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DEVELOPMENT OF A PREDICTION MODEL FOR

DYNAMIC VISUAL INSPECTION TASKS

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ACKNOWLEDGMENTS

Impossible!

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CHAPTER I

INTRODUCTION

In most industry today there is a task, the performance of which is relatively unchanged from what it was immediately after the Industrial Revolution. This is the task of visual inspection. Its objective is to insure that outgoing products are of an acceptable quality. The task involves visual screening of items produced, specifically for certain critical characteristics, in order to separate defective ones from good ones. Although this sounds simple, it is a difficult practical problem to achieve and maintain a high degree of inspector accuracy.

In the past, very few studies have dealt directly with inspection. Many studies have, however, examined some of the variables involved in inspection from a variety of different viewpoints. These studies can all be broken down into two broadly-related areas. The first deals with the ability of the inspector or subject in an experiment to recognize a defect. The second deals with the inspector's alertness or vigilance. This paper is mainly concerned with the first area--the ability of the inspector to see or recognize a defect. Although errors due to lack of alertness cannot be eliminated completely, these effects have been minimized.

The detection problem deals with the individual's ability to see the defect or characteristic desired and to decide whether the item is acceptable or unacceptable. The ability of an individual to detect a small character or to discriminate fine detail is referred to as his visual acuity. Visual acuity is usually expressed as a function (the inverse) of the smallest visual angle (A) which the individual can detect with some pre-determined level of consistency, for example 50 percent of the time under a given illumination level. Here the visual acuity required to see a characteristic and the visual angle of that characteristic subtended in the eye will be identical. The expression for determining A is (see Figure 1):

$$A = 2\ \tan^{-1}\left(\frac{W}{2D}\right)$$

where:

A = visual angle

W = width or size of the character or defect

D = distance from the character

It can be seen from this expression that the visual angle, and therefore visual acuity, is a function of the size of the

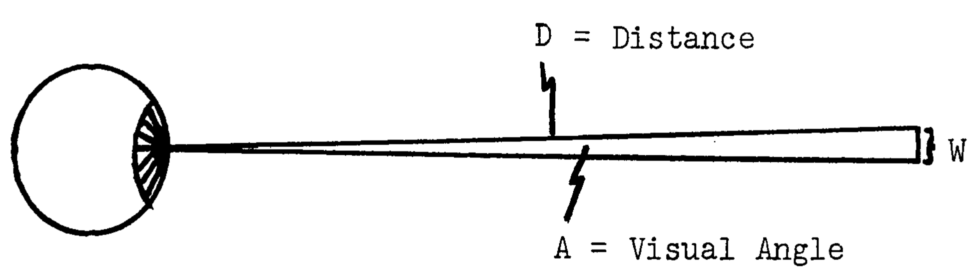


Figure 1.--Visual angle

characteristic being observed and of the distance from which the observation is made. Thus a constant visual angle can be maintained at different distances simply by increasing or decreasing the size of the characteristic or with different sized characteristics by increasing or decreasing the distance from which they are viewed.

There are generally thought to be four types of visual acuity. They are defined by the type of test used to determine each. These types of visual acuity are called line, spot, space, and vernier visual acuity. In the tests to determine each of these types of visual acuity the psychophysical method of limits is used to find the threshold or smallest visual angle which the individual can discriminate. The nature of the characteristic which is required to be discriminated determines the type of visual acuity measured.

Line and spot acuity are very similar and are sometimes called "minimum visible acuity." Line acuity refers to the thinnest line which an individual can detect. Likewise spot acuity refers to the smallest diameter spot which an individual can detect.

Space and vernier acuity are sometimes referred to as "minimum separable acuity." Space acuity is the ability of an individual to see two characteristics as separate. Parallel lines, spots and Landholt Rings are commonly used characteristics in space acuity. The visual angle of the minimum space between characteristics which the individual can detect is his space acuity. Vernier acuity is the ability of an individual to detect a discontinuity in a line. This discontinuity in the line is formed by having the line, at some point, be displaced slightly to one side. The smallest displacement which the individual can detect is his vernier acuity.

The visual acuity and visual angle referred to and discussed above are usually thought of in a static sense in which the characteristic being viewed is stationary with respect to the observer. The ideas are the same for the case in which the characteristic being viewed is moving with respect to the observer. In this case (where the characteristic or target is moving) visual acuity is usually called dynamic visual acuity.

The inspection task is dependent upon visual acuity and often involves dynamic visual acuity. Many industries work on a production line system in which items are mass produced. In these systems, the raw materials enter the production facility at the beginning and at various other points in the production process. The actions of men and/or machines transform these raw materials step by step into a finished product. After many of these operations and after completion, the product must be inspected. Conveyors are often used to transport the product from one operation to the next. It may be infeasible to remove the items from the conveyor, thereby requiring the inspection of moving objects.

Inspecting moving products is very closely associated with dynamic visual acuity. An individual's ability to see or detect a defect in a dynamic situation is a function of many of the same variables as those that affect dynamic visual acuity. A number of variables are believed to have similar effects on dynamic visual inspection as on dynamic visual acuity. These are the first six variables shown in Table 1. The additional eight variables are thought to pertain to dynamic inspection only, as they are not present in the controlled environment in which dynamic visual acuity is tested.

The experimentation to be described later deals with variables 2 through 6 of Table 1. They were selected for several reasons. All but rate of change of the visual angle (ROCVA) have been examined individually or in pairs and found to affect dynamic visual acuity, dynamic visual inspection, or both. ROCVA is a new variable identified by Smith and Barany (1970) as being a possible reason for dynamic visual acuity tests failing to predict good inspectors. The variables numbered 7 through 12 in Table 1 were eliminated since they would be minimized or eliminated in any practical industrial situation.

It should be noted that the variables of size and viewing distance are not included in this experimentation. These are accounted for or controlled in the expression for the visual angle (A) and for this paper are assumed to have

TABLE 1

VARIABLES BELIEVED TO BE INVOLVED
IN DYNAMIC VISUAL INSPECTION

1. Individual Differences
2. Illumination Level
3. Contrast
4. Time to View
5. Angular Velocity
6. Rate of Change of the Visual Angle
7. Glare
8. Direction of Movement
9. External Competing Stimuli
10. Internal Competing Stimuli
11. Atmospheric Conditions--Heat Waves, Smoke, or Toxic Vapors
12. Vibration
13. Size
14. Distance

no effect as long as the correct visual angle is maintained. This assumption is valid as long as the distances are kept within reason such that atmospheric or other conditions do not obscure the vision. In the inspection tasks in industry and the experimentation described later, the distances at which observations are taken are such that they will have no real effect on visual acuity.

CHAPTER II

PROBLEM DEFINITION

Presently there are methods or guides for estimating satisfactory levels for certain variables involved in work situations. Illumination is probably the most important of these. Much work has been published by the Illuminating Engineering Societies of both the U.S. and Britain. This takes the form of standards and specific articles. The standards are published as general guidelines for certain general types of work and situations. Dr. H. R. Blackwell, whose work is discussed in the area of illumination in Chapter III, has been instrumental in setting up these standards for the U.S. In addition to these published standards the specific articles of _Illuminating Engineering_ deal with specific lighting problems and possible solutions. These articles and standards are adequate for specifying general room or factory illumination requirements. They do not, however, take into account the specific task of industrial inspection, nor do they give any idea as to how task variables such as contrast or movement of the item being viewed affect illumination requirements.

Several researchers have worked with the problems of predicting dynamic visual acuity from static visual acuity or predicting inspector performance from some static or dynamic test task. Ludvigh and Miller (1958) showed that static visual acuity was a poor predictor of dynamic visual acuity. Nelson and Barany (1969) devised a dynamic visual recognition test for paced inspection tasks. They were able to set up a test procedure which significantly increased the accuracy of predicting good inspectors over that attained by a static visual acuity test. These tests are adequate for predicting which people might make the best inspectors but they are unsuitable for predicting inspector performance, given a specific task and work environment. They were not designed for this purpose in that they ignored the actual working conditions and task, and they were oriented toward the concept of finding the man for the task rather than which task variables affected the inspector's performance.

It can be seen from the preceding discussion that standards or guidelines have been set up for adequate levels of certain variables in general situations. Also, methods of predicting which person will make a good inspector have been examined. In spite of these measures, defective products still get by and visual inspection is still a major problem to many industries. Neither of these methods attempted to predict inspector performance based on the task itself or variable levels present. That was the objective of this research.

What was needed was a model that would predict performance on a dynamic inspection task, based on the levels of certain variables within that task. Also this model needed to indicate which variable levels to change to improve inspector performances. The objective of this experimentation was to determine such a prediction model as a function of the following five variables:

1. Rate of change of the visual angle of the defect being viewed.
2. Angular velocity of the target.
3. Time to view.
4. Illumination level.
5. Contrast between the defect and the target background.

This model needed to be such that it predicted inspector performance at or near its optimum. This required a series of experiments in which each experiment yielded a prediction model which described a response surface as a function of the five variables listed above. Each succeeding experiment should have come closer than the preceding one to yielding an equation which predicted inspector performance which was at or near optimal.

After completing this phase some additional experimentation was required using a different item to be inspected. This was very important because the regression model attained using one item to be inspected might not be valid for any other item. Considerable time and work was devoted to selection of an appropriate target, or item to be inspected. Past researchers in the area of inspector performance have used numerous types of targets. They ranged from Landholt rings, Barany and Nelson (1969), to actual circuit boards, Patwardhan (1971). Nelson and Barany (1969) used a grid in which four or five of the 100 squares were white while the rest were black. The objective was to identify which targets had less than five white squares. Smith and Barany (1970) used small discs which had either three or four white dots on them. Once again the objective was to determine which discs had three dots and which had four. Wallack and Adams (1969) used batches of conductors which included some defectives (nicks). Badalamente and Ayoub (1969) used printed circuit boards with cuts in any circuit path defined as defects. Moder and Oswalt (1959) used two types of beans as test objects in an inspection study.

As can be seen, a very wide variety of targets have been used in the study of inspection. This has led to problems in interpreting or using the result for a different type of target. Therefore, in this study an experiment using a completely different type of target is required to verify or validate the prediction model derived in the experimentation described later, using similar variable levels.

CHAPTER III

REVIEW OF LITERATURE

This chapter is devoted to the discussion of those variables listed in Table 1 which may have an effect on the dynamic inspection task and were included in this study. Those variables discussed are:

1. Illumination level.
2. Glare.
3. Contrast.
4. Time to view.
5. Rate of change of the visual angle.
6. Angular velocity.

The discussion of each variable includes the most pertinent works related to its effects on the dynamic inspection task or the related idea of dynamic visual acuity.

A. Illumination level

Like many other industrial tasks, inspection accuracy depends on adequate vision, and therefore illumination has a direct bearing on inspector efficiency. The adequacy of illumination is an important variable in the study of the dynamic inspection task.

Illumination level has been shown to be of considerable importance in visual tasks. It has been shown by several investigators that, up to a point, increases in performance levels follow increases in illumination level for various visual tasks. Beyond this point, however, there is little or no improvement in performance accompanying changes in illumination level.

The fact that increases in performance levels coincide with increases in illumination levels up to a point was found by Lythgoe (1932). He found that performance increased with illumination level up to about 50 footlamberts. McCormick and Niven (1952) found a similarly significant increase in performance of the Purdue Hand Precision Test with an increase of illumination level from 5 to 50 foot-candles, but found the performance change insignificant when the illumination level went from 50 to 150 foot-candles. Luckiesh and Moss (1931) had earlier found that worker output in many production activities increased significantly when the illumination level was raised from the very low levels of 5 foot-candles to around 12 foot-candles.

Tinker (1949) set up what he called critical levels of illumination for given tasks. These critical levels represented that point, beyond which increases in illumination had little or no effect on performance. Tinker in this same article stated that:

> . . . there is no justification for suggesting that more than 40 to 50 footcandles are necessary for adequate

> discrimination even for tasks that approach threshold discrimination.

He derived the critical levels for numerous tasks and found them to usually fall somewhere between 10 and 30 foot-candles. As an example, one of the most difficult tasks was that of threading a needle for which the critical level was 30 foot-candles.

Shlaer (1937) found that as the illumination level was increased from absolute threshold there was a corresponding increase in visual acuity. There were two points at which the curve leveled off. The first was thought to occur at the point at which there is a changeover from rod to cone vision. The second leveling off occurred at about "room luminances" (Westheimer, 1965). Due to the units used and the graphical presentation of results this is about all that can be determined from Shlaer's article.

Simonson and Brozek (1948) measured visual performance and fatigue in a situation which "reproduced the essential features of a conveyor inspection operation." They found an optimum of performance at an illumination of 100 foot-candles. They found that the inspectors performance deteriorated above this point.

Dr. H. R. Blackwell has been doing research on illumination for over twenty years. Most of his research is concerned with the ability of an observer to detect a small circle in a uniform background as a function of illumination and contrast. He found that increases in illumination could overcome low levels of contrast and vice versa. His performance curve for 99% accuracy (Faulkner and Murphy, 1971) indicated that for very low levels of contrast (.01) a luminance of 100 footlamberts was adequate.

Most of the studies mentioned support the point of view that above a certain point increases in illumination level do not increase either task performance or visual acuity. There is some disagreement as to what this point is, depending upon the task and the experimenter. Almost all would probably agree, however, that an illumination level of near 100 foot-candles would be more than adequate to see all but the most minute detail.

B. Glare

Glare is usually defined as any brightness within the field of vision which causes discomfort or interference with vision. It can be caused by a light source in the field of view or by the reflectance of a light source which is itself outside of the field of view. Glare can produce actual decreases in performance of visual tasks. Luckiesh and Moss (1932) found that a light source, of 100 watts, at positions between 5° and 40° from the line of sight, reduced visual performance on a given task between 16 and 58 percent. Later researchers have attempted to quantify and categorize glare and its effects.

Since it can cause a decrement in performance and/or discomfort to the observer, every effort was made to reduce or eliminate glare in this research. The methods and precautions taken in the proposed experiment are covered in the controls section of Chapter IV.

C. Contrast

Contrast is defined as the relative brightness difference between the object in the target and the target background and is expressed as a percentage. Two common expressions for contrast are contained in Chapter IV, page 43.

Several researchers have done work relating contrast and visual acuity. Cobb and Moss (1928) showed that 100 percent contrast was necessary to see a target subtending 0.6 minutes of arc but only 1 percent contrast was necessary to see a target subtending 20 minutes of arc. An illumination of 100 millilamberts (107.6 footlamberts) and a time to view of 0.3 seconds were used to arrive at these values. Hendley (1948) obtained results similar to those of Cobb and Moss (1928). These results of Cobb and Moss and of Hendley give values for specific conditions. Because of this it may not be valid to extrapolate them to other situations where conditions are different. The results of the two studies do support the general idea that contrast does have a great influence on visual acuity.

Dr. H. R. Blackwell has also done much research on contrast and its effects on human performance of visual tasks. He (1948 and 1959) was able to plot a series of curves for a given inspector accuracy which showed the relationships between target size, background luminance, and target contrast. He found that contrast had to be high for low illumination levels and could be low for high illumination levels. These findings were discussed earlier under illumination.

Faulkner and Murphy (1971) had some questions as to the validity of Blackwell's findings and compiled a very good listing of these. Probably their most important objection was that he multiplied all illumination values by a "correction" factor of 15 which seems to be somewhat arbitrary. He also extrapolated his data well beyond what would seem to be reasonable limits. Blackwell used a fixed time to view of 0.2 seconds which Graham and Cook (1937) and Niven and Brown (1944) showed was the point at which time to view becomes a controlling factor in visual acuity.

Because of the possible discrepancies in Blackwell's work and because researchers on visual acuity have found it to be an important variable, contrast needs to be investigated more fully. It is important that any model that attempts to predict inspector performance on a visual task should include contrast as a factor.

D. Time to view

The time to view can have very definite effects on inspector accuracy. Blackwell (1952) found that when other factors are held constant there is a linear relationship between subject accuracy on a visual task and the logarithm of the time to view. This relationship holds until accuracy approaches 100 percent; at which time it becomes asymptotic.

Graham and Cook (1941) and Niven and Brown (1944) showed definite relationships between time to view and visual acuity. They both found that in the static case times to view of somewhere less than 0.2 seconds caused a reduction in visual acuity. They also found that increases in illumination would tend to offset the effects of times to view of less than 0.2 seconds.

In Blackwell's (1952) studies a close relationship was found to exist between accuracy on a particular visual task and the variables of time, contrast, and illumination. It was found that to a certain point decreases in one could be offset by increases in one or both of the others. The luminance in these experiments ranged from 5 to 25 footlamberts. According to Murrell (1965) the interaction effects of contrast, illumination and time do not take place unless one or more of them approaches minimal levels.

E. Rate of change of the visual angle

The rate of change of the visual angle is primarily applicable to the straight line conveyor in this experimentation, since it is equal to zero for the circular conveyor with the subject at the center. The mathematical expression for the rate of change of the visual angle is derived in Appendix 3 and is also contained in Appendix 1.

Although a number of studies have been done on dynamic visual acuity and dynamic inspection using a variety of apparati, no one has researched the rate of change of the visual angle as an independent variable. The researchers who have studied dynamic visual acuity have kept the visual angle constant during a single trial. Those studies of dynamic inspection tasks have tended to ignore the change of the visual angle as a possible independent or even controlled variable.

The study of Burg and Hulbert (1961), and those of Burg (1965 and 1966), those of Ludvigh (1949, 1953, 1954a, 1954b, 1955, 1958), and that of Elkin (1962) illustrate the approach normally taken by experimenters in dynamic visual acuity. In these studies the subject was seated at a center point and the target was rotated in a circular path around him. This caused the visual angle to be constant and the rate of change was consequently zero. In this way the rate of change of the visual angle was controlled to zero and eliminated as an independent variable.

Studies of dynamic inspection have typically ignored the rate of change of the visual angle. Blackwell (1959) in evaluating illumination levels required for dynamic versus static visual acuity used a large circular rotating disc on which were placed items to be inspected. The subject was seated outside the disc such that the visual angle was not constant. He found that illumination levels had to be much (about 15 times) higher to achieve the same visual acuity on moving versus stationary targets. Blackwell neglected the change in visual angle and its rate of change while the subject viewed the target. It is possible that this had an effect on his findings.

Most studies of dynamic inspection tasks have been concerned with the effects of such things as incoming quality, inspection rate, vigilance and its related variables, environmental variables, and motivational variables. Few have dealt with the nature of the task or the variables involved in dynamic visual acuity. Sosnowy (1967), investigating the effects of quality and rate, used a small rotating disc with small balls near its perimeter to be inspected. The balls themselves were rotated while occupying a position on the rotating disc. Sosnowy ignored the effect of a complex change of the visual angle of the defect due to the disc and ball rotations. This could be justifiable as these changes were probably very small, although not the same for all trials. Lion _et_ _al_. (1968) studied lighting type and its effect on inspection performance on a straight conveyor. They too ignored the change in visual angle as the target passed by. Since the speed of the conveyor was the same for all trials the changes in the visual angle would also be the same and could therefore be called a controlled variable.

The fact that there is a basic difference in the tasks for testing dynamic visual acuity and the dynamic inspection tasks was recognized by Barany and Nelson (1969). They state that among the differences between dynamic visual acuity tests and dynamic inspection tasks is the fact that the visual angle is not constant. They included this and other factors not simulated in conventional dynamic visual acuity tests in their modified test. They did not, however, specifically investigate the effects of the rate of change of the visual angle on performance. Smith and Barany (1970), did a study in paced visual inspection tasks in which pace, percentage defective, and consequences of errors were the independent variables. To control pace the conveyor speed was varied. This would cause differences in the rate of change of the visual angle which was not a factor in the experiment and was therefore confounded with pace.

The rate of change of the visual angle may be a valid factor affecting inspector performance. If it is, it may explain some of the difficulties in predicting inspector performances from dynamic visual acuity tests.

F. Angular velocity

The angular velocity of a target or object has been shown to have a very definite effect on the inspector's ability to see it. Westheimer's findings show the importance of this factor when the angular velocity is high but not when it is low. He (1954) found that the eye can move smoothly up to about 40 degrees per second. He states:

> When the target image remains stationary on the fovea because the eye is tracking perfectly, there is

no reason to expect a decrement in acuity. But when the target speed is so high that tracking cannot take place, visual acuity suffers.

Elk Ludvigh and James W. Miller (1949, 1953, 1954, 1955) have been responsible for numerous articles on dynamic visual acuity. In their studies angular velocity was varied from 10 degrees per second up to 170 degrees per second. They found that the visual acuity of moving targets decreased rapidly as the angular velocity increased. Burg and Hulbert (1959, 1961) have also done numerous studies on dynamic visual acuity. Burg (1969, 1965, 1966) continued and extended this work. Their findings (1961) support those of Ludvigh and Miller.

Westheimer seems to be in disagreement with Ludvigh and Miller and with Burg and Hulbert about the effects of angular velocity when it is less than 40 degrees per second. This can be explained by the fact that Westheimer found only that eye movement can occur smoothly up to 40 degrees per second and he, therefore, concluded that visual acuity should not suffer up to that point. Ludvigh and Miller and Burg and Hulbert base their ideas on actual data which shows that visual acuity suffers at 10 degrees per second and above. Their findings make it obvious that no study of dynamic visual acuity or dynamic inspection should ignore angular velocity.

CHAPTER IV

EXPERIMENTAL METHOD

The experimental method of this study is really that of three separate experiments. The three experiments, equipment used, and other aspects are examined in some detail here. To facilitate and clarify these discussions the chapter has been broken down into the following seven sections:

1. Design of the First Experiment.
2. Design of the Second Experiment.
3. Design of the Verifying Experiment.
4. Equipment.
5. Method of Testing.
6. Subjects.
7. Controls.

The section on the first experiment contains all the discussion on Response Surface Methodology except those things which are unique to the second experiment. The three design sections give the data that are to be collected, variable levels used and the type of statistical analysis which was used.

The first experiment was designed with the range of variable levels set very broad in order to cover as much of the relevant surface as possible. The second experiment was designed to have its center closer to the optimal point on the surface. Also, both experiments had broad ranges of variable levels so as to make the model and analyses as general as possible.

A. Design of the first experiment

In order to advance the study of the dynamic inspection task some basic research was needed to determine the effects and acceptable levels of the following variables:

1. The rate of change of the visual angle of the defect being viewed.
2. The angular velocity of the target.
3. Time to view the target.
4. Illumination level at the target.
5. The contrast between the target and the background.

This involved testing the effects of these variables on the ability of an alert observer to detect a defect.

The actual experiments that were conducted were handled as a series of two central composite, rotatable, second order, response surface methodology designs. These experiments were to ascertain the effects of the five independent variables and, through the use of regression analysis, determine a second order model which gives the approximate functional relationship between inspector accuracy (error rate) and the five independent variables. (The models, analysis of variance tables, and analyses used are discussed in Chapter V.)

