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# THE HUMAN AS A DETECTOR OF CHANGES IN VARIANCE AND BANDWIDTH

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## Abstract

The humans's function in the control of processes is shifting toward a supervisory or monitoring role with the advent of increasing automation. One of the functions of a monitor is the detection of changes or failures in the characteristics of the random process. In this paper we consider the detection of changes in random process variance and bandwidth. Psychophysical thresholds for these two parameters were determined using an adaptive staircase technique for second order random processes at two nominal periods (1 and 3 seconds) and damping ratios (0.2 and 0.707). Thresholds for bandwidth changes were approximately 9% of nominal except for the (3sec,0.2) process which yielded thresholds of 12%. Variance thresholds averaged 17% of nominal except for the (3sec,0.2) process in which they were 32%. Detection times for suprathreshold changes in the parameters may be roughly described by the changes in RMS velocity of the process. A more complex model is presented which consists of a Kalman Filter designed for the nominal process using velocity as the input, and a modified Wald sequential test for changes in the variance of the residual. The model predictions agree moderately well with the experimental data. Models using heuristics, e.g. level crossing counters, were also examined and were found to be descriptive but do not afford the unification of the Kalman Filter/sequential test model which has previously been used for changes in mean.

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## Introduction

The humans's function in the control of processes is shifting toward a supervisory and monitoring role with the advent of increasing automation. Monitoring seems to imply at least the two functions of performance assessment and failure detection (or change detection), although there is no clear cut definition of monitoring *per se* (Curry and Gai, 1976, Kleinman and Curry, 1977).

Developing descriptive models of human failure detection requires appropriate blending of theory and experiment. Without data, a reasonable starting point is a normative model such as suggested by Phatak and Kleinman (1972). They propose a model of failure detection and identification which requires a Kalman Filter for each alternate hypothesis. Levison (1971) has used estimation theory as a basis for a performance assessment model with good predictions of experimental data for detecting signal limit exceedances.

The emphasis of this paper is to report on experiments yielding information regarding some of the human capabilities and limitations in detecting random process changes, i.e., the psychophysics of random processes. Previous work has involved detection of changes in mean by human observers (Gai and Curry,1976); in this paper we report on other aspects of random process changes which have important applications in the operational setting, viz., changes in bandwidth and variance. A more complete description of the research is contained in Govindaraj (1976).

## Description of The Experiments

### General

Experiments were conducted to determine the thresholds for changes in the variance and bandwidth of a random process, and to study the detection behavior for suprathreshold stimuli. The process consisted of the output of a second order shaping filter with the transfer function

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

and zero mean white Gaussian noise as input. In the above equation K is the filter gain, $\omega_n$ is the natural frequency, and $\zeta$ is the damping ratio. The output of the shaping filter was displayed on the graphics display terminal as a horizontal line moving up and down inside a grid. All the three parameters, the natural frequency, the damping ratio, and gain K may be changed, but only variations in the natural frequency (the bandwidth) and the variance of the input noise (equivalently the output variance) were considered for the present study of failure detection.

## Equipment

A PDP 11/34 computer with graphics capability was used to carry out the experiment. White gaussian noise was digitally generated and used as input to the state equation of (1) which was updated once every 10.5 milliseconds. The subject was seated about 76 cm in front of the screen, the screen being at normal eye level; the standard deviation of the nominal process was 2 cm subtending an angle of 0.0267 radians. The subject held a small box with two switches to indicate his response. A 12 inch diagonal P31 fast phosphor cathode ray tube was used for all displays.

## Procedure

Fifteen people participated for approximately four weeks in the threshold experiment. Their background and age ranged from college sophomores, to graduate students in science and engineering, to a senior citizen. For each subject, one session lasted for approximately an hour with no more than one session per day. Two series of experiments were conducted during a session: one for a change in frequency and the other for a change in variance.

The general nature of the experiment was described to each subject on his first day. A brief explanation of the observed process was given in terms of the physical analog of a spring-mass system. The subjects were told that there would not be any definite pattern, since 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', and 'how fast or slow it is moving'. They were told to observe the 'average behavior of the line'.

After the procedure was explained, the nominal mode was shown for two minutes and then large parameter changes of both sign were shown to familiarize the subject with the nature of failures. For trials in which changes took place the process started with the nominal parameter values and a failure occurred between 8 and 12 seconds after starting. Though it was obvious, the subjects were told about the nature of these first failures (i.e., increase or decrease) during this phase. One nominal and four failures were sufficient for all subjects to become familiar with the changes.

The observers were required to indicate the type of failure (parameter increase or decrease) on each trial and feedback was presented on the CRT. If the failure was detected and identified correctly, it was a 'correct' response. If any switch was pressed prior to an actual failure, it was a 'false alarm'. If the identification was incorrect, it was 'wrong'. Finally, if the failure was 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.





## Stimuli

Stimulus values were chosen according to the following relation:

$$\frac{P}{P_n} = \exp(S \ln R) \tag{2}$$

where

$P_n$ - Nominal values of the parameter
$P$ - Changed or failued value
$R$ - Ratio of initial change ($R = 10$)
$S$ - Stimulus ( $|S| < 1.0$).

