used to give immediate feedback after every trial. The subject was told of the type of response and the result. If the failure were detected and correctly identified, it was a "correct" response. If any switch was pressed prior to an actual failure, it was a "false alarm". If the identification were incorrect, it was "wrong". Finally, if the failure were not detected within the available time, it was a "no detection". ("Wrong" and "no detection" are considered "misses" later on.) After every trial, the result was displayed to the subject on the otherwise blank screen for two seconds. After a blanking period of three seconds, the next trial followed in a similar manner.

2.1.5 Initial Conditions for the Runs

The starting values for the position and velocity were chosen properly so that the statistics of the normal (nominal) random process would not have unduly long transient effects. Ideally, the initial conditions should be chosen such that they correspond to the steady state covariance obtained from

$$\dot{M} = AM + MA' + Q = 0 \qquad (2.2)$$

where

$$\mathrm{cov}(X) = M$$

and

$$\dot{X} = AX + w \qquad E[ww^T] = Q \qquad (2.3)$$

where X is the state vector of the random process driven by zero mean white noise w, and A denotes the system matrix. A set of eigenvectors can be found such that

$$\begin{pmatrix} \underline{e}_1^T \\ \underline{e}_2^T \end{pmatrix} M_\infty (\underline{e}_1 \ \underline{e}_2) = \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \qquad (2.4)$$

whre λ_1 and λ_2 are the variances of the uncorrelated random variables, u_1 and u_2. $X(t_0)$ can be found by choosing u_1 and u_2 with the correct variances and using

$$X(t_0) = (\underline{e}_1 \ \underline{e}_2) \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \qquad (2.5)$$

In our simulations, a simpler approach was used. For every run, the random initial conditions were chosen from the previous run. For any run, the state values were stored when the parameters of the process changed from the normal mode value to those corresponding to failure. This procedure is followed for all runs, except the first which is the nominal for two minutes. The first run started from zero initial conditions.

Stimulus values were chosen according to the following relation:

$$(P/P_n) = \exp[\ln R \times S] \qquad (2.6)$$

where

P_n = nominal value of the parameter

P = changed or failed value

R = ratio of initial change ($R = 10$)

S = stimulus ($|S| < 1.0$)

2.2 Threshold Experiment

2.2.1 Introduction

The existence of a sensory threshold has been a subject of discussion ever since the emergence of psychophysics. For our purposes, it is clear that there is a level below which reliable conclusions cannot be drawn as to whether a process is functioning in the normal mode or has deteriorated. This is the "noise level" for the system. Understanding the magnitude of the threshold is important for at least two reasons. One is to identify the inherent limitations of the human monitor in observing a task. If the failure or the change that may occur falls below the threshold, some other means must be found to make the failure detectable if that failure cannot be tolerated for safe operation. Another possible use is in evaluating the effectiveness of a model for the human as a controller or an observer. If the threshold is known, it would be easier to separate the usefulness of the model and its behavior at the uncertainty level. Even if the model is very good in explaining and/or predicting the phenomenon for a given situation, it cannot be relied on if the parameters are below the threshold level.

The measurement of sensory thresholds is made difficult by physiological and psychological variations in any experimental situation, in addition to the difficulty of maintaining the same physical conditions. Such extraneous factors as the subject's "timidity, warming up, and anxiety" (Titchener, 1905) and his conscious as well as unconscious criteria for making a positive response (Guilford, 1936) have to be taken into account.

For our purposes, the threshold will be defined as the smallest change (from the nominal) that a person can reliably detect. What we mean by reliable will become apparent after an explanation of the procedure for the determination of the threshold is given, but for now can be simply stated as the value that can be detected in approximately 75% of the trials in which it is presented. In psychophysics, there are various methods to measure thresholds. The sensory threshold was usually found by determining the intensity of the stimulus required to be just detectable or by determining the difference between two stimuli that are noticeably different. A brief discussion of possible approaches to threshold measurement is in order, prior to describing the approach finally settled on for this experiment. The four methods of importance are (i) the method of adjustment, (ii) the method of serial exploration, (iii) the method of constant stimuli, and (iv) the staircase method. An excellent review of various definitions of thresholds and pertinent discussions are given in Green and Swets (1966).

2.2.2 Discussion of Various Methods

In the method of adjustment, the subject manipulates a continuously variable stimulus so that it appears just noticeably different from the nominal, or just noticeable, depending on the nature of the process. The mean over a number of runs is taken as the threshold (Green and Swets, 1966). In the method of serial exploration, various levels of stimuli are presented in steps, starting on either side (or both sides with interleaving) of the threshold value. In these methods, the response could be either Yes-No or Yes-No-Doubtful (or Equal). The estimation of the threshold depends on the responses that are permitted of the subject. In these methods, usually the psychometric function (the percentage of correct responses versus stimulus levels) is plotted, and depending on the response category allowed, the stimulus value corresponding to the 50% or 75% correct responses is arbitrarily taken as the threshold. In the method of constant stimuli, a set of stimulus values around the expected threshold is chosen. At any trial, a particular value of the stimulus from this set is presented, and the response is recorded, the order of presentation being random. Again, the psychometric function can be plotted and the threshold estimated.

2.2.3 The Staircase Method

The staircase method is used in our experiments and hence will be explained in greater detail, before a comparison is made between various methods. A detailed discussion of this method can be found in Cornsweet (1962) and also in Levitt (1969). The procedure for determining the threshold starts with the presentation of relatively large stimulus values, just as in the method of serial exploration. The starting value could be from either side of the expected threshold value, and two series could be interleaved. The main difference between the staircase method and the serial exploration method is in the presentation of the stimuli after the first negative response is reached. In the staircase method, once the stimulus that elicits a negative response (or a wrong or no response) is reached, the levels are alternated, with systematic variations of decreases and increases over that level. After the first negative response, the stimulus level is increased by a certain level and the response is determined. If the response is positive, the same level is repeated once more to take care of any responses that may result from a pure guess. If the response is again positive, the stimulus level is reduced by a certain step size. But, for any level, if a "no" response is obtained, the stimulus value is increased. The procedure is repeated until a predetermined number of ups and downs (or "peaks" and "valleys") is obtained in the stimulus-response history. As the experiment proceeds, the stepsizes are adaptively reduced.

With proper stepsizes, the mean of the peaks and valleys gives a good measure of the threshold. Ideally, the reversals in the directions (i.e., increase or decrease from the previous step size) should occur for one or two step size differences. After a pre-determined number of ups and downs are reached, the experiment is terminated, and the asymptotic value of the stimulus is taken to be the threshold.

The threshold estimation by the staircase method is very fast compared to other methods, since the stepsizes can be determined adaptively, depending on the stimulus values, and the number of steps needed before termination is small compared with other methods. Also, the efficiency is higher due to operation near threshold most of the time. The experimental procedure will now be described, and particular attention will be given to how various previous criticisms have been overcome.

For the threshold experiment, the subjects were told that the aim of the experiment was "to determine thresholds", i.e., the "smallest change you can reliably detect when a failure occurs in the process you are observing". The experiment would start with large magnitudes of failure and that magnitude would be reduced gradually "until it becomes very difficult for you to correctly detect the changes that occur". He was also told that towards the end he may not be, and in fact he will not be, able to respond correctly to all the stimuli. He was told not to agonize over any errors in the response when the magnitude becomes very small. The detection time was not of primary concern. But the subjects were aware that their response time was being recorded. Since the subjects had time to give their response even after the trial was over, the number of false alarms, if any were negligibly small. Only in one or two runs, and especially for one subject, was it apparent that the subject was disappointed at the errors; the runs were terminated, and it was explained that it was inherent in the procedure that one could not get all of the responses correctly. For any one parameter, the experiment normally ran for about 30 minutes. Then after a rest period of about 5 minutes, trials for the other parameter were run. For any experiment, the subject was told which of the parameters (frequency or variance) was being changed. A copy of the exact set of instructions given to each subject for the threshold experiment is given in Appendix B.

The stimulus values used until the subject made his first incorrect response were as follows: $|S|$ = 0.8, 0.6, 0.4, 0.2, 0.16, 0.12, 0.08, 0.04, 0.03, 0.02, 0.01, 0.008, 0.006, 0.004, 0.002, 0.0015, 0.0010, 0.0005. The above choice was made by taking into consideration the fact that as the threshold is approached, smaller values are desirable for as accurate an estimate of the threshold as possible. Moreover, the large initial values are needed to "warm up" the subject, and the step size is initially large so as not to spend too much time away from the expected threshold. Both positive and negative values of the stimuli were interleaved, and the experiment was conducted with two single staircases, alternating at random (see also Levitt, 1969). The magnitudes were not presented in strictly descending order lest the subject get an idea of how the stimulus is presented. From the stimuli listed above, two values are taken at a time, and sets of four are formed by having increases and decreases at those magnitudes, i.e., the sets are: (±0.8, ±0.6), (±0.4, ±0.2), ..., etc. Within any set, the stimuli are chosen at random without replacement. Therefore from trial to trial, the consecutive stimuli could be either an increase or a decrease, and the magnitude could be higher or lower (e.g. in the first four trials, the set is formed of ±0.8, ±0.6, and the order could be +0.6, -0.8, +0.8, -0.6 or any other combination).

Now various salient features of the staircase method, its advantages and disadvantages over other methods, criticisms of the method, and the method as used in our experiments will be discussed. An excellent discussion of the staircase method in psychophysics can be found in Cornsweet (1962). He points out four important factors that are to be taken into account. They are: (1) where to start the series, (2) how large a step size to take, (3) when to stop the series, and (4) when to modify the series.

In our experiments, the stepsizes were adaptively chosen as explained below (Section 2.2.4). It was possible to use large stepsizes in the beginning, since the threshold was approached relatively quickly from the start of the experiment. Because of the adaptive stepsizes used, and since the stepsizes were quite small towards the end, it was decided to stop the experiment after 6 or more reversals were observed. This is also the recommended procedure by Levitt (1969) and Wetherill and Levitt (1965). As Cornsweet observed, in most of the cases, "the values of the stimuli presented change relatively rapidly until they reach an asymptotic level or plateau, and then they hover around this level as long as the conditions remain unchanged". He continues, "Obviously, the longer the series the more reliable will be the computed value of the threshold". But, if the series is too long, the subject may get bored and tired, and the psychological and physiological conditions do not remain constant over a long period of time. He also suggests that a certain number of reversals be used as the stopping criterion. The advantages are the small number of trials needed, since once the first few stimuli are out of the way, the remaining stimuli are near threshold, and since an asymptotic fit (i.e., the threshold is assumed to be reached asymptotically (see Section 3.2)) is used, a far fewer number of presentations are needed, compared with other methods. Since both increases and decreases are presented in successive trials, there are two main drawbacks pointed out by Cornsweet: anchoring or series effects (or anticipation of next levels), and the way in which the stimuli are ordered. However, these do not present any problem in our case. Anchoring effects are usually eliminated using the double staircase procedure, where the stimuli presentation is started from both sides of the expected nominal (i.e., at a value much lower than threshold resulting in 100% misses, and at a value much higher than threshold resulting in 100% hits), and changing the stimuli so that they approach the threshold from both sides. In our case, two single staircases, one for threshold for an increase in parameter values from nominal, and the other for a decrease from nominal, are mixed at random. Hence, the subject may not be able to guess the next stimulus from the previous one, i.e., this has the advantages of the double staircase procedure in eliminating or minimizing the anchoring effects, etc.

By proper design, it is also believed that the criticisms of Dallenbach (1966) have been taken into account. He criticized this method because of the following factors: (1) constant errors, in time or space or in both, i.e., the order of presentation, the standard first and the variable next and vice versa, (2) variable errors - practice, fatigue, expectation, and habituation, and (3) accidental errors due to the experimenter's manipulation of the apparatus, mood and health of the subject, etc. Accuracy has not been compromized for efficiency. Since the order of presentation has been randomized, with magnitude as well as sign being nondeterministic, the constant errors have been eliminated. The variable errors due to practice, fatigue, etc., are eliminated by the use of rest periods and even discontinuing the experiment if the subject is not alert. The random order among the set of four stimuli, and adaptive step sizes (smaller nearer threshold), make it almost impossible for the subject to guess. Even the experimenter, who had been working on this problem for a long time, could perform no better (in the sense of getting lower thresholds) than his earlier levels, even after considerable experience.

The thresholds were calculated using an asymptotic least squares fit to the stimulus versus time history. Though a forced choice procedure was used (the subject usually had to respond by indicating either an increase or a decrease), the fact that the stimulus value was not altered until two correct responses were obtained (when it was reduced by one step size), takes out the guessing factor, and in effect makes it a "strictly +" or "strictly -" choice. At any time, the subject cannot make a choice, and get away with it, if it were just a guess, i.e., this cannot continue forever, since, if it were a pure guess, his probability of correctly identifying the same level the next time it is presented is very small. Any accidental errors could occur if the subject pressed the incorrect switch (since everything else was controlled by the computer). If such a thing occurred, the subject was asked to notify the experimenter. Since the subjects were well aware that the reaction time was not the principal factor being determined, they seldom made this kind of error.

2.2.4 Stepsize Control

The adaptive step size control noted above was achieved in the following manner. The stimuli were presented from the initial set with step sizes decreasing as the magnitude itself was decreased, until an incorrect response was made. At the occurrence of the first incorrect response, the step size was chosen as the difference in magnitudes of the stimuli in the next set of four, i.e., the stimuli were grouped in sets of four and the order in any set was random (see Section 2.2.3). If the first incorrect response occurred, say, while the set (±0.16, ±0.12) was being presented, the stepsize in stimulus value was chosen as the magnitude difference in the set (±0.08, ±0.04), which is 0.04. This was used to increment the stepsize for the next stimulus. The sets of four were not used for the rest of the experiment. For the next run, the step size was taken to be 0.8 times the previous value. This practice was found to work very well, since after one or two direction reversals, the number of steps between reversals was about one, two or three. Hence this method of choosing the stepsize was continued for all subsequent runs.

Increases and decreases had separate step lengths depending on the performance of the subject. In an early version of the experiment, both staircases were separately continued until incorrect responses occurred in each of the series. But soon it was discovered that if the stepsizes were far apart to start with, there was a tendency for the subjects to compare the currently observed process with a process observed in the previous run(s), where the failure was easy to identify (due to a comparatively large separation from the nominal) instead of comparing with the nominal. So upon encountering the first incorrect response, both stepsizes started at the same value though they could differ as the experiment continued.

During any trial, the run continued until the subject responded, or for 30 seconds from the onset of failure, whichever occurred earlier. If at the end of 30 seconds, the subject had not indicated his response, the horizontal line came to a stop, the grid disappeared, and he had five seconds to respond. If he did not respond even after this, it was considered a "miss". Since the same random number generator was used to choose the stimuli as well as to form the "white" noise input, and since the stopping time for any run depended on the subject's response, every subject had a unique presentation except for the two minute initial nominal. For every experiment, all the information was stored (i.e., the nature of the response, response time, the stimulus intensity, and the "seed" for the random number generator to generate the whole sequence and time history of the process). The data is presented in the next chapter, and the statistics are discussed.

2.2.5 Order of Presentation of the Nominals

A set of four nominals, obtained by the factorial combination of T = (1.0, 3.0) and ζ = (0.2, 0.707) were used. During any one session, on any particular day, only one nominal was presented. Since all the subjects who participated in the threshold experiments were given all the four sets of nominals, a Latin square design was used to choose the order of presentation. The Latin squares used are shown below. For more subjects (>8), the same Latin squares were used repeatedly (i.e., S9 = S1, S10 = S2, etc.).

	S1	S2	S3	S4	S5	S6	S7	S8
E1	12	17	32	37	32	17	37	12
E2	37	32	12	17	17	37	12	32
E3	32	37	17	12	12	32	17	37
E4	17	12	37	32	37	12	32	17

where S1 through S8 refer to the subjects, E1 through E4 to the stimulus presentation for each subject, and the first digit of the number refers to the period (T), and the second refers to the damping ratio (2 for 0.2 and 7 for 0.707). For any one of the nominals, the decision as to whether to vary the period or variance first in a session was determined with equal probability in the beginning until about half of the planned total experiments were completed. Then the choice was according to the random arrival time of the subjects. (Though the subjects were scheduled a day or two in advance, the scheduling was done according to their individual preferences and availabilities at various times of the day). For any nominal, if the sessions where the period was changed first were more than the corresponding sessions for variance, the variance was changed first for the next subject, and vice versa. This resulted in a fairly equal distribution for period-first and variance-first sessions. (Actual schedules used for the experiments are given in Appendix C.) This arrangement was thought necessary, since it was observed that detecting changes in frequency was easier and less tiring, and took slightly less time for the subjects. Thus, the above arrangement mixes easy and hard tasks with equal likelihood, between subjects, and for any particular subject.

2.3 Detection Time Experiments

A second series of experiments was conducted to determine the time taken for detection of a failure as a function of the stimulus level. The general set-up for this series was the same as before. However, the criterion by which the subject responded was different. It was made clear that the objective was to determine how quickly one detects a failure. The subject was specifically told that "he was expected to detect the failure as quickly as possible without making too many mistakes". Another important difference was in the set of stimuli chosen. From the previous experiments, thresholds were determined for frequency and variance for various nominals. Four levels were chosen with increasing magnitudes, the smallest being slightly higher than the threshold. Four increases and four decreases were mixed to form a group of eight stimuli, and a stimulus was chosen from this group at random (without replacement) and presented.

Since the detection times were of interest, the subjects had to respond in a given time. If they did not respond during this period, it was considered a "miss". The presentation of stimuli and performance feedback were as in the earlier experiment. If, for any session, too many false alarms were observed, the subject was told to reduce the number of false alarms by waiting for sufficient time before responding, to be certain that a failure had occurred. If it persisted, the session was discontinued. This was necessary only for one subject. Two or three sessions out of about 50 sessions were cancelled.

These experiments were conducted for a number of days, running into a few weeks. Since a large number of runs were needed, and a commitment on the part of the subject to participate over a period of several weeks was necessary, only three of the subjects who participated in the earlier series were retained. Due to their experience with the earlier experiments, they were familiar with the random process being observed, and hence no training runs were necessary. However, since the criteria were different, and since only a limited number of stimuli were presented, one initial trial run was given.

CHAPTER III

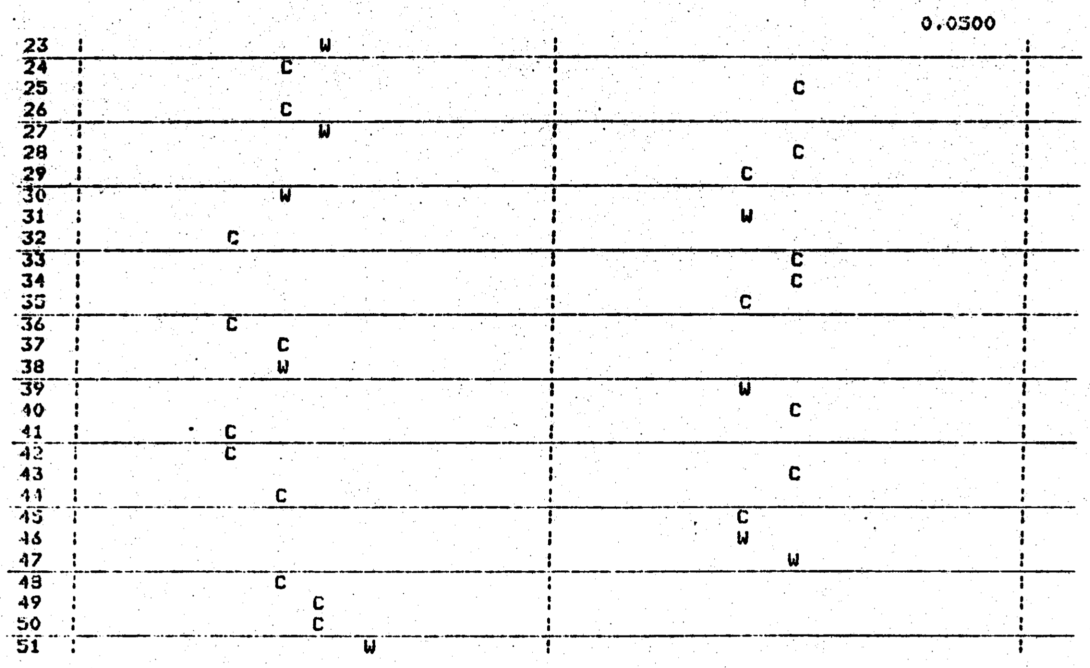
EXPERIMENTAL RESULTS: THRESHOLD

In Chapter II, detailed descriptions of the experiments for measurement of threshold and detection time behavior were given. The data collected during the threshold experiment have been used to estimate various thresholds for frequency and variance for various nominals. The form of the curve used to fit the data to obtain thresholds will be given. Comparisons will be made between various thresholds. Possible explanations for some of the observed effects will be given.

3.1 Stimulus versus Time History

Some of the results from the stimulus versus time history for the staircase method for threshold experiments are shown in the accompanying plots (Figures 3.1a - 3.1f). These plots were obtained while the experiment was in progress, so that the experimenter could follow the progress of the experiment

```
.SET TTY:WIDTH=132

.R TRESH2

NAME, TIME
[redacted]                              8:15

IO,Z,16: 123 ETC.?171

LPLOT : 1(75) 2(121)?1
*WHR04

 DATE: 04-AUG-76

PAUSE -- REALS
```




```
THRESHOLD:          0.02250    3        -0.02917    3
   0.02500     0.02500     0.02500     0.00000     0.00000     0.00000
   0.00000     0.00000     0.00000     0.00000     0.00000     0.00000

   0.02000     0.02000     0.02000     0.00000     0.00000     0.00000
   0.00000     0.00000     0.00000     0.00000     0.00000     0.00000

  -0.02500    -0.03000    -0.02000     0.00000     0.00000     0.00000
   0.00000     0.00000     0.00000     0.00000     0.00000     0.00000

  -0.03000    -0.03500    -0.03500     0.00000     0.00000     0.00000
   0.00000     0.00000     0.00000     0.00000     0.00000     0.00000
```

Figure 3.1a Stimulus versus time history

PAUSE -- END OF EXPERIMENT

PAUSE --
TYPE <CR> TO EXIT

.R TACSIM

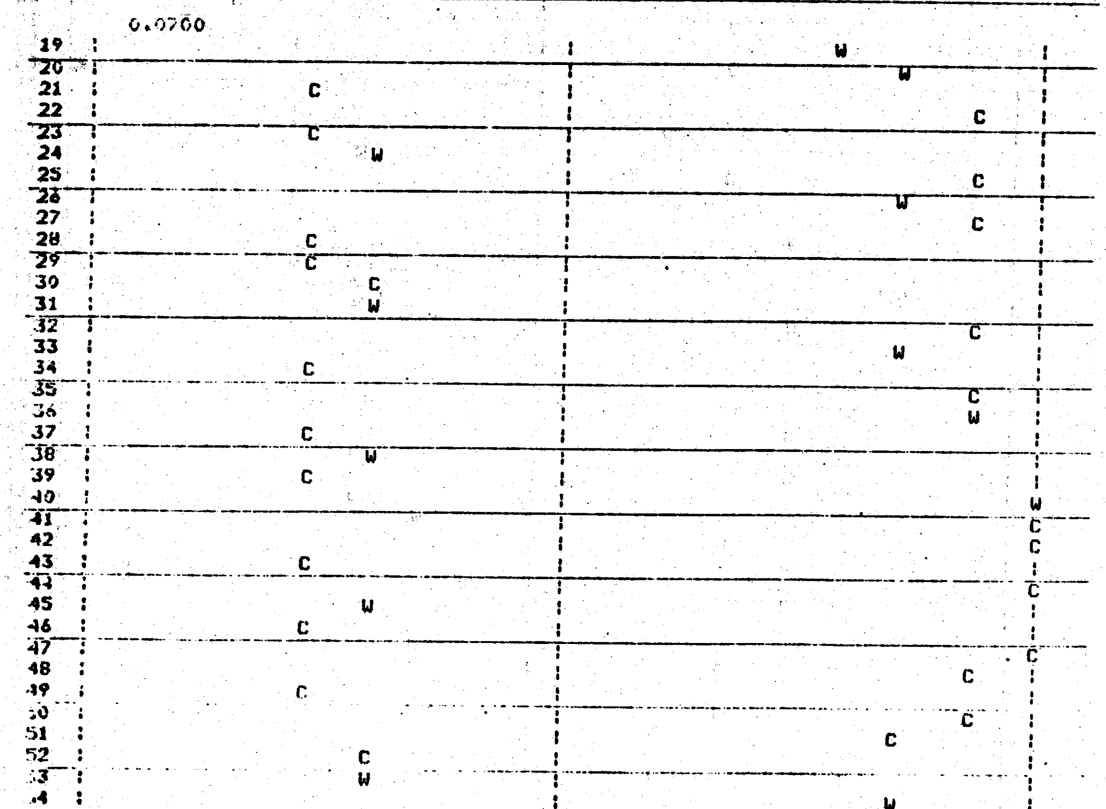
NAME : ...
[redacted] 8:35

(G.....: 1.. ETC.?173

LFLG. : 1(75) 2(121)?1
...

DATE: 04-AUG-76

PAUSE -- REALS



THRESHOLD: 0.05333 3 -0.03500 5
0.06000 0.06000 0.08000 0.00000 0.00000 0.00000
0.00000 0.00000 0.00000 0.00000 0.00000 0.00000

Figure 3.1b Stimulus versus time history.

