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By

Dharam S. Rana, Principal Investigator

Final Report
For the period November 1, 1978 - December 31, 1979

Prepared for the
National Aeronautics and Space Administration
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Under
Research Grant NSG 1565
Marvin C. Waller, Technical Monitor
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AN INVESTIGATION OF THE FEASIBILITY OF IMPROVING OCULOMETER DATA ANALYSIS THROUGH APPLICATION OF ADVANCED STATISTICAL TECHNIQUES

By

Dharam S. Rana[1]

ABSTRACT

Many experimental studies have been conducted by the scientists working on the oculometer project at the NASA/Langley Research Center (LaRC). Some of the studies have generated large volumes of data. The members of the oculometer project were relying mainly on three current data-reduction programs to analyze their measurements. The researchers soon realized that the current programs were not meeting their data analysis requirements, so it was decided that the data-reduction capabilities of the current programs should be assessed and a search for a more comprehensive system with higher data analytic capabilities should be made. Subsequently, the present investigation was undertaken to address these two issues.

INTRODUCTION

For several years, scientists at NASA/LaRC have been studying various possibilities of measuring pilot workload by use of an objective measure based on pilot scanning behavior. Researchers on the oculometer project have made significant advances in modeling pilot workload by using his/her scanning patterns.

The scanning behavior of a pilot is recorded by a modern technique that uses an electro-optical device called an oculometer. The basic principle of its operation is to illuminate the subject's eye with infrared radiation which is reflected from the retina of the eye. The reflected radiation is monitored with an infrared-sensitive television camera, and an associated minicomputer is used for processing the signal. The oculometer tracks a subject's lookpoint as a time function

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and measures it in terms of x and y coordinates. These coordinates are exploited to calculate the values of many variables related to the pilot's scanning pattern. For a complete description of the oculometer see reference 1.

The oculometer has been used in simulation studies of instrument landing system approaches (refs. 2-9) as well as in studies involving actual test flights of airplanes (ref. 10). Most of the simulation studies conducted on the visual motion simulator at NASA/LaRC and elsewhere have measured a large number of variables: for example, the investigation reported in reference 1 recorded values of about 150 variables. Thus, oculometer usage has generated large volumes of data. This raises the question of how to analyze the tremendous amount of data.

The researchers on the oculometer project at NASA/LaRC realized that they were not getting enough information from the data they were collecting, and so decided that there was a need to examine their current data-reduction techniques. If the current programs were found inadequate, a more advanced system of data analysis would be installed at the NASA/LaRC computer center. The current research effort was undertaken to address this problem in two phases: (1) examining the current data-reduction programs and (2) recommending a more comprehensive system of analyzing data that can be used for improving oculometer data analysis through application of advanced statistical techniques.

ASSESSMENT OF CURRENT DATA-REDUCTION PROGRAMS

There is one major data-reduction program in the oculometer project. This program is very well written and is capable of doing several things. Its main features include the ability to compute (1) instrument-to-instrument transition probability matrices, (2) location-to-location transition probability matrices within the flight director (ref. 1), (3) mean and standard deviations of dwell time on the display locations of interest, (4) tallies on miscellaneous information, such as total time on instruments, transition rates, etc., (5) a sequential listing of transitions from one location on the instrument display to the next, and (6) the total time spent on each location. It can also print histograms for the distribution of dwell times on various instruments and the distribution of dwell times on the different displays within the flight director. Also available are two additional data-reduction programs. One of these, called "SUMMARY," summarizes the data from several runs across the subjects or conditions or segments or any combination of these as required by the researcher. SUMMARY also computes F-statistics to test the assumption of equal group variances and t-statistics to compare group means. The second program prints dwell-time histograms.

These programs were examined for their data-reduction capabilities. These programs were written to carry out certain amounts of data analysis, such as calculating means, variances, standard deviations, printing frequency histograms, testing the assumption of equal variances for the two populations case and doing one-way analysis of variance or t-test to compare group means.

The programs were found to be quite efficient in effectively serving the needs for which they were written. However, some of the experimental studies of the oculometer project required the use of more complex statistical techniques not embodied by these programs. The data-reduction capabilities of these programs could be augmented by adding a few more subroutines such as two- or three-way analysis of variance, analysis of covariance, correlation analysis, etc. In spite of these added features, the programs would still be unable to meet most of the data analysis needs of the researchers. Besides, addition of extra subroutines might make the programs unwieldy, less flexible, and less efficient. So, it was decided to search for a system of analyzing data that could handle various needs in the broad spectrum of data analysis.