In the application of response surface methodology a series of experiments is conducted in which variable levels are changed from one experiment to the next such that the value of the dependent variable approaches an optimum. By using canonical analysis and/or maximizing the prediction equation subject to some constraints, each experiment can indicate the direction in which variable levels should be changed in order to improve the value of the dependent variable in the next experiment.

Each experiment gives estimates of the coefficients of the independent variables in a functional relationship (prediction equation) between the dependent and independent variables such as the following:

$$Y = B_0 + B_1X_1 + B_2X_2 \dots + B_5X_5 + B_{11}X_1^2 \dots + B_{55}X_5^2 + B_{12}X_1X_2 + \dots B_{45}X_4X_5 + e$$

where: B_i are the coefficients

X_i are the independent variables

Y is the dependent variable

The estimates of the B_i are arrived at through multiple regression analysis. In addition an ANOVA is performed to determine an estimate of the accuracy of the prediction equation and the significance of each independent variable on determining the value of the dependent variable.

In order to get a second order equation using RSM each independent variable must have five levels. To make computations easier variable values are evenly spread and coded such that the mean is zero. The expression for coding is as follows:

$$\text{Coded Value} = X_i = \frac{Z_i - \overline{Z}_i}{d_i} \cdot K$$

where: Z_i = an actual value of the i^{th} variable

$\overline{Z}_i$ = mean of the values of the i^{th} variable

d_i = difference between successive values of the i^{th} variable

K = constant through which the magnitude of the coded values can be controlled.

As an example 5, 10, 15, 20, and 25 degrees per second are the values of angular velocity used in the first experiment. It can be seen that these are evenly spaced with a d of 5 degrees per second and a mean of 15 degrees per second. "K" was given a value of one in this case. Any of these values can be coded, say 10 degrees per second, as follows:

$$X_2 = \frac{10 - 15}{5} = -1$$

All variables are coded in this manner throughout the experimentation described in this paper unless stated otherwise.

Tables 2 and 3 contain the format for all the possible data points collected in each experiment. This format includes all the points for a 2^5 factorial design in Table 2 plus all the points for a different 3^5 factorial experiment in Table 3.

In order to reduce data collection, the 2^5 part of the experiment was partially replicated. A one half replicate (16 trials) was conducted for each subject as is shown in Table 2. Of all the points of the 3^5 factorial, only eleven were needed to do the desired regression analysis. These eleven points are shown as the crossed blocks in Table 3. These are the center point and the ten points of the star design discussed in Cochran and Cox (1957), Hicks (1964), and Myers (1971) under response surface methodology. To complete the design and be able to get as much information as possible from the data gathered, the center point (0, 0, 0, 0, 0) shown in Table 3 was replicated.

In order to get the desired information for second order regression analysis, 33 trials were necessary for each subject for the first experiment in the series. This first experiment is broken down into two orthogonal blocks in Table 4.

After collecting the data points for both of the blocks a second order regression analyses was performed. An ANOVA was run on this regression analysis. New variable values were selected and the second experiment was run.

TABLE 2

A 2^5 FACTORIAL DESIGN. DARKENED SQUARES ARE THOSE DATA POINTS INCLUDED IN A ONE HALF REPLICATE

		Rate of Change of the Visual Angle -1				Rate of Change of the Visual Angle +1			
		Illumination -1		Illumination +1		Illumination -1		Illumination +1	
		A.V. -1	A.V. +1	A.V. -1	A.V. +1	A.V. -1	A.V. +1	A.V. -1	A.V. +1
Time to View +1	Contrast +1		X	X		X			X
	Contrast -1	X			X		X	X	
Time to View -1	Contrast +1	X			X		X	X	
	Contrast -1		X	X		X			X

TABLE 3

A 3^5 FACTORIAL DESIGN. DARKENED SQUARES ARE THOSE DATA POINTS INCLUDED IN THE STAR OR AXIAL PART OF THE RESPONSE SURFACE DESIGN

		Rate of Change of the Visual Angle																										
		-2									0									+2								
		Illumination -2			Illumination 0			Illumination +2			Illumination -2			Illumination 0			Illumination +2			Illumination -2			Illumination 0			Illumination +2		
Time to View	Cont.	A.V. -2	0	+2	A.V. -2	0	+2	A.V. -2	0	+2	A.V. -2	0	+2	A.V. -2	0	+2	A.V. -2	0	+2	A.V. -2	0	+2	A.V. -2	0	+2	A.V. -2	0	+2
+2	+2																											
+2	0														X													
+2	-2																											
0	+2														X													
0	0					X						X		X	X	X		X						X				
0	-2														X													
-2	+2																											
-2	0														X													
-2	-2																											

TABLE 4

DATA POINTS FOR THE FIRST EXPERIMENT

Block	Data Point No.	Variable X_1	X_2	X_3	X_4	X_5
I	1	-1	-1	-1	-1	1
	2	1	-1	-1	-1	-1
	3	-1	1	-1	-1	-1
	4	1	1	-1	-1	1
	5	-1	-1	1	-1	-1
	6	1	-1	1	-1	1
	7	-1	1	1	-1	1
	8	1	1	1	-1	-1
	9	-1	-1	-1	1	-1
	10	1	-1	-1	1	1
	11	-1	1	-1	1	1
	12	1	1	-1	1	-1
	13	-1	-1	1	1	1
	14	1	-1	1	1	-1
	15	-1	1	1	1	-1
	16	1	1	1	1	1
	17	0	0	0	0	0
	18	0	0	0	0	0
	19	0	0	0	0	0
	20	0	0	0	0	0
	21	0	0	0	0	0
	22	0	0	0	0	0
II	23	0	0	0	0	0
	24	-2	0	0	0	0
	25	2	0	0	0	0
	26	0	-2	0	0	0
	27	0	2	0	0	0
	28	0	0	-2	0	0
	29	0	0	2	0	0
	30	0	0	0	-2	0
	31	0	0	0	2	0
	32	0	0	0	0	-2
	33	0	0	0	0	2

In addition to the five independent variables discussed as part of the experimentation, a sixth one, subjects, was included. All the independent variables and the dependent variables or criteria as well as those variables that were controlled are contained in Table 5 and were part of all experiments.

The measurable characteristics in running any experiment which involves a dynamic inspection task or dynamic visual acuity are (1) the error rates or (2) the smallest visual angle identifiable a given percentage of the time. In most practical situations the visual angle of the defect inspected for is not known, and/or is not constant from item to item. Also, in many instances personnel involved are not inclined to, or are unable to measure visual angles. On the other hand, most people are aware of what is meant by error rate and know that one objective in visual inspection is to minimize the number of bad products leaving the plant. Also the quality control functions within any company are concerned with minimizing the probability of defective items being produced. In reality, minimizing this probability is related to reducing inspector error rate. The problems involved in using visual angles in practical industrial situations and the present acceptance of error rate as a measure of performance caused it to be chosen as the dependent variable for the three experiments conducted. It provides a practical measure of performance that is usable throughout industry.

TABLE 5

INDEPENDENT, DEPENDENT AND CONTROLLED VARIABLES

Independent Variables	Dependent Variables	Controlled Variables
1. Rate of change of the visual angle	1. Percent of Type I errors	1. Visual angle
2. Angular velocity	2. Percent of Type II errors	2. Type of lighting
3. Time to view		3. Glare
4. Illumination		4. Direction of movement
5. Contrast		5. Percent defective
6. Subjects		6. Environmental factors
		7. Medications
		8. Learning
		9. Experience
		10. Fatigue

The following are the two possible types of errors an inspector can make:

1. Type I --reject a good target
2. Type II--accept a bad target

In this experiment both the Type I and Type II errors were counted and converted into percentage figures for each trial. That is, the number of good targets rejected during a trial were divided by the total number of good targets appearing in that trial and multiplied by 100 to find the Type I or percent of Type I errors. The percent of Type II errors were computed in a like manner using bad targets accepted and total bad targets appearing during a trial. These two error percentages were the dependent variables of the experiment.

The Type II error rate was the major dependent variable of the experimentation. This is because the nature of the task and later analyses were concerned with variables affecting detectability of defects and not with errors due to motivation, vigilance or inattention. The Type I error percentages were examined to determine if subjects were guessing excessively. Also, as a control to prevent guessing, subjects were told that all errors (whether Type I or II) would be taken into account.

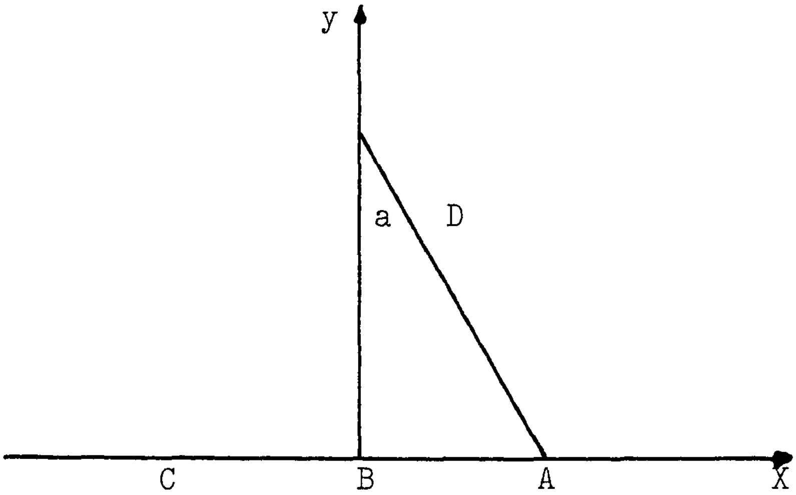
A function of the Type II error rate was used in the actual computation of the regression model such that the prediction equation predicted inspector performance. The function was as follows:

$Y = 100 - \%$ Type II errors.

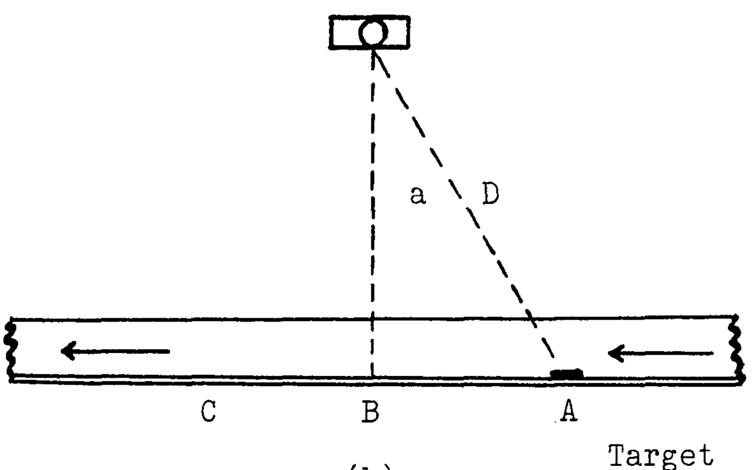
Therefore Y is the accuracy (in percentage form) of the inspector.

A discussion of the independent variables and the levels of each that were used is now in order. The levels discussed and set up here all pertain to the first experiment. It will be recalled from the introductory statements of this chapter that the first experiment was designed to be as general as possible and to attempt to include as much of the surface as possible. Therefore the ranges of the levels set up in the following discussion were intentionally broad so as to cover as much of the surface as possible. This would minimize the number of experiments required by increasing the probability that the optimum or stationary point is either within or near the region.

"Angular velocity," the first independent variable, is defined as the rate of change of the angle "a" with respect to time (see Figures 2, 3, and 4). It can be seen from Figure 3 that if the speed or linear velocity of the item is constant during any test, then the angular velocity $(\frac{da}{dt})$ with respect to the subject on the circular conveyor will be constant. This is not true of the straight conveyor (Figures 2 and 4). When the speed is constant on the straight conveyor, the angular velocity increases as the item approaches from point A to point B (directly in front of the observer) and decreases as it goes from point B to point C



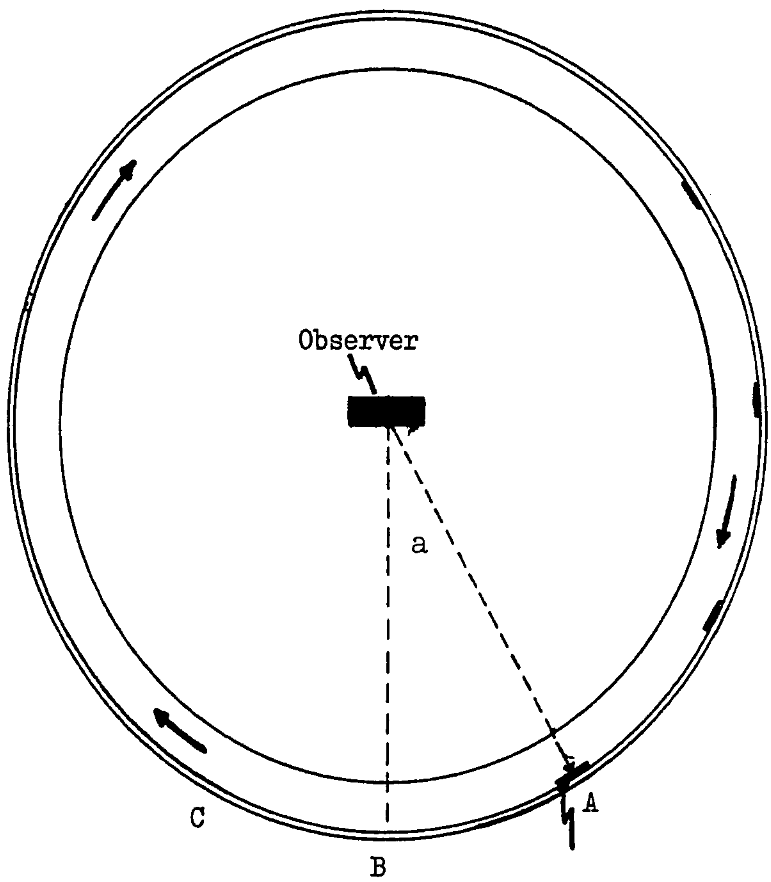
(a)
Graphical Representation



(b)
Schematic Representation

Figure 2

Straight conveyor--top view



(a)

Figure 3

Schematic of the circular conveyor--top view

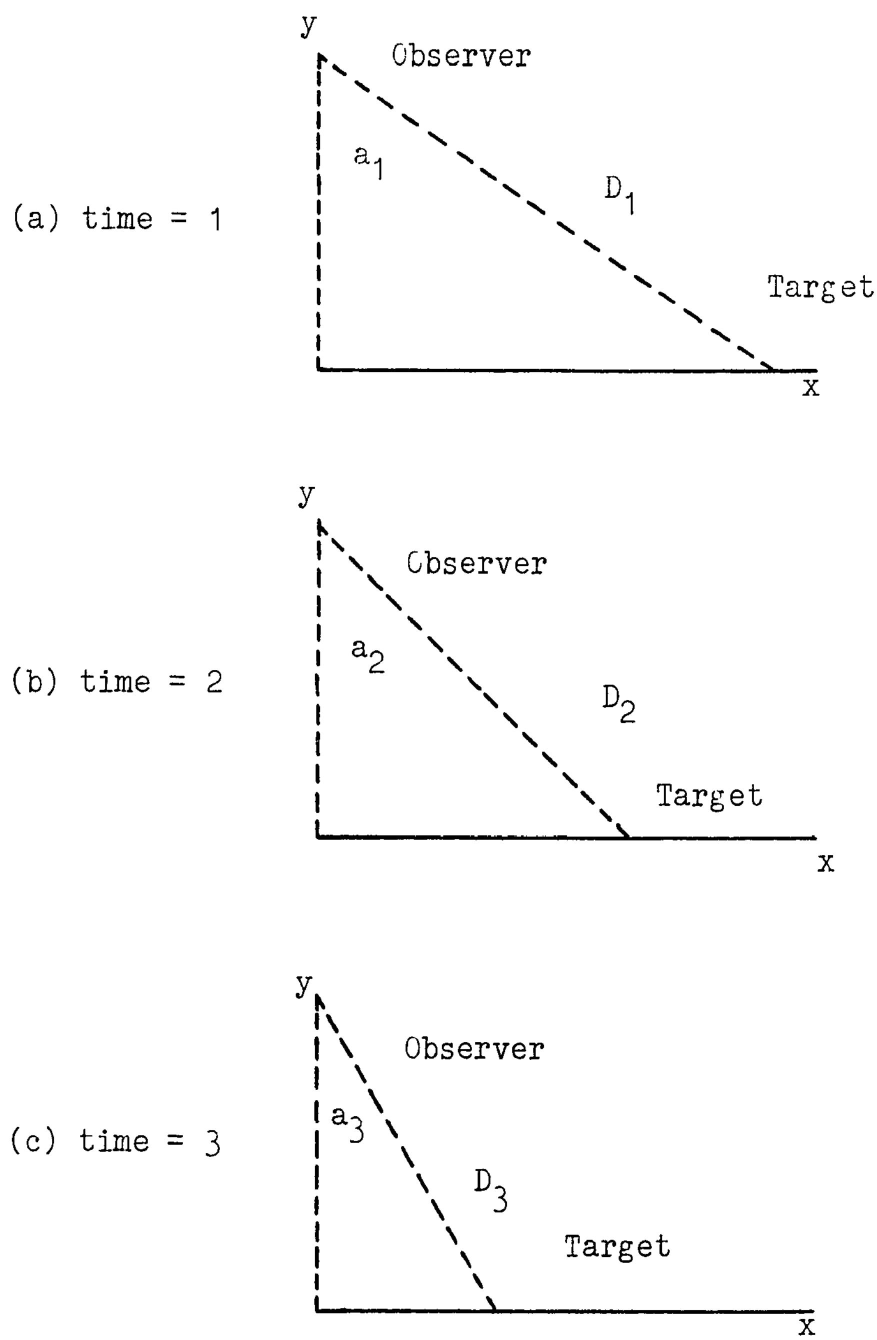


Figure 4

Demonstration of the changes in the angle a and the distance D as the target moves along the conveyor.

(Figure 2). The mathematical expression for this is:

$$\text{Angular Velocity} = \frac{da}{dt} = \frac{da}{dx}\frac{dx}{dt} = \left(\frac{-y}{x^2+y^2}\right)\frac{dx}{dt}\ .$$

This expression is a maximum when the angle a=0 and x=0 (Figures 2 and 4) at which time:

$$\left(\frac{da}{dt}\right)_{straight} = \left(\frac{da}{dt}\right)_{circular}.$$

This means that when a=0 for the straight conveyor the angular velocity of the straight and circular conveyors will be the same, provided the viewing distance and the speed of the conveyors are also the same.

The levels of angular velocity were set between 5 and 25 degrees per second for the first experiment. From the maximum recommended levels given by Reed (1961) and past experiences these levels seemed to be within reason and within the limits of what might be used in industry. It is unlikely that angular velocities much outside these limits would be used in any practical situation.

The rate of change of the visual angle was the second independent variable. The visual angle is equal to:

$$VA = A = 2\ \tan^{-1}\left(\frac{W}{2D}\right) \quad \text{(See Figure 1, page 3).}$$

The rate of change of the visual angle $\left(\frac{dA}{dt}\right)$ is equal to:

$$\frac{dA}{dt} = \frac{Wx}{(x^2+y^2)^{3/2}} \cdot \frac{dx}{dt}\ .$$

In these expressions W is the width of the observed characteristic and D is the distance from the observer to the characteristic. In the case of a circular conveyor the visual angle is constant and therefore the rate of change of the visual angle ($\frac{dA}{dt}$) is equal to zero. In the case of a straight conveyor, however, this is not true. The visual angle changes, as does its rate of change, as the item moves along. The rate of change decreases to zero as the observed item approaches from point A to point B and increases as it goes from B to C (Figures 2 and 4). The relative size or visual angle of the item increases from A to B, where it is maximum, and decreases from B to C (Figure 2) on the straight conveyor. Because the visual angle and its rate of change do not remain constant as the target passes across the field of view, the levels set up for them were calculated for the center of the viewing area. The range of ROCVA for a particular trial did not exceed ± 5 percent of the center value. The levels of the variable of rate of change of the visual angle ranged from -0.705×10^{-4} degrees per second to $+0.705 \times 10^{-4}$ degrees per second.

Time to view, the third independent variable, was controlled by changing the viewing area made available to the subject (Figures 5 and 6). This viewing area could be adjusted by the use of sliding panels. The times to view for the first experiment were set at 0.50, 0.75, 1.00, 1.25 and 1.50 seconds. These times were all above the critical times of 0.10 to 0.20 seconds mentioned in Chapter II. However, they were short enough to make possible a measure of the effects of time and other variables influenced by it on inspector performance.