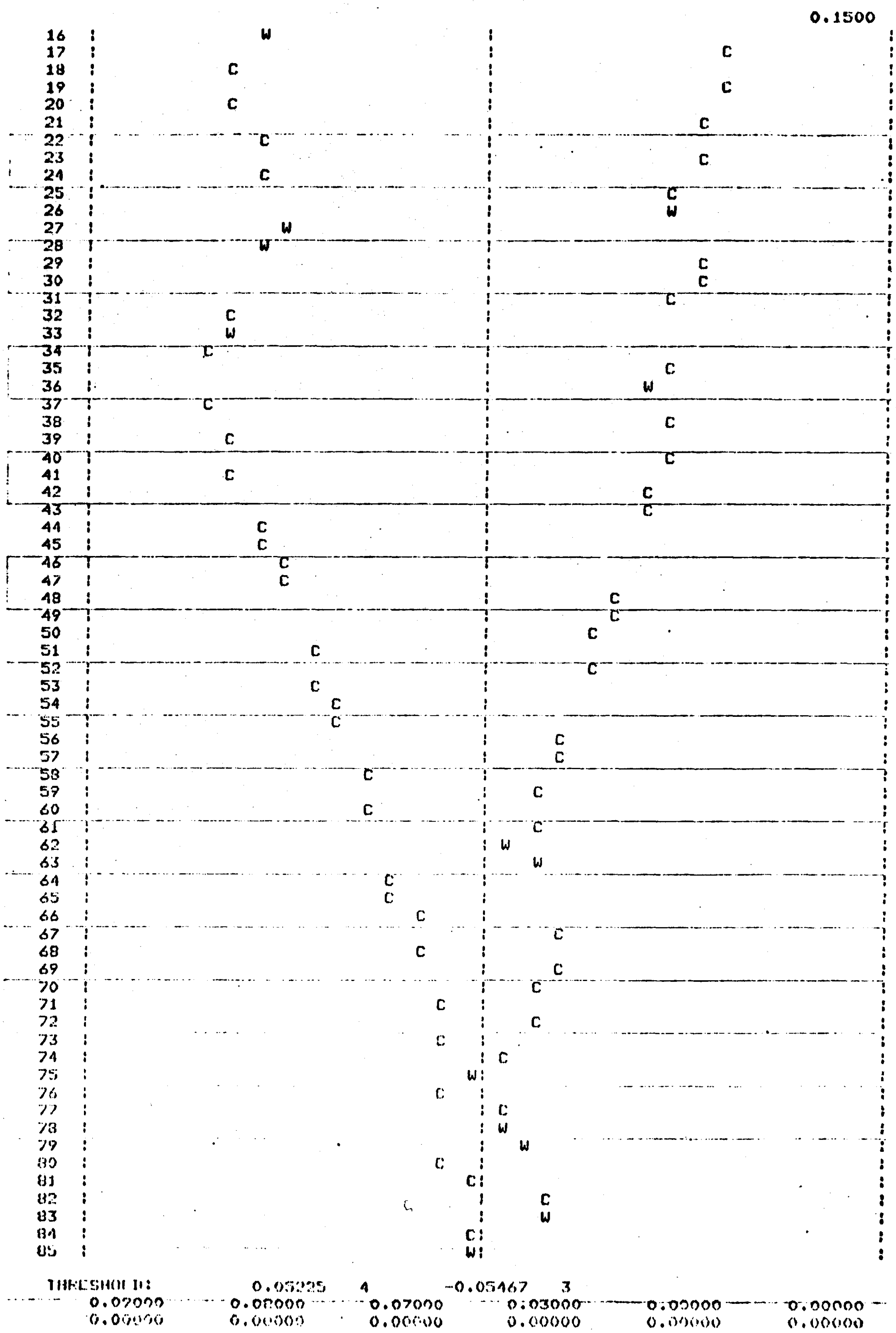
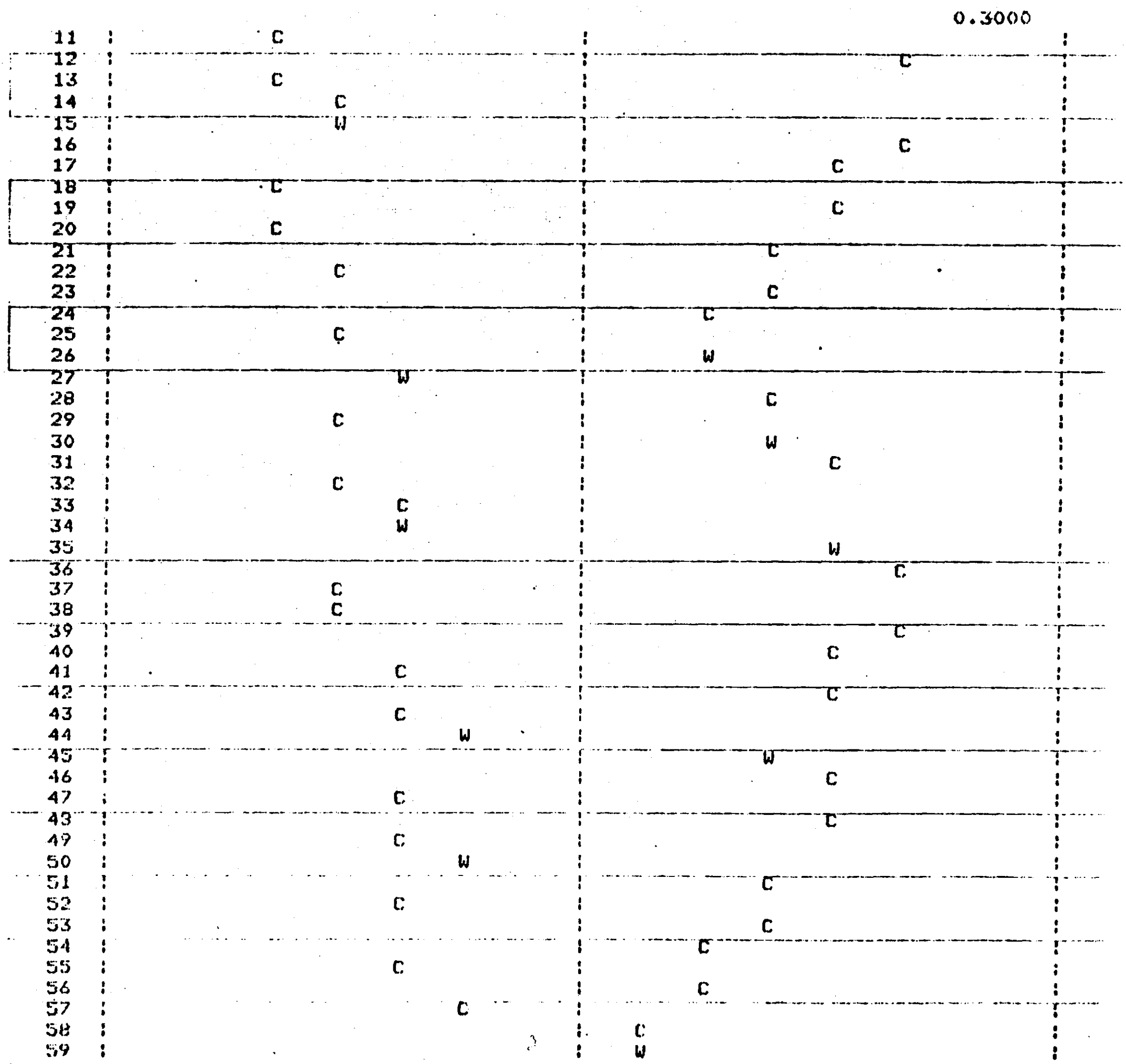


Figure 3.1c Stimulus versus time history

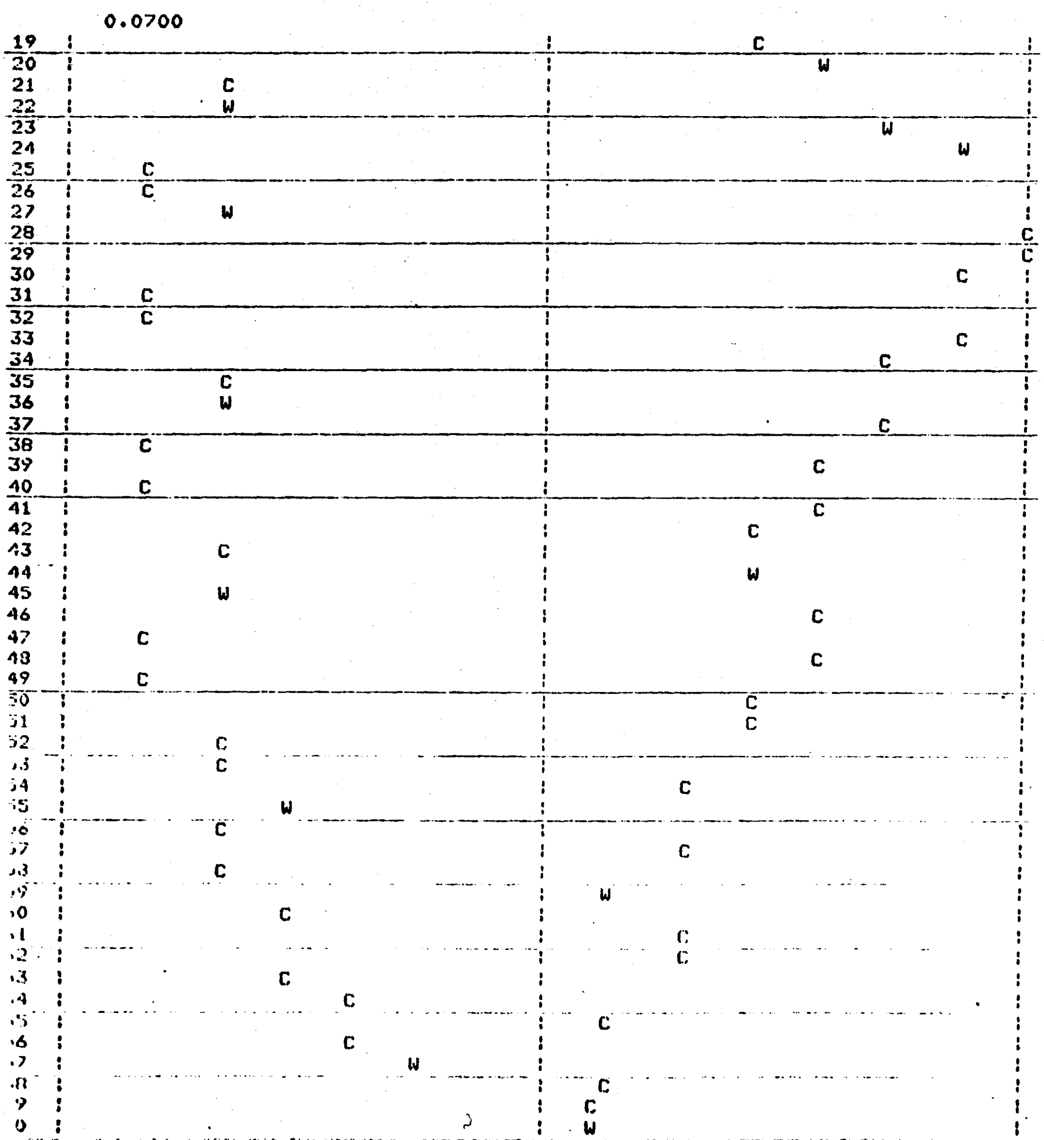
```
.R TRESH2

NAME,TIME
[redacted]                                  9:55

TO,Z,16: 123 ETC.?373

LPLOT : 1(75) 2(121)?1
*WM108

DATE: 10-AUG-76

PAUSE -- REALS
```




```
THRESHOLD:          0.13333    3      -0.14000    5
     0.20000     0.20000     0.16000     0.00000     0.00000     0.00000
```

Figure 3.1d Stimulus versus time history.

```
.R TRESH2

NAME,TIME
[redacted]          10:35

TO,Z,I6: 123 ETC.?321

LPLOT : 1(75) 2(121)?1
*DK:MR157.DAT

 DATE: 15-JUL-76

PAUSE -- REALS
```



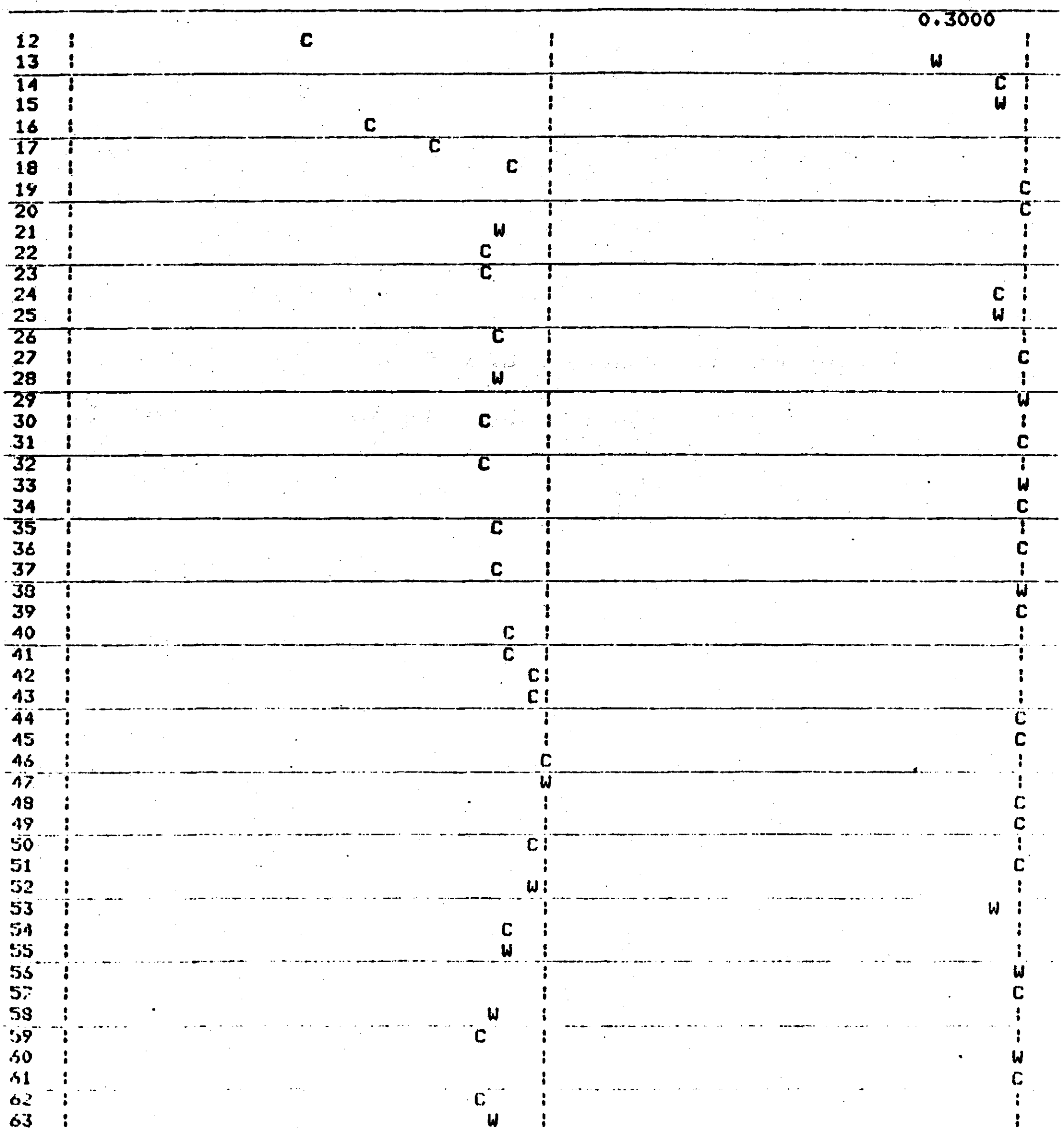

```
THRESHOLD:            0.02967   3        -0.05000   5
    0.07000      0.04000      0.02000      0.00000      0.00000      0.00000
    0.00000      0.00000      0.00000      0.00000      0.00000      0.00000
```

Figure 3.1e Stimulus versus time history.

LPLOT : 1(75) 2(121)?1
*DK:MR715.DAT

DATE: 15-JUL-76

PAUSE -- REALS



THRESHOLD: 0.34000 3 -0.04000 3

0.32000	0.40000	0.40000	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Figure 3.1f Stimulus versus time history.

closely. This was necessary since the subject was in a separate room where the only source of noise was the monitor he was watching. In addition to the lack of distraction, subject isolation did not impose on the subject the feeling of being watched continuously. However, this necessitated the monitoring of the experimental results by the experimenter, which was made possible by the plot display on the typewriter terminal. Any unusual trends in the correct/incorrect/false alarm responses could usually be traced to the subject not being attentive enough (in some cases, the subject was found to be dozing off). When the subject was found to be "not alert", the session was postponed to a different day and the data was discarded for that day. Plots were started only after the first incorrect detection was made. The starting value of the stimulus associated with a particular plot, which is also the full scale value, is shown at the top.

3.2 Exponential Fit

An exponential approximation was used to fit the data. The fitted curve has the form

$$S_n = a + b(\exp(ct)) \qquad (3.1)$$

where S_n is the value of the stimulus at the time instant t. The constant a was assumed to be the threshold value. A least squares fit was found using a conjugate gradient algorithm. A standard program from the IBM Scientific subroutine Package (FMCG) was used, and the convergence was quite fast. The minimization was done for 50 iterations, though the minimum was reached much earlier (to the fourth significant place). Threshold values had been calculated at the end of each session by taking the mean of the last six peaks and valleys of the stimulus versus time history. These values are shown along with the values calculated by the least squres fit in Appendix D (summary in Table 3.1). In most cases, these first approximation values agree very closely with the values found by a better fit.

TABLE 3.1 THRESHOLDS

(1) Change in Period

Period (sec) \ Damping Ratio	0.2	0.707
1	-0.034 (0.022)	-0.033 (0.020)
	0.028 (0.021)	0.038 (0.026)
3	-0.060 (0.039)	-0.037 (0.026)
	0.054 (0.030)	0.047 (0.023)

(2) Change in Variance

	0.2	0.707
1	-0.072 (0.038)	-0.084 (0.035)
	0.077 (0.042)	0.066 (0.044)
3	-0.121 (0.039)	-0.091 (0.034)
	0.150 (0.073)	0.083 (0.037)

Standard deviations are given in parentheses.

Units: $\ln(P/P_0)/\ln(10)$

3.3 Comparison between Nominals

The magnitudes of the thresholds were compared for each of the four nominals, both for a change in frequency and for a change in variance. Equality of variances was tested for each pair being compared using the F-test. If the variances were found to be not significantly different, a t-test was performed on the means. If the variances were different, an approximate t-test was done for comparing the means (Hoel, 1971). The null hypothesis that the means (for increase and decrease in the parameter value from nominal) are the same could not be rejected at 0.01 significance level. Thus the thresholds are not significantly different from one another. The t values along with the F values for the equality of variances have been tabulated in Table 3.2.

The thresholds for a change in variance appear to be higher than those for a change in frequency in all the cases (Table 3.3). Though a direct comparison is not of much value, it is nevertheless important to carry out such a comparison since the stimuli are normalized values in logarithmic units. Again, a t-test on the means was done for each nominal, for a change in variance and for a change in frequency. In all cases except one, the means were found to be significantly

TABLE 3.2 t-TEST FOR THE MEANS (THRESHOLD)

An F test was performed to test for the equivalence of variances.

The table gives the means (magnitudes) for increase and decrease, for the same nominal, along with the t-values (t), degrees of freedom (dt), F values for variance (F), and its degree of freedom (df, same for numerator and denominator).

	Increase	decrease	dt	t	F	df
121	0.034	0.028	16	0.670	1.076	8
123	0.077	0.072	18	0.274	1.266	9
171	0.033	0.019	16	0.494	1.973	8
173	0.084	0.066	14	0.924	1.537	7
321	0.060	0.054	22	0.461	1.678	11
323	0.150	0.121	14	0.979	3.605	7
371	0.047	0.037	22	0.939	1.285	11
373	0.091	0.083	16	0.479	1.196	8

So for the individual nominals, the mean value of the magnitudes of the thresholds are not significantly different. (The tests were made at the 0.010 significance level.)

TABLE 3.3 t-TEST FOR THE MEANS (THRESHOLD)

The table gives the means (magnitudes) for increase (+) and decrease (-) in frequency (fre) and in variance (var) for the same nominal, along with the t-values (t), and degrees of freedom (dof). The last column (diff) shows the difference that is significant at the 95% level.

Nominal (Nm): first digit period (seconds)
second digit damping ratio (0.2 or 0.707)

Nm	dof	t	Th (var)	Th (fre)	diff
12+	17	2.707	0.0769	0.0344	0.000
12-	17	3.126	0.0720	0.0276	0.014
17+	10	1.965	0.0655	0.0329	0.000
17-	15	3.044	0.0838	0.0382	0.014
32+	18	3.583	0.1498	0.0601	0.037
32-	18	4.411	0.1212	0.0536	0.035
37+	19	3.325	0.0831	0.0374	0.017
37-	19	3.588	0.0911	0.0467	0.019

The difference in mean value of the thresholds for frequency and variance are significant, except for 12+ and 17+.

different. As shown by Smith and Sherlock (1957) and Gibson (1958), from experiments at Cornell, one is more sensitive to the frequency with which an object crosses any reference marks. This could explain the somewhat higher threshold for variance, since in the case of a change in variance, the frequency remains constant. It should be noted, however, that the earlier work was not concerned with random processes. Also, as shown by Rice (1954) and Blake and Lindesey (1973), the average number of level crossings of a random process depends only on the passband of the filter for a Gaussian white noise, and not on the filter gain.

It is interesting to observe that one set of nominals ($T = 3$, $\zeta = 0.2$) appears distinctly different from the others. This nominal also resulted in a different type of performance in the detection time experiments. A possible explanation for the discrepancy will be given in the next chapter, where results from the detection time experiments are given.

3.4 Analysis of Variance

An analysis of variance was also performed for both increases and decreases in frequency and variance. These results also have been tabulated (Table 3.4). These were obtained using a standard packaged program (BMDP2V, from the BMDP programs package of the UCLA Computing Facility). A linear hypothesis model of the form

$$y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + e_{ijk} \qquad (3.2)$$

has been used. Taking μ to be the overall mean, α_i to be effects due to frequency, and β_j the effects due to damping ratio in the nominals, the results could be interpreted in the following manner. The results are considered at a significance level of 0.05. For a decrease in frequency, the differential effects due to frequency in different nominals, are significant (i.e., the null hypothesis that

$$\alpha_1 = \alpha_2 = 0 \qquad (3.3)$$

cannot be rejected).

For a change in variance, the frequency is significant for decreases, whereas for an increase, differential effects due to both frequency and damping ratio (between various nominals) are significant.

TABLE 3.4 ANALYSIS OF VARIANCE FOR FREQUENCY (F) AND DAMPING RATIO (D) EFFECTS

(Results from the BMDP2V Program)

M - Overall mean
F - Differential effects due to frequency
D - Differential effects due to damping
FD - Effects due to interaction of P and D
Er - Error

	Sum	dof	Mean Sq.	F	P(F exceeded)
(a) Decrease in Frequency					
M	0.07096	1	0.07096	108.9478	0.0
F	0.00306	1	0.00306	4.7048	0.036
D	0.00004	1	0.00004	0.0554	0.815
FD	0.00078	1	0.00078	1.2052	0.279
Er	0.02475	38	0.00065		
(b) Increase in Frequency					
M	0.06982	1	0.06982	86.9641	0.0
F	0.00237	1	0.00237	2.9439	0.094
D	0.00151	1	0.00151	1.8707	0.179
FD	0.00116	1	0.00116	1.4345	0.238
Er	0.03060	38	0.00081		
(c) Increase in Variance					
M	0.30549	1	0.30549	121.5088	0.0
F	0.01774	1	0.01774	7.0550	0.012
D	0.01324	1	0.01324	5.2673	0.029
FD	0.00664	1	0.00664	2.6429	0.114
Er	0.07794	31	0.00251		
(d) Decrease in Variance					
M	0.29397	1	0.29397	221.9800	0.0
F	0.00694	1	0.00694	5.2381	0.029
D	0.00073	1	0.00073	0.5494	0.464
FD	0.00380	1	0.00380	2.8693	0.100
Er	0.04105	31	0.00132		

In every case above, the null hypothesis $\alpha_1 = \alpha_2 = 0$, or $\beta_1 = \beta_2 = 0$ was tested at a significance level of 0.05. If the probability that F exceeds the value obtained in the analysis of variance procedure (Table 3.4) is less than 0.05, the null hypothesis is rejected for the alternative that the differential effects are significant.

3.5 Explanation of the Observed Results

Now an attempt will be made to explain the results from a physical standpoint. Significant conclusions could not be drawn as to whether an increase in frequency (i.e. decrease in period) is easier to detect than a decrease, though the preliminary experiments suggested such a trend (Curry and Govindaraj, 1976). There is a definite trend for the threshold to be higher for a lower nominal frequency. If threshold is viewed in terms of the angular distance traveled per unit time, a higher frequency motion would travel a given angular distance in a shorter time. Or, in other words, for a given time and angular distance, a higher increment is required for a lower nominal frequency than for a higher nominal frequency. Spigel (1965) defines absolute threshold (for angular motion) as "the minimum angular distance traversed, with the rate held constant". So, in terms of the difference in frequency from the nominal value, it is reasonable to expect that if the angular distance traversed is the threshold, the difference should be higher for a lower frequency. Spigel also states that the thresholds for circular movements follow the same laws as the rectilinear movements. For our case, though the motion is not uniform, (i.e., the motion is random), it may be expected that the thresholds for random processes also follow the same laws. The thresholds shown as a ratio to the nominal frequency are of the order of 0.10 for a change in frequency and agrees with the 0.10 threshold given by Brown (1960), and others in the psychophysics of motion (Spigel, 1965) (see Table 3.5).

For a change in variance, the thresholds are higher for the lower nominal frequencies, and the above explanation could again be used. The thresholds for increase and decrease for any one nominal are not significantly different from one another, though, as will be seen later in the detection time results, increases in variance from the nominal are easier

FIGURE 3.5 THRESHOLDS (Percentage of Nominal)

(1) Change in period

Nm	Th(log)	R	W	$W-W_0$	%Nm
12	-0.078 (0.051, 9)	0.924	6.800	0.517	8.2
	0.064 (0.048, 9)	1.066	5.896	-0.387	6.2
17	-0.076 (0.046, 9)	0.927	6.778	0.495	7.9
	0.087 (0.060, 9)	1.090	5.764	-0.519	8.3
32	-0.138 (0.090,12)	0.871	2.405	0.310	14.8
	0.124 (0.069,12)	1.131	1.852	-0.243	11.6
37	-0.085 (0.060,12)	0.917	2.284	0.186	8.9
	0.108 (0.053,12)	1.114	1.881	-0.214	10.2

(2. Change in variance

Nm	Th(log)	R	%Nm
12	-0.166 (0.87,10)	0.847	15.3
	0.177 (0.097,10)	1.190	19.4
17	-0.193 (0.081, 8)	0.825	17.5
	0.152 (0.101, 8)	1.162	16.2
32	-0.279 (0.090, 8)	0.757	24.3
	0.345 (0.168, 8)	1.410	41.0
37	-0.210 (0.078, 9)	0.811	18.9
	0.191 (0.085, 9)	1.211	21.1

Nm - Nominal: (period and damping ratio)
Th(log) - Threshold in log units ($\ln(P/P_0)$)
R - Ratio of the parameter to nominal
W - Frequency (rad/sec)
$W-W_0$ - Difference from nominal
%Nm - Percent threshold (period or variance)
Standard deviation and number of subjects are shown in parentheses.

consistently to detect than decreases. The fact that this does not affect the threshold is a proof that the form of the staircase method used here has eliminated any extraneous effects, i.e., though it takes a longer time to detect decreases compared to increases, the thresholds do not seem to differ significantly from each other. Similar conclusions can be drawn about detecting a change in frequency.

Finally, a comment is necessary in interpreting these thresholds. Since the experiments were conducted when the subject always anticipated a failure, his performance probably contrasts with what would be observed in a situation where failures are not normally expected. Thus, these results are likely to be a lower bound for the detection thresholds, higher values to be anticipated in situations where "failure-set" is not so strong. Nevertheless, the threshold values found in our work give a good order of magnitude for actual cases. Also, since increases and decreases are interleaved, these values may not depart too far from the values to be expected in real life situations.