SELECTION OF A DATA-ANALYZING SYSTEM WITH HIGHER ANALYTIC CAPABILITIES

There are several systems of analyzing data that are commonly used for data analysis: for example, BMDP (Biomedical Computer Programs), SPSS (Statistical Package for the Social Sciences), SAS, DSIRIS, GENSTAT, etc. There are other standard systems, such as IMSL (International Mathematical and Statistical Library), which may not be so popular; nevertheless, they have analytical capabilities—from elementary to advanced. In the evaluation of a statistical package, the following criteria and considerations play a significant role.

User Interface

If a package is to be useful, it should be well documented. A clear, concise, and well-organized reference manual with index must document exactly what it does. It should not only document language syntax conventions, but also state clearly potential user errors. It should also define procedures in terms of references in the literature, numerical techniques employed, and specification of standard options. Another important consideration is a control statement language. The procedures and options should be named with suitable terms that reflect their functions. Descriptive levels are needed for convenience in input, output statements, and checking control statements. Some other desirable features may include:

(1) Clear indication of how missing values are treated,

(2) Labels and scaling options on graphs,

(3) A control language vocabulary suitable for the users for which it is written,

(4) Clear noncluttered output with some option to request or suppress extra output, and

(5) Some graphical aids such as residual plots and histograms, etc.

Implementation

Implementation of a package at a computer facility is greatly facilitated if the source listing of the program is available. A good package should be portable from one installation to another and should also allow the addition of other programs into the system. Among programming languages, FORTRAN is often preferred for scientific purposes. For analyzing scientific data, a package written in FORTRAN should be preferred.

Statistical Effectiveness

Most data sets require the use of more than one procedure. So, for effective analysis, a convenient file system is needed so that the output from one proceudre can be made available as the input for another procedure: for example, if we want a residual plot, then the residuals from a regression program should be made available as an input for a plotting program. It is equally important that the package have neat and correct formulas. Its algorithms for implementing the formulas must be properly programmed. It must also contain some measures to check the accuracy of the data and procedures used: for example, to verify the accuracy of an inverse of a matrix, it should compute the product of the matrix and its calculated inverse. These comments are based on the report of the Committee on Evaluation of Statistical Program Packages presented at the American Statistical Association annual meeting (ref. 11).

All the characteristic features described above are important, but no one program is universally good with respect to all of them. In addition, the programs of a package must be scrutinized in the context of data analysis needs of the users because a program may be optimal for one problem and may not be so for another. After consulting with researchers at NASA/LaRC and taking other facts into consideration, it was decided to install SPSS (ref. 12) at the NASA computer facility. Several seminars were conducted to explain the usage of SPSS at the NASA facility.

OCULOMETER DATA ANALYSIS USING SOME STATISTICAL TECHNIQUES OF SPSS

Data analysis means different things to different people depending on their needs and level of statistical training. Techniques used in data analysis vary from the simple computation of statistics (e.g. mean, mode, median, variance, etc.) and display of histograms to advanced methods of multivariate analysis. In some cases, data analysis involves a set of computations or graphic displays; in other cases, it may involve a sequence of steps, each of which may lead to further analysis. The data-reduction capabilities of the SPSS package are tremendous; all of the statistical techniques available in SPSS are not likely to be used in solving a particular problem. In the present investigation, some of these analytic methods are used to analyze the data set that comes from the Daytona study.

The data used in the current investigation was generated by an experimental study in which one of the objectives was to determine if the landing and approach displays could be improved by modifying several aspects of the display. The experiment was conducted uder the terminal configured vehicle program on a General Electric Corporation simulation facility. An oculometer system was used to record scanning patterns of the test subjects. For operational details of the oculometer see reference 8. The landing performance was assessed in terms of three touchdown parameters, namely, range from the 1,000-foot (304.8-m) line on the runway, airspeed at touchdown and vertical speed. Some of the control input variables were also recorded during the tests. The experimental facilities employed in the tests had three main components: the aircraft simulator, the oculometer system, and the computer-driven, picture-generating system. The main display used by the pilots during the study for making approaches was an Electronic Altitude Director Indicator (EADI). This display was presented on the CRT in either the heads-up or heads-down position depending on a particular test session. Different levels of magnification were obtained by changing the size of the displayed image on the CRT and/or changing the position of the pilot's eye. All of the pilot's control: roll, pitch, rudder pedals (yaw), throttles (engine thrust), drag and lift and pitch trim were recorded. In addition, 18 aircraft state variables and 6 oculometer variables were recorded on 2 FM wide-band tape recorders.