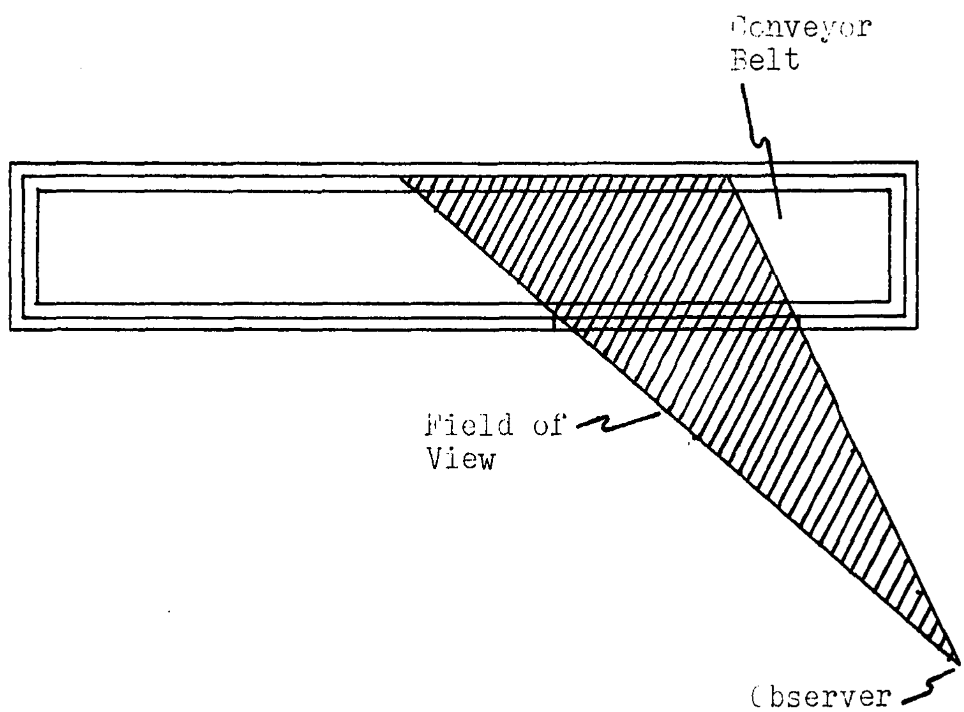


Figure 5

Schematic of the straight conveyor--field of view

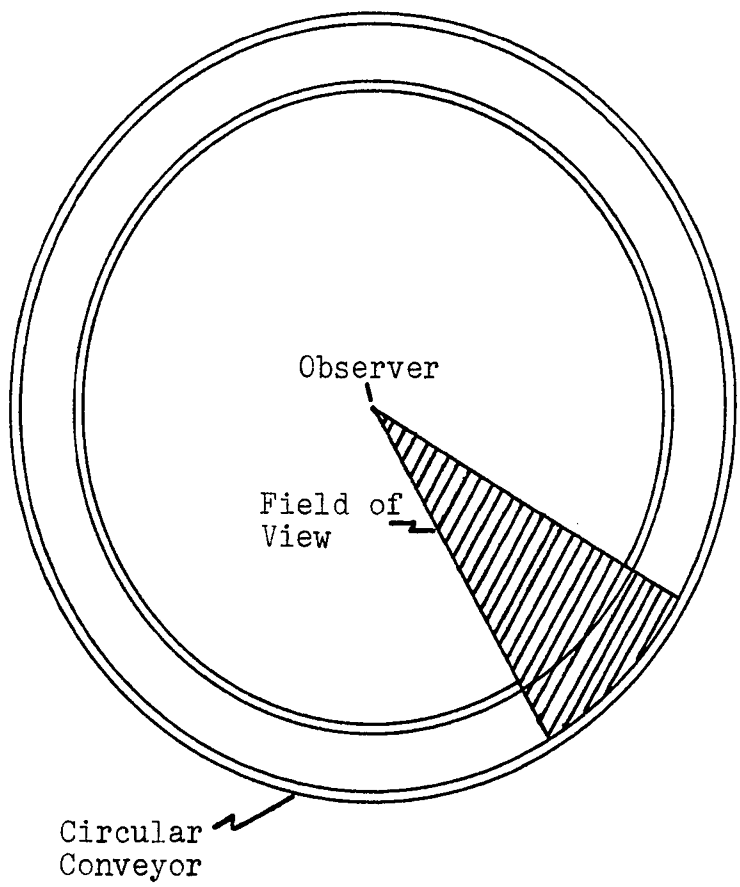


Figure 6

Schematic of the circular conveyor--field of view

Illumination was the fourth independent variable. Illumination levels were controlled by using a series of 75 watt flood lamps to illuminate the conveyor, but shielded from the view of the subject. This method of illumination reduced glare problems while providing the required amounts of light on the targets. Illumination levels ranged from 3.0 to 148.0 footlamberts for the first experiment. This gave a wide range for this variable in order to test the findings of the various researchers discussed in Chapter III.

The fifth independent variable, contrast, is defined for this experiment as the relative brightness difference between the objects in the target that are being inspected and the target background. This relative brightness difference is commonly expressed in one of the following two manners:

$$\text{Relative Brightness Difference} = \frac{B_L - B_D}{B_L} \times 100$$

$$\text{or} = \frac{R_L - R_D}{R_L} \times 100$$

where: B_L = the luminance of the surface of brighter luminance

B_D = the luminance of the surface of darker luminance

R_L = the reflectance of the surface of brighter luminance

R_D = the reflectance of the surface of darker luminance.

Both of the expressions above give a contrast which is a percentage. In the first experiment the values of contrast chosen ranged from 3 percent to 95 percent.

All of the variable values (coded and actual) used in the first experiment are shown in Table 6. For actual coding of parameters see Appendix 8.

B. Design of the second experiment

As will be shown in detail later, it was found in the analysis of the first experiment that the lack of fit term was significant. This term tells how well the regression or prediction model accounts for all of variation of the data. The fact that lack of fit was significant indicates that the true equation is one of third, fourth or even higher order, or of some other form. There are two possible alternative ways to better fit the data:

1. Run a higher order experiment.
2. Minimize the bias or confounding.

In running a higher order experiment an RSM design, or a fractional factorial design might be used. The possibility of using an RSM design of higher than second order was examined. Gardiner et al. (1959) have researched this problem very thoroughly and they found that when the number of variables becomes greater than three the number of data points required becomes prohibitive. They had not developed an RSM third order design for any more than three variables. Because of design complexity, nonavailability, and the prohibitive number of data points required, a third order RSM model was dropped from consideration.

TABLE 6

VARIABLE VALUES AND THEIR CORRESPONDING
CODED VALUES THE FIRST EXPERIMENT

	Coded Values				
Variable	-2	-1	0	1	2
ROCVA	-0.706×10^{-4}	-0.353×10^{-4}	0	0.353×10^{-4}	0.706×10^{-4} °/sec
Angular Velocity	5°/sec	10°/sec	15°/sec	20°/sec	25°/sec
Time to View	0.50 sec	0.75 sec	1.00 sec	1.25 sec	1.50 sec
Illumination	3.00 ft L	39.25	75.50	111.75	148.00
Contrast	3%	26%	49%	72%	95%

The possibility of a factorial design of greater than second order was next considered. To get a third order regression equation in five variables requires a 4^5 factorial design. If a full factorial were run it would require 1024 data points. If a 1/8 or 1/16 fractional factorial were run they would require 128 or 64 data points respectively for each subject. Also the confounding present in these fractional factorials prohibits any real conclusions being drawn or any confidence being put in the prediction equation. Because of prohibitive numbers of data points required and confounding, the factorial designs were eliminated.

The possibility of minimizing the bias in a second order RSM model due to the third order terms was chosen as the only viable alternative. Myers (1971) and Box and Draper (1959) give the methods and criteria for doing this. This involves selecting the coded values of the variable levels and the number of replications of the center point (0, 0, 0, 0, 0) such that the alias matrix is minimized.

The alias matrix is a matrix showing how each of the regression coefficients is biased by, or an alias of, third order coefficients not included in the model. Tables 7 and 8 are the alias matrices of third order terms for the first and second experiments respectively. In these matrices the sum of a column is the sum of those coefficients which bias the estimate of the B at the head of that column. As an example, consider the B_3 column of Table 7. From this it can be seen that:

ALIAS MATRIX - FIRST EXPERIMENT

	B0	B1	B2	B3	B4	B5	B11	B22	B33	B44	B55	B12	B13	B14	B15	B23	B24	B25	B34	B35	B45
B111	0.0	2.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B112	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B113	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B114	0.0	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B115	0.0	0.0	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B122	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B123	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00
B124	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00	0.0
B125	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00	0.0	0.0
B133	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B134	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00	0.0	0.0	0.0
B135	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00	0.0	0.0	0.0	0.0
B144	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B145	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00	0.0	0.0	0.0	0.0	0.0
B155	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B222	0.0	0.0	2.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B223	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B224	0.0	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B225	0.0	0.0	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B233	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B234	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00	0.0	0.0	0.0	0.0	0.0	0.0
B235	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B244	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B245	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B255	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B333	0.0	0.0	0.0	2.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B334	0.0	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B335	0.0	0.0	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B344	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B345	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B355	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B444	0.0	0.0	0.0	0.0	2.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B445	0.0	0.0	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B455	0.0	0.0	0.0	0.0	0.67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B555	0.0	0.0	0.0	0.0	0.0	2.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

TABLE 7

ALIAS MATRIX - SECOND EXPERIMENT

	B0	B1	B2	B3	B4	B5	B11	B22	B33	B44	B55	B12	B13	B14	B15	B23	B24	B25	B34	B35	B45
B111	0.0	0.33	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	-0.00	0.0	0.0	0.0
B112	0.0	0.0	0.11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.00	0.00	0.00	0.0	0.0	0.0	0.0
B113	-0.00	0.0	0.0	0.11	-0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B114	-0.00	0.0	0.0	-0.00	0.11	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B115	0.0	0.0	0.0	0.0	0.0	0.11	0.0	0.0	0.0	0.0	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00
B122	0.0	0.11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	-0.00	0.0	0.0	0.0
B123	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0	0.0	0.0	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.41
B124	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0	0.0	0.0	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.41	0.00
B125	-0.00	0.0	0.0	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.41	0.0	0.0
B133	0.0	0.11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	-0.00	0.0	0.0	0.0
B134	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.00	-0.00	0.0	0.0	0.0	0.41	0.0	0.0	0.0
B135	0.0	0.0	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.00	0.00	0.41	0.0	0.0	0.0	0.0
B144	0.0	0.11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	-0.00	0.0	0.0	0.0
B145	0.0	0.0	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.00	0.41	0.00	0.0	0.0	0.0	0.0
B155	0.0	0.11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	-0.00	0.0	0.0	0.0
B222	0.0	0.0	0.33	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.00	0.00	0.00	0.0	0.0	0.0	0.0
B223	-0.00	0.0	0.0	0.11	-0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B224	-0.00	0.0	0.0	-0.00	0.11	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B225	0.0	0.0	0.0	0.0	0.0	0.11	0.0	0.0	0.0	0.0	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00
B233	0.0	0.0	0.11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.00	0.00	0.00	0.0	0.0	0.0	0.0
B234	0.0	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.41	-0.00	-0.00	0.0	0.0	0.0	0.0
B235	0.0	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.41	0.0	0.0	0.0	-0.00	0.0	0.0	0.0
B244	0.0	0.0	0.11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.00	0.00	0.00	0.0	0.0	0.0	0.0
B245	0.0	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.41	0.00	0.0	0.0	0.0	-0.00	0.0	0.0	0.0
B255	0.0	0.0	0.11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.00	0.00	0.00	0.0	0.0	0.0	0.0
B333	-0.00	0.0	0.0	0.33	-0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B334	-0.00	0.0	0.0	-0.00	0.11	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B335	0.0	0.0	0.0	0.0	0.0	0.11	0.0	0.0	0.0	0.0	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00
B344	-0.00	0.0	0.0	0.11	-0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B345	0.0	0.0	0.0	0.0	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.41	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.00	-0.00
B355	-0.00	0.0	0.0	0.11	-0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B444	-0.00	0.0	0.0	-0.00	0.33	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B445	0.0	0.0	0.0	0.0	0.0	0.11	0.0	0.0	0.0	0.0	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00
B455	-0.00	0.0	0.0	-0.00	0.11	0.0	0.00	0.00	0.00	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	0.0
B555	0.0	0.0	0.0	0.0	0.0	0.33	0.0	0.0	0.0	0.0	0.0	-0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00

TABLE 8

$$\hat{B}_3 = B_3 + 0.67\ B_{113} + 0.67\ B_{223} + 2\ B_{333} + 0.67\ B_{344} + 0.67\ B_{355}$$

This says that the estimate of B_3 obtained by the first experiment is equal to its true value plus these additional values. Therefore it is said that the estimate of B_3 is biased or confounded by these additional coefficient values. The objective is now to minimize this bias for the entire model. This involves selecting the coded variable values and the number of replications such that this bias is minimized. This is a relatively complex process and is discussed in detail in Chapter 8 of Myers (1971). In the case of the second experiment the coded values which minimize the alias matrix are -0.816, -0.408, 0.0, 0.408 and 0.816. Data is taken at the center point twice for each subject. The data points to be collected for each subject are shown in Table 9. For actual coding information see Appendix 8. The alias matrix for this design is presented in Table 8. A comparison of the alias matrices of the two experiments (Table 7) demonstrates that the biasing is greatly reduced in the second experiment.

Variable values were selected for the second experiment by attempting to approach the constrained maximum found in the first experiment. The variable values and their corresponding coded values are pictured in Table 10. The major change was in ROCVA. The zero point or mean value was

TABLE 9

DESIGN MATRIX--SECOND EXPERIMENT

Data Point No.	X_o	Variable X1	X2	X3	X4	X5
1	1	-0.408	-0.408	-0.408	-0.408	0.408
2	1	0.408	-0.408	-0.408	-0.408	-0.408
3	1	0.408	0.408	-0.408	-0.408	0.408
4	1	-0.408	0.408	-0.408	-0.408	-0.408
5	1	-0.408	-0.408	0.408	-0.408	-0.408
6	1	0.408	-0.408	0.408	-0.408	0.408
7	1	-0.408	0.408	0.408	-0.408	0.408
8	1	0.408	0.408	0.408	-0.408	-0.408
9	1	-0.408	-0.408	-0.408	0.408	-0.408
10	1	0.408	-0.408	-0.408	0.408	0.408
11	1	-0.408	0.408	-0.408	0.408	0.408
12	1	0.408	0.408	-0.408	0.408	-0.408
13	1	-0.408	-0.408	0.408	0.408	0.408
14	1	0.408	-0.408	0.408	0.408	-0.408
15	1	-0.408	0.408	0.408	0.408	-0.408
16	1	0.408	0.408	0.408	0.408	0.408
17	1	-0.816	0.0	0.0	0.0	0.0
18	1	0.816	0.0	0.0	0.0	0.0
19	1	0.0	-0.816	0.0	0.0	0.0
20	1	0.0	0.816	0.0	0.0	0.0
21	1	0.0	0.0	-0.816	0.0	0.0
22	1	0.0	0.0	0.816	0.0	0.0
23	1	0.0	0.0	0.0	-0.816	0.0
24	1	0.0	0.0	0.0	0.816	0.0
25	1	0.0	0.0	0.0	0.0	-0.816
26	1	0.0	0.0	0.0	0.0	0.816
27	1	0.0	0.0	0.0	0.0	0.0
28	1	0.0	0.0	0.0	0.0	0.0

TABLE 10

VARIABLE VALUES AND THEIR CORRESPONDING CODED VALUES FOR THE SECOND EXPERIMENT

	Coded Values				
Variables	-0.816	-0.408	0	0.408	0.816
ROCVA	-1.2×10^{-4}	-1.0×10^{-4}	-0.8×10^{-4}	-0.6×10^{4}	-0.4×10^{-4} °/sec
Angular Velocity	10°/sec	15°/sec	20°/sec	25°/sec	30°/sec
Time to View	0.25 sec	0.50 sec	0.75 sec	1.00 sec	1.25 sec
Illumination	3.0 ft L.	41.5	80.0	118.5	157.0
Contrast	3%	26%	49%	72%	95%

changed from 0.0 to -0.8 degrees per second. The zero point of angular velocity was increased 5 degrees per second. The zero point of illumination was increased from 75.5 to 80.0 footlamberts. Contrast remained the same although the first experiment indicated that inspector performance was best for the higher values. Of the five variables the first four (ROCVA, AV, Time, and Illumination) can be manipulated at most inspection stations. Contrast, however, is most likely a characteristic of the item inspected and may not be easily changed. Therefore, to maintain the generality of the prediction model, a large range of contrast was retained.

C. Design of the verifying experiment

A group of data points were collected in which the target used and the variable levels used were different than those used in either the first or second experiments. The targets were of the Landholt ring or "C" type and are discussed in detail in Section D of this chapter. Variable levels used are contained in Table 11. Five subjects were each tested on all nine data points.

The analyses of the data consisted of comparing those values of inspector accuracy obtained in the validation experimentation with the values of predicted inspector performance as given by models of the first two experiments. The two statistics used were the Hotelling T^2 and the correlation coefficient. The Hotelling T^2 was used to test the null hypothesis:

TABLE 11

DATA POINTS FOR THE VERIFYING EXPERIMENT

Data Point Number	ROCVA X_1 Degrees/sec	AV X_2 Degrees/sec	Time X_3 Sec	Illum. X_4 Foot-lamberts	Contrast X_5 Percent
1	$-.4 \times 10^{-4}$	12	.7	30	87
2	$-.4 \times 10^{-4}$	12	1.1	90	73
3	$-.7 \times 10^{-4}$	20	.7	30	73
4	$-.4 \times 10^{-4}$	20	1.1	30	87
5	$-.7 \times 10^{-4}$	12	.7	90	73
6	$-.7 \times 10^{-4}$	20	1.1	90	87
7	$-.7 \times 10^{-4}$	20	.7	7	73
8	$-.7 \times 10^{-4}$	12	.7	7	73
9	$-.7 \times 10^{-4}$	12	.7	7	87

$$H_o : \mu_1 = \mu_o$$

The alternative hypothesis was:

$$H_A : \mu_1 \pm \mu_o$$

In these hypotheses μ_1 represents a vector of the means for the nine data points and μ_o represents a vector of values predicted by one of the prediction equations. A Hotelling T^2 was calculated comparing the mean vector of the verifying data (μ_1) with the vector associated with each of the prediction equations. Inferences were then made about the accuracy of the prediction equations.

Next a correlation coefficient was calculated for the verifying data and the predicted values of each of the prediction equations. These coefficients were computed and the hypothesis that they were different from zero was tested. They were then compared with each other to see which prediction was most highly correlated with the verifying data.

Therefore, through the use of the T^2 and the correlation coefficient, the prediction equations were tested for their ability to predict inspector performance on the verifying task.

D. Equipment

The equipment consisted of:

1. Two conveyors.
2. A subject position controlling device.
3. A subject response device.

4. A response recorder.

5. Targets.

6. Lighting.

With these items of equipment, the experiments described in Sections A, B, and C of this section were conducted with a minimum of effort and a maximum of control. These items of equipment with their required specifications and design will now be discussed.

Conveyors

One of the two conveyors needed was straight and the other was circular. Both conveyors used a variable speed motor with accurate controls such that the linear conveyor speed was quickly adjustable. This adjustability allowed the conveyor speed to range from near 0 up to 50 inches per second. Both conveyors had the same method for maintaining desired times to view under different speeds and angular velocities.

The straight line conveyor was six feet long and similar to the design shown in Figure 7. This design featured a variable viewing area (see Figure 5, page 41) which permitted keeping the time to view constant at different conveyor speeds. In order to keep time to view constant as the angular velocity was increased, the viewing area was enlarged and vice versa. The limited viewing area helped control the rate of change of the visual angle and the angular velocity at which the subject saw the targets. By carefully

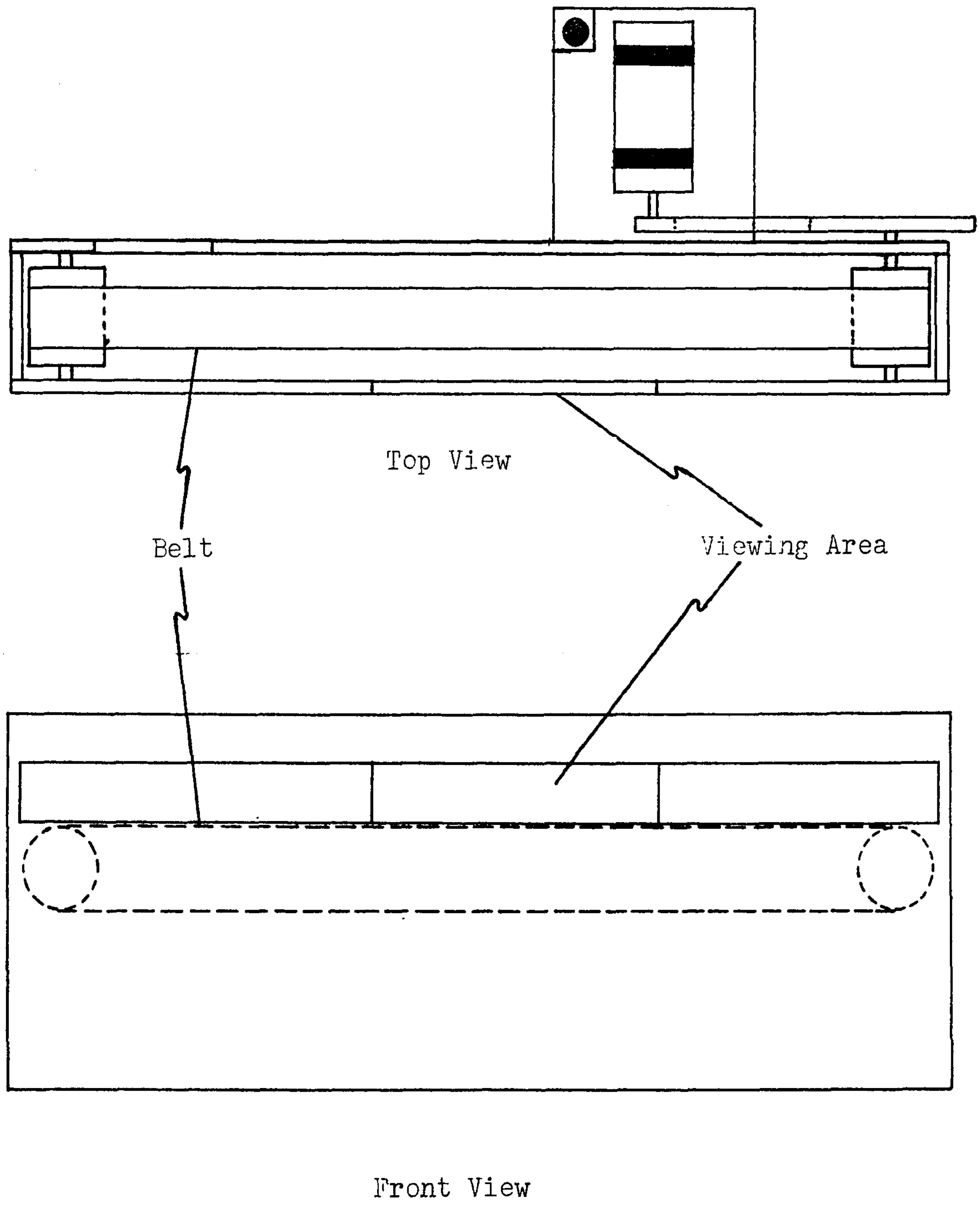


Figure 7

Straight Conveyor

placing the subject, as shown in Figure 5 (page 41) and controlling the viewing area, the target was exposed to the subject only at the desired time when the selected rate of change of the visual angle and the angular velocity were present. An open area in the rear of the conveyor permitted the experimenter to place targets on the belt without being observed by the subject.

The circular conveyor was 94 inches in diameter and similar in design to the one in Figure 3 (page 37). It had the same design feature that the straight conveyor had of limited but variable viewing area allowing for constant viewing time. Once again the time to view was controlled under conditions of different speeds by changing the viewing area. Since angular velocity and the visual angle were constant for the circular conveyor at any given speed, there was no need to control them with subject position and viewing area.

Subject position controlling device

A subject position controlling device was required that controlled:

1. The distance (D) from the subject's eyes to the target he was viewing and
2. In the case of the straight line conveyor, the angle (a) at which he viewed it.

In both conveyors distance (D) from the subject's eyes to the target had to be tightly controlled as it had a direct relationship to the independent variable of relative size or visual angle (see Figures 2 and 3, pages 36 and 37). In the straight line conveyor, the angle (a) at which the subject viewed the target had a direct relationship to the angular velocity of the target with respect to the subject (see Figures 2, 4, 5, and 7, pages 36, 37, 41 and 56). To allow either the distance (D) or the angle (a) to vary would create differences in the relative size, as measured by the visual angle, and the angular velocity of the target with respect to the subject. These differences would be an unnecessary source of error and would probably cause an increase in the variability of the data assumed to be due to random error.