CHAPTER IV

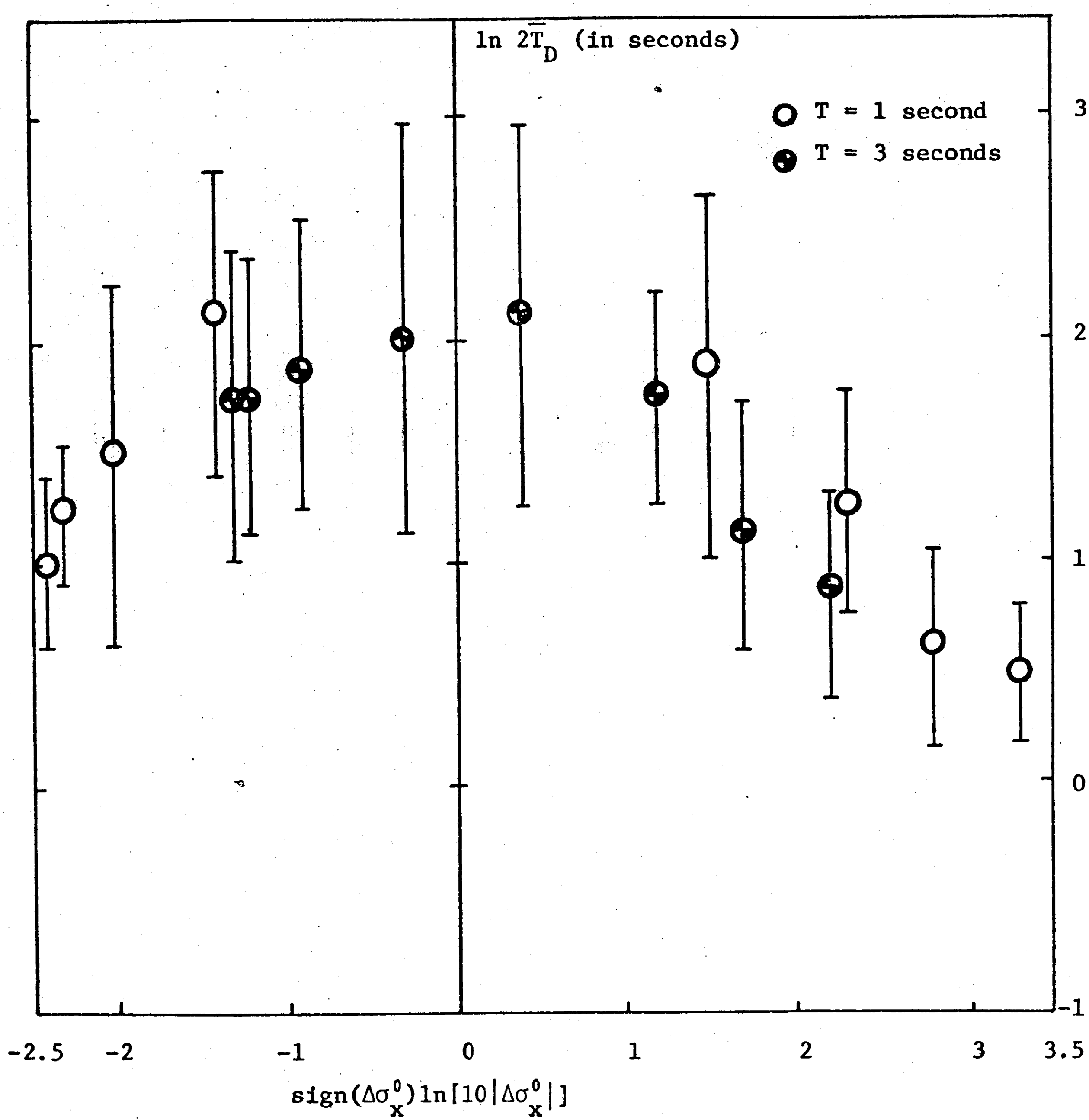
EXPERIMENTAL RESULTS: TIMES FOR DETECTION

Experiments conducted for threshold estimation and for detection time behavior were described in detail in Chapter II. In Chapter III, results from the threshold experiments were discussed. Though a knowledge of thresholds is essential for an understanding of the inherent limitations of the human in failure detection tasks, it is not sufficient for a complete understanding of the failure detection process. Hence, experiments were conducted to examine the detection times for various stimulus levels. This data will be later used in Chapter V for arriving at descriptive models. In this chapter, the results will be discussed and comparisons will be made between changes in frequency and variance.

Since the subjects who took part in these experiments went through the previous series of experiments for threshold determination, they had extensive experience with detection of parameter changes in a random process. This experiment was conducted over a period of several weeks and it is reasonable to assume that the subjects were "well-trained observers". For each nominal, the detection times are plotted as a function of stimulus level, for the population (see Figures 4.1.1, 4.1.2, 4.2.1, and 4.2.2). The data for individual subjects is given in Appendix E. The abscissa was chosen as the logarithm of the difference in standard deviation of the stimulus velocity from the nominal value. This was done because the preliminary experiments suggested that the detection times would be symmetric about the ordinate if plotted against rms velocity. Hence, it was felt that the subject might be more sensitive to velocity and he could be using this as a principal cue. Also, in the case of a change in frequency, rms value of velocity is directly proportional to the change in natural frequency, and in the case of a change in the variance, it is proportional to the standard deviation of stimulus displacement. The detection times are plotted in logarithmic units.

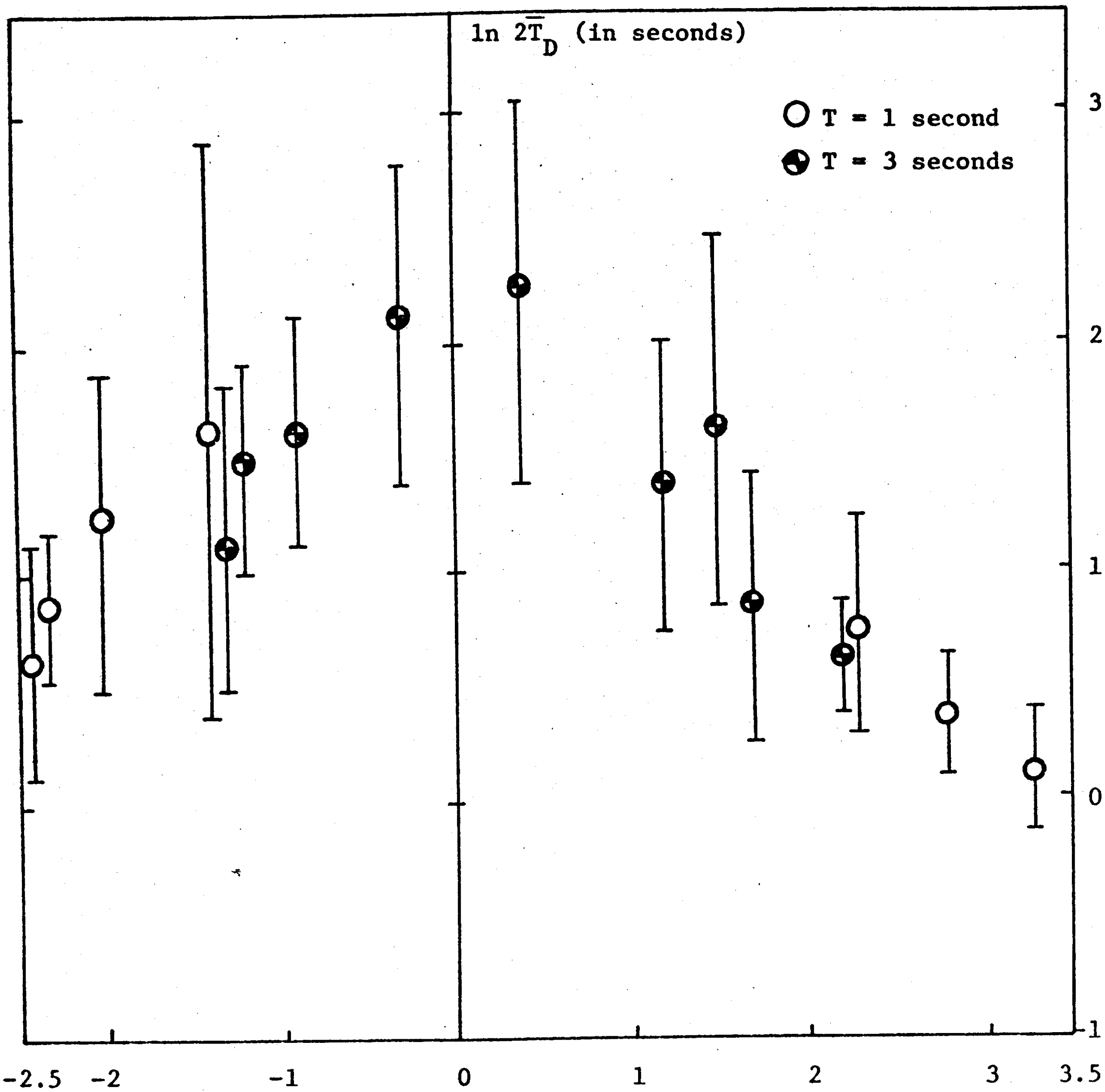
4.1 Symmetry in Detection Times for Frequency

From the plots (Figures 4.1.1 and 4.1.2), the following observations can be made. Detection times for frequency and variance appear nearly symmetric about the Y-axis. However,



Change in Frequency ($\zeta = 0.2$)

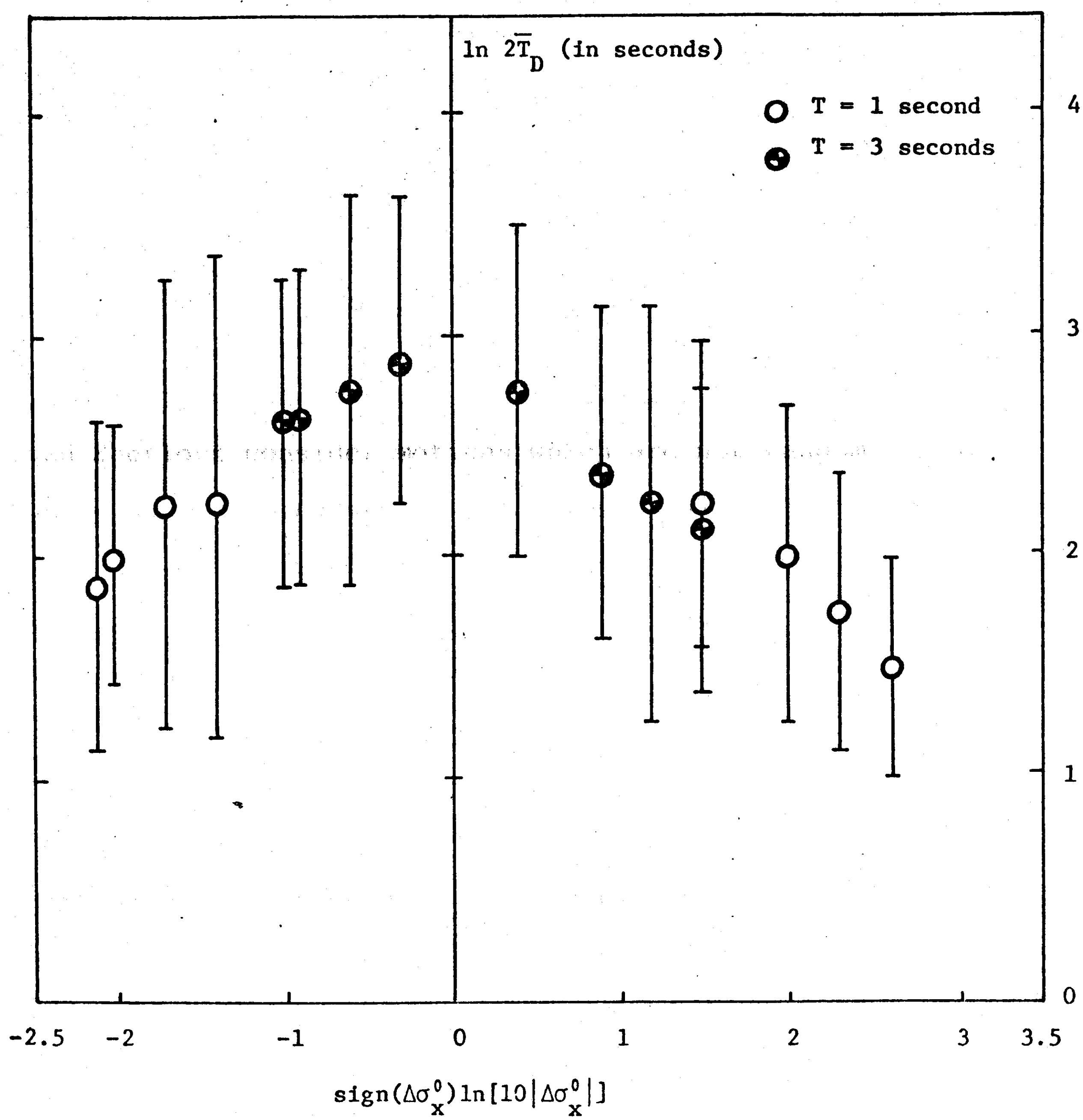
Figure 4.1.1 Data for the population



$\text{sign}(\Delta\sigma_x^0)\ln[10|\Delta\sigma_x^0|]$

Change in Frequency ($\zeta = 0.707$)

Figure 4.1.2   Data for the population.



Change in Variance (ζ = 0.2)

Figure 4.2.1 Data for the population

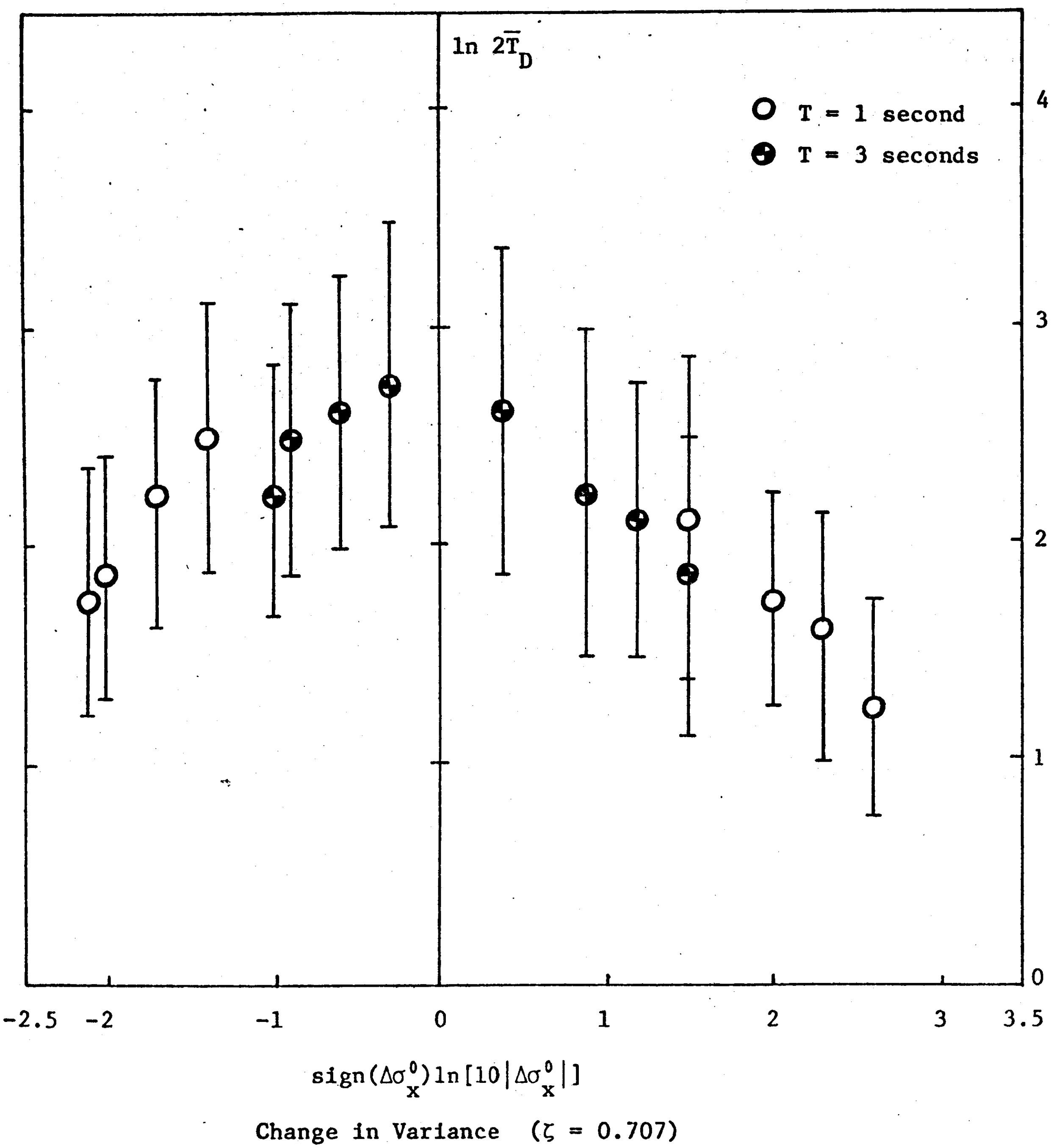


Figure 4.2.2 Data for the population

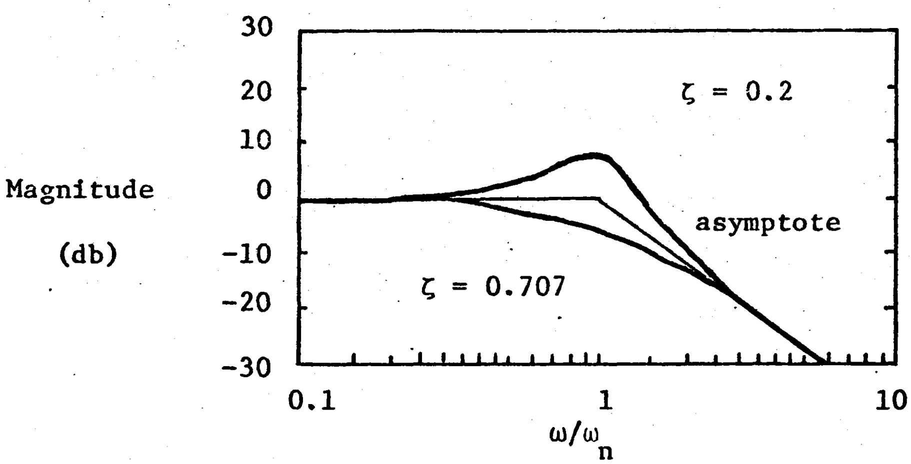
the detection of a change in variance takes a longer time compared to the detection of a change in frequency for the same level of change in rms velocity. The assumption that the subject might be using the rms velocity as a cue to detect changes in frequency seems to be reasonable. As observed by Smith and Sherlock (1957) and Gibson (1958), the observer may be sensitive to the frequency with which the object (line) crosses the reference lines. Though Smith and Sherlock consider motions which are not random (as in our case) it is nevertheless a similar situation. Thus if the subject is using the frequency of level crossings as the cue, the difference in the results obtained for variance and frequency should be expected. The straight line which the subject is observing moves inside a grid, and the grid lines aid in forming an estimate of the frequency with which it crosses the reference lines. If the variance of the displayed process changes, the average rate of level crossings does not change (Blake and Lindesay, 1973); hence the subject cannot use this as a cue. Therefore he may have to estimate the variance, rather than the frequency of level crossings. This may result in longer times for detection.

For a change in variance, it is almost always easier to detect an increase over a decrease. Since the subject knows the normal limits for motion, he could be behaving as a peak detector or a detector of exceedence limits (Curry and Govindaraj, 1976). When the variance decreases from nominal, the line tends to stay nearer to the origin. The subject takes more time to recognize such a change, since that is where the line remains for most of the time under normal circumstances. Thus the failed mode appears almost normal, and the failure is suspected only after some time of observing that the line never exceeds the limits it used to reach under normal circumstances.

4.2 Differences Among Subjects

Finally, a comment is necessary for a more detailed interpretation of the results of the three subjects, and the times at which the experiments were performed. For subjects MR and WM, participation in the experiment was their first activity during their workday, with a few exceptions for WM. They were prompt in arriving, and appeared fresh and alert, and remained so throughout the experiments. There were no no-shows, cancellations or postponements for any run. For SH, the schedule was different from day to day. There were a few days when the experiments were cancelled or postponed, and the subject was not always prompt in reporting at the scheduled times. While running the experiments, it was obvious that MR and WM had set consistent criteria and maintained them throughout. With very few exceptions, the probabilities of a miss or a false alarm increases in the order WM, MR, SH, and the probabilities of correct detections decrease in the same order. (The probabilities are shown in the tables of Appendix E.) This is also consistent with the relatively higher detection times observed for subject WM (Appendix E). It should also be noted that a change in variance was more difficult, and comparatively more tiring for the subject. The subject WM always aimed at 100% correct detections, and though everybody was told to "detect as quickly as possible without making too many mistakes", he seemed to feel highly uncomfortable about any mistakes he made. It may be worth recalling a remark by Green and Swets (1966, p. 336), "At worst, a miss indicates a minor sensory deficit; a false alarm, for the naive observer is a falsehood". It was apparent that WM wanted to avoid both misses and false alarms, and hence one sees an increase in his detection times.

There is one other observation that is worth noting. The nominal of T = 3.0 seconds, $\zeta = 0.2$, appears to be different from the other nominals, in that more false alarms and misses are noted for all subjects, along with higher detection times, when compared to the nominal with a higher damping ratio. Also, it may be recalled from discussions in Chapter III (Sections 3.4, 3.5), that this nominal resulted in higher thresholds for changes in frequency and variance. This is possibly due to the higher frequencies that are passed through an underdamped system. The ratio of upper cut-off frequencies for damping ratios of 0.2 and 0.707 is about 2. Also, the amplitude ratio at any frequency is higher for the underdamped case, reaching as high as 10 db at some frequencies (see Figure 4.3). Though these ratios do not depend on the nominal frequency, the effect may be more noticeable at lower nominal frequencies, and the absolute values of frequencies could have been more important in a lower frequency case in confounding the subject. It was perhaps not obvious as to whether the effect observed was due to a frequency change or some spurious phenomenon. Though the subjects may not have been aware that the difference occurred due to a very low damping ratio, it was obvious that they had difficulty in detection. So, in order



$1/((s/\omega_n)^2 + 2s(\zeta/\omega_n) + 1)$

Figure 4.3 Amplitude ratio for a second order system to make correct detections, they seem to wait a longer time to be certain that the frequency has changed. They either make too many mistakes or take too long a time. In fact, most of the time both these effects appear. Similar behavior is not observed for the case of a higher nominal frequency (T = 1.0 second).

CHAPTER V

MODELS FOR FAILURE DETECTION

In the previous chapters, the experiments for threshold estimation and detection behavior were described. The results obtained from the experiments were analysed. In this chapter, models will be developed which incorporate the data.

5.0 General Discussion

Since the process being monitored is stochastic, the observer cannot know the state of the system with certainty. But, for detection of any failures that might have occurred, the parameters that are significant must be estimated. These estimates should be properly utilized to arrive at conclusions as to whether a failure has or has not occurred. Hence, our model is assumed to consist of two stages: (1) an estimator for system states and (2) a decision mechanism which utilizes these estimates. Since the process is being observed continuously, estimates of system states must be made continuously. For estimation, a linear estimator is used. The decision process uses data, arriving continuously from the estimator, i.e., sequential analysis is performed on the estimates. Hence, the approach is similar to that of Curry and Gai (1976) and Gai (1975), who used two stage models to explain the observed detection time behavior in a monitoring task involving changes in the mean of a random process. Brief descriptions are given for linear estimation theory and sequential analysis.

The two parameter changes, i.e., variance and frequency from their nominal values, are considered separately for modelling purposes. Modifications of sequential analysis for use in the decision strategy are given. Finally, the results obtained from the experiments are compared with results from simulations of the proposed models.

5.1 Linear Estimation

When the process being observed contains noise, an exact determination of the states involved is not possible, and estimates must be obtained. If the associated statistics are known for any process, the problem can be viewed as a Bayesian estimation problem, and when the operations describing the dynamics of the process are linear, it becomes a linear Bayesian problem. Depending on the structure of the problem, various approaches can be used to obtain a solution. Since the dynamics of the process are assumed to be completely known, and since the input is assumed to be white noise, an appropriate choice of estimator would be the Kalman filter. It is the best possible linear estimator for such a system, because it results in a minimum error in its estimates. A brief description of the Kalman filter will be given.

Since the process used in this experiment was generated by a digital computer, and since all the computations were performed digitally, only a discrete time formulation is discussed. A brief discussion of the Kalman filter will be given here. A more detailed description can be found in Jazwinski (1970).

The discrete linear system is described by

$$x_{k+1} = \Phi(t_{k+1}, t_k) x_k + \Gamma(t_k)\omega_{k+1} \qquad k = 0,1,\ldots. \tag{5.1}$$

where x_k is the n-vector of the state at t_k, Φ is an n x n non-singular state transition matrix, Γ is n x r, and

$\{\omega_k, k=1,\ldots\}$ is an r-vector of white Gaussian sequence, where ω_k is normally distributed with zero mean and covariance Q_k. The discrete linear observation is given by

$$y_k = m(t_k)x_k + v_k \tag{5.2}$$

The statistics of v_k and ω_k are assumed known, and they are assumed to be independent.

For this system, the optimal (minimum variance) filter consists of difference equations for the conditional mean, and the covariance matrix. Between observations,

$$\hat{x}_{k+1}^{k} = \Phi(t_{k+1}, t_k)\hat{x}_k^k \tag{5.3}$$

$$P_{k+1}^{k} = \Phi(t_{k+1}, t_k)P_k^k\Phi^T(t_{k+1}, t_k) + \Gamma(t_k)Q_{k+1}\Gamma^T(t_k) \tag{5.4}$$

At observations

$$\hat{x}_k^k = \hat{x}_k^{k-1} + K(t_k)[y_k - M(t_k)\hat{x}_k^{k-1}] \tag{5.5}$$

$$P_k^k = P_k^{k-1} - K(t_k)M(t_k)P_k^{k-1} \tag{5.6}$$

where

$$K(t_k) = P_k^{k-1}M^T(t_k)\{M(t_k)P_k^{k-1}M^T(t_k) + R_k\}^{-1} \tag{5.7}$$

is the Kalman gain. Prediction for $t_\ell > t_k$, (x_ℓ^k, P_ℓ^k) is accomplished via equations with initial condition (x_k^k, P_k^k). Since P_k is a covariance matrix, $P_k^k \geq 0$ if $P_0 \geq 0$.