## Threshold Experiments

Threshold experiments were conducted using a modified staircase technique which allowed subject familiarization in the early trials of a session and threshold determination in the later trials. This was accomplished by starting with a large stimulus value and regulating the average rate of decrease of the stimulus magnitude so that 20 or 30 trials were encountered before the stimuli were near threshold.

A set of four nominal processes obtained by the factorial combination of $T = 2\pi/\omega_n = (1.0, 3.0)$ seconds and $\zeta = (0.2, 0.707)$ were used. During any one session, only one nominal was presented. The subjects who participated in the threshold experiments were given all four sets of nominal processes via a balanced Latin square design.

## Detection Time Experiment

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 subjects 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. Since frequency and variance thresholds were available for the four nominals from the previous experiments, four stimulus magnitudes were chosen with the smallest being slightly higher than the threshold. Four parameter increases and four decreases were mixed to form a group of eight stimuli, and a stimulus was presented from this group at random without replacement.

## Results

### Threshold Values

An exponential approximation was used to fit the stimulus-trial data. The assumed curve had the form

$$|S_n| = a + \exp(-c*n) \tag{3}$$

where $S_n$ is the value of the stimulus at the trial number t, and a is the threshold. A least squares fit was found using as initial values the threshold values calculated at the end of each session by taking the mean of the last six peaks and valleys of the stimulus vs trial history. In most cases, these first approximation values agreed very closely with the values found by the exponential fit. The thresholds determined in this manner and averaged over subjects are displayed in Table 1.

Threshold magnitudes were compared for parameter increases vs. parameter decreases using a modified t-test. The null hypothesis that the thresholds were equal could not be rejected ($p < .05$) although preliminary experiments indicated this might be the case (Curry and Govindaraj, 1976). Threshold values for different nominal conditions were also compared and it was found that changes from the nominal (T=3.0,Z=.2) yielded consistently higher thresholds for both variance and bandwidth than the other three nominal processes (Table 1). The reasons for this difference can not be explained using simple velocity concepts since the RMS velocity for the processes considered here is given by

$$\sigma_{\dot{x}} = \omega_n \sigma_x \tag{4}$$

which is independent of the damping ratio.

### Detection Times

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. In addition, the experiment was conducted over a period of several weeks and it is therefore reasonable to assume that the subjects were 'well-trained observers'.

The detection time data for changes in variance and bandwidth are plotted in Figures 1-4 in the form of log detection time vs, the log of the change in RMS velocity. (Also included for later reference are model predictions.) All curves indicate that using the change in RMS velocity is a reasonable method for summarizing the data. Although there is a tendency for increases in variance and bandwidth to be detected more quickly than decreases, the variability in responses over the population of observers suggests that these differences are of little practical





significance even if statistical significnace were to be achieved.

## Models For Failure Detection

### General Description

The process displayed to the subject consists of up and down motion of a horizontal line and the subject observed the position of the line continuously, but 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, was considered as the observed variable. The observations are assumed corrupted by an additive noise v(t), which was modeled as a zero mean Gaussian process. The input to the failure detection model thus consists of the observation (display rate) plus Gaussian white noise. The failure detector is modeled here as an estimator to generate a sequence of uncorrelated residuals which are utilized in the decision mechanism.

For all the models, the states were updated at 5/60 ths of a second, and the stimulus presentation was the same as in the experiment. The summations needed for the decision function were done with a first order filter with a long time constant, starting at 5 seconds after the start of the trial ($1/(\tau s+1)$, $\tau$ = 0.001). Thus it is effectively a direct summation. In all cases, P(fa) = 0.05 was used for setting the decision boundaries.

### Residual-Variance Detector

A Kalman filter designed for the nominal condition was used for the estimation portion of the model to detect changes in both frequency and variance. There are now two separate problems: (1) the detection of failures in frequency, and (2) the detection of failures in variance. The mean of the residual remains zero for both changes, since the system (the shaping filter), and the Kalman filter are linear, and the overall input is a zero mean white Gaussian process. However, the variance of the residual changes for failures of both types. This characteristic of the residual motivated a modeling approach using residual variance change as a failure indicator.

As with previous models of human failure detection, we use a sequential probability ratio test on the residuals with the further constraint that each time the decision function confirms normal operation, it is reset to zero (Chien and Adams,1976, Gai and Curry, 1976). For increases in residual variance, this leads to a decision function of the form:

$$\lambda_m = \begin{cases} \bar{\lambda}_m, & \bar{\lambda}_m \geq 0 \\ 0, & \bar{\lambda}_m < 0 \end{cases} \tag{5}$$

$$\bar{\lambda}_m = \lambda_{m-1} - \log\left[\frac{\sigma_1}{\sigma_0}\right] - \left[\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}\right]\frac{r_m^2}{2} \tag{6}$$

$$\text{if} \geq A_1, \qquad \text{decide } H_1$$

where $r_m$ is the observed residual at time m, $\sigma_0$ is the nominal residual variance, $\sigma_1$ is the "failed" value of the residual variance ($\sigma_1 > \sigma_0$) and the constant $A_1$ is chosen to provide the specified probability of false alarm (Gai and Curry, 1976). Equations similar to (5,6) can be derived for an hypothesized residual variance decrease. Two such decision mechanisms operating in parallel (one for a residual variance increase, one for a decrease) were applied to the random processes experienced by the observers; the mean model detection time is shown in Figures 1-4. The parameters were chosen for each type of failure to represent the population's detection time rather than to represent each individual's performance.