The test design consisted of 18 different conditions (runway patterns). These conditions were obtained by altering the basic runway that consisted of 1-m wide stripes outlining the runway with cross stripes every 330 m and 1-m longitudinal stripes. The 18 runways with their main features are described below.

(1) 152-m^2 checkerboard pattern distributed over the entire runway,

(2) 76-m^2 checkerboard pattern distributed over the entire runway,

(3) 38-m^2 checkerboard pattern spread over the entire runway,

(4) 152-m^2 checkerboard pattern distributed over the inside half of the runway width,

(5) 76-m^2 checkerboard pattern distributed over the inside half of the runway width,

(6) 38-m^2 checkerboard pattern distributed over the inside half of the runway width,

(7) 152-m^2 checkerboard pattern distributed over the outside half of the runway width,

(8) 76-m^2 checkerboard pattern distributed over the outside half of the runway width,

(9) 38-m^2 checkerboard pattern distributed over the outside half of the runway width,

(10) 1-m wide lines with raster and an extrrnal checkerboard pattern,

(11) 152-m^2 checkerboard pattern distributed over inside half of the runway's width,

(12) 76-m^2 checkerboard pattern distributed over the inside half of the runway's width,

(13) 152-m^2 checkerboard pattern distributed over the outside half of the runway's width,

(14) 76-m^2 checkerboard pattern distributed over the outside half of the width of the runway,

(15) 1-m lines with no raster,

(16) 3-m lines with no raster,

(17) 1-m lines with a raster, and

(18) 3-m lines with a raster.

Seven pilots participated in the experiment, which was carried out in six test sessions. Before a test, each pilot was given an hour and a half training period. During the training period, the pilots made practice runs and familiarized themselves with the simulator and the displays. Before collecting data, the test director made sure that the pilot had learned the display. The six test sessions were conducted; these can be summarized as follows:

Session I: A magnification of 0.8 was used with a heads-down position. All the pilots except the NASA test pilots flew three replications of each runway configuration. Due to scheduling constraints, the NASA test pilots flew an abridged version with less than 18 runways.

Session II: A 0.43 magnification factor in the heads-up configuration was used. Each pilot flew 3 replications with runways 3, 5, 7, 9, 16, and 17.

Session III: All of the pilots made 3 replications with a 0.8 magnification factor in the heads-up position on runways 3, 5, 7, 9, 16, and 17.

Session IV: In this session, runways 7, 9, 10, 14, 15, and 17 were tested. Each pilot flew 3 replications with a 0.32 magnification in heads-down mode.

Session V: In this session, symbols were not used other than the perspective runway and the horizon. All of the pilots flew 3 replications on the selected runways 7, 9, 10, 14, 15, and 17 in the heads-down mode.

Session VI: Using a magnification of 0.8, each of the pilots flew 7 replications in the heads-down configuration. Symbols only and no perspective runways were used.

The preceding details regarding the background of data collection are based on reference 2 and a proposed NASA technical paper by Marvin C. Walier, Randall L. Harris, Sr., and Seymour Salmirs. This proposed technical paper deals with some effects of changing several aspects of an advanced display for instrument approach and landing.

DATA ANALYSIS

Introduction

The first step in the data analysis was to examine the data for errors. This was done by listing the data values and scrutinizing them for outliers, blunders, or nonnumeric symbols. In usual circumstances, when observations are recorded manually by observers, it is rather important to screen and edit data before any elaborate analyses because errors in data can produce fascinating results which are sometimes interpretable, sometimes not, but nevertheless incorrect. To study the distributional characteristics of the variables, SPSS has two subprogram:: CONDESCRIPTIVE and FREQUENCIES. Both these subprograms have several options to obtain basic information about the distribution of the variables. The following symbols are used in this study:

VSI	vertical speed
ASER	airspeed
RANGE	range from the 304.8-m (1,000-ft) line on the runway
ERLOC	localizer error
PITCH	stick position
ROLL	wheel position
THROTT	throttle
RUDPOS	rudder position
PTRIM	pitch trim

PDFD1 to PDFD9 represent the variables related to the scanning behavior of the pilots in the flight director.