The system under consideration, i.e. the shaping filter, is time invariant, and hence Φ, Γ and M are constant. However, when a failure occurs, these system matrices change, and it is this change that results in a discrepancy between observed and expected values, leading to a detection of the change.

The predicted residual or the measurement error is given by

$$r(k+1|k) \triangleq y_{k+1} - E[y_{k+1}|Y_k] \qquad Y_k = \{y_1, y_2 \cdots y_k\}$$

$$= y_{k+1} = M(k+1)\hat{x}_{k+1}^k \qquad (5.8)$$

When the system matrices and the Kalman filter matrices are the same, it can be shown that

$$E[r(k+1|k)] = 0$$

and (5.9)

$$E[r(k+1|k)r(k+1|k)^T] = M(k+1)P(k+1|k)M^T(k+1) + R(k+1)$$

The residual is also called the innovation process, since it is orthogonal to all previous information, i.e., each new sample of the innovation process brings new information, and the residual cannot be predicted from the knowledge of information up to the current point (Schweppe, 1973; Kailath, 1970).

The filter is not optimal if the parameters governing the dynamics of the filter are different from those of the system. The residuals do not remain white for such a situation. An expression for the correlation of the residuals for such a case, for a continuous system is given by Curry and Gai (1976). For discrete systems, a similar formulation can be found in Martin and Stubberud (1976).

In the failure detection situations considered in the current work, the mean of the observed process remains zero. The variance changes. However, for the case of a failure in frequency, the mean speed of the observed process (|velocity|), changes, and this is used for detecting the failures.

5.2 Sequential Analysis

Under the normal hypothesis testing approach, the number of observations or the sample size is fixed. But there are cases where it may be desirable and advantageous to allow the sample size to be a random variable, to be determined by the outcome of the observations. This is the case suited for problems like failure detection, where sufficient information is accumulated over a sequence of observations, so that a decision can be made as to which hypothesis is true. A decision rule is determined in advance so that depending on the observations, one of the following paths is taken (1) the hypothesis H_0 is accepted, (2) the hypothesis H_0 is rejected (alternately, hypothesis H_1 is accepted), or (3) a decision is deferred until an additional observation is made. This procedure is carried out sequentially until a definite decision to accept or reject the hypothesis H_0 is made. An optimal strategy for sequential analysis has been spelled out in detail by Wald (1947). Use of this method for signal detection has been suggested by Birdsall et al (1965), Phatak and Kleinman (1972), and Sheridan and Ferrel (1974). For our purposes, methods given by Wald will be used with some slight modifications. Since details can be found in Wald, only a brief summary relevant to our work will be given.

The sequential decision problem is to test between two hypotheses H_0 and H_1. It will be assumed that (1) the hypotheses are simple hypotheses, meaning that the probability distributions are known under both hypotheses, and (2) that the observations are independent. Under these assumptions, the problem can be formulated as

the distribution is $f(X,\theta_0)$ when H_0 is true

and the distribution is $f(X,\theta_1)$ when H_1 is true,

where θ, the distribution parameter, assumes θ_0 or θ_1 depending on which hypothesis is ture.

Let x_i, i = 1, ..., m, be the realization of the random variable x, for m observations. Then the likelihood of either hypothesis is given by

$$p_{0m} = \pi f(x_i,\theta_0) \tag{5.10}$$

and

$$p_{1m} = \pi f(x_i,\theta_1) \tag{5.11}$$

respectively. In the sequential probability ratio test, the probability ratio

$$PR = (p_{1m}/p_{0m}) \tag{5.12}$$

is found at every stage for the past m observations. Two limits, A and B, are set in advance. At any stage, either of the hypotheses is accepted or a decision is deferred until more information is accumulated. The decision as to which alternative to choose is taken as follows:

(1) If $B < PR < A$, the experiment is continued by taking an additional observation,

(2) If $PR \geq A$, the experiment is terminated with the acceptance of H_1, and

(3) If $PR \leq B$, the experiment is terminated with the acceptance of H_0.

Now the problem is in the proper choice of A and B. It would be desirable to relate these to the following parameters:

P_{FA} - the probability of rejecting H_0 when it is true

P_{MISS} - the probability of accepting H_0 when H_1 is true.

These values are predetermined before sampling is done. The exact functional relationships $A = g_1(P_{MISS}, P_{FA})$ and $B = g_2(P_{MISS}, P_{FA})$ are not available. Wald has suggested very good approximations for these functions. They are $A = (1-P_{MISS})/P_{FA}$ and $B = P_{MISS}/(1-P_{FA})$. The use of the above strategy with the above values for A and B is known as the sequential probability ratio test (SPRT). Some of the advantages of this procedure are: (1) there is no need to calculate any statistic such as t or F, (2) the size of two types of error can be determined apriori, (3) the expected number of samples needed can be calculated, and (4) the expected number of samples needed is less than that for a test with fixed number of observations. For a failure detection task, since the occurence of the failure is itself random, the number of observations cannot be predetermined, and hence the sequential test would appear to be well-suited for the task.

For our purposes, we need to consider two specific forms of the test. Because a change occurs in variance, during one part of the experiment, it is reasonable to expect that the variance of the observed process will be different from the nominal, while the mean will remain at zero independent of variance change (since the input is zero mean). Thus, a test on the means is of no use, and a test for variance is needed. For a change in frequency (under failed conditions), it was found that a test for the mean of certain variables could also be used to detect the failure that occurred. Hence the problem of testing for means (with the same variance) will also be discussed. Since we have a linear system driven by a Gaussian white noise source, the density functions under the two hypotheses are given by

Under H_0:

$$f(x_i,\theta_0) = (1/\sqrt{2\pi}\ \sigma_0)\exp[-(1/2\sigma_0^2)(x_i-\theta)^2] \qquad (5.13)$$

Under H_1:

$$f(x_i,\theta_1) = (1/\sqrt{2\pi}\ \sigma_1)\exp[-(1/2\sigma_1^2)(x_i-\theta)^2] \qquad (5.14)$$

Now the two cases will be considered.

Case A. Variance is constant and known, $\sigma_0 = \sigma_1 = \sigma$ and the means are different.

(i) $\theta_1 > \theta_0$

The probability density of the sample $(x_1,\ldots, x_m)$ is given by

$$p_{0m} = (1/(2\pi)^{m/2}\sigma^m)\exp[-(1/2\sigma^2)\sum_{i=1}^{m}(x_i-\theta_0)^2] \qquad (5.15)$$

if $\theta = \theta_0$, and by

$$p_{1m} = (1/(2\pi)^{m/2}\sigma^m)\exp[-(1/2\sigma^2)\sum_{i=1}^{m}(x_i-\theta_1)^2] \qquad (5.16)$$

if $\theta = \theta_1$. The probability ratio (p_{1m}/p_{0m}) is calculated at each stage of the inspection.

$$\frac{p_{1m}}{p_{0m}} = \frac{\exp[-(1/2\sigma^2)\Sigma(x_i-\theta_1)^2]}{\exp[-(1/2\sigma^2)\Sigma(x_i-\theta_0)^2]} \qquad (5.17)$$

Additional observations are taken as long as

$$B < (p_{1m}/p_{0m}) < A \qquad (5.18a)$$

The hypothesis H_0 is accepted and observations are terminated if

$$(p_{1m}/p_{0m}) \leq B \tag{5.18b}$$

The hypothesis H_0 is rejected and observations are terminated if

$$(p_{1m}/p_{0m}) \geq A \tag{5.18c}$$

A and B are given by

$$\begin{aligned} A &= (1 - P_{MISS})/P_{FA} \\ B &= P_{MISS}/(1 - P_{FA}) \end{aligned} \tag{5.19}$$

After taking logarithms and simplifying, the following inequalities are obtained:

Continue with additional observations if

$$\ln B < [(\theta_1-\theta_0)/\sigma^2]\Sigma\ x_i+(m/2\sigma^2)(\theta_0^2-\theta_1^2) < \ln A \tag{5.20a}$$

Accept H_0 if

$$[(\theta_1-\theta_0)/\sigma^2]\Sigma\ x_i+(m/2\sigma^2)(\theta_0^2-\theta_1^2) \leq \ln B \tag{5.20b}$$

Reject H_0 if

$$[(\theta_1-\theta_0)/\sigma^2]\Sigma\ x_i+(m/2\sigma^2)(\theta_0^2-\theta_1^2) \geq \ln A \tag{5.20c}$$

These can be further simplified to obtain the following:

Continue if

$$(\sigma^2/(\theta_1-\theta_0)\ln B < (\Sigma x_i-(m/2)(\theta_0+\theta_1)) < (\sigma^2/(\theta_1-\theta_0)\ln A \tag{5.21a}$$

Accept H_0 if

$$(\Sigma x_i-(m/2)(\theta_0+\theta_1)) \leq (\sigma^2/(\theta_1-\theta_0)\ln B \tag{5.21b}$$

Reject H_0 if

$$(\Sigma x_i-(m/2)(\theta_0+\theta_1)) \geq (\sigma^2/(\theta_1-\theta_0)\ln A \tag{5.21c}$$

(ii) $\theta_1 < \theta_0$

Since the inequalities in equation 5.20 hold for $\theta_1 > \theta_0$ as well as for $\theta_1 < \theta_0$ (they are obtained just by taking the probability ratios, without imposing any conditions), a convenient form can be obtained by multiplying by -1. The inequalities are reversed when multiplied by -1.

Continue observations if

$$-\ln B > ((\theta_1-\theta_0)/\sigma^2)(\Sigma(-x_i)-(m/2\sigma^2)(\theta_0^2-\theta_1^2)) > -\ln A \tag{5.22a}$$

Accept H_0 if

$$((\theta_1-\theta_0)/\sigma^2)(\Sigma(-x_i)-(m/2\sigma^2)(\theta_0^2-\theta_1^2)) \geq -\ln B \tag{5.22b}$$

Reject H_0 if

$$((\theta_1-\theta_0)/\sigma^2)(\Sigma(-x_i)-(m/2\sigma^2)(\theta_0^2-\theta_1^2)) \leq -\ln A \quad (5.22c)$$

These can be simplified to obtain the following:

Continue observations if:

$$-(\sigma^2/(\theta_0-\theta_1))\ln B > (\Sigma x_i-(m/2)(\theta_0+\theta_1)) > -(\sigma^2/(\theta_0-\theta_1))\ln A \quad (5.23a)$$

Accept H_0 if

$$(\Sigma x_i-(m/2)(\theta_0+\theta_1)) \geq -(\sigma^2/(\theta_0-\theta_1))\ln B \quad (5.23b)$$

Reject H_0 if

$$(\Sigma x_i-(m/2)(\theta_0+\theta_1)) \leq -(\sigma^2/(\theta_0-\theta_1))\ln A \quad (5.23c)$$

A modification is necessary in the above since the mean value under the failed mode is unknown. Wald suggested that an artificial parameter θ_1 could be chosen based on the physical properties. This will be done in our analysis.

Case B. Mean is known ($\theta_0 = \theta_1 = 0$), and variances are different, $\sigma_1 \neq \sigma_0$. (σ_0 is known, σ_1 is unknown, but just as in the Case A, σ_1 can be assumed for tests.

(i) $\sigma_1 > \sigma_0$

The probability densities of the sample $(x_1, \ldots, x_m)$ are given by

$$p_{0m} = (1/((2\pi)^{m/2}\sigma_0^m))\exp[-(1/2\sigma_0^2)\sum_{i=1}^{m}(x_i-\theta)^2] \quad (5.24)$$

if $\sigma = \sigma_0$, and

$$p_{1m} = (1/((2\pi)^{m/2}\sigma_1^m))\exp[-(1/2\sigma_1^2)\sum_{i=1}^{m}(x_i-\theta)^2] \quad (5.25)$$

if $\sigma = \sigma_1$.

The probability ratio p_{1m}/p_{0m} is calculated at each stage of the inspection

$$\frac{p_{1m}}{p_{0m}} = \frac{(1/\sigma_1^m)\exp[-(1/2\sigma_1^2)\Sigma(x_i-\theta)^2]}{(1/\sigma_0^m)\exp[-(1/2\sigma_0^2)\Sigma(x_i-\theta)^2]} \quad (5.26)$$

Observations continue with additional measurements if

$$B < (p_{1m}/p_{0m}) < A \quad (5.27a)$$

Choose H_0 if

$$(p_{1m}/p_{0m}) \leq B \quad (5.27b)$$

Choose H_1 if

$$(p_{1m}/p_{0m}) \geq A \quad (5.27c)$$

Taking logarithms, dividing by $1/2\sigma_0^2 - 1/2\sigma_1^2$, and simplifying, we obtain the following:

Continue observations if

$$\frac{2\ln B + m\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} < \Sigma(x_i-\theta)^2 < \frac{2\ln A + m\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} \qquad (5.28a)$$

Accept H_0 if

$$\Sigma(x_i-\theta)^2 \leq \frac{2\ln B + m\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} \qquad (5.28b)$$

Reject H_0 if

$$\Sigma(x_i-\theta)^2 \geq \frac{2\ln A + m\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} \qquad (5.28c)$$

These can be further simplified to obtain the following:

Continue observations if

$$\frac{2\ln B}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} < \Sigma(x_i-\theta)^2 - \frac{m\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} < \frac{2\ln A}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} \qquad (5.29a)$$

Accept H_0 if

$$\Sigma(x_i-\theta)^2 - \frac{m\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} \leq \frac{2\ln B}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} \qquad (5.29b)$$

Reject H_0 if

$$\Sigma(x_i-\theta)^2 - \frac{m\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} \geq \frac{2\ln A}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} \qquad (5.29c)$$

(ii) When a failure is defined by a reduction in variance (i.e., $\sigma_1 < \sigma_0$), the inequalities are obtained by multiplying by -1 and reversing the inequalities.

Continue with additional observations if

$$(-B) > -(p_{1m}/p_{0m}) > (-A) \qquad (5.30a)$$

Choose H_0 if

$$-(p_{1m}/p_{0m}) \geq (-B) \qquad (5.30b)$$

Reject H_0 if

$$-(p_{1m}/p_{0m}) \leq (-A) \qquad (5.30c)$$

Taking logarithms, we get the following:

Continue observations if

$$-\ln B > \frac{1}{2}\left(\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}\right)\Sigma(x_i-\theta)^2 - m\ln\left(\frac{\sigma_0^2}{\sigma_1^2}\right) > -\ln A \qquad (5.31a)$$

Accept H_0 if

$$\frac{1}{2}\left(\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}\right)\Sigma(x_i-\theta)^2 - m\ln\left(\frac{\sigma_0^2}{\sigma_1^2}\right) \geq -\ln B \qquad (5.31b)$$

Reject H_0 if

$$\frac{1}{2}\left(\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}\right)\Sigma(x_i-\theta)^2 - m\ln\left(\frac{\sigma_0^2}{\sigma_1^2}\right) \leq -\ln A \qquad (5.31c)$$

These inequalities can be rewritten as follows:

Continue observations if

$$-\frac{2\ln B + m\ln\left(\frac{\sigma_1^2}{\sigma_0^2}\right)}{\left(\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}\right)} > \Sigma(x_i-\theta)^2 > -\frac{2\ln A + m\ln\left(\frac{\sigma_1^2}{\sigma_0^2}\right)}{\left(\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}\right)} \qquad (5.32a)$$

Accept H_0 if

$$\Sigma(x_i-\theta)^2 \geq -\frac{2\ln B + m\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_1^2}-\frac{1}{\sigma_0^2}} \qquad (5.32b)$$

Reject H_0 if

$$\Sigma(x_i-\theta)^2 \leq -\frac{2\ln A + m\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_1^2}-\frac{1}{\sigma_0^2}} \qquad (5.32c)$$

The slope can be subtracted to obtain the following

Continue observations if

$$-\frac{2\ln B}{\frac{1}{\sigma_1^2}-\frac{1}{\sigma_0^2}} > \Sigma(x_i-\theta)^2 - \frac{m\ln(\frac{\sigma_0^2}{\sigma_1^2})}{\frac{1}{\sigma_1^2}-\frac{1}{\sigma_0^2}} > -\frac{2\ln A}{\frac{1}{\sigma_1^2}-\frac{1}{\sigma_0^2}} \qquad (5.33a)$$

Accept H_0 if

$$\Sigma(x_i-\theta)^2 - \frac{m\ln(\frac{\sigma_0^2}{\sigma_1^2})}{\frac{1}{\sigma_1^2}-\frac{1}{\sigma_0^2}} \geq -\frac{2\ln B}{\frac{1}{\sigma_1^2}-\frac{1}{\sigma_0^2}} \qquad (5.33b)$$

Reject H_0 if

$$\Sigma(x_i-\theta)^2 - \frac{m\ln(\frac{\sigma_0^2}{\sigma_1^2})}{\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}} \leq - \frac{2\ln A}{\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}} \qquad (5.33c)$$

The decision regions for both cases are shown in Figures 5.1 and 5.2.

Modification to account for change of mode

The basic sequential test does not anticipate any change in modes during the observation process, while a change is to be expected in a failure detection process (see also Gai, 1975). Consequently, a method suggested by Chien (1972) and also used by Gai is used. Chien suggested that if a failure detection process involves checking for the normal operation, i.e., checking if the process continues to function normally, more observations are needed to detect a failure, because the decision function might have strayed too far into the region indicating normal operation. He suggested a suboptimal strategy where the decision function is reset to its initial value whenever normal mode of operation is likely. When this is done,

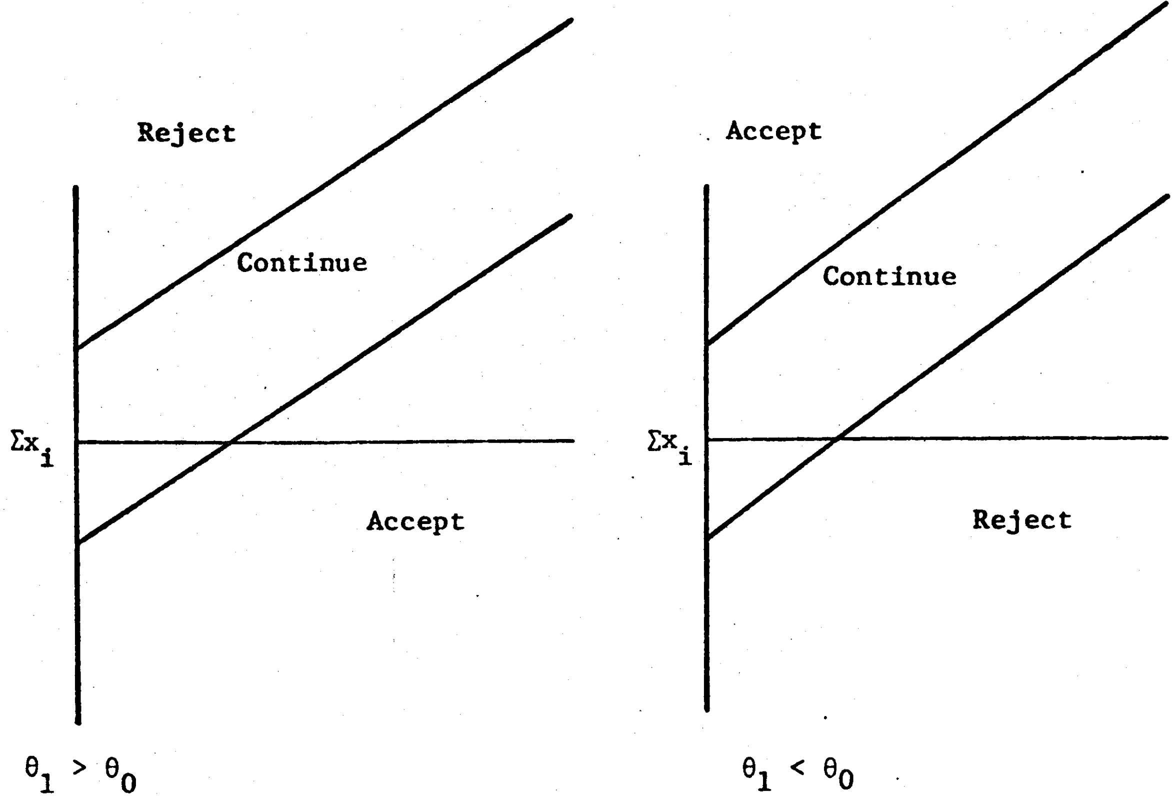


Figure 5.1 Test for Means

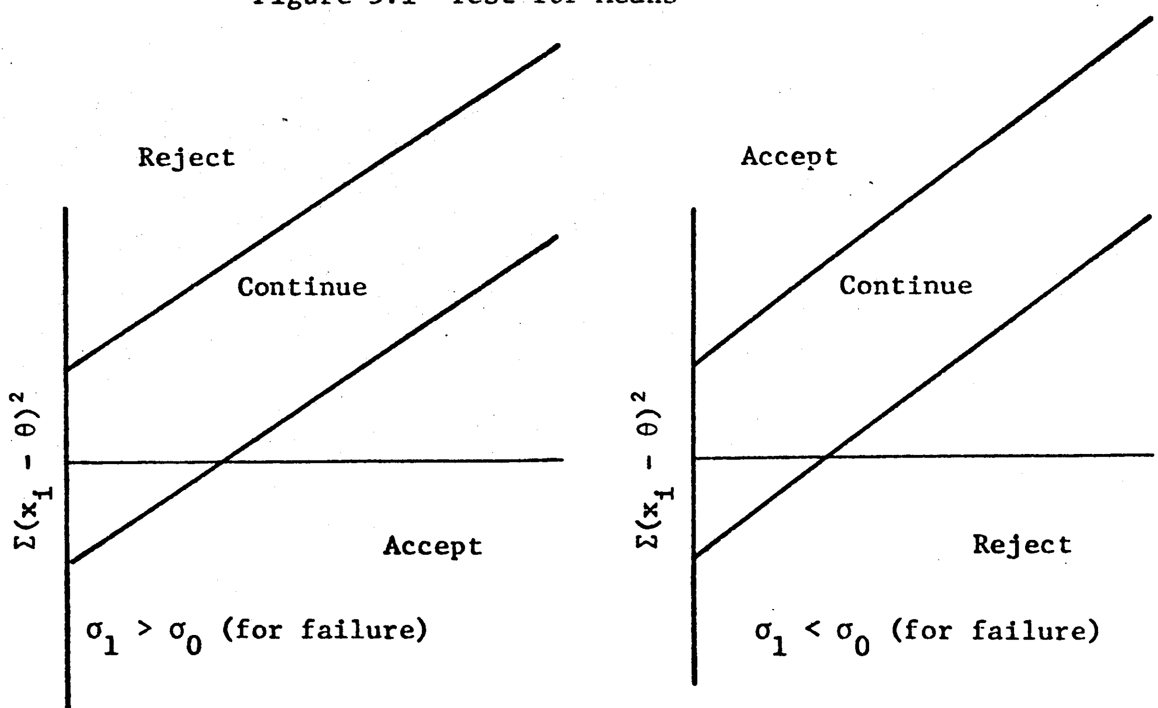


Figure 5.2 Test for Variance

the number of observations required to drive the decision function into the failure region is less than the case with no reset. This resetting helps to reduce the time between the onset of a failure and its subsequent detection.

In both cases described above, the normal mode is given by the zero-mean horizontal line; thus the decision function should be reset whenever it crosses the zero line (Figure 5.3). Now only one criterion level is needed, since the normal mode is not reported. However, the same level as before cannot be used, if the same false alarm probability is to be maintained. This is because, for the same level, more false alarms would occur due to the resets. The criterion level should thus be raised to A1, where A1 is given by the following:

$$A1 - \ln A1 - 1 = -[\ln A + ((A-1)/(1-B))\ln B] \quad (5.34)$$

(Chien, 1972)

In the following sections, models for the decision strategy will be discussed both for failures in frequency and for failures in variance.

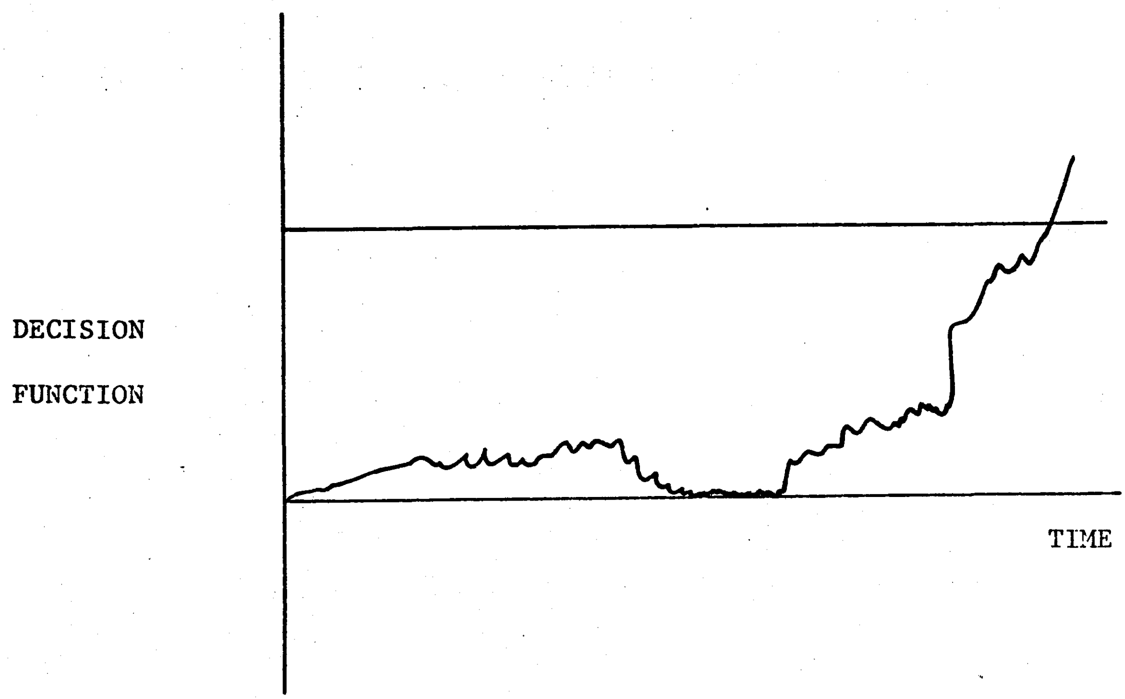


Figure 5.3 Decision Function for the case with resetting.

5.3 Modelling: General Description

The process displayed to the subject consists of up and down motion of a horizontal line (see Section 2.1). The subject observed the position of the line continuously. It is well known that a human is also sensitive to the velocity of the motion being observed. Initial analysis showed that if velocity were to form the basis of the detection task, more accurate predictions could be made of the experimentally observed detection times. Hence, a scalar observation, consisting of the rate of motion will be considered as the observed variable. The observations are assumed corrupted by an additive noise, v(t), which can be modelled as a zero mean Gaussian process. The input to the failure detection system then consists of the observation plus Gaussian white noise. The failure detector is modelled here as an estimator cascaded with a decision mechanism.