The agreement between model and data is good, even to the point of mimicing differences resulting from nominal bandwidths differences.

## Velocity Magnitude Discriminator

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 the mean speed. After this estimate is made , 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 mean speed changes, and this is reflected in the mean of the residuals. A modified sequential probability ratio test as described above is then used to detect changes in mean speed. Detection time results of this model compared as favorably with the data as the variance detection model described above.





## Comparisons Among 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 0.2-0.3 seconds.) Also, it was interesting to test if 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, 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 failures with an increase in frequency, but decreases had a very high false alarm rate compared with the subjects. A different decision criterion that accounts for the subject's prior information that the failure occurs at least after 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.

In view of the above comments the Kalman Filter/Sequential Decision model appears to be the more parsimonous choice because it accommodates both variance and bandwidth changes in one framework. Moreover, it is consistent with the model philosophy previously established for changes in means. A major difference yet to be resolved is the fact that display position input is used in the detection of changes of mean, and display velocity is used in the detection of changes of variance and bandwidth.

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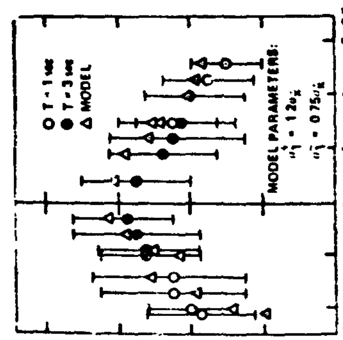
FIGURE 1
DETECTION TIME FOR VARIANCE CHANGE (Z = 0.2)

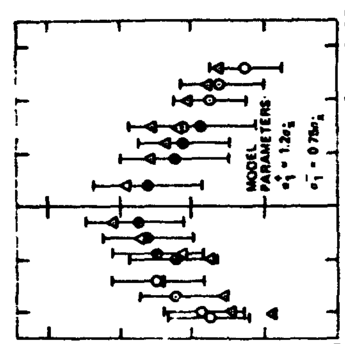
FIGURE 2
DETECTION TIME FOR VARIANCE CHANGE (Z = 0.707)

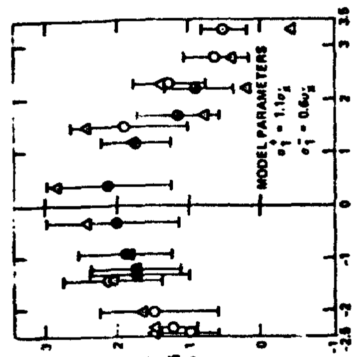
FIGURE 3
DETECTION TIME FOR BANDWIDTH CHANGE (Z = 0.2)

(1) Change in period

| Nm | Th (log) | R | W | W-Wo | %Nm |
|---|---|---|---|---|---|
| 12 | -0.078 (0.061, 9) | 0.924 | 6.800 | 0.517 | 8.2 |
| | 0.084 (0.048, 9) | 1.088 | 5.886 | -0.387 | 6.2 |
| 17 | -0.076 (0.046, 9) | 0.927 | 6.778 | 0.495 | 7.9 |
| | 0.087 (0.050, 9) | 1.080 | 5.764 | -0.519 | 8.3 |
| 32 | -0.138 (0.080, 12) | 0.871 | 2.405 | 0.310 | 14.8 |
| | 0.124 (0.068, 12) | 1.131 | 1.862 | -0.243 | 11.6 |
| 37 | -0.085 (0.050, 12) | 0.917 | 2.284 | 0.189 | 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 (0.087, 10) | 0.847 | 15.3 |
| | 0.177 (0.097, 10) | 1.190 | 18.4 |
| 17 | -0.183 (0.101, 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 (0.108, 8) | 1.410 | 41.0 |
| 37 | -0.210 (0.078, 9) | 0.811 | 18.9 |
| | 0.191 (0.086, 9) | 1.211 | 21.1 |

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

TABLE 1
THRESHOLDS FOR PERIOD (BANDWIDTH) AND VARIANCE CHANGES

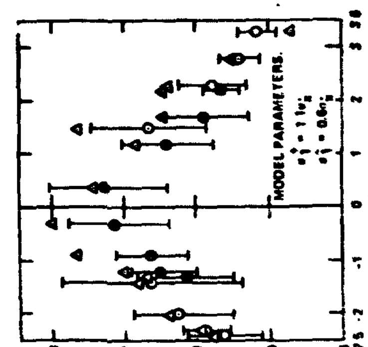
FIGURE 4
DETECTION TIME FOR BANDWIDTH CHANGE (Z = 0.707)