To control the subject's position, a chair with arm rests, a back rest, and a head rest was provided (see Figure 8). Prior to starting each trial, the chair was positioned with the subject in it. This fixed the point from which he observed. The seated subject was required to have his back against the back rest and his head against the head rest at all times during a trial.

Subject response device

During a trial the subject saw both good and bad targets and had to indicate which they were. To indicate whether the target was good or bad, a small box containing two buttons was provided (see Figure 9). Pushing the right

Figure 8

Subject Chair

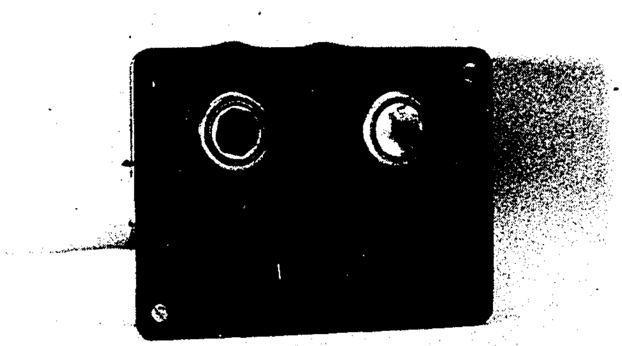


Figure 9

Response Box

(or green) button indicated a good target and the left (or black) one a bad target.

Response recorder

To facilitate data collection, a strip chart recorder was used to record the subject's response and record the actual quality of the target. A Physiograph model PNP-4 was chosen. The first channel recorded the subject's response and the second channel indicated the quality (good or bad) of the target. Good and bad targets were differentiated by having a coil sense a magnet in the base of the bad targets. This automatic method helped avoid experimenter error.

Targets

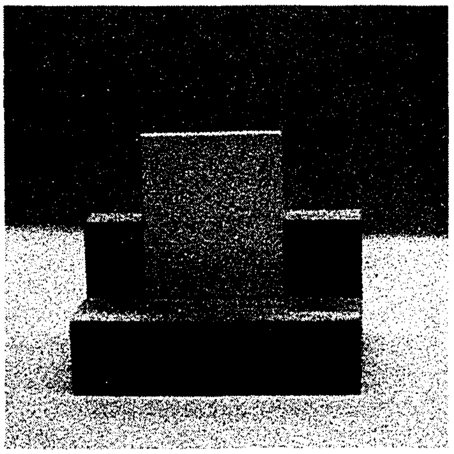
As was mentioned briefly at the end of Chapter II the targets selected for past experiments have not been standard. The number of different targets used is approximately equal to the number of experimental results published. Nelson and Barany (1969) used two types of targets, Landholt ring and a grid pattern. Smith and Barany (1970) used discs with three or four dots on them. These appear to be attempts to develop some general target such that information gleaned from work done with it may be applied to real situations. Some targets have been actual items such as the circuit boards used by Patwardhan (1971) and by Badalamente and Ayoub (1969). These targets were rejected as possibly being too specific to achieve the general model desired in this experimentation. The inspection of beans as were used by Moder and Oswalt (1959) also seems oriented toward a certain industry. Blackwell, in his numerous studies of illumination and contrast, attempted to use a target from which very general results could be derived. His target consisted of a small circle on a uniform background. The contrast between the background and the circle was varied. This target required only a simple observation and a yes or no response as to whether the dot was present or not. It seems that this is the case with most inspection tasks. The inspector must detect a defective item.

Targets for inspection tasks can be divided into the two major classes of missing item targets and defective item targets. When using the missing item type of target the subject must detect a missing component or symbol within the target. This was the type used by Patwardhan and also by Nelson and Barany (1969). Patwardhan required the inspection of circuit boards for missing components and components in the wrong position. Nelson and Barany required searching a grid to detect whether the required number of white squares were present. These tasks are very close to being a pattern recognition task.

When using the defective item target the subject is required to detect any item in the target previously designated as defective and the object of the inspection. It is believed that many industrial inspection tasks have as their purpose the detection of defective parts rather than pattern recognition. The inspection of circuit boards for breaks was used by Badalamente and Ayoub (1969) as a target which simulated a possible real inspection. Blackwell's task required inspecting for a small circle on a uniform background, which represented a defect present on an otherwise smooth surface. The target chosen for the present study was one in which the subject inspected for defective items.

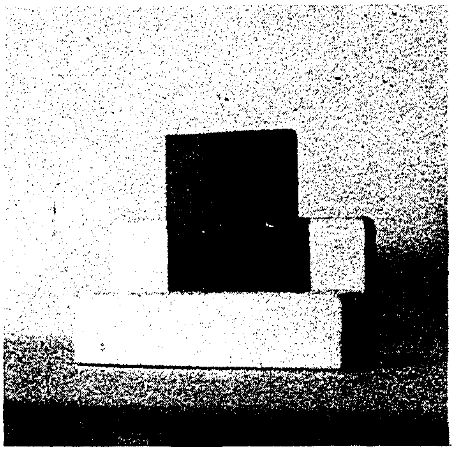
The primary targets used in these experiments consisted of a 1 1/2 inch by 1 5/8 inch painted surface (see Figure 10). Defective targets had a piece of black wire randomly attached somewhere on the surface. This wire was 1/8 inches long and 0.008 inches in diameter. The visual angle of 0.008 inches at 46 inches was 36 seconds, or 0.5997 minutes of arc. Contrast was varied by painting surface one of five shades of gray ranging from almost white to almost black.

In addition to the primary target described above, a secondary target was used to attempt to verify the generality of the response surface obtained with the first target. These targets consisted of either a black Landholt ring or a black circle each having the same line thickness on a gray background (see Figure 10). Those targets with a Landholt ring were designated as defective. The gap was 0.0267 inches giving a visual angle of 2 minutes of arc at 46 inches. The



Regular Target

(a)



Verification Target

(b)

Figure 10

gaps in the defectives were oriented on the diagonals to minimize the effect of the direction of movement on its detectability. This was done in a related study by Nelson and Barany (1969).

Lighting

Lighting was designed to achieve five levels of illumination ranging between 3 and 160 footlamberts without glare. Four 75 watt flood lamps and one 150 watt flood lamp used in combinations were required to achieve these illumination levels. They were positioned such that the subject received no direct or indirect glare from them. The reflected light was measured using a Spectra Brightness Spot Meter model S. B. 1-1/2.

E. Method of testing

In the course of conducting this experiment, each subject was tested under those chosen combinations of levels of the independent variables shown in Table 6 (page 45). Each subject participated in 33 trials in the first experiment. The sequence in which the trials were conducted was randomized with a different random sequence of trials for each subject. Each trial lasted less than 5 minutes and involved 40 targets. The sequence of targets within a given trial was random. Ten different random sequences of targets were created using a random number table. The randomizations eliminated any bias in the selection or creation of sequences of trials or targets.

An established procedure was followed for each trial. The subject was seated, the head rest was adjusted, and the chair was positioned. After insuring that he was comfortable, a written set of instructions was handed to him (Appendix 5). He was told to follow these instructions while listening to a tape recording of them. The instructions conferred the purpose of the tests, their importance, his position for observing, the type of visual search he was to perform, and how to respond. He was also told that he would not be informed of the results of any trial or combination of trials until all subjects had completed all trials. After reading the instructions, the subject was asked if he had any questions. After all questions were answered, he was given several minutes of practice in which the experimenter told him whether he was responding correctly. Where necessary the experimenter pointed out deficiencies in responding. After practice the subject was again asked for questions. After answering any further questions, a practice trial was completed. On the first day each subject participated in sufficient practice trials to obtain a 100 percent score. These practice trials were conducted using the combination of variable levels (1, 1, 1, 1, 1) for the first experiment and (0.408, 0.408, 0.408, 0.408, 0.408) for the second experiment. This procedure of practice was dropped after the subject's second session because further training was not needed. A short practice of 10 targets was, however, given before each session.

F. Subjects

The selection of subjects is always a difficult practical problem. Ideally, they should be drawn at random from the total population of industrial inspectors of the United States in order to facilitate making inferences about industrial inspectors. As this is not possible, some tradeoffs or concessions had to be made. It was assumed that these concessions have little or no effect on the data gathered and therefore the outcome of the experiment. There were however, some valid criteria which subjects for any experiment in inspection or visual acuity of any kind should meet. They should be between the ages of 18 and 65 years, in good health, and have at least 20/20 corrected vision in both eyes as tested by the Snellen eye test. In addition, subjects had to have a willingness to cooperate and make a sincere effort to do each trial as best they could. This selection was based on the subjective judgment of the experimenter.

Due to availability, university students and local working people between the ages of 18 and 30 years were recruited. Both male and female subjects were used. Five subjects were used for each of the two experiments plus the verification trials. Two female and three male subjects were used for each of the three experiments. The subjects for the verifying experiment were selected randomly from those of the first two experiments.

G. Controls

Throughout the experimentation certain variables were either held constant or varied randomly. These procedures insured that the effects these variables had on the subject's performance were the same for every trial or were random in occurrence. Those variables held constant are listed in Table 6 (page 45).

Glare problems were eliminated through the placement of light sources and the use of matte finishes. Light sources were placed out of the subject's field of view and in such a position as to minimize reflections into the subject's eyes. To further reduce the possibility of reflected glare, the parts of the apparatus seen by the subject were given a matte finish.

Although the direction of movement might affect inspector accuracy it was not thought to be a factor in this experiment. Since it is probably a cultural or learned phenomenon it was assumed to be eliminated by sufficient training time and by having the direction of movement of the targets the same for all trials.

The percent of defective targets for each trial remained a constant throughout the experiment at 25 percent. This seemed to be a reasonable amount and is in the range (5 percent to 40 percent) found to be typical by McCormack (1961). Twenty-five percent defects provided enough defects to prevent the task from becoming a vigilance task where the occurrence of a signal is relatively infrequent. The sequences of trials and of good and bad targets for a given trial were randomized.

The environmental factors such as heat, humidity, noise, and ventilation were maintained at constant levels so far as it is possible in a centrally air conditioned building. Temperature was maintained between 71 and 75 degrees. Noise levels due to the apparatus and background noise did not exceed 75 decibels.

To control for fatigue, no subject was allowed to run more than six trials in one session. There was at least a five minute break between any two trials. Also the sequences of trials and targets were randomized to prevent biasing of the data by these factors.

CHAPTER V

ANALYSIS OF RESULTS

The analysis will be broken down into three sections. The first and second will deal with analyses of the first and second experiments respectively. The third section will discuss the analysis of the verifying experiment. Before going into the analyses themselves a few remarks which apply to all experiments are in order now.

The level of significance used throughout was that of 0.05. This level of α was selected such that all but the most significant variables or terms would be eliminated. The resulting prediction equation, therefore, adhered to the law of parsimony which says the simplest possible relationship which will adequately explain the situation should be used. The maximum β levels possible were calculated to be .35 and .38 for the first and second experiments respectively.

The regression analysis was done using a computer program developed by Clark, et al. (1971) and run on an IBM 360/50. Eigen values were computed using the program of Appendix 13. The programs to find the stationary points and the constrained maximum respectively are listed in Appendices

11 and 12. Finally the program used for computing correlation coefficients and Hotelling T^2 statistics is contained in Appendix 14. Where subroutines are called which are not in the Appendices, they are standard IBM Scientific Subroutine Package programs.

A. Analysis of the first experiment

The first experiment was run using the second order RSM model mentioned on page 26 and the design matrix of Table 4. Data for this experiment are contained in Appendix 6. The prediction model which resulted is as follows:

$$\begin{aligned} Y1 = 100.8913 &+ 1.1250\ X_1 - 0.2083\ X_2 + 0.4583\ X_3 + 5.3750\ X_4 \\ &+ 11.6216\ X_5 - 1.5027\ X_1^2 - 1.5027\ X_2^2 - 1.7527\ X_3^2 \\ &- 6.7527\ X_4^2 - 4.5077\ X_5^2 + 0.8125\ X_1X_2 \\ &+ 0.0625\ X_1X_3 + 1.6875\ X_1X_4 - 3.9375\ X_1X_5 \\ &+ 0.0625\ X_2X_3 - 1.8125\ X_2X_4 + 2.5625\ X_2X_5 \\ &+ 1.4375\ X_3X_4 - 2.1875\ X_3X_5 - 1.0625\ X_4X_5 \end{aligned}$$

In this equation Y1 represents the percent of correct responses to bad targets and X_i is the coded value of the ith variable. The ANOVA associated with this prediction equation is presented in Table 12. The F ratios in this table are obtained by dividing each mean square due to regression by the mean square of the replications or error term.

Using the ANOVA table, those variables which have a significant effect on the value of the dependent variable (Y1) can be determined. In order for a regression coefficient

TABLE 12

ANALYSIS OF VARIANCE TABLE FOR THE REGRESSION--Y1

Source		Per Cent	Degrees of Freedom	Sum of Squares	Mean Square	F Value
Regression		51.23	20	32700.1528	1635.0076	10.999
B_1	X_1	0.24	1	151.8750	151.8750	1.022
B_2	X_2	0.01	1	5.2083	5.2083	0.035
B_3	X_3	0.04	1	25.2083	25.2083	0.170
B_4	X_4	5.43	1	3466.8750	3466.8750	23.322**
B_5	X_5	25.39	1	16207.5763	16207.5763	109.038**
B_{11}	X_1^2	0.53	1	341.2678	341.2678	2.296
B_{22}	X_2^2	0.53	1	341.2678	341.2678	2.296
B_{33}	X_3^2	0.73	1	464.2567	464.2567	3.123
B_{44}	X_4^2	10.80	1	6890.7011	6890.7011	46.354**
B_{55}	X_5^2	4.81	1	3070.6091	3070.6091	20.656**
B_{12}	X_1X_2	0.08	1	52.8125	52.8125	0.355
B_{13}	X_1X_3	0.00	1	0.3125	0.3125	0.002
B_{14}	X_1X_4	0.36	1	227.8125	227.8125	1.532

TABLE 12--Continued

Source		Per Cent	Degrees of Freedom	Sum of Squares	Mean Square	F Value
B_{15}	X_1X_5	1.94	1	1240.3125	1240.3125	8.344**
B_{23}	X_2X_3	0.00	1	0.3125	0.3125	0.002
B_{24}	X_2X_4	0.41	1	262.8125	262.8125	1.768
B_{25}	X_2X_5	0.82	1	525.3125	525.3125	3.534
B_{34}	X_3X_4	0.26	1	165.3125	165.3125	1.112
B_{35}	X_3X_5	0.60	1	382.8125	382.8125	2.575
B_{45}	X_4X_5	0.14	1	90.3125	90.3125	0.608
Residual		48.77	144	31131.8669	216.1935	
Blocks		2.70	1	1725.5186	1725.5186	11.608**
Subjects		6.51	4	4153.2427	1038.3106	6.985**
Lack of Fit		8.36	5	5333.3648	1066.6729	7.176**
Replications		31.21	134	19919.7406	148.6547	
Total		100.00	164	63832.0197		** α = .01

to be significant to the level where α equals 0.05 or 0.01 the F ratio must be greater than 3.9 or 6.8 respectively. Each variable, its interactions with other variables, and their significance will now be discussed.

The rate of change of the visual angle (ROCVA) is the first variable in the table and is represented by X_1. It can be seen that the main effect and all but one of its interaction terms are insignificant. This indicates that ROCVA has little or no direct effect on the predicted inspector accuracy for the range of values included in this study. It does however interact significantly (greater than the 0.01 level) with contrast. This result, coupled with the fact that the regression coefficient B_{15} is negative, would tend to indicate that the interaction between ROCVA and contrast can have both good and bad effects on predicted inspector accuracy. If the coded value of contrast is negative, increases in the coded value of ROCVA will result in increases in the value of predicted inspector performance. If the coded value of contrast is positive, increases in ROCVA will result in decreases in predicted performance. This same relationship holds true if the roles of contrast and ROCVA are reversed in the preceding discussion.

Angular Velocity (AV) is represented by X_2 in Table 12. It is very evident that the main effect of AV has negligible effect on predicted inspector performance. The other terms of the regression in which AV is involved also fail to be significant at the 0.05 level. The interaction between AV and contrast is significant at the 0.10 level which does not meet the criteria for significance set forth earlier in this paper.

The main effect of time to view (X_3) is insignificant. The squared term is only significant to the 0.1 level. Interactions with the other four variables are insignificant. This indicates that time to view, over the range of values used in this experiment--0.5 to 1.5 seconds, has little or no bearing on inspector performance.

The fourth variable is illumination (X_4). The main effect and the squared term associated with illumination are shown to be highly significant ($\alpha = 0.01$). This indicates that illumination can have a great deal to do with inspector performance. Illumination level does not interact significantly with the other four variables of the experiment. It is remarkable that the interaction between illumination and contrast is not even close to being significant. The importance of this result will be discussed later in Chapter VI.

The last variable, contrast (X_5), is the most significant of all variables in its main effect. The squared term of contrast is also highly significant. As was mentioned before, the interaction between contrast and ROCVA is significant to the 0.01 level. It can be seen from the values of the contrast regression coefficients and their significance that contrast is a very important variable in determining inspector performance.

In addition to the regression coefficients, or experimental variables, several other variables were shown to be significant. Blocks (shown in the design matrix of Table 4), subjects, and lack of fit were found to be significant at a level greater than 0.01. Blocks and subjects were expected to be significant, but it was hoped lack of fit would not be significant. The significance of lack of fit indicated that a higher order equation would better fit the data. That is, some third or higher order interaction terms would probably add significantly to the accuracy of the prediction equation. Attempts were made to remedy this in the second experiment by minimizing the bias due to third order terms.

An attempt was made to find the stationary point for the response function Y1. A stationary point (maximum, minimum, or saddle point) is found by first taking the partial derivatives of Y1 with respect to each of the five variables and setting each equation equal to zero. Then the system of equations is solved simultaneously. This solution, or the stationary point can either be a maximum, a minimum, or a saddle point. The eigen values (the characteristic roots) of a matrix made up of the regression coefficients indicate the type of stationary point. If all eigen values are negative then the point is a maximum. If they are positive the point is a minimum. If they are mixed in sign the point is then a saddle point.

By using the program of Appendix 11, the stationary point for the Y1 equation was found to have the following variable values:

ROCVA = 7.6×10^{-4} degrees/second

AV = 68.7 degrees/second

Time to view = -2.08 seconds

Illumination = -58.6 footlamberts

Contrast = 444.6 percent

Eigen values were calculated and were all found to be negative, indicating a maximum point. The variable values given above were examined and found to be far out of the experimental region. In addition three of the variables had values which were physically impossible--time to view and illumination of less than zero and contrast greater than 100 percent. The other two values (ROCVA and AV) were very large and would never be present in any practical situation. Because of these problems, the attempt to determine a global maximum point was abandoned for the first experiment.

To determine the maximum in or around the experimental region a constrained maximization was performed by the program of Appendix 12. This yielded a local maximum within the constraints that AV be between zero and 50 degrees per second and contrast be between zero and 100 percent. The coded values of this point were 2.22, -2.28, 1.00, -1.27, 2.22.

This corresponded to a ROCVA of -0.805×10^{-4} degrees per second, an AV of 20 degrees per second, a time to view of 0.68 seconds, an illumination of 76.2 footlamberts and a contrast of 100 percent. All of these values were within or not very far out of the experimental region. In the second experiment an attempt was made to make the center point of the RSM design as close to this point as possible.

A merging of the information in the prediction model and the related ANOVA is now appropriate. The following new prediction equation was derived as before; this time using only those terms found to be significant:

$$\begin{aligned} Y1A = 97.0846 &+ 5.3750\ X_4 + 11.6217\ X_5 - 6.5149\ X_4^2 \\ &- 4.7699\ X_5^2 - 3.9375\ X_1X_5 \end{aligned}$$

The confidence intervals for the regression coefficients of equation Y1A are in Table 13. An α of 0.05 was used in calculating these intervals. Each of these variables and their effects on the value of the prediction equation need to be examined. In the following discussions the values were determined using the Y1A equation with the coded values of the variables not being discussed set at zero.

The first variable to be examined is the rate of change of the visual angle (ROCVA). The only significant term in which it is involved is its interaction with contrast. The regression coefficient associated with this term is equal to -3.9. Given a -2.0 coded value of contrast (X_5), as ROCVA (X_1) goes from coded -2.0 to +2.0 there can be an

TABLE 13

CONFIDENCE INTERVAL FOR THE REGRESSION COEFFICIENTS OF Y1A OF THE FIRST EXPERIMENT

Regression Coefficient	Regression Coefficient Value	Confidence Interval α = .05
B_4	5.3750	±2.6453
B_5	11.6217	±2.6453
B_{44}	- 6.5149	±2.3474
B_{55}	- 4.7699	±2.3474
B_{15}	- 3.9735	±3.2398
B_0	97.0847	±3.3460

increase in the value of Y1A of up to 31.5 (see Figure 11). If contrast is +2.0 then there will be a like change of 31.5 in the value of Y1A but in the negative direction. In other words, if contrast is less than 49 percent, (coded value of zero) then increases in ROCVA should result in better inspector performance and vice versa.