For the estimation process, a Kalman filter was assumed for both changes in frequency and variance. The output of this estimator was used in the decision mechanism for detection of failures. Since the process being observed was a second order system operating on white noise, a second order

Kalman filter with the same parameters as the nominal system parameters was used. Since the observed system as well as the estimator are linear, and the input is Gaussian and zero mean, the states (or a linear combination of the states) from either one can be used for the decision process. The observation estimate of the model is used in the decision mechanism, since the states are non-unique, and the dimension of the state vector is larger than that of the observation, which is a scalar. It is also assumed that the measurement residual, i.e., the difference between estimated and observed values, rather than the observation estimate itself, is used for the decision mechanism. This can be justified because (1) the residual is more sensitive to the effect of failure than the observation estimate, and (2) for the nominal process, the residual is a white Gaussian process (Schweppe, 1973; Kailath, 1970).

There are now two separate problems: (1) the detection of failures in frequency, and (2) the detection of failures in variance. As noted earlier, the mean of the residual remains zero for both changes, since the system (the shaping filter), and the Kalman filter are both linear, and the input is a zero mean white Gaussian process. However, the variance of the residual changes for a failed process. This characteristic of the residual thus motivated a modelling approach using residual variance changes as a failure indicator. This approach satisfactorily explained the results observed experimentally in response to a change in display process variance and a change in frequency.

5.4 Notes on the Implementation of the Models

For all of the models, the states were updated at 5/60ths of a second. Since the same program was used, the stimulus presentation was the same as in the experiment. Observation noise with variance equal to 0.01 that of the observed variables was added prior to any processing. For any stimulus value, there were 15 runs for the model. The summations needed for the decision function were done with a first order filter with a long time constant, starting 5 seconds after the start of the process ($1/(Ts + 1)$, $T = 1000$). Thus it is effectively a direct summation. In all cases, $P_{FA} = P_{MISS} = 0.05$ was used for setting the bounds.

5.5 Model for a Change in Variance

For the normal process, the variance of the residual is given by equation (5.9), and hence is known in advance. For a failed process, the variance is unknown. Assuming that $\theta_1 > \theta_0$ for $t > t_f$ where t_f is the time of failure, the decision function is calculated as explained earlier.

$$\tilde{\lambda}_m = \sum_{i=1}^{m} (x_i-\theta)^2 - \frac{\ln\left(\frac{\sigma_1^2}{\sigma_0^2}\right)}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}} \qquad (5.35)$$

Introducting the resetting feedback

$$\begin{aligned} \lambda_m &= \tilde{\lambda}_m \quad \text{if } \tilde{\lambda}_m > 0 \\ \lambda_m &= 0 \quad \text{if } \tilde{\lambda}_m < 0 \end{aligned} \qquad (5.36)$$

where

$$\tilde{\lambda}_m = \lambda_{m-1} + \{(x_m-\theta)^2 - \frac{\ln(\frac{\sigma_1^2}{\sigma_0^2})}{\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}}\} \tag{5.36}$$

When the magnitude and sign of variance change is unknown for a failed process, an additional set of hypotheses must also be tested for $\sigma_1^2 > \sigma_0^2$. The subject was not told if the failure was going to be an increase or a decrease. This was necessary to avoid guessing by the subject. An additional strategy could be given as follows:

$$\tilde{\lambda}'_m = \sum_{i=1}^{m}\{(x_i-\theta)^2 - \frac{\ln(\frac{\sigma_0^2}{\sigma_1^2})}{\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}}\} \tag{5.37}$$

with resetting

$$\begin{aligned} \lambda'_m &= \tilde{\lambda}_m \text{ if } \tilde{\lambda}_m < 0 \\ &= 0 \text{ if } \tilde{\lambda}_m > 0 \end{aligned} \tag{5.38}$$

and

$$\tilde{\lambda}'_m = \lambda_{m-1} + \{(x_m-\theta)^2 - \frac{\ln(\frac{\sigma_0^2}{\sigma_1^2})}{\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}}\} \tag{5.38}$$

Block diagrams of the complete model and the linear estimator are given in Figures 5.4 through 5.7.

The parameters α and β are assumed to be 0.05, and the parameter σ_1 was found such that the model detection times agreed as closely as possible with the experimental values. The results are plotted in Figures 5.8 and 5.9. It can be seen that the model values predict the experimental results very well. Detection times as a function of change in rms velocity show discontinuities where the nominal period changes from T = 1 sec to T = 3 sec. However, the model appears to have the same discontinuity as the experimental data obtained from the subjects.

5.6 Modelling a Change in Frequency

Two approaches were used to model detection of changes in frequency. In the first approach, the model used to detect changes in variance was used. Hence, only the results will be presented for that model. In another approach, the magitude of velocity is used as the basic variable for detecting a failure.

5.6.1 Results of the Model Using Residual Variance

The results are displayed along with the experimental

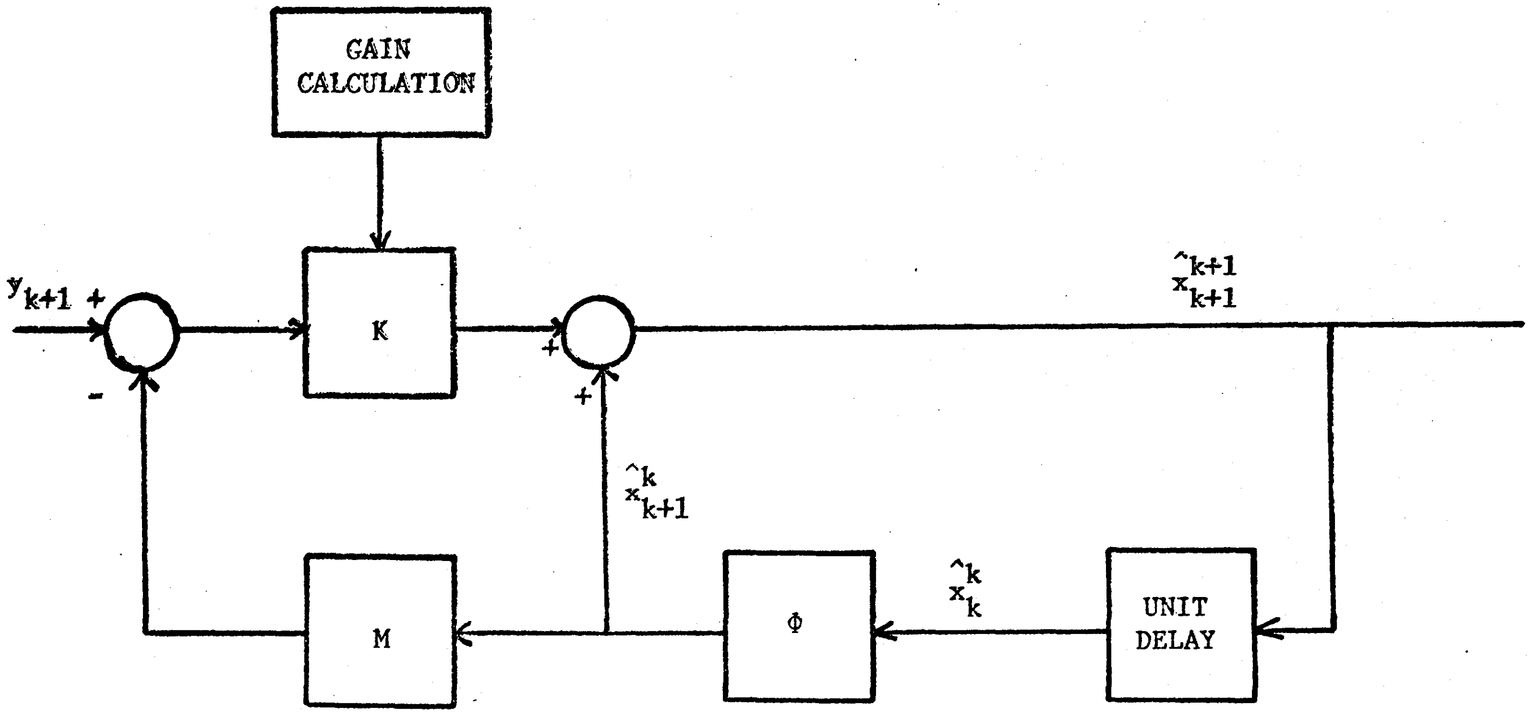


Figure 5.4 Kalman Filter

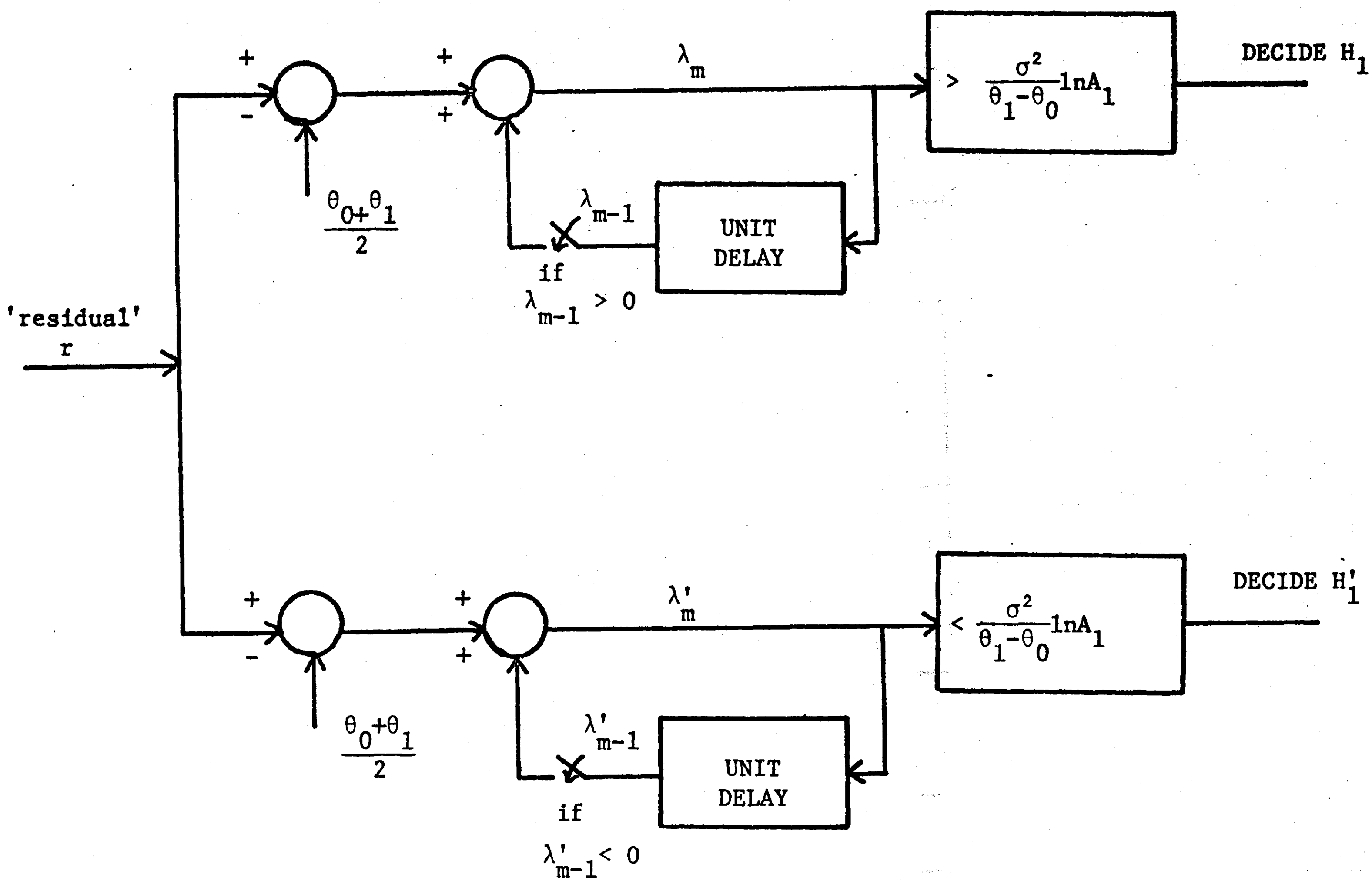


Figure 5.5 Decision mechanism for a change in frequency

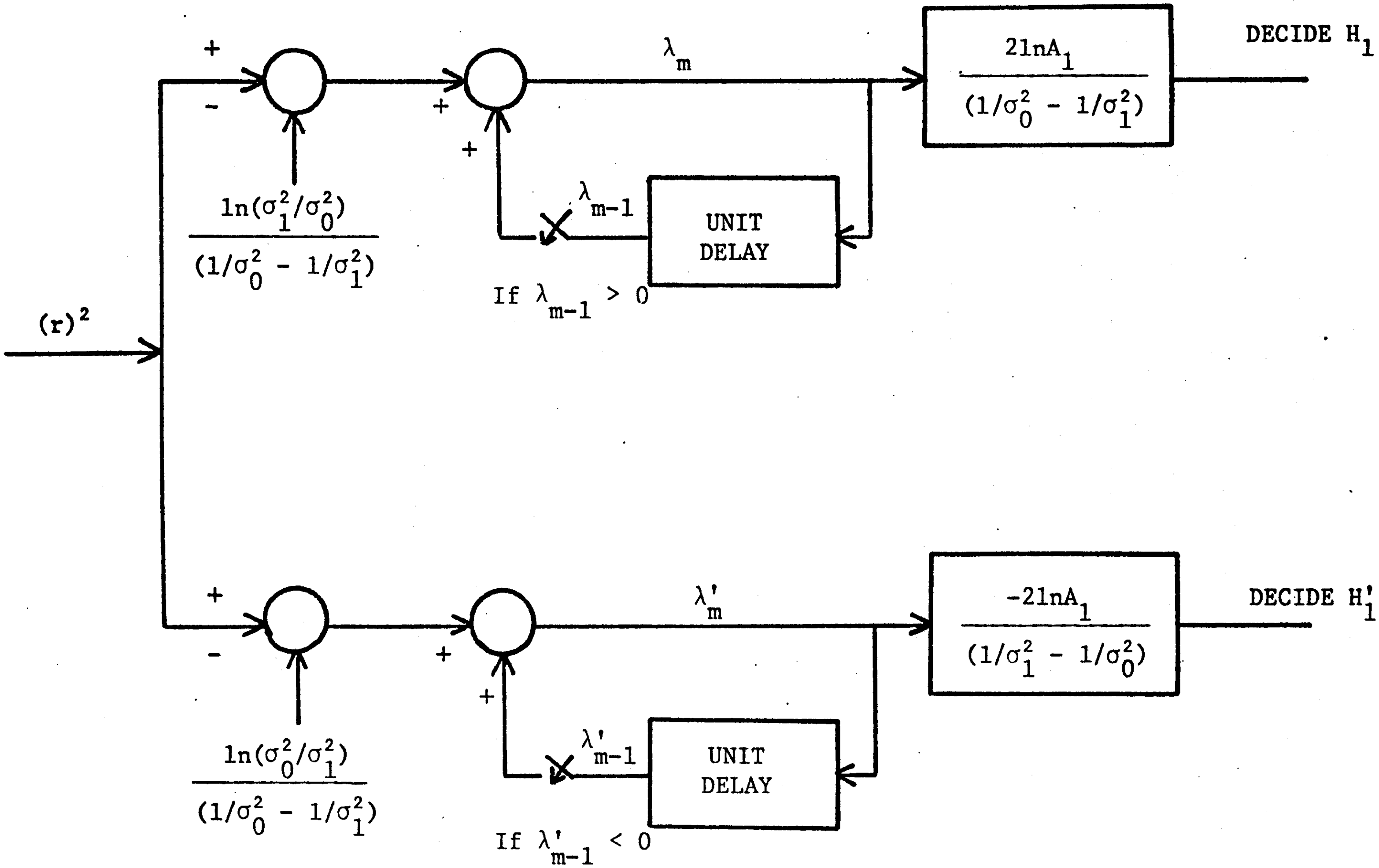


Figure 5.6 Decision mechanism for a change in variance.

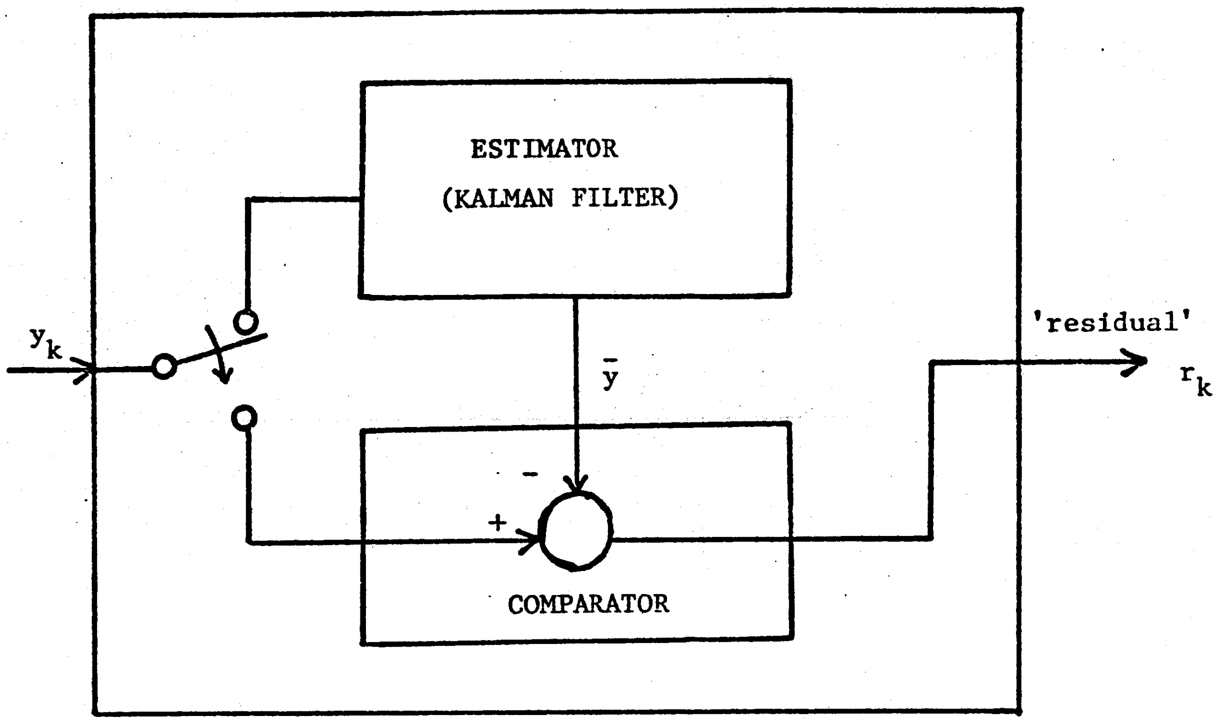


Figure 5.7 "Estimator" for frequency change.

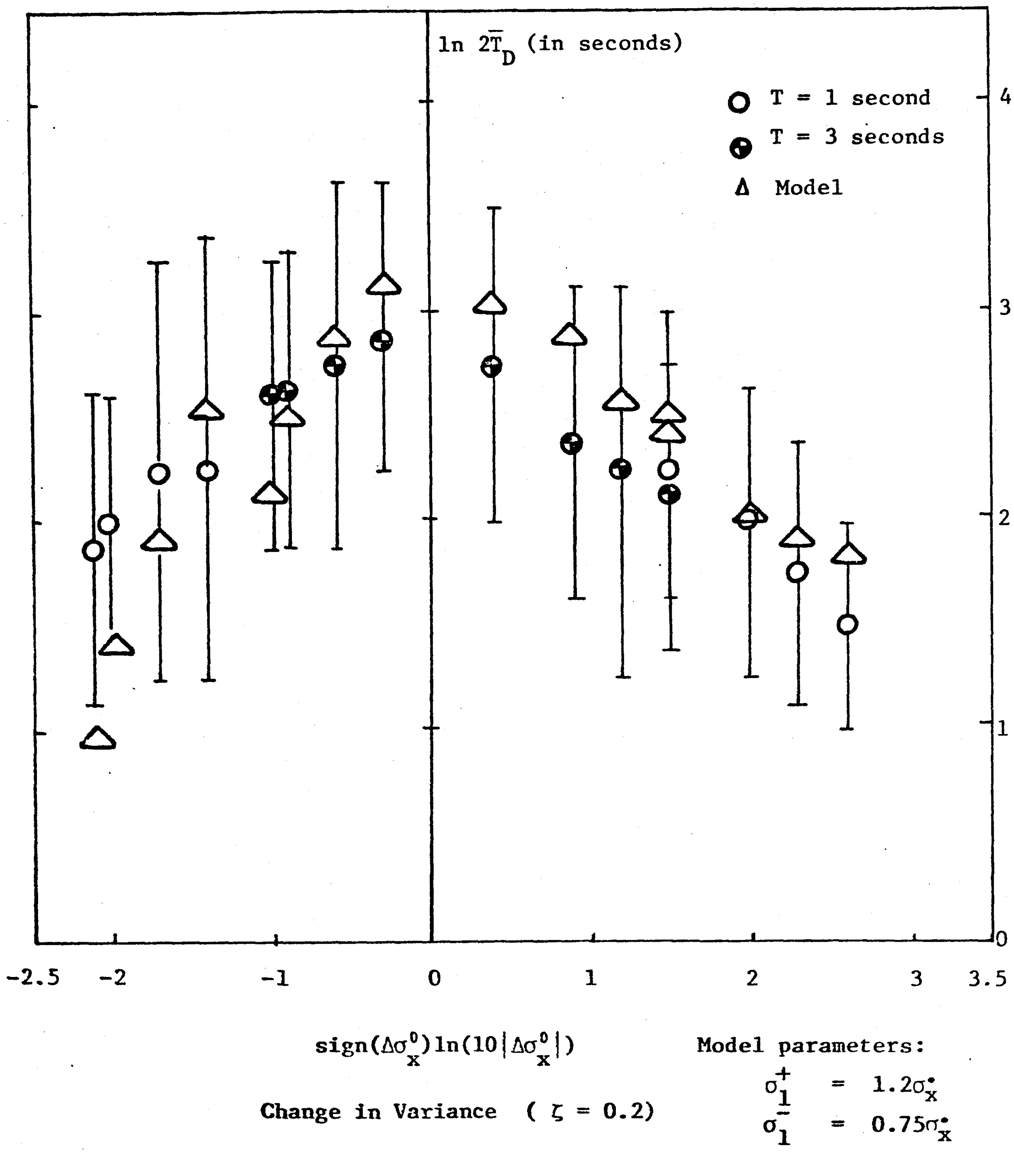
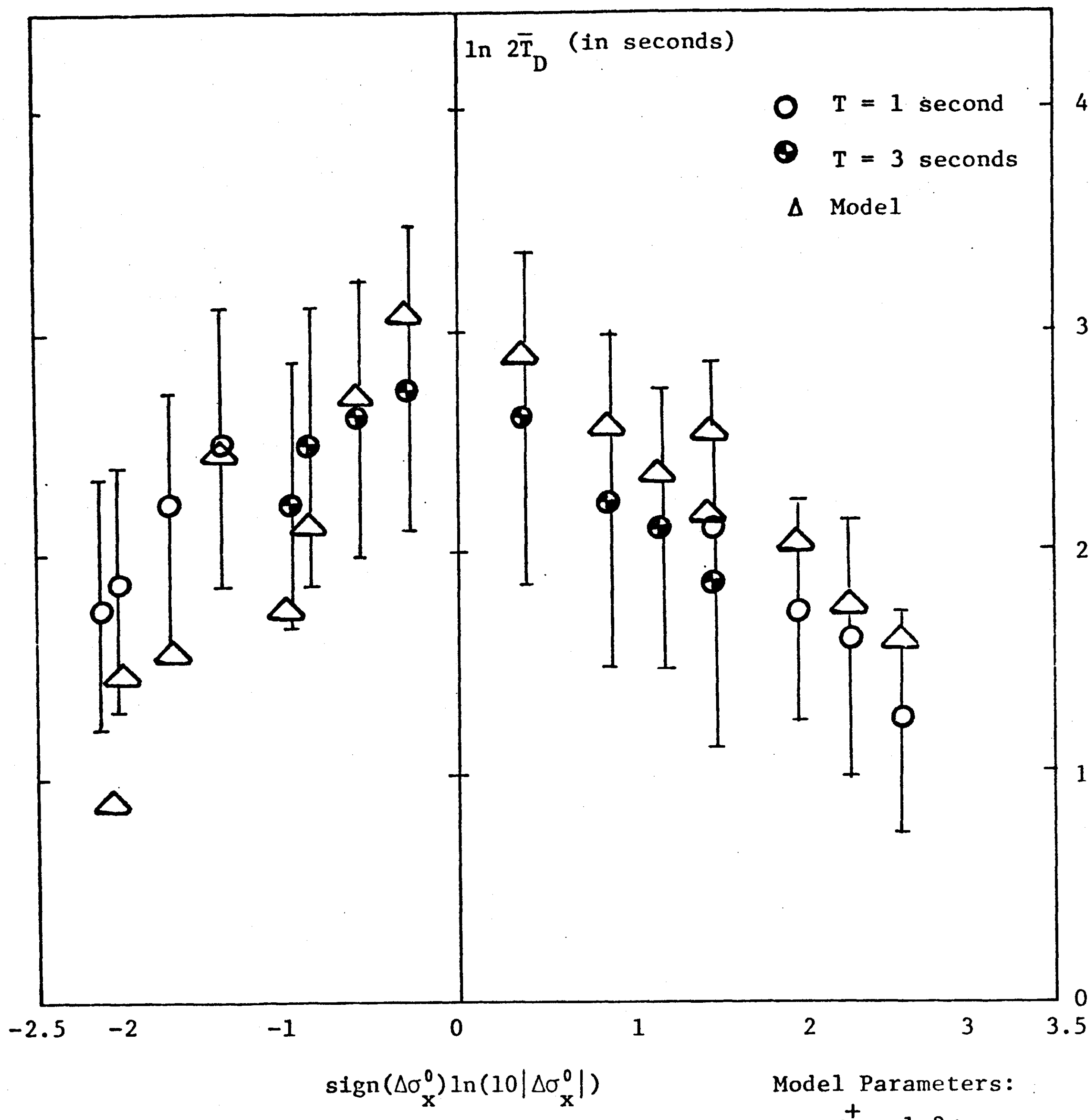


Figure 5.8 Data for the population

results in Figures 5.10 and 5.11. One value of θ for increases and another value for decreases was chosen for all the nominals. The agreement with the experimental results is very good. As in the case of a change in variance, slight discontinuities are observed in detection times when the nominal changes from T=1 to T=3. Again, the model as well as the subject appear to have the same discontinuity.