Subprogram CONDESCRIPTIVE

The subprogram CONDESCRIPTIVE is appropriate to obtain descriptive statistics for any variable(s) which is more or less continuous and has measurement at inverval scale. So this subprogram was applied to performance variables: VSI, ASER, RANGE and ERLOC. Some of the results are arranged in tables 1 and 2. The descriptive statistics in these tables were obtained by considering only segment 3 (the part of the flight below 21.3 m). The various summary statistics give us a general idea about the underlying distributional characteristics of the variables. The mean measures the central tendency; standard deviation and variance indicate the amount of variability. Similarly kurtosis and skewness are useful to study the shape of variables' distribution. Kurtosis provides a measure of relative flatness or peakedness of the distributional curve of a variable, and its value is zero for a normal distribution. A negative value of kurtosis implies that the curve of the distribution is flatter than the normal distribution curve, while a positive value of kurtosis means that the underlying distribution of the variable is more peaked than the normal curve. Skewness indicates the departure from symmetry of a normal curve. The value of skewness for normal distribution is zero because its curve is perfectly symmetrical. A positive value of skewness means that the distribution has a long tail to the right, that is, the cases are clustered more to the left of the mean with most of the extreme values to the right. A negative skewness means that the distribution of cases tails out on the left. From table 1, it seems that the distribution shapes of the variables ASER and ERLOC are similar to normal distribution because their skewness and kurtosis have values close to zero. The kurtosis for variable RANGE is 8.05 and suggests that the distribution of the RANGE has a sharp (narrow) peak. Similar observations can be made regarding distribution of the variables in table 2.

Subprogram FREQUENCIES

Subprogram FREQUENCIES is used to compute frequency distribution tables of discrete or classificatory variables. An initial examination of frequency tables will help the user to determine that each variable has sufficient variability to be used in subsequent relational analysis. In addition to the frequency distribution tables, FREQUENCIES computes descriptive statistics and also prints frequency histograms. Before requesting a full range of descriptive statistics, the user must consider their relevance by examining the scale of measurement of the variables. FREQUENCIES operates under two modes: GENERAL and INTEGER. The control input variables PTRIM, PITCH, ROLL, RUDPOS, and THROTT are analyzed by this subprogram in GENERAL mode. Some of the results are presented in tables 3, 4, and 5.

The subprogram also produced adjusted frequencies and histograms not reported in the tables. The observations from tables 3, 4, and 5 reveal that the underlying distributions of all the control variables are positively skewed (tailing out on the right). They all have significant positive values of kurtosis which indicate sharper distribution peaks. Some interesting observations regarding the number of inputs can be made by simple examination of the relative frequency and cumulative frequency columns of table 4 and 5. All except PITCH have modes equal to zero. It appears that pilots made a maximum number of inputs for PITCH and a minimum number of inputs for THROTT.

Summary statistics, frequency tables, and frequency histograms seem to suggest departure from shape and symmetry, and hence lack of normality exists in the distributions of the variables. Further assessment of deviation from normality can be made by looking at normal probability plot, half-normal probability plot, and detrended normal probability plot. Unfortunately these plots are not available in the SPSS package, but the subprogram P5D of the BMDP package has this data analysis capability. Most standard tests of hypotheses about means and variances assume that the variables are normally distributed. If it is not reasonable to make the assumption of normality in a particular case, certain transformations can be used to induce normality. Since the histograms of ROLL, PITCH, and RUDPOS are highly skewed with a long tail to the right, a logarithmic or square root transformation might be appropriate. Transformations induce normality by changing scale. It is rather difficult to determine exact change of scale, and success in finding a good transformation depends on experience in a particular field of application. In the present case, however, one can choose to do further analysis without trying transformations because the number of cases is large. Since most statistical procedures assume normality of the populations, it may be useful to make further comments concerning normality. In actual practice, very few populations satisfy completely the assumption of normality. It has been observed that small departures from normality do not seriously affect the precision of the estimates and the reliability of statistical inferences. It is very difficult to determine precisely the effects of nonnormality: different statistical techniques are affected to different extents. Furthermore, since no single measure of nonnormality is generally accepted, it is not possible to state general rules that will apply in all cases. At the best, the selection of an appropriate method when nonnormality exists is something of an art at present. However, there are certain guidelines that one can use: for example, if we know very little about the distributional aspects of a population, the nonparametric methods may provide the best solution. In some cases certain transformations may help induce normality: for example, the distribution of measurements on plants and animals can be made approximately normal by using logarithmic transformations.