This reversal of effect does not seem to be logical. It is a characteristic of the interaction terms of the model used. The value of any interaction term of this model is the product of three signed quantities as follows

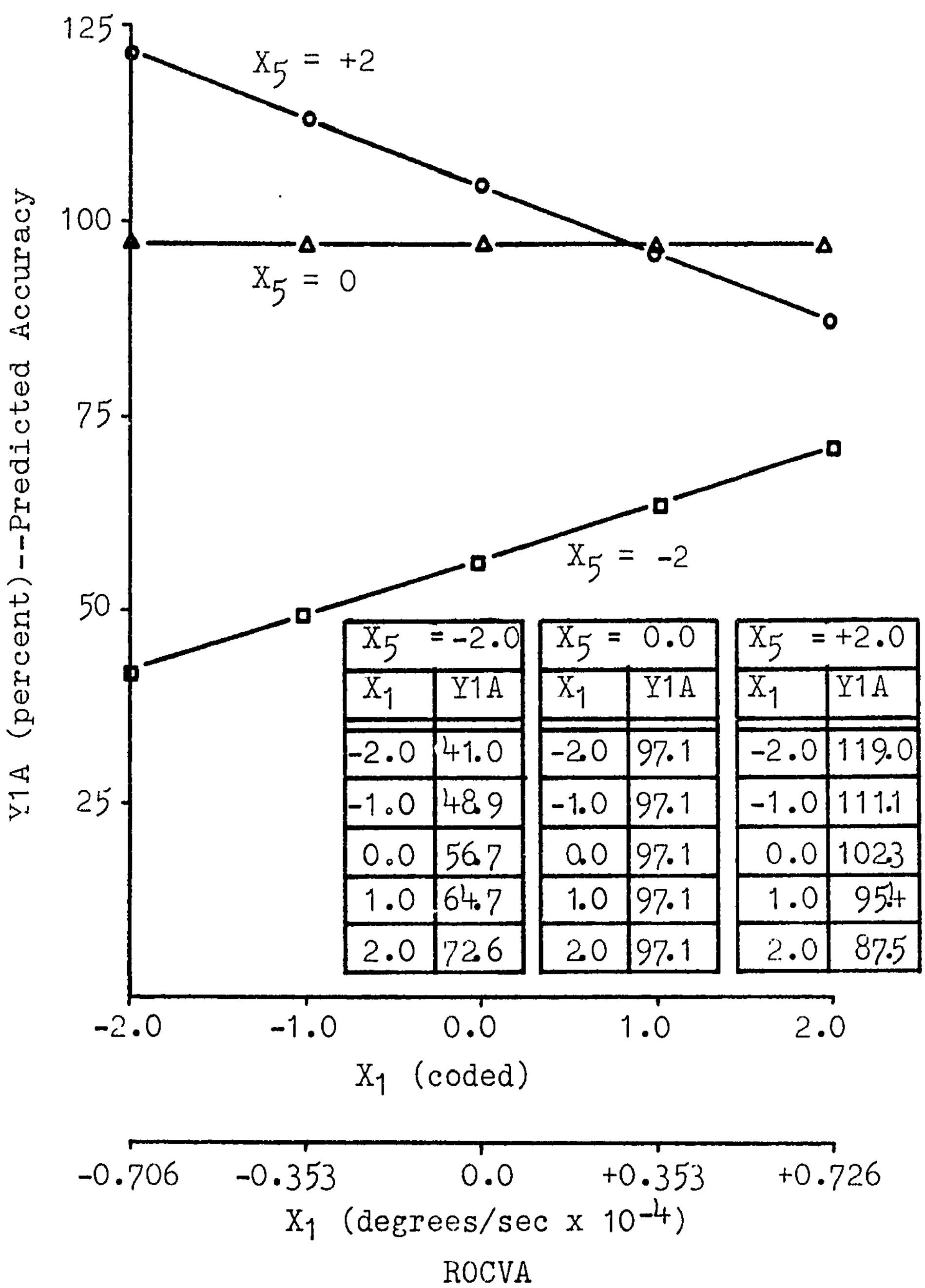
$B_{ij}X_iX_j$ = X_i interaction with X_j

where: B_{ij} - coefficient determined by regression

X_i - coded value of variable "i"

X_j - coded value of variable "j"

The value of B_{ij} is fixed by the regression analysis and is -3.9 in this case (B_{15}). The values of X_1 and X_5 can be either positive or negative. Upon examination of the interaction term it can be seen that as long as the regression coefficient and one variable have like signs the value of the term will increase with increases of the other variable. If the regression coefficient and one variable have different signs then the value of the interaction term will decrease with increases of the other variable. Therefore, the reversal of the effect of a variable on the value of an interaction term, due to the change of sign of the other variable, is an inherent characteristic of the term.



X_5 = -2.0	
X_1	Y1A
-2.0	41.0
-1.0	48.9
0.0	56.7
1.0	64.7
2.0	72.6

X_5 = 0.0	
X_1	Y1A
-2.0	97.1
-1.0	97.1
0.0	97.1
1.0	97.1
2.0	97.1

X_5 = +2.0	
X_1	Y1A
-2.0	119.0
-1.0	111.1
0.0	102.3
1.0	95.4
2.0	87.5

Figure 11.--Plots of Predicted Inspector Accuracy versus Rate of Change of the Visual Angle at three given levels of contrast--First Experiment.

The next important variable is that of illumination (X_4). Both its main effect and its squared term are highly significant. The coefficient associated with the main effect (B_4) is 5.375 and that of the squared term (B_{44}) is -6.515. As the coded value of illumination increases from -2.0 to 0.4 the value of Y1A will increase by 37.9 (see Figure 12). However as the coded value goes from 0.4 to +2.0 the value of Y1A is decreased by 16.4. Using footlamberts instead of coded values, this says that increases in illumination from 3.0 to 90.5 footlamberts will result in an increase in predicted performance. Farther increases from 90.5 to 147.0 footlamberts will result in a decrease in predicted performance.

The last variable that has been shown to be significant in the prediction equation is that of contrast (X_5). The coefficients associated with X_5 and X_5^2 are 11.622 and -4.270 respectively. Since the interaction of contrast and ROCVA is significant it must be taken into account when discussing the effects of contrast. Therefore there will be three cases--case 1 when ROCVA is -2.0, case 2 when it is zero and case 3 when it is +2.0 (see Figure 13).

For case 1 (X_1 = -2.0) when the coded value of contrast increases from -2.0 to +2.0 there is an increase of 78.0 in the value of Y1A (see Figure 13). This means that as contrast increases over the experimental region from 3.0 to 95.0 percent there will also be an increase in the value of Y1A.

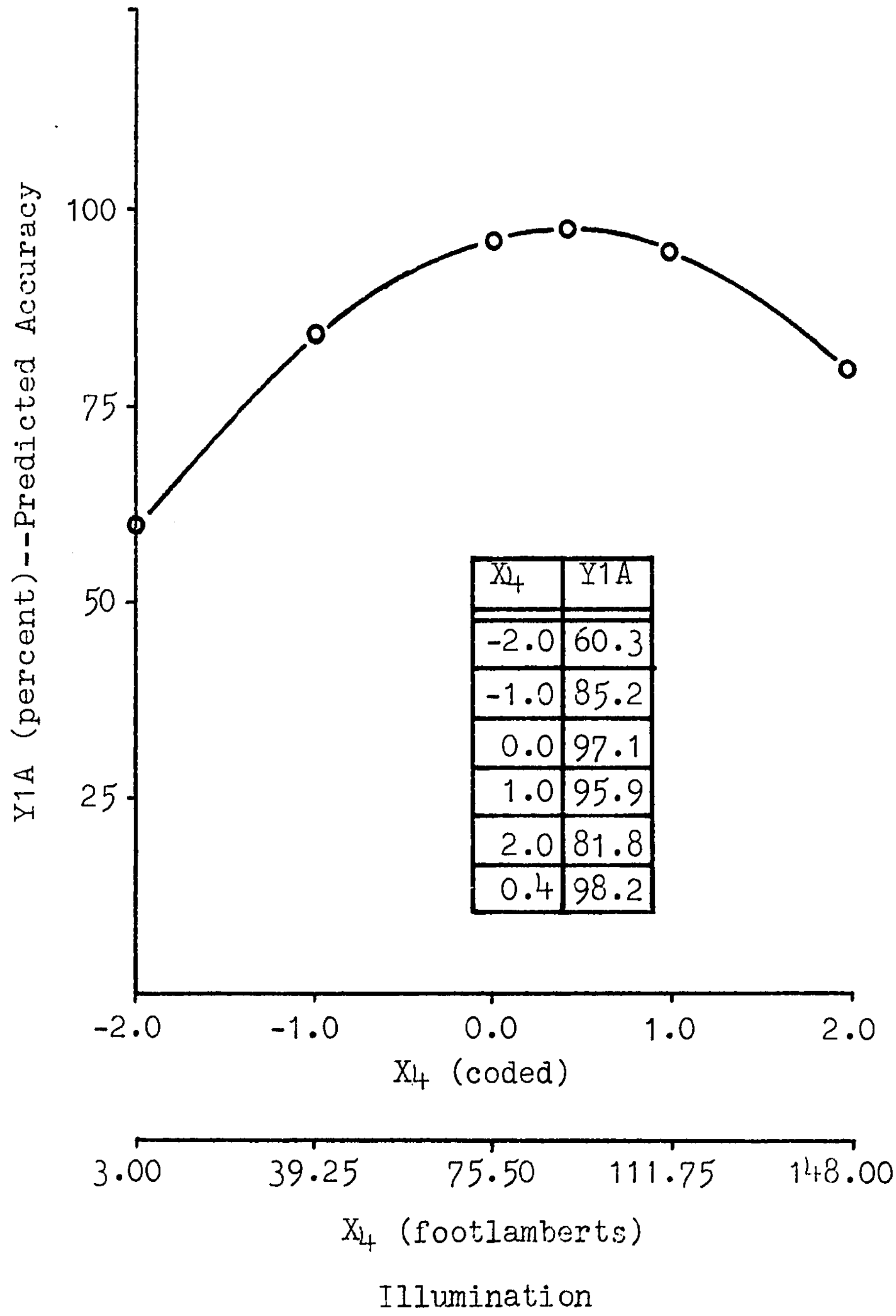
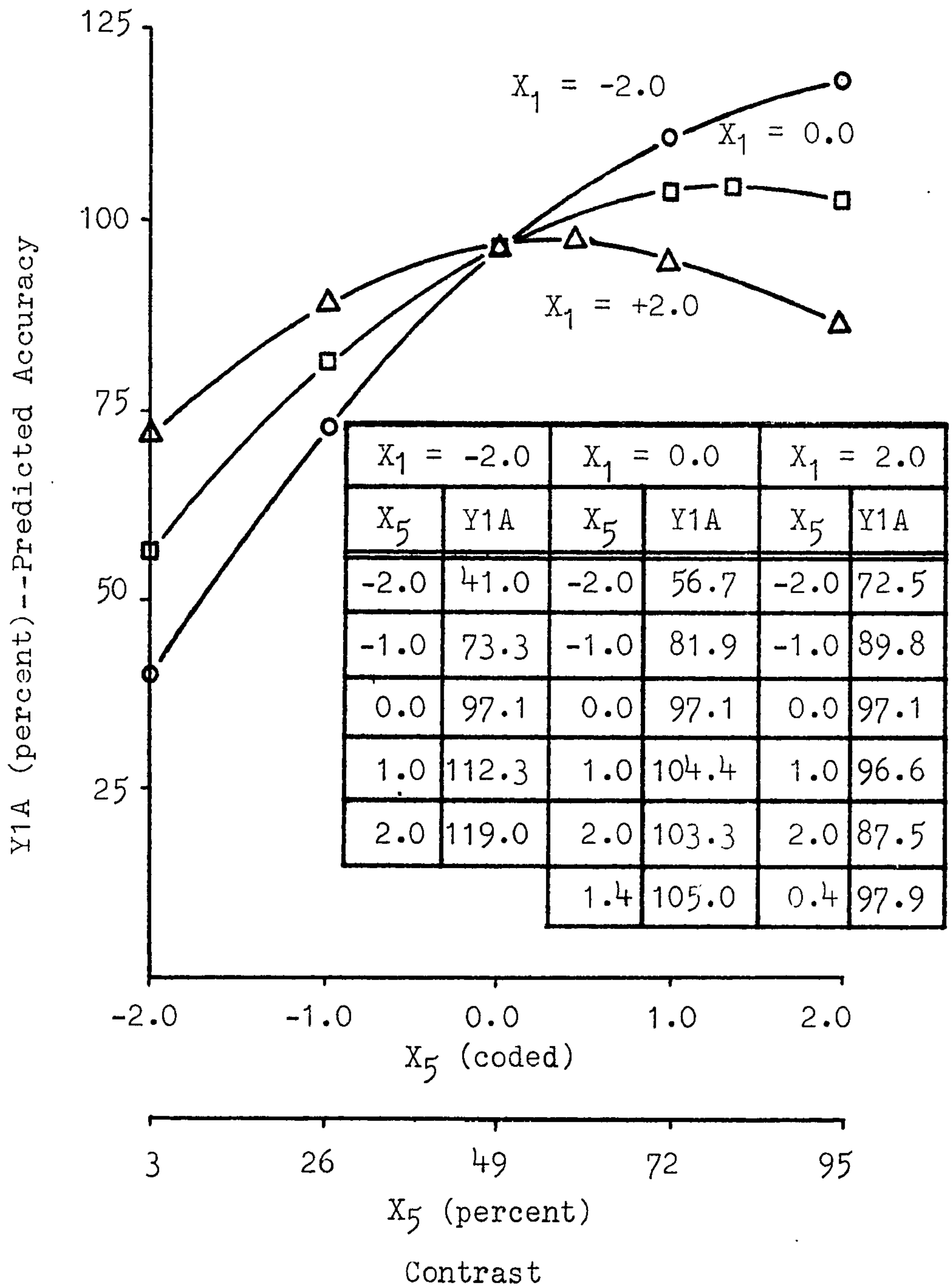


Figure 12.--Plot of Predicted Inspector Accuracy versus Illumination--First Experiment.



X_1 = -2.0		X_1 = 0.0		X_1 = 2.0	
X_5	Y1A	X_5	Y1A	X_5	Y1A
-2.0	41.0	-2.0	56.7	-2.0	72.5
-1.0	73.3	-1.0	81.9	-1.0	89.8
0.0	97.1	0.0	97.1	0.0	97.1
1.0	112.3	1.0	104.4	1.0	96.6
2.0	119.0	2.0	103.3	2.0	87.5
		1.4	105.0	0.4	97.9

Figure 13.--Plots of Predicted Inspector Accuracy versus Contrast at three given levels of ROCVA--First Experiment.

For case 2 ($X_1 = 0.0$) when the contrast is increased from -2.0 to about 1.4 there is an increase in the value of Y1A of 48.3. As contrast increases from 1.4 to +2 there is a decrease in the value of predicted performance Y1A of 1.7. This means that as contrast increases from 3.0 to 80.0 percent there is an increase in predicted performance. Beyond 80.0 percent there is a slight decrease in performance.

When $X_1 = +2.0$ (case 3) and there is an increase in contrast from -2.0 to 0.4 there is an increase in Y1A of 25.4. For an increase in contrast from 0.4 to +2.0 there is a decrease in Y1A of 10.4. This says that when ROCVA is equal to -2.0 predicted performance increases as contrast increases from 3.0 to 59.0 percent and it decreases above this point.

The point at which the three curves of Figure 12 intersect is of some interest. This intersection occurs at the point where X_5 is zero and the value of the function Y1A is 97.1 (B_o). With the exception of the B_o term, contrast (X_5) is in each term of the Y1A function. (Remember that all variable values except ROCVA and contrast are taken to be zero for this figure.) Therefore when X_5 is equal to zero the value of Y1A will simply be B_o or 97.1. Similar intersections will occur in the analysis of the second experiment and are caused by the same type of functional relationship.

B. Analysis of the second experiment

As in the first experiment, the second experiment was run using the second order model mentioned on page 26. The design matrix used is that of Table 12 (page 71) with two modifications. The number of replications of the center point is reduced from seven to two in order to maintain a central composite, rotatable, second order, design. The data is not divided into two blocks as was done in the first experiment. The variable levels and their coded values are contained in Table 10. Data collected for this experiment is contained in Appendix 7. The prediction equation which resulted is as follows:

$$\begin{aligned} Y2 = 91.1340 &+ 1.3623\ X_1 - 4.3075\ X_2 + 15.6515\ X_3 \\ &+ 23.5886\ X_4 + 26.7749\ X_5 + 17.1249\ X_1^2 \\ &+ 15.7883\ X_2^2 - 10.9139\ X_3^2 - 51.0875\ X_4^2 \\ &- 13.9176\ X_5^2 - 17.4140\ X_1X_2 - 1.4943\ X_1X_3 \\ &+ 2.5306\ X_1X_4 + 0.8936\ X_1X_5 - 2.5306\ X_2X_3 \\ &+ 4.4980\ X_2X_4 + 11.0612\ X_2X_5 + 5.6695\ X_3X_4 \\ &- 13.9898\ X_3X_5 - 2.9962\ X_4X_5 \end{aligned}$$

In this equation, as before, Y2 represents the percent of bad targets identified as bad. The ANOVA associated with this prediction equation is in Table 14.

The ANOVA shows those variables which have a significant effect on the value of Y2, the dependent variable. In order for a regression coefficient to be significant at a level where $\alpha = 0.05$ or 0.01 the F ratio must be greater

TABLE 14

ANALYSIS OF VARIANCE FOR THE REGRESSION--Y2

Source		Per Cent	Degrees of Freedom	Sum of Squares	Mean Square	F Value
Regression		57.57	20	46477.5971	2323.8798	20.376**
B_1	X_1	0.05	1	37.0740	37.0740	0.325
B_2	X_2	0.46	1	370.6567	370.6567	3.250
B_3	X_3	6.06	1	4893.4640	4893.4640	42.906**
B_4	X_4	13.77	1	11114.9500	11114.9500	97.457**
B_5	X_5	17.74	1	14320.4900	14320.4900	125.563**
B_6	X_1^2	1.07	1	866.7972	866.7972	7.600**
B_7	X_2^2	0.91	1	736.7691	736.7691	6.460*
B_8	X_3^2	0.44	1	352.0677	352.0677	3.087
B_9	X_4^2	9.56	1	7714.1897	7714.1897	67.639**
B_{10}	X_5^2	0.71	1	572.5182	572.5182	5.020*
B_{11}	X_1X_2	0.83	1	672.2201	672.2201	5.894*
B_{12}	X_1X_3	0.01	1	4.9501	4.9501	0.043
B_{13}	X_1X_4	0.02	1	14.1961	14.1961	0.124

TABLE 14--Continued

Source		Per Cent	Degrees of Freedom	Sum of Squares	Mean Square	F Value
B_{14}	X_1X_5	0.00	1	1.7701	1.7701	0.016
B_{15}	X_2X_3	0.02	1	14.1961	14.1961	0.124
B_{16}	X_2X_4	0.06	1	44.8501	44.8501	0.393
B_{17}	X_2X_5	0.34	1	271.2161	271.2161	2.378
B_{18}	X_3X_4	0.09	1	71.2531	71.2531	0.625
B_{19}	X_3X_5	0.54	1	433.8461	433.8461	3.804
B_{20}	X_4X_5	0.02	1	19.9001	19.9001	0.174
Residual		42.43	119	34254.1322	187.8498	
Subjects		5.11	4	4128.0797	1032.0199	9.049
Lack of Fit		21.92	6	17694.5802	2949.0967	25.858
Replications		15.40	109	12431.4722	114.0502	
Total		100.00	139	80731.7293		

* α = .05
** α = .01

than 3.93 or 6.89 respectively. Each variable, its interaction with other variables, and their significance will now be discussed.

The first variable is that of rate of change of the visual angle--ROCVA (X_1). Although its main effect is insignificant, its squared term is significant to the 0.01 level. In addition the interaction (X_1X_2) of ROCVA and angular velocity (AV) is significant to the 0.05 level. This says that the square of ROCVA and the interaction of ROCVA and AV both have an effect on the predicted value of inspector performance (Y2).

Angular velocity, like ROCVA, is significant in its squared term at an alpha level of 0.05. Also as discussed above the interaction of ROCVA and AV is significant at a level of 0.05. Therefore, predicted inspector accuracy is influenced significantly by the square of AV and the interaction of AV and ROCVA.

Time to view is found to be significant at the 0.01 level of confidence. All other terms involving time to view are insignificant. From this result it is concluded that the predicted performance is affected only by the main effect term of time to view.

It is apparent from the ANOVA results presented in Table 14 that the main effect term of illumination (X_4) and the squared term of illumination are both highly significant. The interaction terms in which illumination is involved are all found to be insignificant. Therefore, the main effect and squared term for illumination have a dominant effect on the value of Y2. On the other hand, the interaction terms of illumination have little or no effect on the value of predicted inspector performance.

Contrast (X_5), like illumination, is significant in its main effect and squared term. Therefore the same conclusions may be drawn about contrast as were drawn about illumination above.

In addition to the regression coefficients the factor of subjects is found to be significant. Also the lack of fit is highly significant. Since the design used minimizes the bias due to third order terms, the significance of lack of fit indicates that some of the higher order terms such as fourth, fifth, etcetera are significant or that some other form of model such as exponential or logarithmic would better fit the data. Although this is a problem, it does not make the prediction equations invalid. It means that they must be interpreted with caution in view of the fact that the influences of some or all of the variables through their higher order components are unknown. This will be discussed in some detail in Chapter VI.

The stationary point of equation Y2 is found using the program of Appendix 11. This point has coded values of -0.15, -0.18, 0.37, 0.22, and 0.67 for the variables X_1 through X_5 respectively. This corresponds to real variable values of ROCVA of 0.87×10^{-4} degrees per second, AV of 17.78 degrees per second, time to view of 0.98 seconds, illumination of 100.78 footlamberts, and a contrast of 86.98 percent. The value of the function Y2 at this point is 105.96.

It should be noted at this point that the value of Y2 is greater than 100 percent. Although it is a physical impossibility to have inspector accuracy of greater than 100 percent, the regression technique is unable to recognize this boundary. When this occurs the prediction equation value may be thought of as:

1. An index of inspector performance in which the higher the number the better the conditions for maximum inspector accuracy.
2. A measure of how much one or more of the variables are above the level required for maximum inspector accuracy (100 percent detection).

The eigen values are calculated using the program of Appendix 13. The eigen values are 25.38, 9.12, -6.12, -19.94 and -51.45. This indicates that the stationary point is a saddle point. If it were a maximum or minimum point all of the signs of the eigen values would be the same. From the eigen values and the value of Y2 at the stationary point the following function is derived:

$$YSP = 105.96 + 25.38W_1^2 + 9.12W_2^2 - 6.12W_3^2 - 19.94W_4^2 - 51.45W_5^2$$

This is the form of the function Y2 after translating the origin to the stationary point and after rotating the axes such that the interaction terms are eliminated. This function is called the "canonical form" and is helpful in examining the response surface. Its usefulness ends there as its axes are often complicated functions of all five of the original variables and are therefore physically uninterpretable.

From the canonical form (YSP) it can be seen that the stationary point is in a fairly sharp saddle point. A move in any direction results in fairly drastic changes in the value of YSP due to fact that no coefficient is small and the coefficient corresponds to the slope in a linear equation. If the term of the smallest coefficient (-6.12) is examined it can be seen that a move of 1 unit of W_3 results in a decrease in YSP of 6.12 and a move of 2 units of W_3 results in a decrease of 24.5. Because none of the coefficients or eigen values is near zero there is no way this response surface could be interpreted as ridge-like. The surface described increases with any movement along W_1 or W_2--most drastically along W_1. It decreases with any change from the translated origin along W_3, W_4 or W_5 axes--most drastically along the W_5 axis. A change in W_1 of 1 unit results in a change of YSP of 51.5 and a change of 2 in a change of 205.8. A change of 2 in this direction would undoubtedly be outside the experimental region and may be impossible--that is physically unobtainable.

Analysis of the cononical form shows that the surface is a saddle point and a very steep one.