5.6.2 Velocity Magnitude Estimator

In this approach, the velocity of the line is used to test for the means in the following manner. Since the velocity itself is a zero mean process, the magnitude of velocity, i.e. without regard to the direction in which it is moving, is taken as the basis for the model. In the initial learning phase, the Kalman filter is used to obtain an estimate of velocity magnitude. The estimator is a two stage process. After an estimate is made for the velocity magnitude, the Kalman filter stage is "shut off", and the second stage is used as a comparator. This compares the observed speed (velocity magnitude) with the estimated mean value and generates the error residuals. Under normal conditions with no failure, this is a zero mean process. But when a failure does occur, the speed changes (increases or decreases with a similar change in frequency), and this is reflected in the mean of the

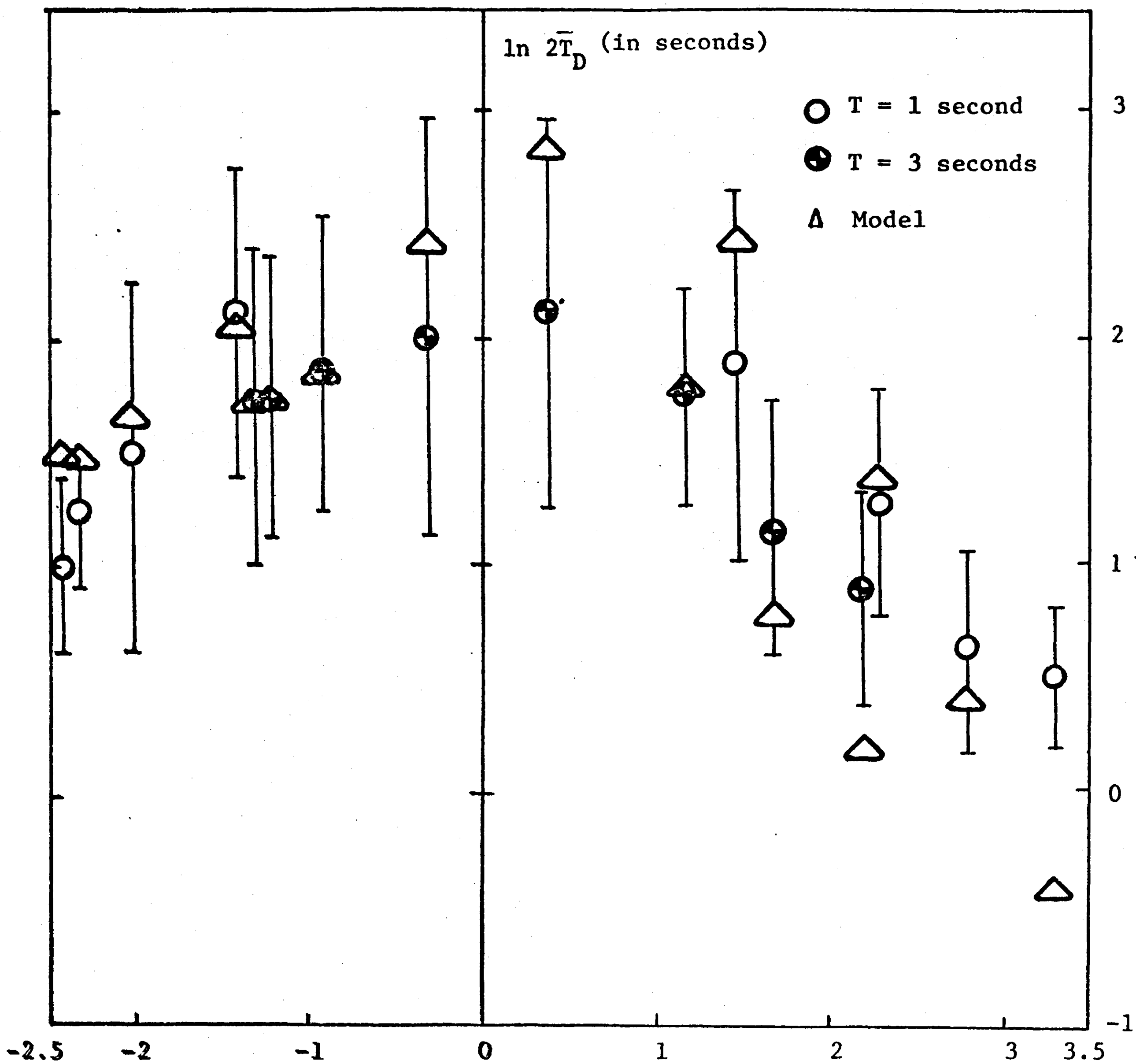


Model Parameters:

$\sigma_1^+ = 1.2\sigma_{\dot{x}}$

$\sigma_1^- = 0.75\sigma_{\dot{x}}$

Figure 5.9 Data for the population



$\text{sign}(\Delta\sigma_x^0)\ln(10|\Delta\sigma_x^0|)$

Model: residual sum of squares

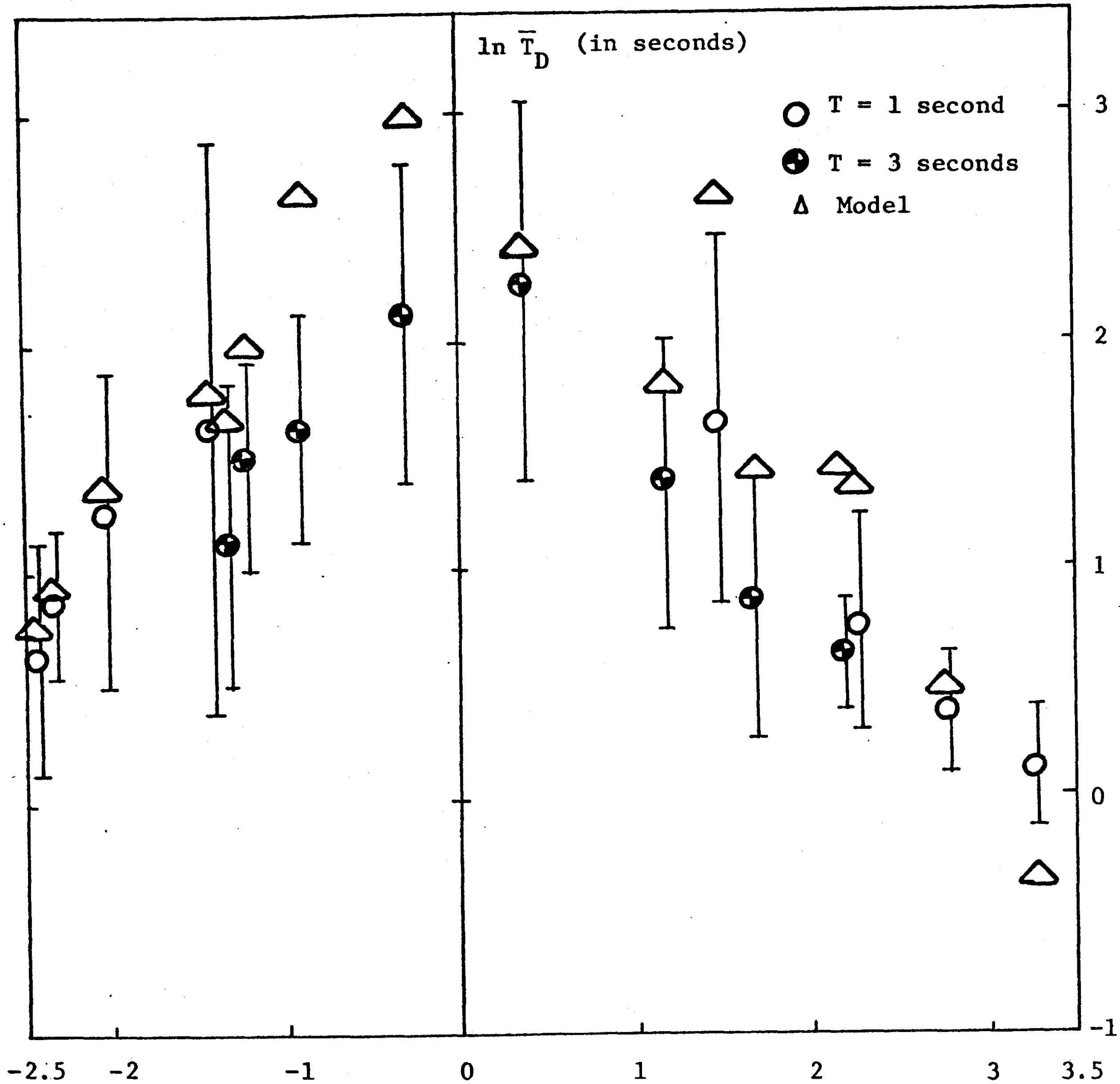
Change in Frequency ($\zeta = 0.2$)

Model Parameters:

$\theta_1^+ = 1.1\dot{\sigma}_x$

$\theta_1^- = 0.6\dot{\sigma}_x$

Figure 5.10 Data for the population



$sign(\Delta\sigma_x^0)\ln(10|\Delta\sigma_x^0|)$

Model: Residual sum of squares

Changes in Frequency ($\zeta = 0.707$)

Model Parameters:

$\theta_1^+ = 1.1\sigma_{\dot{x}}$

$\theta_1^- = 0.6\sigma_{\dot{x}}$

Figure 5.11 Data for the population

residuals. A sequential probability ratio test could then be used to test for the mean.

When a failure occurs

$$m(t) > 0 \qquad t > t_f \tag{5.39}$$

where m(t) is the mean at time t. The decision function is calculated with resetting feedback

$$\begin{aligned} \lambda_m &= \tilde{\lambda}_m \text{ if } \tilde{\lambda}_m < 0 \\ &= 0 \text{ if } \tilde{\lambda}_m > 0 \end{aligned}$$

where (5.40)

$$\tilde{\lambda}_m = \lambda_{m-1} + (x_m - (\theta_0 + \theta_1)/2)$$

Simultaneously, another set of hypotheses is tested for a failure with a reduction in frequency from the nominal.

for $\theta_1 < \theta_0$

$$\begin{aligned} \lambda'_m = &\ \tilde{\lambda}'_m \text{ if } \tilde{\lambda}'_m < 0 \\ &\ 0 \text{ if } \tilde{\lambda}'_m > 0 \end{aligned} \tag{5.41}$$

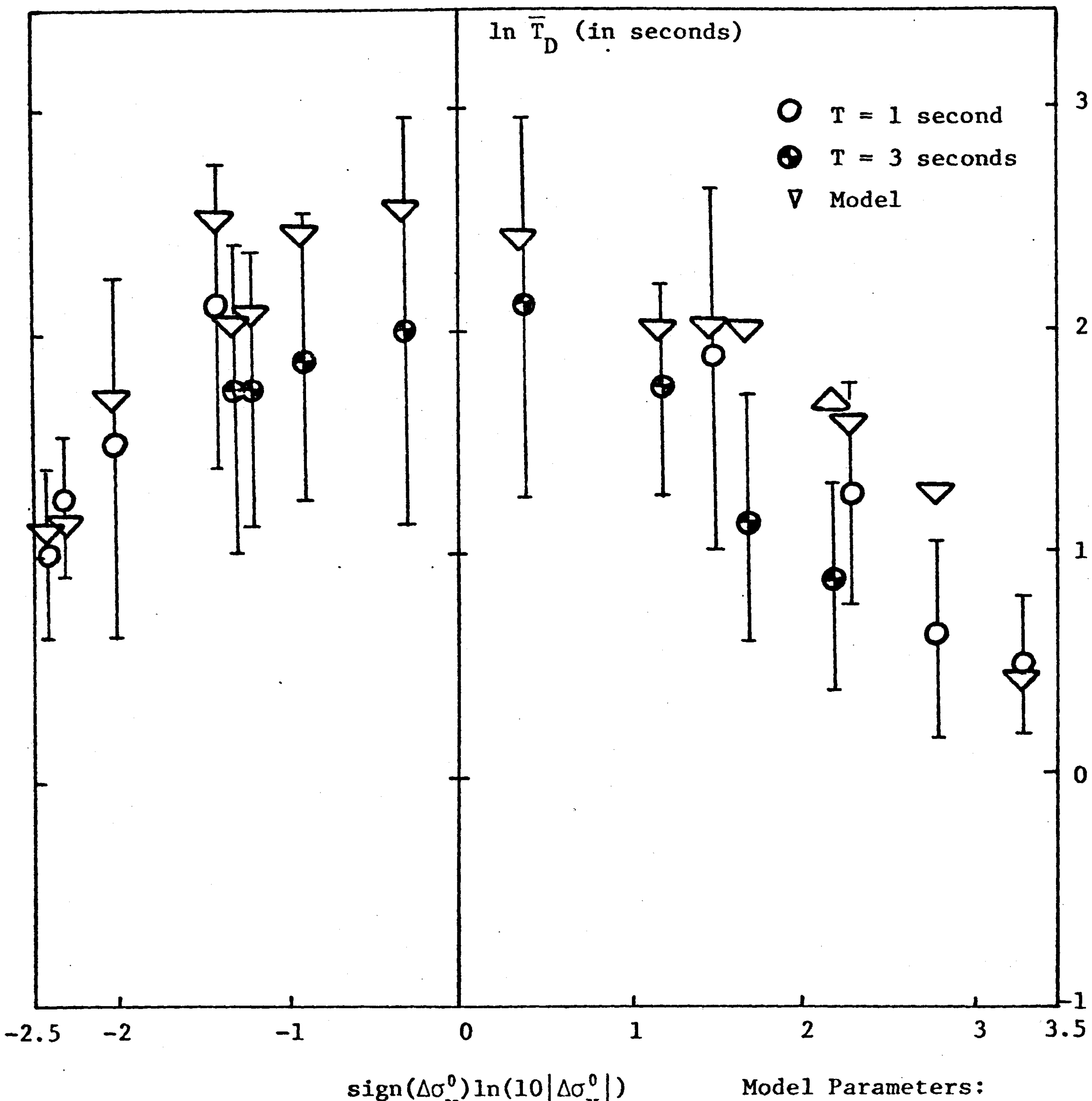
and

$$\tilde{\lambda}'_m = \lambda'_{m-1} + (x_m + (\theta_0 + \theta_1)/2)$$

For a given α and β, Al can be determined as before, and the parameter θ_1 can be determined. This model was tried for all the subjects, for all the nominals. The results obtained with this model are shown in Figures 5.12 and 5.13. For most cases, the correspondence appears to be very good.

5.5.3 Uncertainty About the Variance and Its Consequences

For the model appropriate to detecting a change in frequency, the variance was assumed constant and known (5.6.2). This variance (for speed) was calculated during the first stage of operation, i.e., the learning phase. But in the actual situation, when the frequency changes both the mean and the variance change. Though the variance changes, for large magnitudes of failure, there is no problem in detection, either for an increase or a decrease. The difficulty in detection occurs only for smaller magnitudes of change. For these the variance can be assumed not to depart too much from the nominal value.



Model: Velocity Magnitude Discriminator

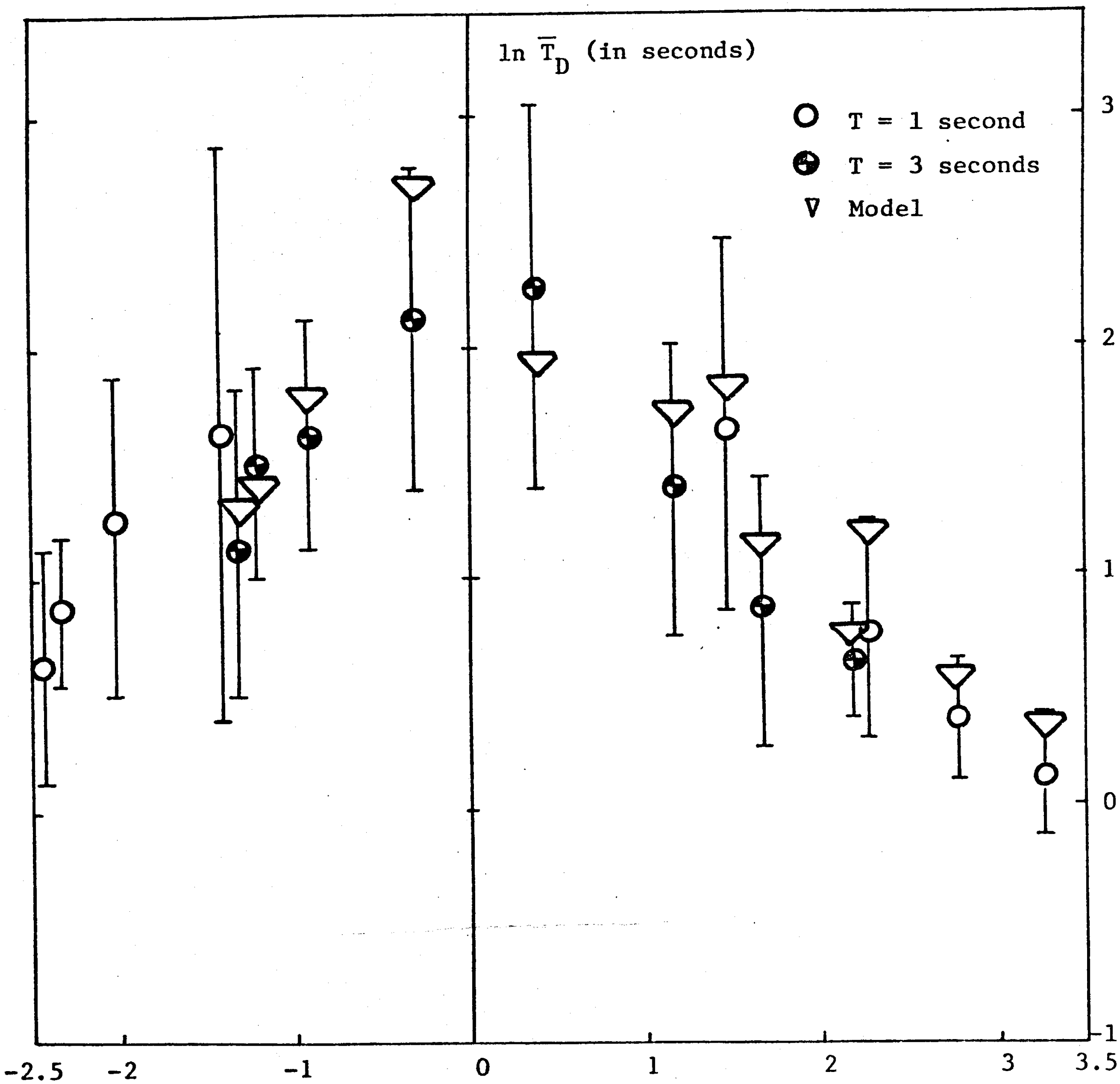
Change in Frequency (ζ = 0.2)

Model Parameters:

$\theta_1^+ = 0.06\sigma_{\dot{x}}$

$\theta_1^- = -0.4\sigma_{\dot{x}}$ for T = 1 sec.; $-0.1\sigma_{\dot{x}}$ for T = 3 sec.

Figure 5.12 Data for the population



$sign(\Delta\sigma_x^0) \ln(10|\Delta\sigma_x^0|)$

Model Parameters:

$$\theta_1^+ = \begin{cases} 0.025\sigma_{\dot{x}} & \text{for } T = 1 \text{ sec.} \\ 0.060\sigma_{\dot{x}} & \text{for } T = 3 \text{ sec} \end{cases}$$

$$\theta_1^- = -0.4\sigma_{\dot{x}} \quad \text{for } T = 3 \text{ sec.}$$

Model: Velocity Magnitude Detector
Change in Frequency (ζ = 0.707)

Figure 5.13 Data for the population

5.6.4 Previous Evidence for the Applicability of this Model

While the model was being tried, some evidence was found in the literature which was consistent with our approach. Gibson (1958), on a study of the perception of motion, observed that in a two window situation in which different objects were moving in two different visual surrounds, the observer could easily compare speed independent of velocity. That is, he could match the speeds even when the directions were opposite, or at right angles, to one another. He also conjectured that in such a situation, the observer may be responding to frequency of level crossings rather than to velocity.

The fact that certain nominals do not give satisfactory results could be due to the effect of a need to separate various effects as discussed earlier. A simple hypothesis may not be satisfactory. A composite hypothesis or composite strategy might give better results. One such possibility is to have two stages of testing. It was observed that larger magnitudes (of either sign) could easily be detected. In a situation where a failure is expected, tests could be made for larger magnitude failures, and for increases in frequency (since they are easier to detect). If the test indicates no such failure, and if sufficient time has elapsed, tests could be made for decreases with a different strategy. Since this does not appear to have general applicability, and since no reasonable alternative strategy could be found, this procedure has not been tried.

5.7 Comparison Between the Models

An important motivation for trying to determine models other than the one used for variance changes was the observation that the higher stimulus values predicted very low detection times. (Low detection times from the model seem reasonable if the human's reaction time is taken into account. This may be taken to be in the range of 0.2 to 0.3 seconds. (Sheridan and Ferrel, 1974).) Also, it was interesting to test if the velocity could be used without regard to its sign. For the cases under consideration, both the models appear to perform well. A third approach was also tried. This is based on the idea that the subject might be estimating the average number of zero-crossings or level crossings to obtain an estimate of frequency. This model performed well for failurs with an increase in frequency, but decreases had a very high false alarm rate. A different decision criterion that accounts for the subject's prior information that the failure occurs at least 8 seconds after starting might give fewer false alarms. A more detailed investigation is necessary to test the validity of this "zero-crossing detector" model.

Satisfactory parameter values for θ_1^- could not be obtained that result in proper detection times for 1 Hz and a damping ratio of 0.707. Various values were tried. They either resulted in a high false alarm rate (>90%) or went undetected. Judging from the overall performance, the model where the residuals are tested for variance appears very good. Aslo this model satisfactorily explains the detection of failures in variance as well.

CHAPTER VI

CONCLUSIONS AND SUGGESTIONS FOR FURTHER RESEARCH

Certain aspects of failure detection by human observers were investigated in detail in this thesis. The process being monitored consisted of a random process of filtered white noise. To obtain an understanding of the detection processes involved, it was thought necessary to know the various thresholds for changes in parameters that describe the dynamics of the system. Experiments were conducted to determine the thresholds for four nominals of a second order shaping filter for changes in frequency and for changes in the variance of the output. For the nominals, frequencies were chosen corresponding to periods of one and three seconds, and damping ratios of 0.2 and 0.707 were used.

Further experiments were performed to determine the detection times for failures as a function of failure magnitude. The results from this study have been used to form models for the detection process. A summary of the work reported in this thesis is given below.

6.1 Summary

Thresholds obtained for the frequency and variance are consistent with what is to be expected. For changes in frequency, thresholds were higher for a lower nominal frequency. For an increase in variance, thresholds were higher for a lower nominal frequency and for a lower damping ratio. When comparing the thresholds obtained for the frequency with those for variance, the thresholds were found to be significantly higher for variance than for frequency. For changes in frequency the thresholds were of the order of 10% of the nominal (usually less), consistent with the psychophysical data of Gibson (1958), Brown (1960) and others. Though their data pertain to changes in constant velocity (and not for random processes), a similar trend seems to be present in our case.

Another series of experiments was conducted to study the detection time behavior of the subjects for various failures. Only two sets of stimuli were presented, one for increases in parameter value and the other for decreases in parameter values from the nominal. They were also told that the objective was to see how quickly they could detect failures without making too many mistakes. The stimuli were chosen with decreasing order of difficulty (increasing magnitudes), the first being slightly above threshold. As could have been expected, the detection times were found to be higher for smaller magnitudes of failure (and with a large variability) than for larger failure magnitudes. It was also noted that increases in variance could be detected more easily than the corresponding decreases, in terms of detection times for the same level of failure.

For changes in frequency, the detection time curves are found to be nearly symmetric about the Y-axis, when plotted against the logarithm of the rms velocity difference from the nominal, though increases are slightly easier to detect than decreases.

In tasks where the variance changes from its nominal value, it appears that the human may be behaving as a peak detector, or an exceedance level monitor. Under normal conditions, he knows how far the line should move, on the average, and if this is exceeded, an increase is detected. But, for a decrease, the line stays closer to the origin, where it is expected to stay most of the time under normal conditions. So it takes a longer time to realize that it does not come up as far as it used to . More evidence with specially designed experiments may be needed to prove this conclusively.

Finally, an attempt was made to develop models to explain the observed effects. A two stage model was used, consisting of an estimator and a decision mechanism. For a change in variance, an estimator (consisting of a Kalman filter) and a decision mechanism operating on the observation errors (a sequential probability ratio test), were found to explain the results adequately. Two models were tried for a change in frequency. One is the same as that for variance, where the residual is tested for a change in variance. A simpler model was also tried: the model uses an estimator (a Kalman filter) to estimate the velocity initially, and uses its magnitude (i.e., speed) to compare with the observed speed. The error between the observed and expected speeds was used in a decision mechanism to perform a sequential probability ratio test. As indicated earlier, the nominal of $T = 3.0$ seconds, $\zeta = 0.2$ was found to give somewhat different results.

The correspondence obtained with these models is probably the best that could be obtained using the simple strategies described above with simple hypotheses. A better correspondence may be possible with some composite hypothesis testing, with alternate strategies.

In conclusion, it was observed that changes in frequency are easier to detect than changes in variance, if, of course, such comparisons are meaningful. This could be due to the fact that humans are sensitive to frequency even when they are not consciously aware of it. Failures at lower nominal frequency are comparatively harder to detect. Also, as is intuitively evident, making the field more heterogeneous by providing a finer grid is better (but not too fine, making it tiring to watch), since the frequency could be better discerned in such a field.

6.2 Recommendations for Further Research

(1) In our work, only changes in frequency and variance were investigated in detail. However, as discussed earlier, damping ratio may also be an important parameter for study. This may be especially important since there was a tendency among some subjects in the earlier investigation, to interpret increased damping as a decrease and vice versa. This suggests that detecting such a failure might be harder than detecting mean, frequency, or variance failures. Only a detailed investigation can resolve this problem.

(2) So far, only individual parameter failures were considered. Though this is essential for a basic understanding of the processes involved, a task more relevant to real life situations would be to study the failure detection capabilities of the human when two or more combinations of parameters fail (either together or at different instants in time). Such a study should explain any interactions that are important. With proper observation variables, such as velocity, it may be possible to predict such a failure by considering a linear combination of various effects separately.

(3) It would be interesting and worthwhile to study the effects on detection when auditory and other cues are presented simultaneously. It is perhaps reasonable to expect that a combined stimulus will aid in faster detection of failures.

(4) A more realistic study would include simultaneous monitoring of various instruments, with similar or dissimilar behavior for different types of failures. Also when attention must be shared between various instruments, and also control system components, the performance would differ from that where only a single instrument is being monitored. Simulations

with actual instruments in tasks like automatic landing could be studied (Gai and Curry, 1976).

(5) When a failure is not expected during every run, the monitor may not be alert continuously and modifications may be needed in the model. Experiments could be performed when failures do not occur as frequently as in the experiments described in this thesis.