Comparison of Group Means by t-Test

The planning of test sessions allows the following meaningful comparisons:

(1) Comparison of the effects due to levels of magnification, e.g. magnification = 0.8 vs. magnification = 0.32 in the heads-down case with runways 7, 9, 10, 14, 15, and 17, and magnification = 0.8 vs. magnification = 0.43 in the heads-up position with runways 3, 5, 7, 9, 16, and 17;

(2) Study of the effects of runways and symbols vs. runways only vs. symbols only using a magnification of 0.8 in heads-down mode with runways 7, 9, 10, 14, 15, 17, and 20;

(3) Comparison of the effects of heads up vs. heads down using runways 3, 5, 7, 9, 16, and 17 with a magnification of 0.8.

The above comparison of group means can be studied by applying t-test. The SPSS package offers two types of t-tests: independent samples t-test and paired (correlated) samples t-test. In the present case, the independent samples t-test was used. The analytical capabilities of the subprogram t-test are divided into two cases described below.

Case I: It compares group means assuming equal group variances ($\sigma_1^2 = \sigma_2^2 = \sigma^2$). If $\overline{X}_1$ and $\overline{X}_2$ represent means of two independent random samples of sizes N_1 and N_2 with variances S_1^2 and S_2^2, selected from two populations, then the subprogram tests the following type of hypotheses:

$$H_o:\ \mu_1 = \mu_2 \text{ vs. } H_a:\ \mu_1 \neq \mu_2$$

The decision rule uses the test statistics computed as

$$t = \Big((\overline{X}_1 - \overline{X}_2) - (\mu_1 - \mu_2)\Big)/\Big(S_p^2(\frac{1}{n_1} + \frac{1}{n_2})\Big)^{1/2}$$

where

$$S_p^2 = \Big((n_1 - 1)\ S_1^2 + (n_2 - 1)\ S_2^2\Big)/(n_1 + n_2 - 2)$$

represents a pooled estimate of the common variance σ^2. The statistic t follows t-distribution with $(n_1 + n_2 - 2)$ degree of freedom.

Case II: In this case the two population variances σ_1^2 and σ_2^2 are not equal. The hypotheses tested are the same as in case I, but the test statistic is computed as

$$t = \left((\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)\right) / \left((S_1^2/n_1 + S_2^2/n_2)\right)^{1/2}$$

It follows approximately the student's t-distribution with degrees of freedom (df) given by the formula

$$df = \left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)^2 \Bigg/ \left[\frac{(S_1^2/n_1)^2}{n_1-1} + \frac{(S_2^2/n_2)^2}{n_2-1}\right]$$

In addition, the subprogram t-test verifies the assumption of equal variances by testing the hypotheses

$$H_o:\ \sigma_1^2 = \sigma_2^2 \text{ vs. } H_1:\ \sigma_1^2 \neq \sigma_2^2$$

If the null hypothesis H_o: $\sigma_1^2 = \sigma_2^2$ is accepted, results obtained in case I are used to draw statistical inference, otherwise the results of case II should be used to make inference.

We applied the t-test to compare three groups: runways ana ,ymbols (G_1) vs. runways only (G_2) vs. symbols only (G_3). Magnification of 0.8 was used in heads-down mode with runways 7, 9, 10, 14, 15, and 17. Some of the results for the selected variables are arranged in tables 6 and 7. It is observed from table 6 that the effects of runways and symbols and runways only differ significantly in terms of the variables ROLL and VSI at a five percent level of significance. It is noted that the pilots made fewer inputs when symbols were removed. This may be due to the fact that a smaller amount of information presented on the display does not encourage the pilots to make as many control inputs. From table 7, it follows that the effects of the groups runways and symbols and symbols only are significantly different for the control variables PITCH and ROLL at a five percent level of significance. The differences among the performance variables (listed in the table) were not found statistically significant. The level of significance used in all the tables is five percent. Comparison of symbols only and runways only was also made, but the results are not included in the tables.

Although the complete set of the variables regarding scanning behavior, control inputs, and landing performance was analyzed, only some selected variables are reported in the tables. The observations made here apply strictly to only these variables. One of the objectives of this investigation was to explore and recommend a general course of data analysis, so an exhaustive analysis of any particular study was not attempted.