As was done in the first experiment the following new prediction equation is derived using only those terms found to be significant:

$$\begin{aligned} Y2A = 87.5003 &+ 15.6515\,X_3 + 23.5886\,X_4 + 26.7749\,X_5 \\ &+ 20.7631\,X_1^2 + 19.4265\,X_2^2 - 47.4493\,X_4^2 \\ &- 10.2793\,X_5^2 - 17.4140\,X_1X_2 \end{aligned}$$

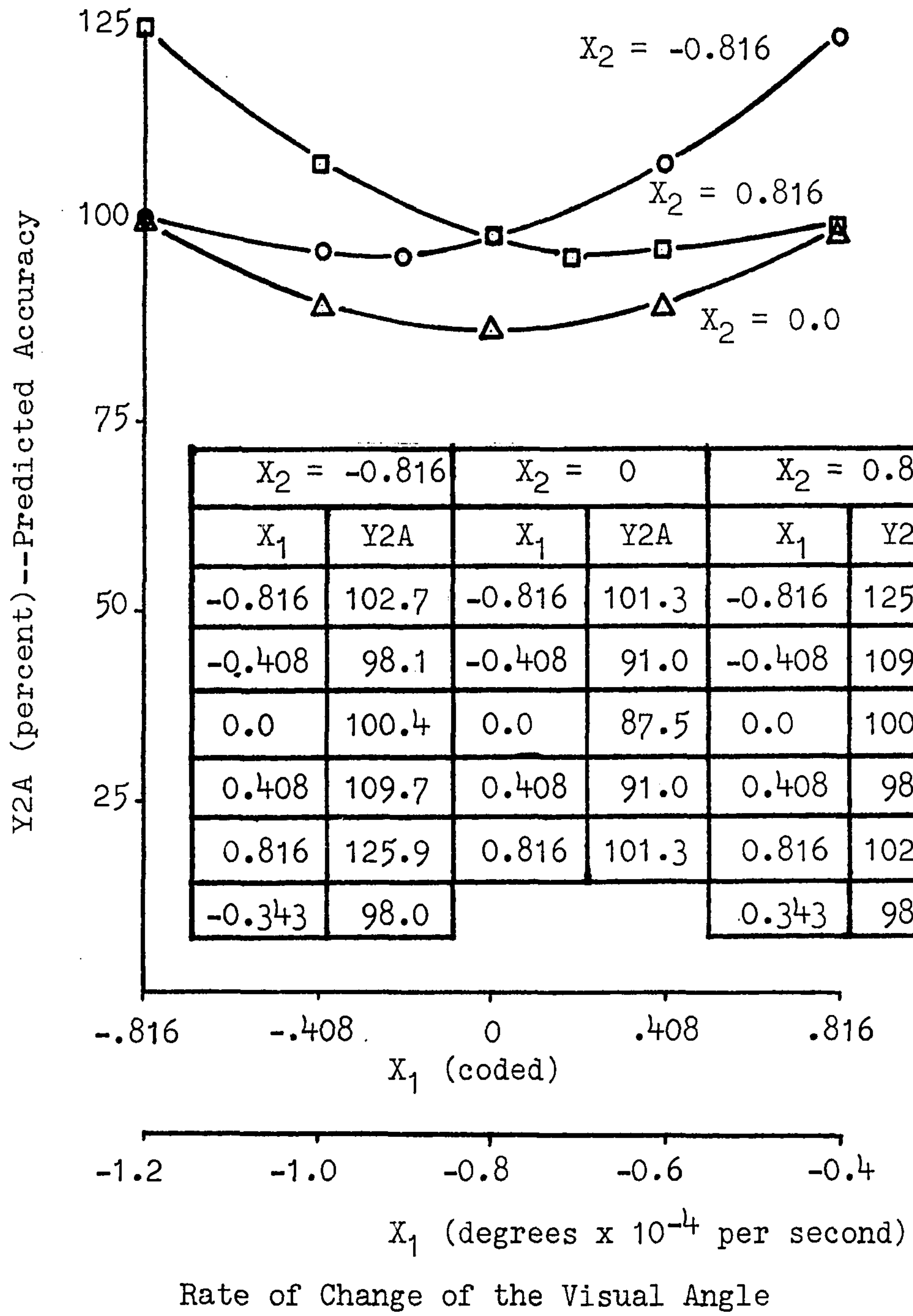
The confidence intervals for the regression coefficients of equation Y2A are shown in Table 15. An α of 0.05 is used in calculating these confidence intervals. Each of these variables and their effects on the predicted value of inspector accuracy now need to be examined.

The first variable (X_1) to be examined is the rate of change of the visual angle (ROCVA). This variable is found to be significant in both its squared term and its interaction with angular velocity (X_2). To thoroughly examine this variable (ROCVA) it must be investigated when AV is equal to -0.816, 0.0 and -0.816 as is done in Figure 14. Note that unlike Figure 12 the three lines do not cross at a single point. This is made possible by the fact that ROCVA (X_1) is not in all of the terms of the reduced Y2A equation. The presence of terms not containing X_1 prevent Y2A from being equal to 87.5 or B_0 when X_1 is equal to zero. From the equation for Y2A or Figure 13 it can be determined that when AV is -0.816 and ROCVA is increased from a coded value of

TABLE 15

CONFIDENCE INTERVAL FOR THE REGRESSION COEFFICIENTS OF Y2A OF THE SECOND EXPERIMENT

Regression Coefficient	Regression Coefficient Value	Confidence Interval $\alpha = .05$
B_3	15.6516	$\pm$ 7.3327
B_4	23.5886	$\pm$ 7.3327
B_5	26.7749	$\pm$ 7.3327
B_{11}	20.7632	$\pm$17.9724
B_{22}	19.4266	$\pm$17.9724
B_{44}	-47.4493	$\pm$17.9724
B_{55}	-10.2794	$\pm$17.9724
B_{12}	-17.4141	$\pm$22.0121
B_0	87.5003	$\pm$ 7.328



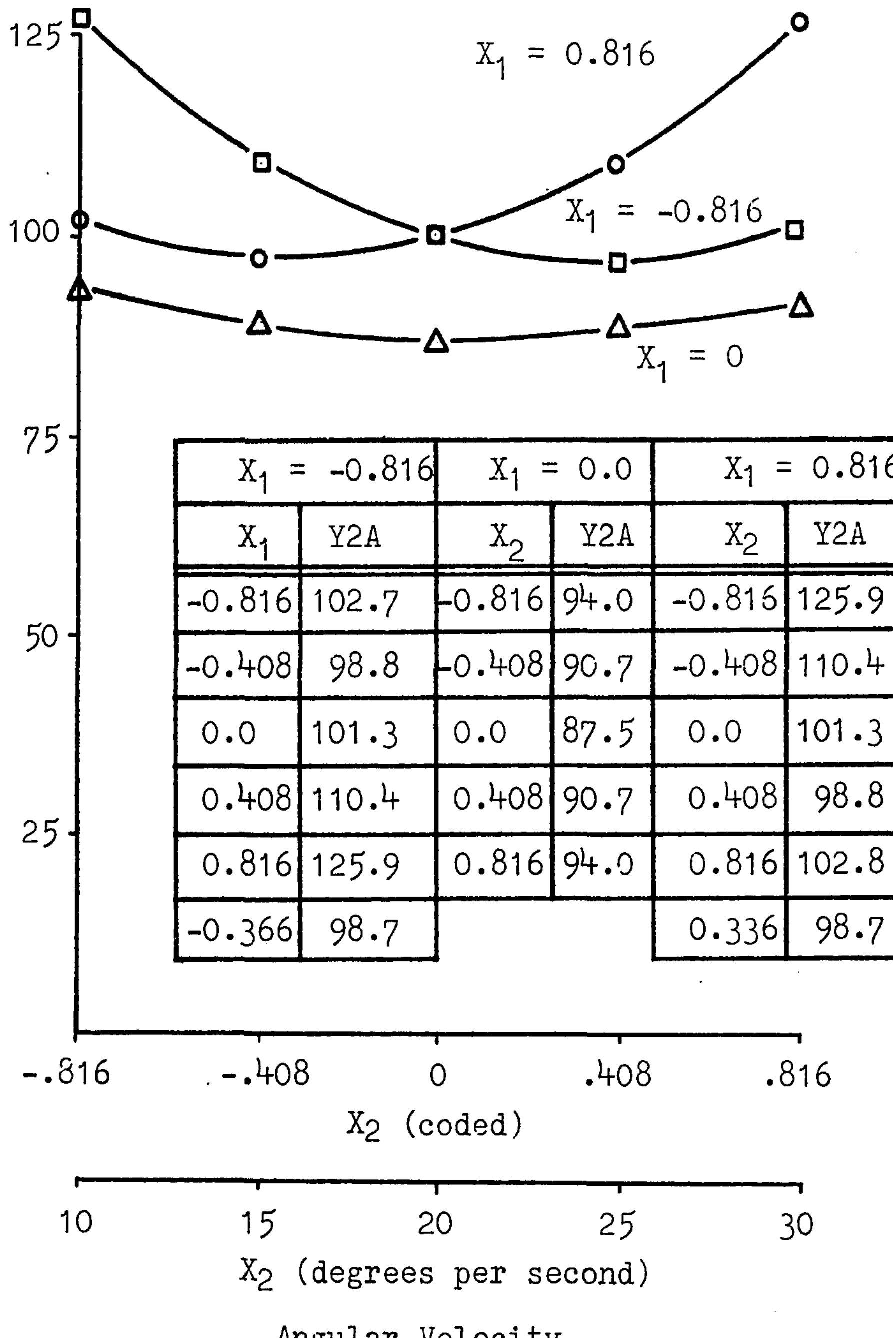
X_2 = -0.816		X_2 = 0		X_2 = 0.816	
X_1	Y2A	X_1	Y2A	X_1	Y2A
-0.816	102.7	-0.816	101.3	-0.816	125.9
-0.408	98.1	-0.408	91.0	-0.408	109.7
0.0	100.4	0.0	87.5	0.0	100.5
0.408	109.7	0.408	91.0	0.408	98.1
0.816	125.9	0.816	101.3	0.816	102.7
-0.343	98.0			0.343	98.0

Figure 14.--Plots of Predicted Inspector Accuracy versus ROCVA at three given levels of Angular Velocity--Second Experiment.

-0.816 to -0.343 there is a decrease in Y2A of 4.7. However as ROCVA is increased above -0.34 to +0.816 there is an increase of 27.9. When AV is 0.0 then as ROCVA is increased from -0.816 to 0.0 there is a decrease of 13.8 in the value of predicted performance. There is a like increase in Y2A as ROCVA increases from 0.0 to +0.816. When AV is +0.816 then as ROCVA increases from 0.816 to 0.343 there is a decrease in Y2 of 27.8. As ROCVA increases above this there is an increase of 4.7 in Y2A.

From the graphs of Figure 14 it can be seen that there is no value of ROCVA which gives an optimal value of Y2A. Given a value of X_2, there is a value for X_1 such that Y2A is minimal. Any deviation of ROCVA from this minimal point will result in an increase in the value of Y2A and, therefore, predicted inspector performance. These same relationships hold in the next figure (Figure 15) with ROCVA (X_1) and AV (X_2) exchanging roles.

The next variable is that of angular velocity (X_2). To adequately examine AV it needs to be examined when ROCVA is -0.816, 0.0 and +0.816. This is done in Figure 15. When ROCVA is -0.816 then the value of Y2A decreases 4.0 as AV goes from -0.816 to -0.366 and increases 27.2 as AV goes from -0.366 to +0.816. This says that Y2 is a minimum on this curve at the coded point = 0.366 or the actual variable value of 15.5 degrees per second. When ROCVA is 0.0 then as AV goes from -0.816 to 0.0 there is a decrease in the value



X_1 = -0.816		X_1 = 0.0		X_1 = 0.816	
X_1	Y2A	X_2	Y2A	X_2	Y2A
-0.816	102.7	-0.816	94.0	-0.816	125.9
-0.408	98.8	-0.408	90.7	-0.408	110.4
0.0	101.3	0.0	87.5	0.0	101.3
0.408	110.4	0.408	90.7	0.408	98.8
0.816	125.9	0.816	94.0	0.816	102.8
-0.366	98.7			0.336	98.7

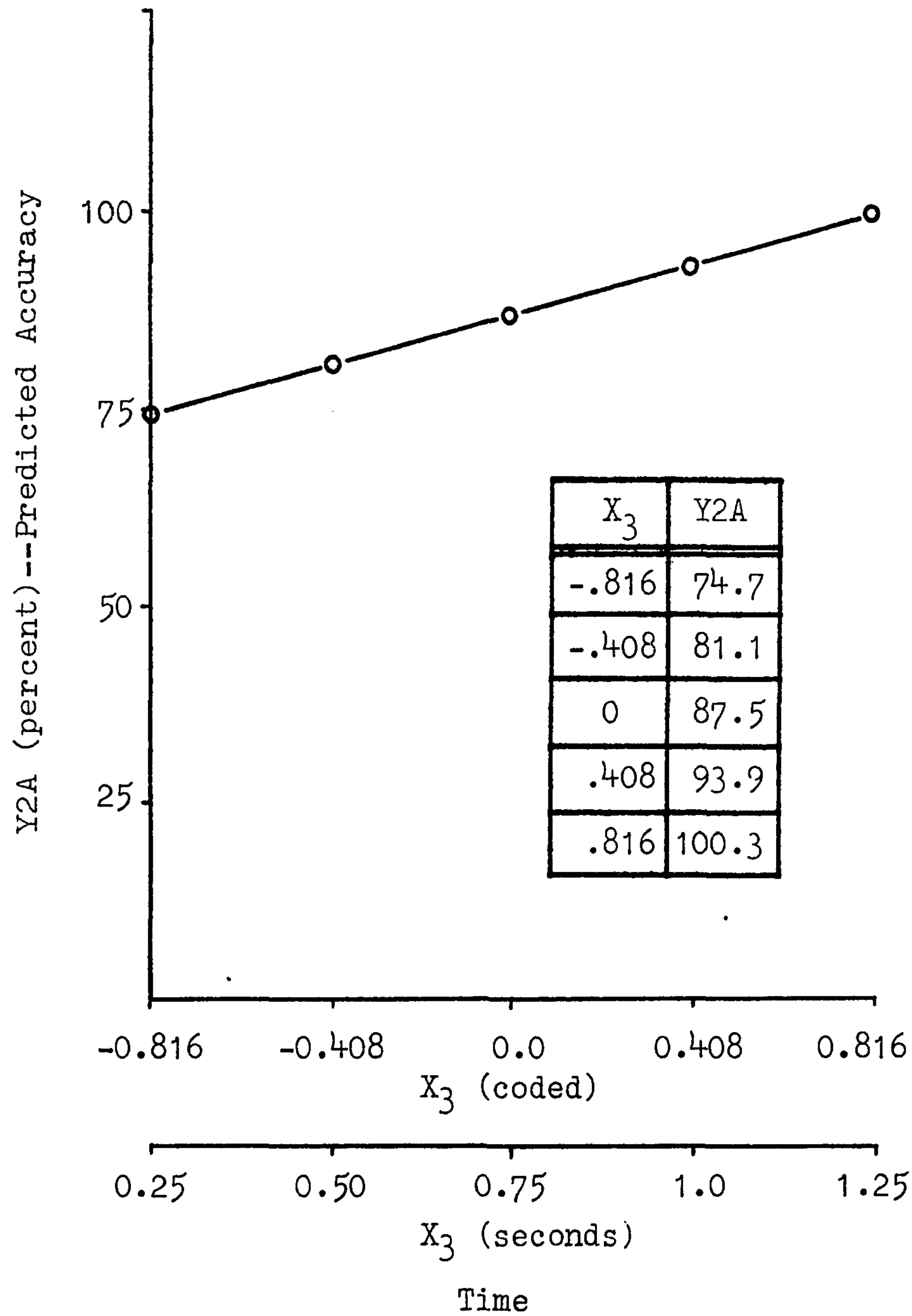
Figure 15. Plots of Predicted Inspector Accuracy versus Angular Velocity at three given levels of ROCVA--Second Experiment.

of the predicted inspector performance of 6.5. As AV goes from 0.0 to +0.816 there is an increase in Y2A of 6.5. When ROCVA is +0.816 then as AV is increased from -0.816 to +0.366 there is a decrease in Y2A of 27.2. As AV increases beyond this point to +0.816 there is an increase in the value of Y2A of 4.0. The overall effects of AV seem to be to decrease the value of the predicted performance as one moves from the extremities of the experimental region toward the center.

The time to view (X_3) is the next significant variable contained in the prediction equation for Y2A. Its effects are strictly linear (Figure 16). As time is increased from -0.816 to +0.816 there is an increase of 25.5 in the predicted performance. This says that as time is increased from 0.25 to 1.25 seconds, predicted performance increases 25.5.

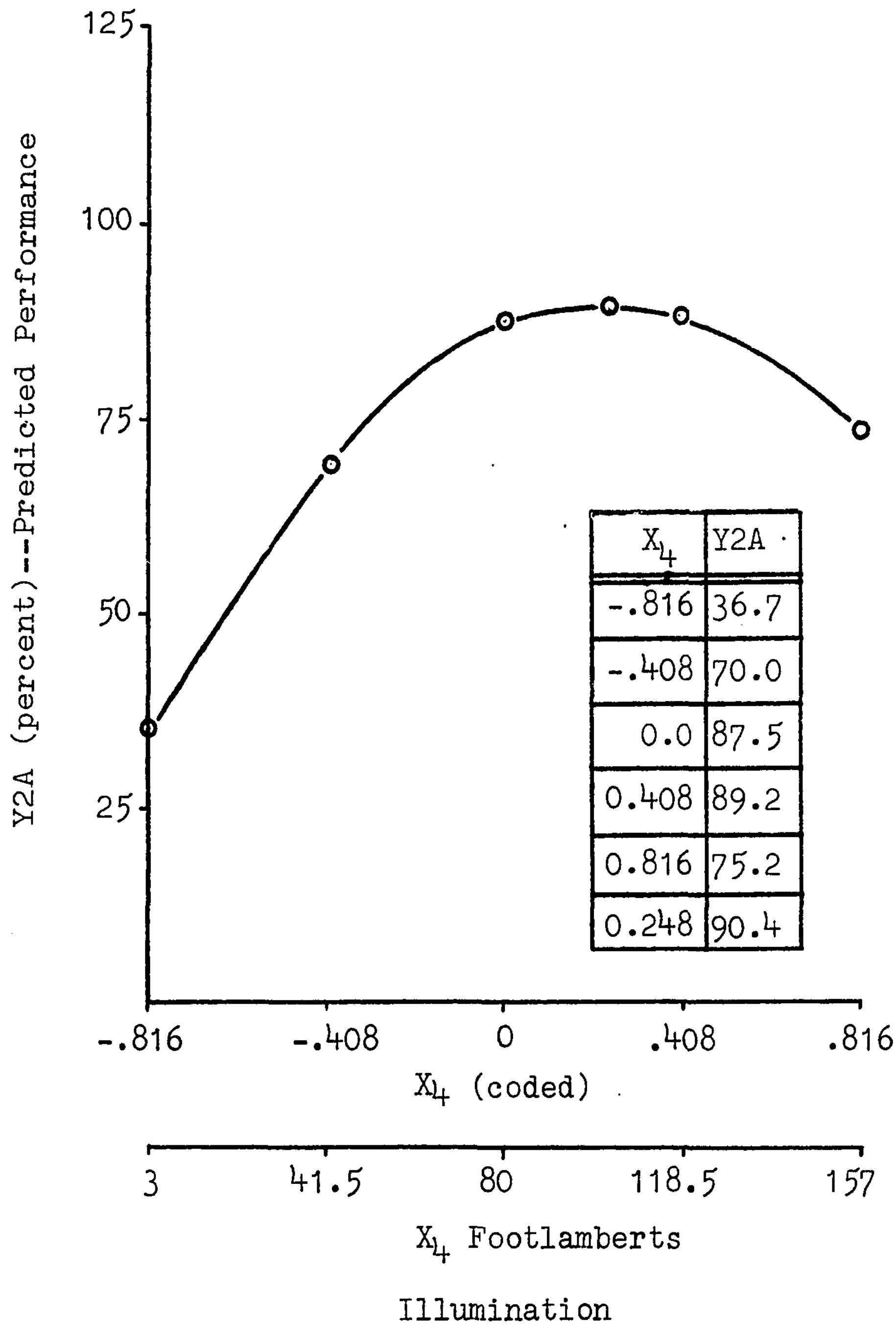
Illumination (X_4) has very definite effects on predicted performance (Figure 17). As it is increased from a coded value of -0.816 to +0.248 there is an increase of 53.7 in the value of Y2A. An increase from 0.248 to 0.816 causes a decrease in predicted performance of 15.2. This says that as illumination is increased from 3.0 to 103.0 footlamberts there is an increase in predicted performance. Above this point there is a decrease.

The effect of increases in contrast (X_5) within the experimental region can be seen in Figure 18. The value of Y2A increases by 43.7 as contrast increases from 3 percent to



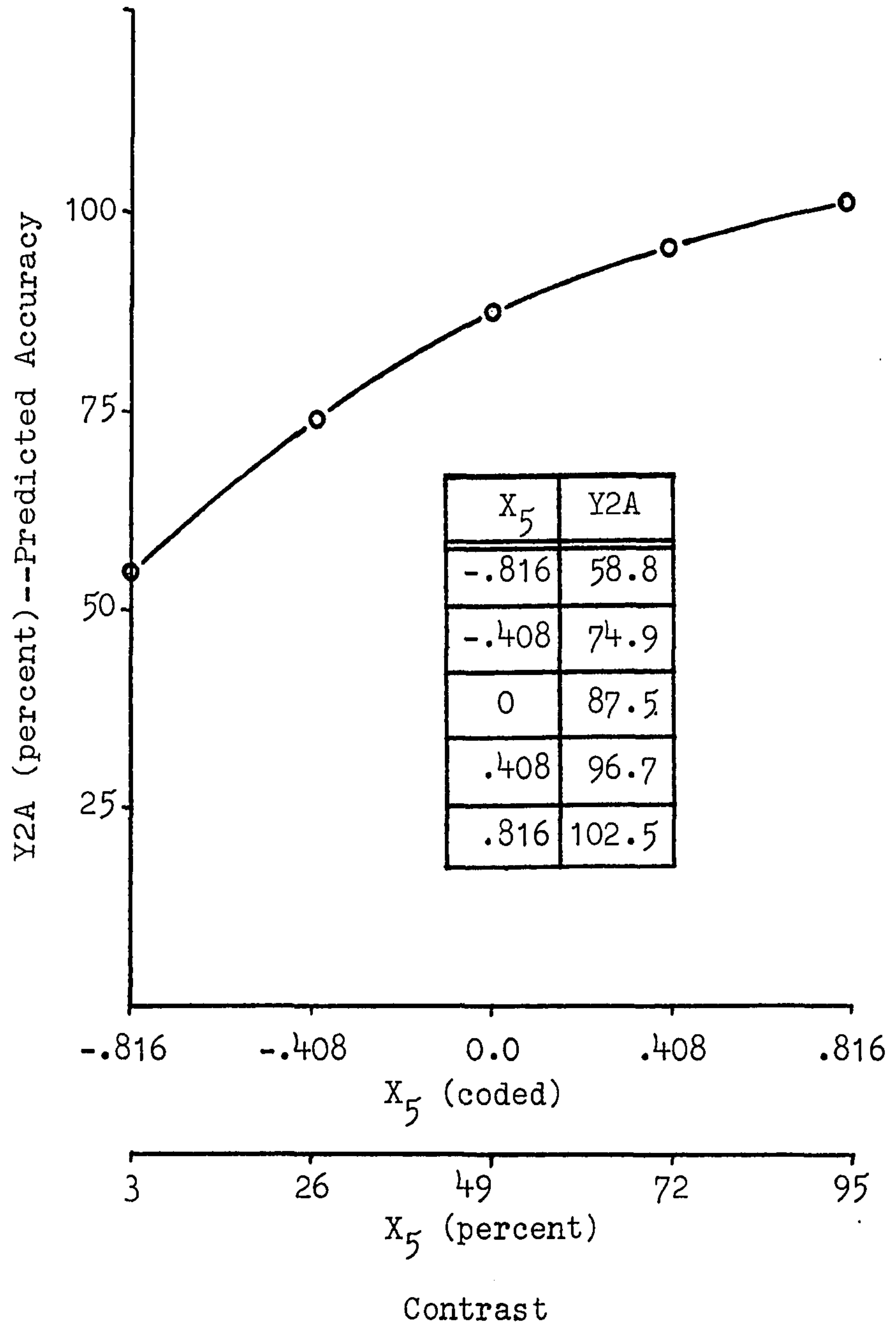
X_3	Y2A
-.816	74.7
-.408	81.1
0	87.5
.408	93.9
.816	100.3

Figure 16.--Plot of Predicted Inspector Accuracy versus Time to View--Second Experiment.