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APPENDIX A

DISCRETE TIME REPRESENTATION FOR A CONTINUOUS TIME SYSTEM

$$F(s) = \frac{1}{s^2+2\zeta\omega_n s+\omega_n^2}$$

Roots:

$$s = \frac{-2\zeta\omega \pm \sqrt{4\zeta^2\omega^2-4\omega^2}}{2}$$

$$= -\zeta\omega \pm i\omega\sqrt{1-\zeta^2}$$

$$F(s) = \frac{1}{(s+a+jb)}\,\frac{1}{(s+a-jb)}$$

where $a = \zeta\omega$ $b = \omega\sqrt{1-\zeta^2}$

$$= \frac{j}{2b}\left[\frac{1}{s+a+jb} - \frac{1}{s+a-jb}\right]$$

In the Z-transform representation (Saucedo and Schiring, 1968)

$$E(z) = \sum_k \text{residues}\left\{ \frac{E(\lambda)}{1-e^{\lambda T}z^{-1}} \right\} \Bigg|_{\lambda = s_k}$$

$$= \sum_k \frac{1}{1-e^{\lambda T}z^{-1}} \ \text{res}\{ E(\lambda) \} \Bigg|_{\lambda = s_k}$$

$s = -a-jb$, and $-a+jb$

Therefore

$$F(z) = \frac{j}{2b}\left[\frac{1}{1-e^{-aT}e^{-jbT}z^{-1}} - \frac{1}{1-e^{-aT}e^{jbT}z^{-1}} \right]$$

Simplifying, we obtain

$$F(z) = (e^{-aT}/b)\left\{ \frac{z\sin bT}{z^2-2ze^{-aT}\cos bT+e^{-2aT}} \right\}$$

For real roots, jb can be replaced by b.

$$\sin(jbT) = (e^{-bT}-e^{bT})/2 \ ; \quad \cos(jbT) = e^{bT}(1+e^{-2bT})/2$$

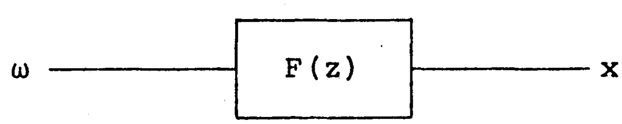
$s = -a-b, \quad -a+b$

Substituting these equations into F(z), we get

$$F(z) = \frac{1}{2b}\left[\frac{ze^{-aT}(e^{-bT}-e^{bT})}{z^2-ze^{-aT}(e^{bT}+e^{-bT})+e^{-2aT}} \right]$$

The roots are real and the above case holds for $\zeta > 1.0$.

State Variable Diagram (and Formulation) for the Discrete Time Problem (Saucedo and Schiring, 1968).

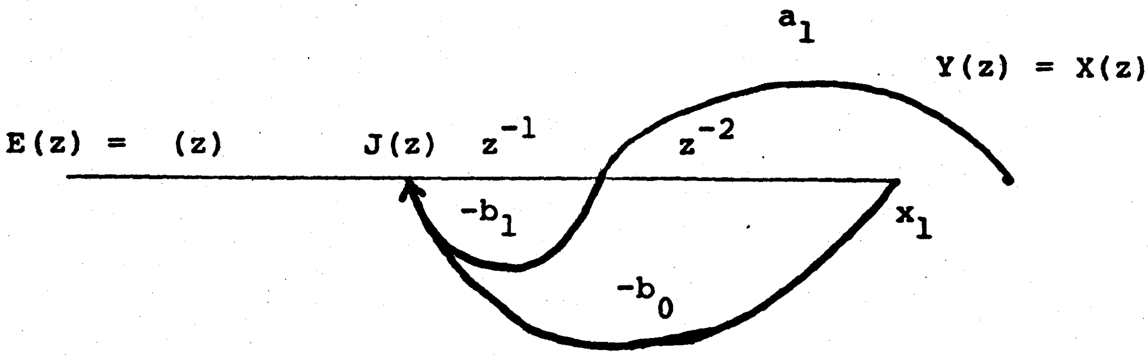


$$F(z) = \frac{Y(z)}{U(z)} = \frac{a_1 z}{z^2+b_1 z+b_0} = \left\{ \frac{x}{\omega} \right\}$$

$$(a_1 z)\omega = (z^2 + b_1 z + b_0 z^{-2})x$$

$$(1 + b_1 z^{-1} + b_0 z^{-2})J(z) = E(z)$$

$$(a_1 z^{-1})J(z) = Y(z)$$



$$x_1(z) = z^{-1}x_2(z)$$

$$x_2(z) = z^{-1}[\omega(z) - b_1x_2(z) - b_0x_1(z)]$$

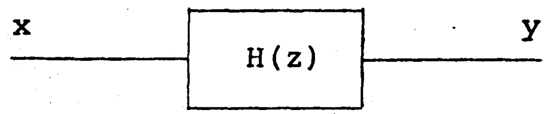
$$x_1(n+1) = x_2(n)$$
$$x_2(n+1) = \omega(n) - b_1x_2(n) - b_0x_1(n)$$

$$C^T = [0 \ a_1] \qquad\qquad y(n) = a_1x_2(n)$$

$$\underline{x}(n+1) = \begin{bmatrix} 0 & 1 \\ -b_0 & -b_1 \end{bmatrix} \underline{x}(n) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \omega(n)$$

$$A = \begin{bmatrix} 0 & 1 \\ -b_0 & -b_1 \end{bmatrix} \qquad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \qquad C = \begin{bmatrix} 0 \\ a_1 \end{bmatrix}$$

Relationship between gain, variances and the other parameters of a discrete (z-transform) second order system.



$$S_{yy}(z) = H(z)H(z^{-1})S_{xx}(z)$$

$$S_{xx}(z) = q_1$$

$$H(z) = \frac{a_1 z^{-1}\{P\}}{b_0 + b_1 z + z^2}$$

with poles at

$[z_1, z_2]$

$$z = (b_1/2)\{-1 \pm \sqrt{1 - (4b_0/b_1{}^2)}\}$$

$$H(z^{-1}) = \frac{a_1 z^{-1}\{P\}}{b_0 + b_1 z^{-1} + z^{-2}} = \frac{a_1 z}{b_0 z^2 + b_1 z + 1}$$

with poles at

$[z_3, z_4]$

$$z = \{(-b_1/b_0) \pm \sqrt{(b_1/b_0)^2 - 4/b_0}\ \}$$

$$\Phi_{yy}(0) = \sigma_y^2 = \frac{1}{2\pi j}\int_\Gamma S_{yy}(z)z^{-1}dz \qquad \Gamma \text{ - unit circle}$$

Poles are real:

$$z_{1,2} = -\frac{b_1}{2}[1 \pm \sqrt{1 - 4b_0/b_1^2}\ ]$$

$$z_{3,4} = -\frac{b_1}{2b_0}\ [1 \pm \sqrt{1 - 4b_0/b_1^2}\ ]$$

For $|z| \leq 1$, take the residues to get σ_y^2

$$\Phi_{yy}(0) = \frac{1}{2\pi j}\int_\Gamma H(z)H(z^{-1})z^{-1}S_{xx}(z)dz$$

$$= \text{residues in the unit circle}$$

$$\sigma_y^2 = (P^2q_1)(a_1^2/b_0)\ \{\sum_{res} \frac{z}{(z-z_1)(z-z_2)(z-z_3)(z-z_4)}\}$$

Poles are imaginary:

$$z = (-b_1/2)[1 \pm i\sqrt{(4b_0/b_1^2) - 1}\ ]$$

$$|z|_{1,2} = |-b_1/2|\ [1 + (4b_0/b_1^2) - 1]^{1/2} = (b_1/2)\sqrt{4b_0/b_1^2} = \sqrt{b_0}$$

$$= \sqrt{e^{-2aT}} = e^{-aT} \leq 1$$

$$|z|_{3,4} = \sqrt{1/b_0} = e^{aT} \geq 1$$

So only $z_{1,2}$ need be considered for residues

$$\left(\frac{\sigma_y^2}{q_1}\right) = \left(\frac{P^2 a_1^2}{b_0}\right)\left\{\frac{z_1}{(z_1-z_2)(z_1-z_3)(z_1-z_4)} + \frac{z_2}{(z_2-z_1)(z_2-z_3)(z_2-z_4)}\right\}$$

$$= \left(\frac{P^2 a_1^2}{b_0}\right)\left\{\frac{z_3 z_4 - z_1 z_2}{(z_1-z_3)(z_1-z_4)(z_2-z_3)(z_2-z_4)}\right\}$$

$$\text{Denominator} = (z_1z_2-z_2z_3-z_4z_1+z_3z_4)(z_1z_2-z_2z_4-z_1z_3+z_3z_4)$$

$$= \{(z_1z_2 + z_3z_4) - (z_2z_3 + z_4z_1)\}\{(z_1z_2 + z_3z_4) - (z_1z_3 + z_2z_4)\}$$

Using the relationships

$z_1 = a + jb \quad z_2 = a - jb \quad z_3 = a/b_0 + jb/b_0$ and

$$z_4 = a/b_0 - jb/b_0$$

we obtain

$$z_1z_3 + z_2z_4 = (2/b_0)(a^2 - b^2)$$

$$z_1z_2 + z_3z_4 = (1/b_0^2 + 1)(a^2 + b^2)$$

$$z_2z_3 = (1/b_0)(a^2 + b^2)$$

$$z_4z_1 = (1/b_0)(a^2 + b^2)$$

$$z_2z_3 + z_4z_1 = (a^2 + b^2)(2/b_0)$$
$$z_3z_4 - z_1z_2 = (a^2 + b^2)(1/b_0^2 - 1)$$

where $a = -b_1/2$ and $b = (b_1/2)\sqrt{1 - (4b_0^2/b_1)}$

Substitution of these in the equation for $(\sigma_y^2)q_1)$ gives

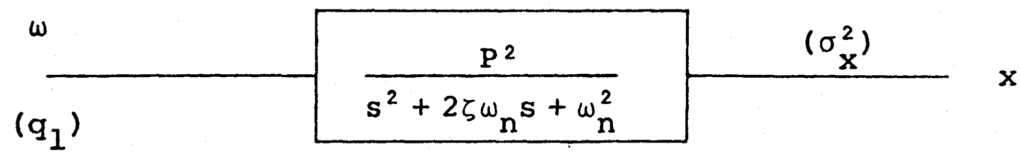
$$(\sigma_y^2/q_1) = (\frac{P^2a_1^2}{b_0}) \frac{(a^2+b^2)([1/b_0^2] - 1)}{(a^2+ b^2)(1-[1/b_0])^2[a^2(1-1/b_0)^2+b^2(1+1/b_0)^2]}$$

$$= (\frac{P^2a_1^2}{b_0})\{\frac{1 - b_0^2}{(b_0-1)^2[(a^2/b_0^2)(b_0-1)^2+(b/b_0^2)(1-b_0)^2]}\}$$

$$= (P^2a_1^2)\{\frac{(1-b_0^2)b_0}{(b_0-1)^2[a^2(b_0-1)^2+b^2(1+b_0)^2]}\}$$

$$P = \{\frac{(b_0-1)^2[a^2(b_0-1)^2+b^2(1+b_0)^2]}{(1-b_0^2)b_0a_1^2}\}(\sigma_y^2/q_1)$$

Relation between gain, frequency, damping ratio and variance of the input and output



$$G_{xx}(s) = \left(\frac{P\sqrt{q_1}}{s^2 + 2\zeta\omega_n s + \omega_n^2} \right) \left(\frac{P\sqrt{q_1}}{s^2 - 2\zeta\omega_n s + \omega_n^2} \right)$$

$$C_0 = P\sqrt{q_1} \qquad C_1 = 0$$

$$d_0 = \omega_n \qquad d_1 = 2\zeta\omega_n \qquad d_2 = 1$$

$$\sigma_x^2 = \frac{C_1^2 d_0 + C_0^2 d_2}{2 d_0 d_1 d_2} \qquad \frac{P^2 q_1}{2\omega_n^2 (2\zeta\omega_n)} \qquad \frac{P^2 q_1}{4\omega_n^3 \zeta}$$

$\sigma_x^2/q_1 = x =$ ratio of variance of output to variance of input

$$= P^2/4\omega_n^3\zeta$$

Therefore

$$P = \sqrt{4\omega_n^3 \zeta x}$$

Programming details:

Real roots

$$P = (\sigma_y^2/q_1)\,\frac{b_0}{a_1(\text{sum of residues})}$$

where residues are calculated at z such that $|z| \leq 1$.

Real if $(4b_0/b_1) < 1$ (since cosh( ) ≥ 1) b - imaginary

$\zeta > 1$.

For $\zeta < 1$, the roots are imaginary since

$$(4b_0/b_1^2) = 1/\cos^2\omega\sqrt{1-\zeta^2}T \geq 1.$$

So, for our problem, the imaginary case is relevant.

APPENDIX B

INSTRUCTIONS GIVEN TO THE SUBJECTS

WELCOME

TO

MAN-VEHICLE LABORATORY

You are going to participate in an Experiment in Failure Detection. You will be observing a random process, in which a failure will occur at some random time. The nature of the process and the failure will become clear after the initial trial runs. A brief explanation is now given about the details.

This is an experiment to find out the threshold (i.e., the smallest change you can reliably detect) when a failure occurs in a (second order) process driven by random input. The process consists of up and down motion of a straight line.

[1] When a failure occurs, either the FREQUENCY or the VARIANCE (swing away from the mean) will change from the

nominal value. During any one set of trials, only one parameter will change. Initially the NOMINAL (i.e. NORMAL) PROCESS will be shown for two minutes.

[2] After the nominal, failed modes with large increase/decrease will be shown for lesser times.

During these trials you are advised to observe the motion of the line. You may note how fast or slow it moves, how far away from the center it goes, etc.

After the first two minute nominal, for every run the process will start normally, and the failure will occur between 8 and 12 seconds.

[3] The experiment will start when the procedure is clear. If it is not clear the trials will be repeated.

[4] For any run, the process will continue for 30 seconds after the occurence of failure. If a decision has not been made by then, the line will stop and you will have 5 seconds to decide. You will respond by using one of the two switches.

[5] You will use the UPPER SWITCH to indicate what you perceive as an INCREASE, and the LOWER one for a

DECREASE, from the nominal parameter value. Pressing any switch at any time will terminate the current run. Hence, the decision cannot be changed.

[6] NOT DETECTING the failure in the available time, "detecting" a failure before one occurs (FALSE ALARM), and making a WRONG choice are the three possible errors one might make.

[7] The result of your decision will be displayed on the screen soon after you respond.

[8] Between trials, there is a blanking period of 5 seconds (including the time for showing the result).

[9] The experiment proceeds until the threshold is determined for one parameter. The entire procedure is repeated for the other parameter.

PLEASE CLARIFY ANY QUESTIONS YOU MAY HAVE.

APPENDIX C

Table of first experiments in a session [For threshold]

(chronological order for each nominal)

121	123	171	173	321	323	371	373
SH706	VA629	SH701	WS706	MR630	SH707	LI701	SH630
CM707	MR701	MF706	VL709	DL706	RB708	VL708	WS707
VL714	RB709	DL708	RB712	VA630	MF708	CM711	SH712
WS714	LM711	MR712	VA715	WS708	MR715	LM712	MF712
RB715	LI713	LI714	LM719	LI715	LM716	RB713	VA713
MF715	DL714	WS718	CM722	CM721	VL718	MR714	LI716
LM721	VA720	MF719		DL722	VL720	VL719	DL720
	WM803	WM804		SH720	WM809	WM802	
	WM811				MR719	WM810	
						MR720	

Two experiments per session, one session per day.

Nominal:

1st digit: Period in seconds
2nd digit: Damping ratio (2 -> 0.2, 7 -> 0.707)
3rd digit: Parameter changed (1 for period,
3 for variance)

Two letters for subject; 3 digits for date
1st digit: month, 2nd 3rd digits: day

Table C1

Table of first experiments in a session

If the frequency was changed first, for the second experiment, the variance was changed (and vice versa)

Nominal:

1st digit: Period in seconds
2nd digit: Damping ratio (2 -> 0.2, 7 -> 0.707)
3rd digit: Parameter changed (1 for period,
3 for variance)

Three digit + (F or R, where applicable):

1st digit: month, 2nd 3rd digits: day
F: First for the subject, data not used.
R: Repeat, previous data discarded.

Nominal	121	123	171	173	321	323	371	373
Subject								
CM	707F	-	-	722	721	-	711	-
DL	-	714	708	-	706F 722	-	-	720
LI	-	713	714	-	715	-	701F	716
LM	721	711F	-	719	-	716	712	-
MF	715	-	706F 719	-	-	708	-	712
MR	-	701	712	-	630	715 719R	714 720R	-
RB	715	709	-	712	-	708	713	-
SH	706	-	701	-	720R	707	-	630 712
VA	-	629F 720	-	715	630	-	-	713
VL	714	-	-	709	-	718 720R	708F 719	-
WM	-	803 811R	804	-	-	809	802F 810	-
WS	714	-	718	706F	708	-	-	707

Table C2

Chronological order for detection time data.

(individual subjects)

	121	123	171	173	321	323	371	373
SH	721	237		816	227	207	804	048
	723	267		168	726	722	8044	068
	728	287			277	727	806	809
		819				817	098	818
		198				178		188
						826		
						268		
MR	307	730	297	729	722	217	227	207
	038	803	048	804	197	727	267	726
	805	058	802	028	277	806	728	287
		068						
WM		817		818		816		819
		178		188		820		198
		823		827		208		826
		238		278		824		268
		825		910		248		099
		258		109				909

(two digits for date, one for month in the proper order)

Table C3

APPENDIX D

Table D1

Nominal: Period = 1.0 Second.

Damping ratio = 0.200.

Thresholds for change in PERIOD.

	Subject	Decrease		Increase	
1	MR	0.021	(0.021)	0.014	(0.015)
2	SH	0.048	(0.052)	0.013	(0.028)
3	VL	0.030	(0.037)	0.063	(0.067)
4	WS	0.009	(0.018)	0.027	(0.037)
5	RB	0.016	(0.018)	0.014	(0.018)
6	MF	0.016	(0.014)	0.002	(0.010)
7	VA	0.040	(0.047)	0.059	(0.062)
8	LM	0.058	(0.075)	0.024	(0.062)
9	WM	0.072	(0.070)	0.030	(0.032)
	Mean	0.034		0.028	
	Sigma	0.022		0.021	

Thresholds for change in VARIANCE.

	Subject	Decrease		Increase	
1	MR	0.021	(0.025)	0.152	(0.165)
2	CM	0.056	(0.057)	0.118	(0.123)
3	WS	0.071	(0.078)	0.051	(0.101)
4	RB	0.090	(0.087)	0.0003	(0.007)
5	MF	0.026	(0.033)	0.052	(0.055)
6	VA	0.112	(0.106)	0.081	(0.080)
7	SH	0.139	(0.141)	0.105	(0.103)
8	LM	0.070		0.055	
9	LI	0.093	(0.091)	0.064	(0.079)
10	WM	0.042	(0.048)	0.091	(0.082)
	Mean	0.072		0.077	
	Sigma	0.038		0.042	

The magnitudes shown in paranthesis are estimates calculated by taking the means of 'peaks and valleys'.

Table D2

Nominal: Period = 1.0 Second.

Damping ratio = 0.707.

Thresholds for change in PERIOD.

	Subject	Decrease		Increase	
1	SH	0.026	(0.030)	0.075	(0.080)
2	DL	0.069	(0.080)	0.048	(0.047)
3	MR	0.014	(0.015)	0.024	(0.029)
4	VA	0.026	(0.029)	0.029	(0.032)
5	WS	0.029	(0.032)	0.054	(0.055)
6	MF	0.016	(0.022)	0.008	(0.016)
7	CM	0.026	(0.080)	0.078	(0.090)
8	LI	0.061		0.016	
9	WM	0.028	(0.029)	0.012	(0.023)
	Mean	0.033		0.038	
	Sigma	0.019		0.026	

Thresholds for change in VARIANCE.

	Subject	Decrease		Increase	
1	SH	0.082	(0.091)	0.020	(0.025)
2	MR	0.079	(0.083)	0.063	(0.065)
3	RB	0.048	(0.057)	0.113	(0.120)
4	LM	0.105	(0.120)	0.045	(0.111)
5	MF	0.073	(0.077)	0.058	(0.066)
6	VA	0.104	(0.135)	0.146	(0.145)
7	CM	0.147	(0.137)	0.021	(0.025)
8	WM	0.034	(0.035)	0.059	(0.058)
	Mean	0.084		0.066	
	Sigma	0.035		0.044	

The magnitudes shown in paranthesis are estimates calculated by taking the means of 'peaks and valleys'.

Nominal: Period = 3.0 Second. Table D3

Damping ratio = 0.200.

Thresholds for change in PERIOD.

	Subject	Decrease		Increase	
1	VA	0.016	(0.024)	0.025	(0.031)
2	WS	0.015	(0.015)	0.064	(0.065)
3	RB	0.033	(0.033)	0.041	(0.045)
4	MR	0.048	(0.050)	0.028	(0.030)
5	LM	0.084	(0.096)	0.023	(0.025)
6	VL	0.088	(0.098)	0.050	(0.060)
7	SH	0.135	(0.137)	0.097	(0.103)
8	CM	0.033	(0.040)	0.056	(0.052)
9	MF	0.072	(0.075)	0.039	(0.035)
10	DL	0.113	(0.119)	0.117	(0.118)
11	LI	0.058	(0.061)	0.028	(0.030)
12	WM	0.027		0.075	
	Mean	0.060		0.054	
	Sigma	0.039		0.030	

Thresholds for change in VARIANCE.

	Subject	Decrease		Increase	
1	MF	0.062	(0.061)	0.055	(0.060)
2	RB	0.101	(0.131)	0.185	(0.200)
3	MR	0.170	(0.200)	0.279	(0.313)
4	VL	0.131	(0.153)	0.079	(0.140)
5	CM	0.105	(0.112)	0.159	(0.168)
6	VA	0.162	(0.174)	0.200	(0.193)
7	DL	0.152	(0.157)	0.146	(0.147)
8	WM	0.087	(0.089)	0.095	(0.103)
	Mean	0.121		0.150	
	Sigma	0.039		0.073	

The magnitudes shown in paranthesis are estimates calculated by taking the means of 'peaks and valleys'.

Nominal: Period = 3.0 Second. Table D4

Damping ratio = 0.707.

Thresholds for change in PERIOD.

	Subject	Decrease		Increase	
1	WS	0.041	(0.052)	0.021	(0.022)
2	CM	0.034	(0.035)	0.080	(0.090)
3	SH	0.100	(0.108)	0.089	(0.088)
4	LM	0.015	(0.023)	0.065	(0.071)
5	MF	0.046	(0.045)	0.011	(0.018)
6	RB	0.005	(0.015)	0.042	(0.041)
7	VA	0.015	(0.018)	0.039	(0.040)
8	VL	0.039	(0.037)	0.034	(0.033)
9	MR	0.051	(0.050)	0.053	(0.057)
10	DL	0.036	(0.040)	0.040	(0.047)
11	LI	0.012	(0.018)	0.051	(0.051)
12	WM	0.055	(0.055)	0.036	(0.052)
	Mean	0.037		0.047	
	Sigma	0.026		0.023	

Thresholds for change in VARIANCE.

	Subject	Decrease		Increase	
1	CM	0.110	(0.107)	0.142	(0.145)
2	SH	0.021	(0.020)	0.057	(0.073)
3	LM	0.071	(0.072)	0.019	(0.025)
4	MF	0.091	(0.092)	0.094	(0.133)
5	RB	0.107	(0.115)	0.084	(0.090)
6	VA	0.062	(0.063)	0.057	(0.069)
7	MR	0.115	(0.123)	0.073	(0.075)
8	VL	0.110	(0.115)	0.094	(0.095)
9	WM	0.132	(0.140)	0.126	(0.133)
	Mean	0.091		0.083	
	Sigma	0.034		0.037	

The magnitudes shown in paranthesis are estimates calculated by taking the means of 'peaks and valleys'.

APPENDIX E

Nominal: Period = 1.0 Seconds. Table E1

Damping ratio = 0.200.

Change in FREQUENCY Subject: MR

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.37	-1.32	1.91	0.52
2	-0.2	-0.67	-1.90	1.33	0.64
3	-0.3	-0.90	-2.20	0.89	0.36
4	-0.4	-1.09	-2.39	0.76	0.29
5	0.1	0.47	1.55	1.72	0.81
6	0.2	1.06	2.36	0.82	0.55
7	0.3	1.80	2.89	0.25	0.40
8	0.4	2.74	3.31	0.20	0.27

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	0.958	0.042	0.000	23	1	0	24
2	-0.2	1.000	0.000	0.000	24	0	0	24
3	-0.3	0.958	0.000	0.042	23	0	1	24
4	-0.4	0.958	0.000	0.042	23	0	1	24
5	0.1	0.958	0.000	0.042	23	0	1	24
6	0.2	1.000	0.000	0.000	24	0	0	24
7	0.3	1.000	0.000	0.000	24	0	0	24
8	0.4	1.000	0.000	0.000	24	0	0	24
Summary		0.979	0.005	0.016	188	1	3	192

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E2

Damping ratio = 0.200.

Change in FREQUENCY Subject: SH

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.37	-1.32	2.27	0.85
2	-0.2	-0.67	-1.90	1.62	0.97
3	-0.3	-0.90	-2.20	1.51	0.33
4	-0.4	-1.09	-2.39	1.29	0.41
5	0.1	0.47	1.55	1.92	0.91
6	0.2	1.06	2.36	1.68	0.46
7	0.3	1.80	2.89	0.92	0.52
8	0.4	2.74	3.31	0.74	0.35

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	0.913	0.043	0.043	21	1	1	23
2	-0.2	1.000	0.000	0.000	23	0	0	23
3	-0.3	1.000	0.000	0.000	23	0	0	23
4	-0.4	1.000	0.000	0.000	23	0	0	23
5	0.1	0.957	0.043	0.000	22	1	0	23
6	0.2	1.000	0.000	0.000	23	0	0	23
7	0.3	1.000	0.000	0.000	23	0	0	23
8	0.4	0.957	0.000	0.043	22	0	1	23
Summary		0.978	0.011	0.011	180	2	2	184

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E3

Damping ratio = 0.200.

Change in FREQUENCY Summary (all subjects)

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.37	-1.32	2.09	0.71
2	-0.2	-0.67	-1.90	1.48	0.82
3	-0.3	-0.90	-2.20	1.20	0.34
4	-0.4	-1.09	-2.39	1.02	0.35
5	0.1	0.47	1.55	1.82	0.86
6	0.2	1.06	2.36	1.25	0.51
7	0.3	1.80	2.89	0.58	0.47
8	0.4	2.74	3.31	0.47	0.31

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	0.936	0.043	0.021	44	2	1	47
2	-0.2	1.000	0.000	0.000	47	0	0	47
3	-0.3	0.979	0.000	0.021	46	0	1	47
4	-0.4	0.979	0.000	0.021	46	0	1	47
5	0.1	0.957	0.021	0.021	45	1	1	47
6	0.2	1.000	0.000	0.000	47	0	0	47
7	0.3	1.000	0.000	0.000	47	0	0	47
8	0.4	0.979	0.000	0.021	46	0	1	47
Summary		0.979	0.008	0.013	368	3	5	376

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E4

Damping ratio = 0.200.