Table 8 shows the comparison of heads up vs. heads down. Nine of the variables related to a pilot's scanning behavior are listed. These variables represent the pilot's dwell times on various locations within the flight director. From table 8, it is observed that the effects of heads up vs. heads down differ significantly for three variables only: PDFD3, PDFD5, and PDFD8. On the average, the scanning activity of the pilots in the heads-up mode is consistently higher in these three locations of the flight director. Table 9 is a continuation of table 8, and it shows the comparison of heads-up and heads-down modes for four control inputs and four performance variables. It is shown in table 9 that the control activity in the heads-down mode was higher for the variables RUDPOS, THROTT and PITCH, and it was found significant at the five percent level. Among the performance variables, VSI, RANGE, and ERLOC were found to have significant differences at the five percent level. The results in tables 8 and 9 were obtained by using runways 3, 5, 7, 9, 16, and 17.

Three different levels of magnification were studied, and some of the results are listed in tables 10 and 11. Table 10 compares 0.8 magnification with 0.32 magnification in the heads-down mode. Differences in PITCH, ASER, and ERLOC were found statistically significant at the five percent level. In case of PITCH, there was more control input for 0.8 magnification. Performance considerations also favored a magnification level of 0.8. Results in table 11 indicate that the effects of magnification = 0.8 vs. magnification = 0.43 differed significantly at the 5 percent level for the variables PITCH, ROLL, and ERLOC. It appears that 0.8 magnification resulted in higher control activity and smaller localizer error (ERLOC). In all the tables it should be noted that, when F-value is found significant, it implies that the assumption of equal group variances is violated; hence, the appropriate t-test that uses separate variance estimate should be employed.

n-Way Analysis of Variance

The present study involves three factors of interest: magnification at three levels (0.8, 0.43, 0.32), head position at two levels (heads up, heads down), and displays at three levels (runways and symbols, runways, only, symbols only). The structure of test sessions clearly reveals that the study was not planned as a factorial experiment. One traditional approach was adopted, that is, to hold all other factors constant except the one whose different levels are to be compared. But this approach does not permit the study of different n-way interactions among the factors. The planning of the experiment was not appropriate for the application of statistical techniques with higher analytical capabilities such as n-way analysis of variance and convariance.

Factor Analysis

Factor analysis assumes that the observed variables are a linear combination of some underlying factors which cannot be observed. Some of these hypothetical factors are unique to each variable and some are assumed to be common to two or more variables. It is only the common factors that contribute to the covariation among the observed variables. The uses of factor analysis are primarily exploratory or confirmatory depending on the major objectives of the experimenters. In each case, three basic steps are involved: preparation of covariance matrix, extraction of initial factors, and rotation to a terminal solution. In the present investigation, the factor analysis was used for exploratory purpose only. The subprogram FACTOR was applied to the set of variables consisting of IN1-IN3, IN7-IN9, IN13-IN15, PDFD1-PDFD9, PITCH, ROLL, RUDPOS, THROTT, VSI, ASER, RANGE, and ERLOC.

There is a large variety of options in factor analysis, and most of these options are to a large degree superficial. The subprogram FACTOR offers five different methods of factoring and four methods of rotating factors. We used principal factoring without iteration (PA1) and principal factoring with iteration (PA2) to obtain initial factors. For rotating factors, all four methods were tried. For the sake of illustration, some of the results obtained by PA2 with VARIMAX are presented in table 12.

Eigenvalues associated with each factor represent the total variance accounted for by that factor. The factors extracted are in the order of their importance.

Factor analysis is a complex, time consuming, but powerful technique. Unfortunately we did not have the time to pursue the applications of this technique in detail, and no attempt has been made to draw inference from the limited results.

CONCLUDING REMARKS

The data-reduction capabilities of the programs currently used by the researchers on the oculometer project at NASA/LaRC were examined. It was noted that the major data-reduction program called SUPER and another program called SUMMARY were well-written programs. These programs were designed for limited data analysis such as computing mean, variance, standard errors, comparing group means, verifying assumption of equal population variances, and printing histograms. Although these are quite efficient programs for the limited purposes they were designed for, they lack the flexibility and options to handle missing values, obtain the full range of summary statistics, and have no analytical capability to verify certain basic assumptions such as normality and constant error variance. The data analysis needs of the scientists on the oculometer project were growing rapidly, and the current programs were found inadequate to meet these growing needs. Under the current investigation, a search was opened to find a suitable system of analyzing oculometer data on the NASA/LaRC computer facility. Several standard packages including SPSS, BMDP, SAS, and IMSL were considered. After carefully considering the merits of the various packages and the data analysis requirements of the researchers at NASA/LaRC, it was decided to install the SPSS package on the NASA computer. In addition, two seminars and several meetings with the oculometer researchers were conducted to discuss and illustrate data-analyzing capabilities of the subprograms in the SPSS package.