X_4	Y2A
-.816	36.7
-.408	70.0
0.0	87.5
0.408	89.2
0.816	75.2
0.248	90.4

Figure 17.--Plot of Predicted Inspector Accuracy versus Illumination--Second Experiment.



X_5	Y2A
-.816	58.8
-.408	74.9
0	87.5
.408	96.7
.816	102.5

Figure 18.--Plot of Predicted Inspector Accuracy versus Contrast--Second Experiment.

95 percent. This says that any increase in contrast will result in an increase in predicted inspector performance.

C. Analysis of the verifying experiment

The nine data points shown in Table 11 (page 52) were collected for each of 5 subjects using the targets (Landholt ring type) of Figure 10 (page 62). As was explained earlier the purpose of this experiment was to verify the first and second experiments using a different type of target. The variable levels used are contained in Table 16 where they are also coded for the models of the first and second experiments. These variable levels were selected so that they were within the experimental regions and near the optimal or saddle points of both experiments.

In Table 17 a slightly different method of coding ROCVA is used. The ROCVA (degrees per second) is divided by the actual size of the defect being viewed. This could have been done in the first and second experiments and then the standard method of coding utilized as shown in Appendices 8 and 9. Of course $\overline{Z}$ and d_i would be different but the coded values could still be the same as before. In this case there would be no difference in the prediction models obtained. The only difference is that coding of ROCVA has an additional step.

The reason for this method of coding is to eliminate the effect of the actual size of the defect on the coded

TABLE 16

VARIABLE VALUES OF THE VERIFYING EXPERIMENT AND THE CORRESPONDING CODED VALUES FOR THE FIRST AND SECOND EXPERIMENTS

Variable	Variable Values--Verifying Experiment	Coded Values--First Experiment	Coded Values--Second Experiment
ROCVA	-0.7×10^{-4}	-1.98	+0.5
	-0.4×10^{-4}	-1.13	+2.0
Angular Velocity	12	-0.6	-1.6
	20	+1.0	0.0
Time to View	0.7	-1.2	-0.20
	1.1	+0.4	+1.40
Illumination	30	-1.25	-1.30
	10	-1.81	-1.82
	90	+0.4	+0.26
Contrast	73	1.04	0.426
	87	1.65	0.674

TABLE 17

VARIABLE VALUES OF THE VERIFYING EXPERIMENT USING ROCVA* AND THE CORRESPONDING CODED VALUES FOR THE FIRST AND SECOND EXPERIMENTS

Variable	Variable Values-- Verifying Experiment	Coded Values-- First Experiment	Coded Values-- Second Experiment
ROCVA*	-.0026	-0.59	+2.96
	-.0015	- .34	+3.41
Angular Velocity	12.0	-0.6	-1.6
	20.0	+1.0	0.0
Time to View	0.7	-1.2	-0.20
	1.1	+0.4	+1.40
Illumination	30	-1.25	-1.30
	10	-1.81	-1.82
	90	+0.4	+0.26
Contrast	73	1.04	0.426
	87	1.65	0.674

value of ROCVA. From the expression for ROCVA (Appendix 3) it can be seen that ROCVA is not independent of the actual size of the object being viewed. To illustrate this consider two identical situations where two objects are approaching an observer at the same speed, along the same line, and at the same distance from the observer. The first object is 0.01 inches wide and the second is 0.02 inches wide. In this case the ROCVA of the first is one half that of the second. Difference in size alone accounts for this difference in ROCVA. If, however, the ROCVA of each is divided by its size the new variable values (ROCVA*) will be equal and independent of size.

ROCVA* may be a more useful variable than is ROCVA. The major advantage to ROCVA* is that it eliminates the practical problem of measuring the exact visual angle of what is being inspected. It eliminates problems in practical situations where the size of the defect may vary from item to item. Finally it makes the model more general in that the actual size or visual angle is not important to this variable.

By use of the program of Appendix 14 values of a prediction model were calculated for each of the 9 data points of Table 11 (page 52). These were compared with the observed values of the verifying experiment and a correlation coefficient calculated. In addition the program calculated a Hotelling T^2 statistic using data point means and the predicted values. This was done for each of the four prediction models or equations of the first and second experiments using first ROCVA and then ROCVA*. The results are shown in Table 18.

The following two hypotheses were tested for each model:

1. H_{o1}: $\rho = 0$

   H_{A1}: $\rho \neq 0$

   where ρ is the correlation coefficient

2. H_{o2}: $\mu_1 = \mu_o$

   H_{A2}: $\mu_1 \neq \mu_o$

   where: μ_1 is the vector of the six means of the data
   μ_o is the vector of the six predicted values

In order for the correlation coefficient to be significantly ($\alpha = 0.10$) different from zero (reject H_{o1}), the statistic "r" must be greater than .5822. The α level was selected such that the verifying experiment would be a reasonable test of the prediction models already developed.

The second null hypothesis (H_{o2}: $\mu_1 = \mu_o$) was accepted at an α level of 0.05 if the T^2 statistic was less than 23.98. Since the selection of the α levels for T^2 and correlation used similar reasoning the process need not be repeated here.

From Table 18 it can be seen that, with one exception, all the correlation coefficients of the verifying data with the predicted values of the various models were

TABLE 18

CORRELATION COEFFICIENTS AND T^2 STATISTICS CALCULATED FROM THE VERIFYING EXPERIMENTAL DATA AND THE FOUR PREDICTION MODELS OF THE FIRST AND SECOND EXPERIMENTS

Prediction Model	Using ROCVA		Using ROCVA*	
	Correlation Coefficient r	Hotelling T^2	Correlation Coefficient r	Hotelling T^2
Y1	0.7151	16.98	0.6629	6.37
Y1A	0.6405	13.4104	0.6509	39.32
Y2	0.5907	3555.62	0.5013	15,752.94
Y2A	0.6716	5784.61	0.6754	42,128.46

significantly different from zero. Although some were higher than others the difference between the largest and the smallest was not significant at the 0.05 level. The one model for which the correlation coefficient was not significant, at $\alpha = 0.10$, was the one from the second experiment which retains all variables and interactions and used ROCVA* in place of ROCVA. This coefficient was, however, significant at the 0.20 level.

Again referring to the contents of Table 18, the T^2 statistics associated with the first experiment are all insignificant except one. The one which is significant is associated with the abbreviated prediction model of the first experiment using ROCVA*. The T^2 statistics associated with the second experiment were all highly significant.

Briefly the analyses of the verifying experiment indicated that the actual data on a different target:

1. correlated with those values predicted by all models developed,
2. were not significantly different from those values predicted by the models developed from the first experiment,
3. were significantly different from those values predicted by the models developed from the second experiment.

CHAPTER VI

SUMMARY AND CONCLUSIONS

This chapter summarizes the results of the analyses performed in Chapter V. From the first and second experiments quite a bit of information can be gleaned. The similarities and differences of the models derived can be examined and related to past research on the same variables. The significance of the lack of fit terms in both experiments is a subject that needs further discussion. Finally the verifying experiment will be examined and its significances discussed.

From the data of the first experiment, the prediction model, Y1, of page 70 was derived and an ANOVA run on it. The ANOVA showed only five of the possible twenty terms of the second order model significant. These were the main effects of illumination and contrast, the squared effects of illumination and contrast, and the interaction of ROCVA and contrast. From this ANOVA it became evident that of the five independent variables illumination and contrast were dominant in determining inspector accuracy. The lack of significance of the interaction between illumination and contrast is worthy of further examination. Also the fact that neither angular velocity nor time to view were significant is of interest. Finally the significance of the ROCVA-contrast interaction term requires further examination.

The significances of illumination and contrast were not out of step with past research. All references cited in Chapter III from Lythgoe (1932) to Blackwell's more recent work indicated increases in illumination will increase performance. Most have found that at some point increases in illumination have little or no positive effect on performance. As Figure 12 (page 82) shows, performance peaked at about 100 footlamberts. This was higher than found by Lythgoe (1932), McCormick and Niven (1952) and Tinker (1949). Simonson and Brozek (1948) using a conveyor inspection operation as a task found optimum performance at an illumination of 100 foot candles, with target reflectance of about 80 percent, and deterioration beyond this level. This agreed closely with the findings of the first experiment. Therefore the relationship between illumination and performance was consistent with the findings of past researchers.

Contrast tended to follow the same pattern as illumination as seen in Figure 13. Performance tended to be at its maximum somewhere between 60 and 100 percent depending upon the value of ROCVA. This was in general agreement with the findings of Blackwell (1959). It also agreed with the studies of Cobb and Moss (1928) and Hendley (1948) which showed high contrast necessary for discrimination of fine detail.

The lack of significance of the interaction between contrast and illumination was totally unexpected. Blackwell in his studies had found a high degree of interaction of these variables as was related to visual performances on an inspection type task. He found that decreases in one could be overcome by increases in the other. Blackwell's (1959) findings were for greater ranges of illumination and contrast. They included levels of contrast of less than 1 percent and of illumination of less than 1 footlambert. Interaction seemed to be most pronounced at these lower levels and either less pronounced or nonexistent at higher levels. The lack of significance and therefore the lack of agreement with Blackwell could be explained by the failure to include extremely low levels of either contrast or illumination.

The significance of the interaction of ROCVA and contrast was of some interest. Its importance was diminished by the fact that it was found to be insignificant in the second experiment. It is worth noting that when contrast was low increases in ROCVA tended to increase inspector performance and when contrast was high increases in ROCVA tended to decrease inspector performance. This reversal in effect is unexplainable and as was discussed in the preceding chapter, may be an inherent characteristic of the second order model used.

In summary of the first experiment the significance of the main effects and squared terms of illumination and contrast were consistent with past research. At first glance the lack of significance of the interaction of illumination and contrast appeared to be inconsistent with the findings of Blackwell. Upon examination of the ranges of the variables of this experiment and those ranges used by Blackwell the reason for this lack of significance became explainable. The interaction of ROCVA and contrast was discounted as it was insignificant in the second experiment.

The design of the second experiment was modified from that of the first experiment in an attempt to minimize biasing due to third order terms. The data from this modified design was used to find the prediction model for the second experiment. The ANOVA which was run showed that eight terms of the model were significant. Four of the eight corresponded with terms found significant in the first experiment. These were the main and squared effects of illumination and contrast. Those found significant in the second experiment only were the main effects term of time to view and the squared terms of both ROCVA and angular velocity and their interaction.

As was the case in the first experiment the terms of illumination and contrast appeared to have the greatest effect on predicted inspector performance. Once again the interaction of illumination and contrast proved to be insignificant. The explanations of these significances or lack of significance and the related past research was covered in the discussion of the first experiment.

Time to view was insignificant in the first experiment and yet was significant (main effects) in the second experiment. Although this appeared to be inconsistent it was in fact reasonable. The shortest time of the first experiment was 0.50 seconds as compared with 0.25 seconds in the second experiment. This shortest time of the second experiment was very near the range of 0.1 to 0.2, within which, Graham and Cook (1941) and Niven and Brown (1949) found time to become critical in determining static visual acuity. Therefore the two results were consistent with past research. These results implied that somewhere between 0.50 and 0.25 seconds time to view became critical in a simple dynamic inspection task. Additional experimentation is required to verify this and possibly narrow the range.

The squared terms of both ROCVA and angular velocity were found to be significant in the second experiment. They had been insignificant in the first experiment. This could be due to the use of more extreme levels of both variables in the second experiment than in the first. These more extreme levels could also account for the fact that the interaction between the two variables also became significant in the second experiment.

The significance of ROCVA was difficult to interpret in the absence of past related research. It did indicate that problems encountered in applying concepts based on dynamic visual acuity data to industrial inspection tasks might have been related to ignoring ROCVA as a variable. This might have been the problem in predicting good inspectors from static or dynamic visual acuity tests as had been hypothesized by Nelson and Barany (1969). Although the second experiment did indicate a significance of ROCVA, the lack of significance in the first experiment should be kept in mind. There is a need for more experimentation on this variable to fully explore its effects.

The significance of angular velocity was not surprising in light of past research. Ludvigh and Miller, in their numerous studies, found that dynamic visual acuity was affected by angular velocities from 10 to 170 degrees per second. The differences they found for the range of values used in this experiment (10 to 30 degrees per second) were, however, very small. The fact that the angular velocity term found to be significant here was the squared term was important. This indicated that the rate of decrease in performance increased as the angular velocity increased. Therefore, at lower values there might have been very little change in performance corresponding to changes in angular velocity whereas at higher values, equivalent changes in angular velocity, would have significant effects on performance. Since for the first experiment, the range of angular velocities was lower than for the second, it was reasonable for angular velocity to be significant in the second experiment and not in the first. It appeared, therefore, that the first and second experiments were consistent with themselves and with the studies of Ludvigh and Miller with respect to the angular velocity.

In summary of the second experiment the significance of the main and squared effects terms of illumination and contrast were consistent with past research and the first experiment of this research. As with the first experiment the interaction of illumination and contrast was insignificant probably due to the range of levels tested. The significance of the squared terms of ROCVA and angular velocity was thought to be due to the use of more extreme values used in the second experiment than in the first. Although there was no past research on ROCVA, its significance appeared to be consistent in that it might help explain the lack of correlation between static visual acuity and inspector performance.

In both the first and second experiments the lack of fit term was found to be highly significant. This indicated that the second order equation was not the best model for in predicting inspector performance. The design of the second experiment was chosen such that any biasing due to third order terms was minimized. The only possible conclusions that could be drawn from this were that the lack of fit was due to third, fourth, fifth or higher order terms or that the polynomial type of regression model used was inappropriate. It is possible that some other functional form would better fit the data. Several transformations such as exponential and logarithmic were tried with no improvement in the fit.

The significance of the lack of fit terms did give cause for concern about the accuracy of the prediction model. Although this fact should be considered in any attempt to apply the model to a practical situation it did not invalidate it. It should be considerably better than guessing and might help in setting design parameters for particular inspection stations. Although they might not give expected inspector performance levels as accurately as might be desired, the models would indicate which situations are better than others. They would also give an indication of which variable levels to change to improve the inspector's ability to see the required defect.

The purpose of the verifying experiment was to test the generality of the prediction models from the first and second experiments. A target, which was different from that used in the first and second experiments, was used for the verification. Variable values of ROCVA, angular velocity, time to view, illumination, and contrast were selected such that they were within the experimental regions of both previous experiments. The actual performance levels of a group of subjects at nine combinations of variable values (see Table 11, page 53) were compared with those predicted by each of the four prediction models previously derived. The methods or statistics of comparison used were the correlation coefficient and the Hotelling T^2.

The correlation coefficient ranged from 0.5013 to 0.7151. With one exception, all correlation coefficients were found to be significantly different from zero at an $\alpha = 0.10$. The exception was, however, significant at $\alpha = 0.20$. The difference between the largest and smallest correlation coefficient was not found to be significant at $\alpha = 0.05$. Through the use of the correlation coefficient the verifying experiment showed that all prediction models gave values that correlated with actual performance and that no model could be said to be significantly better than another.

The Hotelling T^2s showed that the models of the first experiment predicted performance values much closer to those actually observed than did those of the second experiment (see Table 18, page 106). Three of these four T^2 values associated with first experiment models were small enough that the null hypothesis could not be rejected at $\alpha = 0.05$. The null hypothesis was that the observed and predicted inspector performances were equal.

Overall, the verifying experiment demonstrated that the values predicted by all models derived here correlated significantly with those observed and that the prediction values of three of four first experiment models did not differ significantly from those observed. This indicated that the models of both experiments were able to predict change in performance and its direction with the change of certain pertinent variable levels. However, only the models of the first experiment could be used to predict the actual values of inspector performance.

It can be said that the models from both experiments correlated about equally well with the data of the verifying experiment. The models of the two experiments did not, however, predict actual performance levels equally well. The models of the first experiment were distinctly better at this than those of the second experiment. This appears to be contrary to the overall objective of this experimentation--through progressive steps, to find better and better predictive models about the most favorable or optimal point of the response surface. A careful examination of the possible causes of the apparent inferiority of the second experiment's models is required.

There are several possible reasons for the second experiment's models being judged inferior by the verifying experiment. The first possibility is that the method of calculating the stationary point was invalid. The stationary points of the first and second experiments were calculated using the entire second order models as described in Myers (1971). Within these models were terms shown by analysis of variance to be statistically insignificant and therefore essentially equal to zero. By allowing these terms to remain in the model for calculation of the stationary points, unnecessary error may have been introduced. The stationary points of the abbreviated models (Y1A Normal and Y2A Normal) were calculated and are shown in Table 19 (numbers 5 and 11). Comparisons of these stationary points of the abbreviated models with those of the full models (Y1 Normal, Y1 Normal-constrained, and Y2 Normal--numbers 1, 4, and 8 respectively in Table 19) reveal considerable differences. Further examination does not show any systematic change in the stationary points when going from the full models to the abbreviated models. The use of the full models for calculation of stationary points may have caused the response surface methodology optimum-seeking procedure to seek and find a false optimum, a false optimum being one based on an inappropriate model. If this is true, then the second experiment's models may not describe the region about the optimum point and may not include it within the experimental region. Therefore, the inability of the second experiment's models to predict performance values as well as those of the first experiment may be a result of being at a false optimum.

The second possible reason for the apparent inferiority of the second experiment's models is chance. Chance is always present in any design using sample data to estimate population parameters. The greater the number of

TABLE 19

STATIONARY POINTS. AN ANALYSIS OF THEIR SENSITIVITY TO THE CONFIDENCE INTERVALS OF THE REGRESSION COEFFICIENTS

Model	Confidence Interval Point Used	ROCVA (x 10^{-4} degrees/sec.)	Angular Velocity (degrees/sec.)	Time to View (sec.)	Illumination (foot-lamberts)	Contrast (percent)
1. Y1	Normal	-7.60	68.70	(-2.08)*	(-58.60)	(444.60)
2. Y1	High	0.34	- 2.65	1.22	116.10	30.14
3. Y1	Low	-0.67	18.55	0.70	65.35	98.91
4. Y1	Normal-Constrained	-0.81	20.00	0.68	76.20	100.00
5. Y1A	Normal	-1.05	--	--	(-22.01)	49.00
6. Y1A	High	7.00	--	--	(-69.86)	49.00
7. Y1A	Low	- .44	--	--	(-26.20)	49.00
8. Y2	Normal	0.87	17.68	0.98	100.78	86.98
9. Y2	High	0.93	14.74	0.51	85.59	(108.77)
10. Y2	Low	-0.93	14.75	0.51	85.78	(108.80)
11. Y2A	Normal	-0.80	20.00	(-1.21)	(-374.30)	(258.97)
12. Y2A	High	-0.80	20.00	(-2.12)	(-484.90)	(-343.15)
13. Y2A	Low	-0.80	20.00	(-0.29)	(-233.00)	(-174.56)

*( ) indicate variable levels which are physically impossible.

estimates and tests of hypotheses made the greater the probability of making one or more errors. Given the large number of parameters estimated and the numerous tests of hypotheses made in this experimentation, it is not inconceivable that sufficient error was present to cause the models of the second experiment to be judged inferior predictors by a verifying experiment.

To investigate the possible ramifications of chance, the stationary points for all models derived in this experimentation were calculated using the limits of the confidence intervals of the estimated regression coefficients as shown in Table 13 (page 78) and Table 15 (page 93). These stationary points are contained in Table 19 (page 119). The second column shows which regression coefficient values were used as follows:

1. Normal--the original regression coefficients.
2. Normal-Constrained--the original regression coefficients with the values of angular velocity and contrast constrained.
3. High--the original regression coefficients with the confidence interval of Table 13 or 15 added to it.
4. Low--the original regression coefficients with the confidence interval of Table 13 or 15 subtracted from it.

The values of angular velocity and time to view for the abbreviated models of the first experiment (Y1A) are not given in Table 19. All of the terms of the full model (Y1) in which these variables appeared were found by analysis of variance to be insignificant. Therefore, they do not appear in any term in the abbreviated model (Y1A). The finding of insignificance indicates that, over the region investigated, these variables have no real effect on inspector performance. The implication here is that they can take on any value within the region without any significant consequences. This tabulation indicates the extreme effects chance can have on the stationary point. It adds new basis for the possibility of the second experiment describing the region around a false optimum or stationary point with the same results as discussed before.

A third possible reason for the verifying experiment's indication that the first experiment models were superior to those of the second experiment is related to the fact that both models predicted values of inspector performance in excess of 100 percent (discussed earlier in Chapter V). The second experiment models, perhaps because of their proximity to the saddle point, did predict values which were in excess of 100 percent and in excess of those predicted by the first experiment models. Since actual performance values cannot exceed 100 percent, predicted values of much greater than 100 percent are invariably going to cause large Hotelling T^2 statistics. These large T^2 values are then used to reject the null hypothesis that the models do predict the value of inspector performance. Therefore the fact that the second experiment's models gave prediction values which greatly exceeded 100 percent seems to be responsible for large T^2 values and their judged inferiority.

A fourth possibility for this unexpected outcome might be that the models were sensitive to the particular target used. If this were true then the indication here would be that the second experiment's models were just not as good as those of the first experiment for this particular target. This emphasizes the problem of target selection discussed in Chapter IV. There is probably no target from which truly general results can be obtained over wide ranges of levels of the various variables. This points toward an interaction between the targets and the variable levels which may defeat all attempts at deriving a general prediction model.