Change in VARIANCE. Subject: SH

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.47	1.55	2.37	0.72
2	0.3	0.75	2.01	2.16	0.61
3	0.4	1.06	2.36	2.18	0.61
4	0.5	1.41	2.65	1.75	0.57
5	-0.2	-0.37	-1.32	2.22	1.46
6	-0.3	-0.53	-1.67	2.26	1.26
7	-0.4	-0.67	-1.90	2.24	0.58
8	-0.5	-0.79	-2.07	1.95	0.74

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.800	0.075	0.125	32	3	5	40
2	0.3	0.900	0.050	0.050	36	2	2	40
3	0.4	0.900	0.025	0.075	36	1	3	40
4	0.5	0.950	0.000	0.050	38	0	2	40
5	-0.2	0.900	0.075	0.025	36	3	1	40
6	-0.3	0.975	0.025	0.000	39	1	0	40
7	-0.4	0.850	0.050	0.100	34	2	4	40
8	-0.5	0.875	0.050	0.075	35	2	3	40
Summary		0.894	0.044	0.062	286	14	20	320

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E5

Damping ratio = 0.200.

Change in VARIANCE. Subject: MR

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.47	1.55	2.05	0.76
2	0.3	0.75	2.01	1.86	0.83
3	0.4	1.06	2.36	1.52	0.53
4	0.5	1.41	2.65	1.29	0.45
5	-0.2	-0.37	-1.32	2.09	0.81
6	-0.3	-0.53	-1.67	2.02	0.77
7	-0.4	-0.67	-1.90	1.67	0.49
8	-0.5	-0.79	-2.07	1.59	0.61

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.889	0.022	0.089	40	1	4	45
2	0.3	0.978	0.022	0.000	44	1	0	45
3	0.4	0.867	0.044	0.089	39	2	4	45
4	0.5	0.889	0.022	0.089	40	1	4	45
5	-0.2	0.911	0.067	0.022	41	3	1	45
6	-0.3	0.933	0.022	0.044	42	1	2	45
7	-0.4	0.933	0.000	0.067	42	0	3	45
8	-0.5	0.978	0.000	0.022	44	0	1	45
Summary		0.922	0.025	0.053	332	9	19	360

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E6

Damping ratio = 0.200.

Change in VARIANCE. Subject: WM

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.47	1.55	2.36	0.57
2	0.3	0.75	2.01	1.85	0.65
3	0.4	1.06	2.36	1.72	0.73
4	0.5	1.41	2.65	1.44	0.60
5	-0.2	-0.37	-1.32	2.50	0.71
6	-0.3	-0.53	-1.67	2.41	0.82
7	-0.4	-0.67	-1.90	2.26	0.59
8	-0.5	-0.79	-2.07	2.09	0.78

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.875	0.062	0.062	42	3	3	48
2	0.3	0.937	0.000	0.062	45	0	3	48
3	0.4	1.000	0.000	0.000	48	0	0	48
4	0.5	0.958	0.021	0.021	46	1	1	48
5	-0.2	0.958	0.042	0.000	46	2	0	48
6	-0.3	0.958	0.000	0.042	46	0	2	48
7	-0.4	1.000	0.000	0.000	48	0	0	48
8	-0.5	0.937	0.042	0.021	45	2	1	48
Summary		0.953	0.021	0.026	366	8	10	384

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E7

Damping ratio = 0.200.

Change in VARIANCE. Summary (all subjects)

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.47	1.55	2.26	0.69
2	0.3	0.75	2.01	1.96	0.70
3	0.4	1.06	2.36	1.81	0.63
4	0.5	1.41	2.65	1.49	0.54
5	-0.2	-0.37	-1.32	2.27	1.05
6	-0.3	-0.53	-1.67	2.23	0.98
7	-0.4	-0.67	-1.90	2.06	0.56
8	-0.5	-0.79	-2.07	1.88	0.71

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.857	0.053	0.090	114	7	12	133
2	0.3	0.940	0.023	0.038	125	3	5	133
3	0.4	0.925	0.023	0.053	123	3	7	133
4	0.5	0.932	0.015	0.053	124	2	7	133
5	-0.2	0.925	0.060	0.015	123	8	2	133
6	-0.3	0.955	0.015	0.030	127	2	4	133
7	-0.4	0.932	0.015	0.053	124	2	7	133
8	-0.5	0.932	0.030	0.038	124	4	5	133
Summary		0.925	0.029	0.046	984	31	491064	

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E8

Damping ratio = 0.707.

Change in FREQUENCY Subject: MR

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.37	-1.32	1.62	1.28
2	-0.2	-0.67	-1.90	1.20	0.67
3	-0.3	-0.90	-2.20	0.86	0.32
4	-0.4	-1.09	-2.39	0.65	0.53
5	0.1	0.47	1.55	1.68	0.79
6	0.2	1.06	2.36	0.71	0.48
7	0.3	1.80	2.89	0.32	0.34
8	0.4	2.74	3.31	0.17	0.18

	Stimulus	P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	0.958	0.000	0.042	23	0	1	24
2	-0.2	1.000	0.000	0.000	24	0	0	24
3	-0.3	1.000	0.000	0.000	24	0	0	24
4	-0.4	1.000	0.000	0.000	24	0	0	24
5	0.1	1.000	0.000	0.000	24	0	0	24
6	0.2	0.958	0.000	0.042	23	0	1	24
7	0.3	0.958	0.042	0.000	23	1	0	24
8	0.4	1.000	0.000	0.000	24	0	0	24
Summary		0.984	0.005	0.010	189	1	2	192

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E9

Damping ratio = 0.707.

Change in FREQUENCY Summary (all subjects)

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.37	-1.32	1.62	1.28
2	-0.2	-0.67	-1.90	1.20	0.67
3	-0.3	-0.90	-2.20	0.86	0.32
4	-0.4	-1.09	-2.39	0.65	0.53
5	0.1	0.47	1.55	1.68	0.79
6	0.2	1.06	2.36	0.71	0.48
7	0.3	1.80	2.89	0.32	0.34
8	0.4	2.74	3.31	0.17	0.18

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	0.958	0.000	0.042	23	0	1	24
2	-0.2	1.000	0.000	0.000	24	0	0	24
3	-0.3	1.000	0.000	0.000	24	0	0	24
4	-0.4	1.000	0.000	0.000	24	0	0	24
5	0.1	1.000	0.000	0.000	24	0	0	24
6	0.2	0.958	0.000	0.042	23	0	1	24
7	0.3	0.958	0.042	0.000	23	1	0	24
8	0.4	1.000	0.000	0.000	24	0	0	24
Summary		0.984	0.005	0.010	189	1	2	192

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E10

Damping ratio = 0.707.

Change in VARIANCE. Subject: SH

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.47	1.55	2.25	0.66
2	0.3	0.75	2.01	1.81	0.45
3	0.4	1.06	2.36	1.83	0.65
4	0.5	1.41	2.65	1.37	0.42
5	-0.2	-0.37	-1.32	2.81	0.62
6	-0.3	-0.53	-1.67	2.54	0.57
7	-0.4	-0.67	-1.90	2.00	0.60
8	-0.5	-0.79	-2.07	2.26	0.57

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	1.000	0.000	0.000	16	0	0	16
2	0.3	0.937	0.000	0.062	15	0	1	16
3	0.4	1.000	0.000	0.000	16	0	0	16
4	0.5	0.937	0.000	0.062	15	0	1	16
5	-0.2	0.750	0.187	0.062	12	3	1	16
6	-0.3	1.000	0.000	0.000	16	0	0	16
7	-0.4	1.000	0.000	0.000	16	0	0	16
8	-0.5	0.937	0.000	0.062	15	0	1	16
Summary		0.945	0.023	0.031	121	3	4	128

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E11

Damping ratio = 0.707.

Change in VARIANCE. Subject: MR

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.47	1.55	1.72	0.77
2	0.3	0.75	2.01	1.51	0.58
3	0.4	1.06	2.36	1.23	0.44
4	0.5	1.41	2.65	0.89	0.48
5	-0.2	-0.37	-1.32	2.12	0.68
6	-0.3	-0.53	-1.67	1.94	0.54
7	-0.4	-0.67	-1.90	1.63	0.58
8	-0.5	-0.79	-2.07	1.29	0.43

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.875	0.050	0.075	35	2	3	40
2	0.3	1.000	0.000	0.000	40	0	0	40
3	0.4	0.975	0.025	0.000	39	1	0	40
4	0.5	0.925	0.000	0.075	37	0	3	40
5	-0.2	0.900	0.075	0.025	36	3	1	40
6	-0.3	1.000	0.000	0.000	40	0	0	40
7	-0.4	0.975	0.025	0.000	39	1	0	40
8	-0.5	0.900	0.025	0.075	36	1	3	40
Summary		0.944	0.025	0.031	302	8	10	320

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E12

Damping ratio = 0.707.

Change in VARIANCE. Subject: WM

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.47	1.55	2.39	0.66
2	0.3	0.75	2.01	1.86	0.53
3	0.4	1.06	2.36	1.71	0.66
4	0.5	1.41	2.65	1.41	0.50
5	-0.2	-0.37	-1.32	2.55	0.67
6	-0.3	-0.53	-1.67	2.24	0.60
7	-0.4	-0.67	-1.90	1.96	0.48
8	-0.5	-0.79	-2.07	1.83	0.58

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.958	0.042	0.000	46	2	0	48
2	0.3	1.000	0.000	0.000	48	0	0	48
3	0.4	1.000	0.000	0.000	48	0	0	48
4	0.5	0.958	0.021	0.021	46	1	1	48
5	-0.2	0.958	0.021	0.021	46	1	1	48
6	-0.3	0.979	0.021	0.000	47	1	0	48
7	-0.4	0.958	0.000	0.042	46	0	2	48
8	-0.5	0.979	0.000	0.021	47	0	1	48
Summary		0.974	0.013	0.013	374	5	5	384

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 1.0 Seconds. Table E13

Damping ratio = 0.707.

Change in VARIANCE. Summary (all subjects)

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.47	1.55	2.12	0.70
2	0.3	0.75	2.01	1.73	0.52
3	0.4	1.06	2.36	1.59	0.59
4	0.5	1.41	2.65	1.22	0.47
5	-0.2	-0.37	-1.32	2.49	0.65
6	-0.3	-0.53	-1.67	2.24	0.57
7	-0.4	-0.67	-1.90	1.86	0.55
8	-0.5	-0.79	-2.07	1.80	0.53

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.933	0.038	0.029	97	4	3	104
2	0.3	0.990	0.000	0.010	103	0	1	104
3	0.4	0.990	0.010	0.000	103	1	0	104
4	0.5	0.942	0.010	0.048	98	1	5	104
5	-0.2	0.904	0.067	0.029	94	7	3	104
6	-0.3	0.990	0.010	0.000	103	1	0	104
7	-0.4	0.971	0.010	0.019	101	1	2	104
8	-0.5	0.942	0.010	0.048	98	1	5	104
Summary		0.958	0.019	0.023	797	16	19	832

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E14

Damping ratio = 0.200.

Change in FREQUENCY Subject: SH

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.12	-0.22	2.26	0.67
2	-0.2	-0.22	-0.80	1.98	0.64
3	-0.3	-0.30	-1.10	1.96	0.78
4	-0.4	-0.36	-1.29	1.93	0.83
5	0.1	0.16	0.45	2.16	0.93
6	0.2	0.35	1.26	2.16	0.66
7	0.3	0.60	1.79	1.38	0.64
8	0.4	0.91	2.21	1.04	0.36

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	0.957	0.043	0.000	22	1	0	23
2	-0.2	1.000	0.000	0.000	23	0	0	23
3	-0.3	0.957	0.000	0.043	22	0	1	23
4	-0.4	0.957	0.000	0.043	22	0	1	23
5	0.1	0.652	0.348	0.000	15	8	0	23
6	0.2	0.957	0.000	0.043	22	0	1	23
7	0.3	0.957	0.000	0.043	22	0	1	23
8	0.4	1.000	0.000	0.000	23	0	0	23
Summary		0.929	0.049	0.022	171	9	4	184

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E15

Damping ratio = 0.200.

Change in FREQUENCY Subject: MR

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.12	-0.22	1.86	1.21
2	-0.2	-0.22	-0.80	1.88	0.70
3	-0.3	-0.30	-1.10	1.58	0.53
4	-0.4	-0.36	-1.29	1.48	0.45
5	0.1	0.16	0.45	2.17	0.77
6	0.2	0.35	1.26	1.37	0.38
7	0.3	0.60	1.79	0.94	0.55
8	0.4	0.91	2.21	0.59	0.46

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	0.909	0.045	0.045	20	1	1	22
2	-0.2	1.000	0.000	0.000	22	0	0	22
3	-0.3	1.000	0.000	0.000	22	0	0	22
4	-0.4	0.955	0.000	0.045	21	0	1	22
5	0.1	0.909	0.091	0.000	20	2	0	22
6	0.2	0.955	0.000	0.045	21	0	1	22
7	0.3	1.000	0.000	0.000	22	0	0	22
8	0.4	0.909	0.000	0.091	20	0	2	22
Summary		0.955	0.017	0.028	168	3	5	176

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E16

Damping ratio = 0.200.

Change in FREQUENCY Summary (all subjects)

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.12	-0.22	2.06	0.98
2	-0.2	-0.22	-0.80	1.93	0.67
3	-0.3	-0.30	-1.10	1.77	0.66
4	-0.4	-0.36	-1.29	1.71	0.67
5	0.1	0.16	0.45	2.17	0.86
6	0.2	0.35	1.26	1.76	0.54
7	0.3	0.60	1.79	1.16	0.60
8	0.4	0.91	2.21	0.81	0.41

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	0.933	0.044	0.022	42	2	1	45
2	-0.2	1.000	0.000	0.000	45	0	0	45
3	-0.3	0.978	0.000	0.022	44	0	1	45
4	-0.4	0.956	0.000	0.044	43	0	2	45
5	0.1	0.778	0.222	0.000	35	10	0	45
6	0.2	0.956	0.000	0.044	43	0	2	45
7	0.3	0.978	0.000	0.022	44	0	1	45
8	0.4	0.956	0.000	0.044	43	0	2	45
Summary		0.942	0.033	0.025	339	12	9	360

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E17

Damping ratio = 0.200.

Change in VARIANCE. Subject: SH

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.16	0.45	3.08	0.75
2	0.3	0.25	0.91	2.52	0.82
3	0.4	0.35	1.26	2.35	1.33
4	0.5	0.47	1.55	2.47	0.80
5	-0.2	-0.12	-0.22	2.89	0.76
6	-0.3	-0.18	-0.57	2.60	1.23
7	-0.4	-0.22	-0.80	2.56	0.94
8	-0.5	-0.26	-0.97	2.50	0.95

	Stimulus	P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.667	0.278	0.056	36	15	3	54
2	0.3	0.796	0.185	0.019	43	10	1	54
3	0.4	0.889	0.056	0.056	48	3	3	54
4	0.5	1.000	0.000	0.000	40	0	0	40
5	-0.2	0.759	0.241	0.000	41	13	0	54
6	-0.3	0.833	0.148	0.019	45	8	1	54
7	-0.4	0.981	0.019	0.000	53	1	0	54
8	-0.5	0.975	0.025	0.000	39	1	0	40
Summary		0.854	0.126	0.020	345	51	8	404

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E18

Damping ratio = 0.200.

Change in VARIANCE. Subject: MR

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.16	0.45	2.49	0.59
2	0.3	0.25	0.91	2.26	0.71
3	0.4	0.35	1.26	2.16	0.64
4	0.5	0.47	1.55	1.97	0.57
5	-0.2	-0.12	-0.22	2.59	0.71
6	-0.3	-0.18	-0.57	2.37	0.72
7	-0.4	-0.22	-0.80	2.29	0.56
8	-0.5	-0.26	-0.97	2.26	0.43

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.667	0.308	0.026	26	12	1	39
2	0.3	0.897	0.077	0.026	35	3	1	39
3	0.4	0.923	0.026	0.051	36	1	2	39
4	0.5	0.969	0.000	0.031	31	0	1	32
5	-0.2	0.923	0.051	0.026	36	2	1	39
6	-0.3	0.974	0.000	0.026	38	0	1	39
7	-0.4	0.949	0.026	0.026	37	1	1	39
8	-0.5	1.000	0.000	0.000	32	0	0	32
Summary		0.909	0.064	0.027	271	19	8	298

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E19

Damping ratio = 0.200.

Change in VARIANCE. Subject: WM

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.16	0.45	2.69	0.73
2	0.3	0.25	0.91	2.42	0.66
3	0.4	0.35	1.26	2.10	0.67
4	0.5	0.47	1.55	1.80	0.55
5	-0.2	-0.12	-0.22	3.32	0.41
6	-0.3	-0.18	-0.57	3.11	0.53
7	-0.4	-0.22	-0.80	2.96	0.55
8	-0.5	-0.26	-0.97	2.94	0.62

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.975	0.025	0.000	39	1	0	40
2	0.3	0.925	0.075	0.000	37	3	0	40
3	0.4	1.000	0.000	0.000	40	0	0	40
4	0.5	1.000	0.000	0.000	40	0	0	40
5	-0.2	0.825	0.125	0.050	33	5	2	40
6	-0.3	0.950	0.050	0.000	38	2	0	40
7	-0.4	1.000	0.000	0.000	40	0	0	40
8	-0.5	0.950	0.025	0.025	38	1	1	40
Summary		0.953	0.038	0.009	305	12	3	320

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E20

Damping ratio = 0.200.

Change in VARIANCE. Summary (all subjects)

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.16	0.45	2.75	0.69
2	0.3	0.25	0.91	2.40	0.73
3	0.4	0.35	1.26	2.20	0.94
4	0.5	0.47	1.55	2.08	0.65
5	-0.2	-0.12	-0.22	2.93	0.65
6	-0.3	-0.18	-0.57	2.69	0.88
7	-0.4	-0.22	-0.80	2.60	0.71
8	-0.5	-0.26	-0.97	2.57	0.70

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.759	0.211	0.030	101	28	4	133
2	0.3	0.865	0.120	0.015	115	16	2	133
3	0.4	0.932	0.030	0.038	124	4	5	133
4	0.5	0.991	0.000	0.009	111	0	1	112
5	-0.2	0.827	0.150	0.023	110	20	3	133
6	-0.3	0.910	0.075	0.015	121	10	2	133
7	-0.4	0.977	0.015	0.008	130	2	1	133
8	-0.5	0.973	0.018	0.009	109	2	1	112
Summary		0.901	0.080	0.019	921	82	191022	

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E21

Damping ratio = 0.707.

Change in FREQUENCY Subject: SH

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.12	-0.22	2.29	0.73
2	-0.2	-0.22	-0.80	1.95	0.54
3	-0.3	-0.30	-1.10	1.75	0.48
4	-0.4	-0.36	-1.29	1.28	0.93
5	0.1	0.16	0.45	2.36	0.88
6	0.2	0.35	1.26	1.51	0.68
7	0.3	0.60	1.79	1.11	0.48
8	0.4	0.91	2.21	0.70	0.31

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	1.000	0.000	0.000	32	0	0	32
2	-0.2	0.969	0.000	0.031	31	0	1	32
3	-0.3	0.906	0.000	0.094	29	0	3	32
4	-0.4	0.969	0.000	0.031	31	0	1	32
5	0.1	0.906	0.062	0.031	29	2	1	32
6	0.2	0.969	0.031	0.000	31	1	0	32
7	0.3	0.969	0.031	0.000	31	1	0	32
8	0.4	0.937	0.000	0.062	30	0	2	32
Summary		0.953	0.016	0.031	244	4	8	256

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E22

Damping ratio = 0.707.

Change in FREQUENCY Subject: MR

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.12	-0.22	1.88	0.63
2	-0.2	-0.22	-0.80	1.24	0.50
3	-0.3	-0.30	-1.10	1.14	0.40
4	-0.4	-0.36	-1.29	1.09	0.35
5	0.1	0.16	0.45	2.06	0.72
6	0.2	0.35	1.26	1.32	0.52
7	0.3	0.60	1.79	0.59	0.60
8	0.4	0.91	2.21	0.51	0.28

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	1.000	0.000	0.000	23	0	0	23
2	-0.2	1.000	0.000	0.000	23	0	0	23
3	-0.3	0.957	0.000	0.043	22	0	1	23
4	-0.4	0.913	0.000	0.087	21	0	2	23
5	0.1	1.000	0.000	0.000	23	0	0	23
6	0.2	1.000	0.000	0.000	23	0	0	23
7	0.3	0.957	0.000	0.043	22	0	1	23
8	0.4	0.957	0.043	0.000	22	1	0	23
Summary		0.973	0.005	0.022	179	1	4	184

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E23

Damping ratio = 0.707.

Change in FREQUENCY Summary (all subjects)

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	-0.1	-0.12	-0.22	2.09	0.68
2	-0.2	-0.22	-0.80	1.59	0.52
3	-0.3	-0.30	-1.10	1.44	0.45
4	-0.4	-0.36	-1.29	1.18	0.70
5	0.1	0.16	0.45	2.21	0.80
6	0.2	0.35	1.26	1.41	0.61
7	0.3	0.60	1.79	0.85	0.54
8	0.4	0.91	2.21	0.61	0.30

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	-0.1	1.000	0.000	0.000	55	0	0	55
2	-0.2	0.982	0.000	0.018	54	0	1	55
3	-0.3	0.927	0.000	0.073	51	0	4	55
4	-0.4	0.945	0.000	0.055	52	0	3	55
5	0.1	0.945	0.036	0.018	52	2	1	55
6	0.2	0.982	0.018	0.000	54	1	0	55
7	0.3	0.964	0.018	0.018	53	1	1	55
8	0.4	0.945	0.018	0.036	52	1	2	55
Summary		0.961	0.011	0.027	423	5	12	440

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E24

Damping ratio = 0.707.

Change in VARIANCE. Subject: SH

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.16	0.45	2.75	0.56
2	0.3	0.25	0.91	2.32	0.98
3	0.4	0.35	1.26	2.45	0.72
4	0.5	0.47	1.55	2.03	0.77
5	-0.2	-0.12	-0.22	2.86	0.70
6	-0.3	-0.18	-0.57	2.70	0.71
7	-0.4	-0.22	-0.80	2.68	0.78
8	-0.5	-0.26	-0.97	2.28	0.65

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.775	0.225	0.000	31	9	0	40
2	0.3	0.925	0.050	0.025	37	2	1	40
3	0.4	0.975	0.000	0.025	39	0	1	40
4	0.5	0.975	0.000	0.025	39	0	1	40
5	-0.2	0.875	0.125	0.000	35	5	0	40
6	-0.3	0.950	0.000	0.050	38	0	2	40
7	-0.4	0.925	0.000	0.075	37	0	3	40
8	-0.5	0.950	0.025	0.025	38	1	1	40
Summary		0.919	0.053	0.028	294	17	9	320

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E25

Damping ratio = 0.707.

Change in VARIANCE. Subject: MR

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.16	0.45	2.37	0.84
2	0.3	0.25	0.91	2.02	0.54
3	0.4	0.35	1.26	1.83	0.47
4	0.5	0.47	1.55	1.66	0.61
5	-0.2	-0.12	-0.22	2.58	0.56
6	-0.3	-0.18	-0.57	2.21	0.65
7	-0.4	-0.22	-0.80	2.17	0.59
8	-0.5	-0.26	-0.97	2.01	0.57

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.795	0.205	0.000	31	8	0	39
2	0.3	1.000	0.000	0.000	39	0	0	39
3	0.4	0.897	0.026	0.077	35	1	3	39
4	0.5	1.000	0.000	0.000	32	0	0	32
5	-0.2	0.974	0.026	0.000	38	1	0	39
6	-0.3	0.974	0.000	0.026	38	0	1	39
7	-0.4	0.974	0.026	0.000	38	1	0	39
8	-0.5	1.000	0.000	0.000	32	0	0	32
Summary		0.950	0.037	0.013	283	11	4	298

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E26

Damping ratio = 0.707.

Change in VARIANCE. Subject: WM

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.16	0.45	2.68	0.70
2	0.3	0.25	0.91	2.36	0.68
3	0.4	0.35	1.26	2.18	0.61
4	0.5	0.47	1.55	1.80	0.65
5	-0.2	-0.12	-0.22	2.93	0.69
6	-0.3	-0.18	-0.57	3.02	0.51
7	-0.4	-0.22	-0.80	2.74	0.48
8	-0.5	-0.26	-0.97	2.64	0.56

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.875	0.125	0.000	42	6	0	48
2	0.3	1.000	0.000	0.000	48	0	0	48
3	0.4	0.979	0.021	0.000	47	1	0	48
4	0.5	1.000	0.000	0.000	48	0	0	48
5	-0.2	0.979	0.021	0.000	47	1	0	48
6	-0.3	0.958	0.042	0.000	46	2	0	48
7	-0.4	0.979	0.000	0.021	47	0	1	48
8	-0.5	0.979	0.000	0.021	47	0	1	48
Summary		0.969	0.026	0.005	372	10	2	384

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..

Nominal: Period = 3.0 Seconds. Table E27

Damping ratio = 0.707.

Change in VARIANCE. Summary (all subjects)

	Stimulus			Detection time	
	X0	X1	X2	Mean	Sigma
1	0.2	0.16	0.45	2.60	0.71
2	0.3	0.25	0.91	2.23	0.76
3	0.4	0.35	1.26	2.15	0.61
4	0.5	0.47	1.55	1.83	0.68
5	-0.2	-0.12	-0.22	2.79	0.65
6	-0.3	-0.18	-0.57	2.65	0.63
7	-0.4	-0.22	-0.80	2.53	0.63
8	-0.5	-0.26	-0.97	2.31	0.60

Stimulus		P(C)	P(M)	P(F)	C	M	F	T
1	0.2	0.819	0.181	0.000	104	23	0	127
2	0.3	0.976	0.016	0.008	124	2	1	127
3	0.4	0.953	0.016	0.031	121	2	4	127
4	0.5	0.992	0.000	0.008	119	0	1	120
5	-0.2	0.945	0.055	0.000	120	7	0	127
6	-0.3	0.961	0.016	0.024	122	2	3	127
7	-0.4	0.961	0.008	0.031	122	1	4	127
8	-0.5	0.975	0.008	0.017	117	1	2	120
Summary		0.947	0.038	0.015	949	38	151002	

Detection time units: ln(2*time in seconds).

Stimulus: X0 - ln(P/Pn) / ln(10)
X1 - Difference in sigma of velocity from the nominal
X2 - (sign) ln (abs(10X1))

C - Correct M - Miss F - False alarm T - Total

P(C),.. - Probability of Correct detection etc..