Many studies have been conducted on the oculometer project. Data analysis needs differ from one study to another and include a wide variety of statistical procedures—from elementary to advanced, so the research efforts were directed toward exploring a general system of analyzing oculometer data rather than focusing on a particular study. There are certain techniques that are commonly employed by most studies at the preliminary stages of data analysis, such as data screening and editing subroutines. The Daytona study provided the data for the present investigation. The data set was screened to detect recording errors, blunders, or outliers, but no such errors were found. Two subprograms, CONDESCRIPTIVE and FREQUENCIES, were applied to obtain summary statistics and frequency tables and histograms in order to study the distributional characteristics of the variables. It was noted that some of the variables had highly skewed distributions with long tails. The Daytona study was planned to investigate the effects of three factors: magnification at three levels (0.8, 0.43, 0.32), head position at 2 levels (head up, heads down), and displays at 3 levels (runways and symbols, runways only, symbols only). The various comparisons of interest were made by the subprogram T-TEST. The planning of the experiment did not allow the use of more powerful techniques, such as analysis of variance (subprogram ANOVA) and analysis of covariance. Application of the t-test revealed significant (at 5% level) differences in the effects due to different levels of factors. Subprogram FACTOR was applied to explore the data reduction possibilities. Initial factors were extracted using PA2 and VARIMAX. Applications of this technique were not followed in detail due to time constraints.

Certain other programs, such as subprograms PARTIAL CORR and DISCRIMINANT, would have been useful in the current study but were not applied due to time limitations. The SPSS package offers several other advanced techniques, such as subprograms CANCORR and GUTTMAN SCALE, etc., which were not appropriate for the present study. There are also available numerous nonparametric methods which would be useful to the studies measuring data on nominal and ordinal scales.

It should be noted here that the selection of the pilots who participated in the experiment was not random. The criterion of availability makes the basic sample somewhat like a convenience sample rather than a random sample. One needs be very careful in interpreting the inference drawn from such a sample.

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Table 1. Descriptive statistics; magnification = 0.8, heads up, symbols, runway.

	Variables			
	VSI	ASER	RANGE	ERLOC
Mean	-487.64	-3.51	569.98	-35.39
Standard Error	20.79	0.43	117.84	4.61
Standard Deviation	260.55	5.39	1476.56	57.70
Variance	67886.01	29.04	2180217.2	3328.8
Kurtosis	2.81	0.52	8.05	-0.25
Skewness	-1.25	-0.74	1.92	-1.22
Minimum	-1711.48	-19.56	-2628.5	-176.45
Maximum	-92.57	8.91	9357.2	31.38
Sum	-76559.9	-550.88	89486.2	-5556.5

No. of valid cases = 157

Table 2. Descriptive statistics; magnification = 0.8, heads down, no symbols, runway.

	Variables			
	VSI	ASER	RANGE	ERLOC
Mean	-678.71	-1.30	256.93	-19.71
Standard Error	28.38	0.59	115.75	4.50
Standard Deviation	329.69	6.84	1344.91	52.26
Variance	108698.2	46.82	1808789.6	2730.68
Kurtosis	-1.22	-0.52	11.42	2.76
Skewness	-0.08	-0.34	2.34	-2.10
Minimum	-1317.78	-16.94	-3442.4	-187.89
Maximum	-141.43	12.67	8244.04	26.24
Sum	-91626.1	-175.54	34685.8	-2660.35

No. of valid cases = 135

Table 3. Summary statistics; magnification = 0.8, heads down, symbols, runway.

	Variables				
	PITCH	ROLL	THROTT	RUDPOS	PTRIM
Mean	2.88	1.74	0.65	0.88	0
Standard Error	0.14	0.12	0.05	0.087	0
Median	2.25	0.99	0.44	0.32	0
Mode	1.00	0	0	0	0
Standard Deviation	2.41	2.11	0.84	1.51	0
Variance	5.82	4.45	0.699	2.28	0
Kurtosis	4.17	0.996	1.997	8.92	0
Skewness	1.72	1.32	1.38	2.53	0
Range	15.00	10.00	4.00	10.00	0
Minimum	0	0	0	0	0
Maximum	15.00	10.00	4.00	10.00	
Sum	871.00	526.00	197.00	265.00	

No. of valid cases = 302

Table 4. Frequency distributions of control variables; magnification = 0.8, heads down, symbols, runway.