A fifth possible reason is that levels of unknown, uncontrolled or experimental variables were different for the second than for the first and verifying experiments. This possibility seems remote as the same variables were controlled and the same experimental procedures were used for all three experiments.

Of the models derived, either of those of the first experiment would be preferred over those of the second. This preference is based on the fact that, although there is no significant difference in their correlation, the models of the first experiment came much closer to predicting the actual values of inspector performance. Of the two models of the first experiment, the Y1A or abbreviated model would be preferred. The simplicity of the model and its use is the basis for this preference. A selection based on simplicity follows the law of parsimony which says to use the simplest that will do the job. Another argument in favor of the abbreviated model is that the probability of any model being used in industrial situations increases as it becomes simpler. Since the two models of the first experiment are essentially equal, the abbreviated one should be chosen for its simplicity.

In summary, more and more emphasis is being placed by industry on inspection and inspector performance. The human component of the inspection operation is often expected to perform without error. Although error free inspection is not feasible in many of these situations, there may be some levels or ranges of levels of variables for which inspector performance would be optimized.

A series of two experiments using response surface methodology has been conducted to determine the effects of the following five variables on a dynamic visual inspection task:

1. Rate of change of the visual angle.
2. Angular Velocity.

3. Time to View.

4. Illumination.

5. Contrast.

The experimentation shows illumination and contrast to be dominant in determining inspector performance. Time to view, rate of change of the visual angle and angular velocity have significant effects on performance--especially when at the more extreme values.

The major outputs of this experimentation are four prediction models. These models were verified using a different task and found to be significant predictors. These models are capable of assisting in the design of inspection stations in industrial situations and will indicate how existing stations need to be changed to improve inspector accuracy.

An unexpected problem arose pertaining to the use of response surface methodology as an optimum-seeking technique. This methodology requires that a series of experiments be conducted such that each successive one comes closer to describing the area about the optimum or stationary point. In this study the second experiment achieved this goal. However, in an attempt to verify that the models of the second experiment were superior to those of the first, the opposite was shown. The most important possible cause is in the method of finding the optimum or stationary point. Perhaps instead of the full second order model an abbreviated model, in which insignificant terms were omitted, should have been used.

APPENDICES

APPENDIX 1

FORMULAS INVOLVED IN THE STRAIGHT CONVEYOR

W = Width of the defect

D = Distance from observer (O) to the target (T)

A = Visual angle

y = Perpendicular distance from the conveyor to the observer

x = Distance from the perpendicular from "O" to the conveyor to the target "T"

$$\theta = \frac{A}{2}$$

$$D = (x^2 + y^2)^{1/2}$$

$$A = 2\tan^{-1}(\frac{W}{2D})$$

$$W = 2D\tan(\frac{A}{2}) = 2d(\frac{A}{2})(.00029) = D(A)(.00029)$$

a = The angle between the perpendicular with the conveyor through the observer and the line of sight from the observer to the target

$\frac{da}{dt}$ = The angular velocity of the target with respect to the observer

$$\tan a = \frac{x}{y}$$

$$a = \tan^{-1}(\frac{x}{y})$$

$$\frac{da}{dt} = \frac{y}{x^2+y^2} \cdot \frac{dx}{dt}$$

$$\frac{d(A)}{dt} = \frac{Wx}{(x^2+y^2\ 3/2} \cdot \frac{dx}{dt}$$

APPENDIX 2

DERIVATION OF ANGULAR VELOCITY ON A STRAIGHT CONVEYOR

$$a = \text{The angle in Figure 2}$$

$$= \tan^{-1}\left(\frac{x}{y}\right)$$

$$\tan a = \frac{x}{y}$$

$$x = y \tan a \qquad y = \text{a constant}$$

$$\frac{dx}{dt} = y \sec^2 a \frac{da}{dt}$$

$$\frac{da}{dt} = \frac{1}{y\sec^2 a} \cdot \frac{dx}{dt} \qquad \sec^2 a = \frac{D^2}{y^2} = \frac{x^2+y^2}{y^2}$$

$$= \frac{y}{x^2+y^2} \quad \frac{dx}{dt}$$

APPENDIX 3

DERIVATION OF THE RATE OF CHANGE OF THE VISUAL ANGLE ON A STRAIGHT CONVEYOR

A = The Visual Angle

w = The size of the defect or characteristic being observed

$D = (x^2+y^2)^{1/2}$ = Distance

$A = 2\tan^{-1}\ (\frac{w}{2D})$

$$\frac{dA}{dt} = 2 \cdot \frac{1}{1+\frac{w^2}{4D^2}} \cdot \frac{d}{dt}\ (\frac{w}{2D})$$

$$= 2 \cdot \frac{4D^2 w}{4D^2+w^2} \cdot \frac{d(x^2+y^2)^{-1/2}}{dt} \cdot \frac{1}{2}$$

$$= \frac{4D^2 w}{4D^2+w^2}\ (-\frac{1}{2})\ (x^2+y^2)^{-3/2}\frac{d(x^2)}{dt}$$

$$= \frac{4(x^2+y^2)w}{4(x^2+y^2)+w^2} \cdot (-\frac{1}{2})\ (x^2+y^2)^{-3/2}\ 2x\ \frac{dx}{dt}$$

$$= - \frac{4(x^2+y^2)^{-1/2}\ wx}{4(x^2+y^2)\ +\ w^2}\ \frac{dx}{dt}$$

$$= - \frac{4wx}{4(x^2+y^2)^{3/2}\ +\ w^2\ (x^2+y^2)^{1/2}}\ \frac{dx}{dt}$$

$$w^2(x^2+y^2)^{1/2} \qquad 4(x^2+y^2)^{3/2}$$

$$- \frac{wx}{(x^2+y^2)^{3/2}}\ \frac{dx}{dt}$$

APPENDIX 4

FORMULAS INVOLVED IN THE CIRCULAR CONVEYOR

Angular Velocity (Figure 3) = AV

Radius = R = 45"

$$AV = \frac{da}{dt}$$

$$\text{Speed (linear)} = \frac{dx}{dt}$$

$$\frac{da}{dt} = \frac{1}{R} \cdot \frac{dx}{dt} = \text{radians/sec}$$

Visual Angle

$$A = 2\tan^{-1}\left(\frac{W}{2D}\right)$$

Rate of Change of the Visual Angle

$$\frac{d(A)}{dt} = 0$$

APPENDIX 5

INSTRUCTIONS TO SUBJECTS

You are here to participate in an experiment on industrial Inspector Accuracy. The purpose of this experiment is to check some of the variables which can affect an inspector's performance on the job. The information gathered here will be analyzed to see how the inspector's performance can be improved or optimized.

During each trial you will see a series of 40 targets. Each target will be a square with a painted surface as is shown in front of you now. Some of the targets will have a small black mark or line on them. Those with this mark are designated as defective. As you watch a target go past you you are to look at it, determine if there is a black line or mark, and indicate whether the target is good (has no defect) or bad (has a defect). If the target is good press the button on your right, marked green. If it is bad press the button on your left, marked black. This is green for good and black for bad is indicated on the apparatus in case you become confused.

You will now have a practice session of ten targets.

You will respond in the correct manner to each one as you see it. The experimenter will tell you if you are correct or not during this practice run. Later you will not be told of your performance on the actual trials.

Your objective should be to correctly identify all targets in a trial. You will be scored on the number of errors you make--failure to identify a bad target as bad and identifying a good target as bad. Therefore it is important that you identify each target correctly.

Are there any questions before you start the practice targets?

(Practice)

Now that you have seen the practice targets are there any questions?

(Answers?)

We will now start a real trial for record. Be sure to try to identify each target correctly. Remember the green button is for good targets and the black button is for bad targets.

APPENDIX 6

DATA FOR THE FIRST EXPERIMENT

DATA PT. NUMBER	SUBJECT NO. 1 100 - TYPE I	SUBJECT NO. 1 100 - TYPE II	SUBJECT NO. 2 100 - TYPE I	SUBJECT NO. 2 100 - TYPE II	SUBJECT NO. 3 100 - TYPE I	SUBJECT NO. 3 100 - TYPE II
1	100.0	100.0	100.0	100.0	100.0	100.0
2	100.0	80.0	83.5	80.0	97.7	50.0
3	93.4	50.0	80.2	80.0	97.7	50.0
4	100.0	100.0	100.0	100.0	100.0	100.0
5	80.2	60.0	80.2	80.0	93.6	60.0
6	100.0	100.0	100.0	90.0	90.1	30.0
7	100.0	100.0	100.0	100.0	100.0	100.0
8	90.1	80.0	76.9	80.0	93.4	80.0
9	97.7	60.0	97.7	75.0	93.4	90.0
10	100.0	100.0	100.0	100.0	100.0	100.0
11	100.0	100.0	90.1	100.0	100.0	100.0
12	93.4	80.0	83.5	70.0	90.1	70.0
13	100.0	100.0	100.0	100.0	100.0	100.0
14	100.0	100.0	73.6	90.0	86.8	90.0
15	97.7	60.0	73.6	60.0	100.0	50.0
16	100.0	100.0	100.0	100.0	100.0	100.0
17	97.7	100.0	100.0	100.0	97.7	100.0
18	100.0	100.0	100.0	100.0	100.0	100.0
19	100.0	100.0	97.7	100.0	100.0	90.0
20	100.0	100.0	100.0	100.0	97.7	100.0
21	100.0	100.0	100.0	100.0	97.7	100.0
22	100.0	100.0	100.0	100.0	97.7	100.0
23	100.0	100.0	97.7	100.0	100.0	100.0
24	100.0	100.0	100.0	100.0	100.0	100.0
25	100.0	100.0	100.0	100.0	100.0	100.0
26	100.0	100.0	100.0	100.0	100.0	100.0
27	100.0	100.0	100.0	100.0	100.0	100.0
28	100.0	100.0	97.7	100.0	100.0	100.0
29	100.0	100.0	100.0	100.0	97.7	100.0
30	93.4	60.0	100.0	80.0	100.0	40.0
31	100.0	100.0	100.0	100.0	100.0	100.0
32	97.7	90.0	100.0	80.0	100.0	90.0
33	100.0	88.9	100.0	90.9	100.0	100.0

DATA PT. NUMBER	SUBJECT NO. 4		SUBJECT NO. 5	
	100 - TYPE I	100 - TYPE II	100 - TYPE I	100 - TYPE II
1	100.0	100.0	100.0	100.0
2	100.0	100.0	90.1	20.0
3	100.0	70.0	83.5	30.0
4	100.0	100.0	100.0	100.0
5	97.7	80.0	83.5	30.0
6	100.0	100.0	100.0	100.0
7	100.0	100.0	100.0	100.0
8	100.0	90.0	86.8	10.0
9	97.7	60.0	83.5	40.0
10	100.0	100.0	100.0	90.0
11	100.0	100.0	100.0	100.0
12	100.0	60.0	86.8	70.0
13	100.0	100.0	100.0	100.0
14	100.0	90.0	100.0	60.0
15	100.0	80.0	80.2	60.0
16	100.0	100.0	100.0	100.0
17	100.0	100.0	100.0	100.0
18	100.0	100.0	100.0	100.0
19	100.0	100.0	100.0	90.0
20	100.0	100.0	100.0	100.0
21	100.0	100.0	100.0	100.0
22	100.0	100.0	100.0	100.0
23	100.0	100.0	100.0	100.0
24	100.0	100.0	97.7	100.0
25	100.0	100.0	100.0	100.0
26	100.0	100.0	100.0	100.0
27	100.0	100.0	97.7	100.0
28	100.0	100.0	100.0	90.0
29	100.0	100.0	100.0	100.0
30	100.0	90.0	97.7	20.0
31	100.0	100.0	100.0	100.0
32	97.7	100.0	90.1	40.0
33	100.0	100.0	100.0	100.0

APPENDIX 7

DATA FOR THE SECOND EXPERIMENT

DATA PT. NUMBER	SUBJECT NO. 1		SUBJECT NO. 2		SUBJECT NO. 3	
	100 - TYPE I	100 - TYPE II	100 - TYPE I	100 - TYPE II	100 - TYPE I	100 - TYPE II
1	100.0	90.0	100.0	80.0	100.0	90.9
2	96.7	50.0	93.4	40.0	100.0	100.0
3	93.4	81.8	93.4	40.0	100.0	60.0
4	100.0	100.0	100.0	80.0	100.0	100.0
5	100.0	70.0	96.3	60.0	100.0	100.0
6	100.0	100.0	100.0	100.0	100.0	100.0
7	100.0	100.0	100.0	100.0	100.0	100.0
8	90.1	63.6	84.5	41.4	100.0	90.9
9	96.7	70.0	93.4	70.0	100.0	70.0
10	96.7	100.0	100.0	100.0	100.0	100.0
11	100.0	100.0	100.0	100.0	100.0	100.0
12	96.7	50.0	98.3	60.0	100.0	72.7
13	100.0	100.0	100.0	90.9	100.0	100.0
14	100.0	90.0	90.1	80.0	100.0	100.0
15	100.0	80.0	100.0	72.7	100.0	90.0
16	100.0	100.0	100.0	100.0	100.0	100.0
17	100.0	100.0	100.0	100.0	100.0	100.0
18	100.0	100.0	100.0	90.0	100.0	100.0
19	100.0	100.0	100.0	77.8	100.0	100.0
20	100.0	100.0	100.0	88.9	100.0	100.0
21	100.0	100.0	100.0	88.9	100.0	100.0
22	100.0	80.0	100.0	88.9	96.3	100.0
23	100.0	60.0	87.8	30.0	100.0	60.0
24	100.0	100.0	100.0	100.0	96.3	100.0
25	100.0	0.0	100.0	12.5	100.0	0.0
26	100.0	100.0	100.0	100.0	100.0	90.0
27	93.4	50.0	87.8	40.0	100.0	80.0
28	100.0	100.0	100.0	100.0	100.0	100.0

DATA PT. NUMBER	SUBJECT NO. 4		SUBJECT NO. 5	
	100 - TYPE I	100 - TYPE II	100 - TYPE I	100 - TYPE II
1	100.0	100.0	100.0	100.0
2	100.0	100.0	96.3	90.0
3	90.1	80.0	100.0	77.8
4	100.0	90.0	100.0	90.0
5	93.4	90.0	100.0	90.0
6	100.0	100.0	100.0	100.0
7	100.0	100.0	100.0	90.0
8	93.4	80.0	100.0	80.0
9	100.0	90.0	100.0	60.0
10	100.0	100.0	100.0	100.0
11	96.3	100.0	100.0	100.0
12	93.4	90.0	100.0	70.0
13	100.0	100.0	100.0	100.0
14	100.0	100.0	100.0	100.0
15	100.0	100.0	100.0	90.0
16	100.0	100.0	100.0	100.0
17	100.0	100.0	100.0	100.0
18	100.0	100.0	96.3	90.0
19	96.3	100.0	100.0	90.0
20	96.3	100.0	100.0	100.0
21	100.0	100.0	100.0	100.0
22	100.0	100.0	100.0	90.0
23	100.0	100.0	100.0	20.0
24	100.0	100.0	100.0	100.0
25	93.4	0.0	100.0	0.0
26	100.0	100.0	100.0	100.0
27	93.4	50.0	100.0	30.0
28	100.0	100.0	100.0	100.0

APPENDIX 8

CODING OF VARIABLE VALUES FOR THE FIRST EXPERIMENT

Variable	$\bar{Z}_i$	d_i
X_1	0°/sec	$.353 \times 10^{-4}$ degrees/sec
X_2	15°/sec	5 degrees/sec
X_3	1.0 sec	.25 sec
X_4	75.5 foot lamberts	36.25 foot lamberts
X_5	49%	23%

$$\text{Coded value} = X_i = \frac{Z_i - \bar{Z}_i}{d_i}$$

where: Z_i--actual value of the variable

$\bar{Z}_i$--mean of the values of the ith variable

d_i--the difference or interval between successive values of Z_i

APPENDIX 9

CODING VARIABLE VALUES FOR THE SECOND EXPERIMENT

Variable	$\bar{Z}_i$	d_i
X_1	$-.8 \times 10^{-4}$ degrees per sec	$.2 \times 10^{-4}$ degrees per sec
X_2	20 degrees per sec	5 degrees per sec
X_3	.75 sec	.25 sec
X_4	80 foot lamberts	38.5 foot lamberts
X_5	49%	23%

$$\text{Coded value} = X_i = \frac{Z_i - \bar{Z}_i}{d_i} \cdot .408$$

Z_i --actual value of the variable

$\bar{Z}_i$ --mean of the values of the ith variable

d_i --the difference or interval between successive values of Z_i

APPENDIX 10

DATA FOR THE VERIFYING EXPERIMENT

Data Pt. Number	Subject #1		Student #2		Student #3	
	Type I	Type II	Type I	Type II	Type I	Type II
1	100	100	100	100	100	100
2	100	100	100	100	100	100
3	100	100	100	100	96.6	100
4	100	100	100	100	100	100
5	100	100	100	100	100	100
6	100	100	100	100	100	100
7	93.2	36.4	96.6	70.0	46.6	77.7
8	93.2	40.0	93.2	90.0	16.6	90.0
9	100	75.0	100	100	43.9	85.7

Data Pt. Number	Subject #4		Subject #5	
	Type I	Type II	Type I	Type II
1	100	100	100	100
2	100	100	100	100
3	100	100	100	100
4	100	100	100	100
5	100	100	100	100
6	100	100	100	100
7	100	36.8	93.2	30
8	100	20.0	100	50
9	100	58.4	100	53.9

APPENDIX 11

PROGRAM FOR CALCULATING THE STATIONARY POINT

```
      DIMENSION C(5,5),B(5,5),CH(5),BH(5) DHH(5),XBX1(5)
      READ(5,99)C
   99 FORMAT(5F10.4)
      WRITE(6,95)
   95 FORMAT(5X,3HC    )
      WRITE(6,98)C
   98 FORMAT(1H,5F10.5)
      READ (5,99)CH
      WRITE(6,92)
   92 FORMAT(5X,3HCH   )
      WRITE(6,98)CH
      DO 10 I=1,5
      EH(I)=-CH(I)/2.0
      DO 10 J=1,5
   10 E(I,J)=C(I,J)
      N=5
      NN=1
      KS=0
      CALL SIMQ(B,BH,N,KS)
      CALL GMPRD (BH,CH,XB,NN,N,NN)
      CALL GMPRD (BH,C,XBX1,NN,N,N)
      CALL GMPRD (XBX1,BH,XBX,NN,N,NN)
      B0=91.1340
      Y0=BC+XB+XBX
      WRITE(6,96)
   96 FORMAT(1H0,60H      X1          X2          X3          X4          X5
     1     Y0          )
      WRITE(6,97)          BH,Y0
   97 FORMAT(1H0,6F10.4)
  101 CONTINUE
      END
```

APPENDIX 12

PROGRAM FOR CALCULATING THE RESTRAINED MAXIMUM POINT

```
      DIMENSION C(7,7),B(7,7),CH(7),BH(7),CHH(7),XBX1(7)
      READ(5,99)C
   99 FORMAT(7F10.4)
      WRITE(6,95)
   95 FORMAT(5X,3HC   )
      WRITE(6,98)C
   98 FORMAT(1H,7F10.5)
      READ (5,99)CH
      WRITE(6,92)
   92 FORMAT(5X,3HCH  )
      WRITE(6,98)CH
      N=7
      NN=1
      KS=0
      DO 101 II=1,11
      WRITE(6,102)
  102 FORMAT(1H1)
      WRITE(6,90)
   90 FORMAT(1H,100H      C2         C5         X1         X2         X3
     I     X4         X5         L2         L5         Y0                )
      C2=II-4
      C2=C2*.408
      DO 101 JJ=1,10
      XJJ=JJ*0.435
      C5=XJJ-2.13
      C5=C5*.408
      CH(6)=-C2
      CH(7)=-C5
      DO 10 I=1,7
      BH(I)=-CH(I)/2.0
      CHH(I)=BH(I)
      DO 10 J=1,7
   10 B(I,J)=C(I,J)
      CALL SIMQ(B,BH,N,KS)
      CALL GMPRD (BH,CH,XB,NN,N,NN)
      CALL GMPRD (BH,C,XBX1,NN,N,N)
      CALL GMPRD (XBX1,BH,XBX,NN,N,NN)
      B0=91.1340
      Y0=B0+XB+XBX
      WRITE(6,97)C2,C5,BH,Y0
   97 FORMAT(1H0,10F10.5)
  101 CONTINUE
      END
```

APPENDIX 13

PROGRAM FOR CALCULATING EIGEN VALUES

```
      SUBROUTINE EIGEN(B,C,E,NF,M)
C     B=MATRIX OF EIGENVECTORS
C     C=MATRIX TO BE DECOMPOSED
C     E=VECTOR OF EIGENVALUES
C     NF=NO. OF FACTORS
C     M=ORDER OF B AND C
      DIMENSION B(5,5),C(5,5),E(5)
      DOUBLE PRECISION DIJ,DEN,ALPHA
      MONT=NF*(NF-1)/2+(M-NF)*NF
      DO 465 I=1,M
      DO 463 J=1,M
      B(I,J)=0.0
      IF(I.EQ.J)B(I,J)=1.0
  463 CONTINUE
  465 CONTINUE
      IF(MONT) 450,450,325
  325 CONTINUE
      DO 350 II=1,NF
      DO 345 JJ=II,M
      IF(II.EQ.JJ) GO TO 345
      IF (ABS(C(II,JJ)).LT.1.0E-06) GO TO 200
      NTRN=0
      SIGN=+1.0
      IF(C(II,JJ).LT.0.0) SIGN=-1.0
      DIJ=C(II,II)-C(JJ,JJ)
      DEN=DSQRT(DIJ*DIJ+4.0D0*DBLE(C(II,JJ)*C(II,JJ)))
      ALPHA=DSQRT((DEN+DIJ)/(2.0D0*DEN))
      ALPH=ALPHA
      BETA=DSQRT(1.0D0-ALPHA*ALPHA)
      B1=BETA*SIGN
      B1B=-B1
      DO 405 J=1,M
      TEMA=C(II,J)*ALPH+C(JJ,J)*B1
      C(JJ,J)=C(II,J)*B1B+C(JJ,J)*ALPH
      C(II,J)=TEMA
  405 CONTINUE
      DO 410 I=1,M
      TEMA=C(I,II)*ALPH+C(I,JJ)*B1
      C(I,JJ)=C(I,II)*B1B+C(I,JJ)*ALPH
      C(I,II)=TEMA
      TEMA=B(I,II)*ALPH+B(I,JJ)*B1
      B(I,JJ)=B(I,II)*B1B+B(I,JJ)*ALPH
      B(I,II)=TEMA
  410 CONTINUE
      GO TO 345
  200 CONTINUE
      NTRN=NTRN+1
      IF(NTRN.GE.MONT) GO TO 450
```