ROLL				PITCH			
Code	Abs. Freq.	Relative Freq. (Pct)	Cumulative Freq. (Pct)	Code	Abs. Freq.	Relative Freq. (Pct)	Cumulative Freq. (Pct)
0	22	7.3	7.3	0	115	38.1	38.1
1	78	25.8	33.1	1	73	24.2	62.3
2	68	22.5	55.6	2	35	11.6	73.8
3	43	14.2	69.9	3	17	5.6	79.5
4	30	9.9	79.8	4	20	6.6	86.1
5	26	8.6	88.4	5	19	6.3	92.4
6	13	4.3	92.7	6	11	3.6	96.0
7	6	2.0	94.7	7	7	2.3	98.3
8	6	2.0	96.7	8	4	1.3	99.7
9	4	1.3	98.0	10	1	0.3	100.0
10	1	0.3	98.3				
11	1	0.3	98.7				
12	1	0.3	99.0				
13	2	0.7	99.7				
15	1	0.3	100.0				

Table 5. Frequency distributions of control variables; magnification = 0.8, heads down, symbols, runway.

	RUDPOS				THROTT		
Code	Abs. Freq.	Relative Freq. (Pct)	Cumulative Freq. (Pct)	Code	Abs. Freq.	Relative Freq. (Pct)	Cumulative Freq. (Pct)
0	185	61.3	61.3	0	160	53.0	53.0
1	52	17.2	78.5	1	100	33.1	86.1
2	25	8.3	86.8	2	32	10.6	96.7
3	19	6.3	93.0	3	7	2.3	99.0
4	10	3.3	96.4	4	3	1.0	100.0
5	8	2.6	99.0				
6	1	0.3	99.3				
10	2	0.7	100.0				

Table 6. Runways and symbols (G_1) vs. runways only (G_2).

Variable	Mean	F Value	2-Tail Prob.	Pooled Variance Estimate T Value	Pooled Variance Estimate 2-Tail Prob.	Separate Variance Estimate T Value	Separate Variance Estimate 2-Tail Prob.
PITCH							
G_1	3.13	1.26	0.23	0.57	0.57	0.57	0.56
G_2	2.94						
ROLL							
G_1	1.77	2.21	0.000*	2.78	0.006*	2.74	0.007*
G_2	1.08						
VSI							
G_1	-539.02	1.87	0.001*	4.53	0.000*	4.58	0.000*
G_2	-713.17						
ASER							
G_1	-1.736	1.71	0.005*	-1.02	0.309	-1.03	0.305
G_2	-0.898						
RANGE							
G_1	51.85	1.13	0.523	1.53	0.128	1.53	0.127
G_2	-95.80						
ERLOC							
G_1	0.164	1.12	0.548	-0.69	0.491	-0.69	0.492
G_2	0.896						

*Significant at $\alpha = 0.05$

Table 7. Runways and symbols (G_1) vs. symbols only (G_3).

Variable	Mean	F Value	2-Tail Prob.	Pooled Variance Estimate: T Value	Pooled Variance Estimate: 2-Tail Prob.	Separate Variance Estimate: T Value	Separate Variance Estimate: 2-Tail Prob.
PITCH							
G_1	3.128	1.81	0.012*	2.26	0.025*	2.44	0.016*
G_3	2.365						
ROLL							
G_1	1.771	3.37	0.000*	1.92	0.056*	2.23	0.027*
G_3	1.91						
VSI							
G_1	-539.02	1.30	0.262	-0.84	0.401	-0.87	0.384
G_3	-508.52						
ASER							
G_1	-1.736	1.17	0.505	-0.44	0.661	-0.45	0.655
G_3	-1.380						
RANGE							
G_1	51.85	2.56	0.000*	0.86	0.393	0.76	0.449
G_3	-67.20						
ERLOC							
G_1	0.164	1.09	0.687	-0.77	0.441	-0.76	0.447
G_3	1.179						

*Significant at $\alpha = 0.5$

Table 8. Heads up (HU) vs. heads down (HD).

				Pooled Variance Estimate		Separate Variance Estimate	
Variable	Mean	F Value	2-Tail Prob.	T Value	2-Tail Prob.	T Value	2-Tail Prob.
PDFD1							
HU	1.37	0	1.00	1.07	0.285	1.00	0.320
HD	0						
PDFD2							
HU	90.52	24.49	0.000*	-1.66	0.099	-1.77	0.080
HD	250.03						
PDFD3							
HU	157.70	2.88	0.000*	2.05	0.041*	1.98	0.049*
HD	79.09						
PDFD4							
HU	90.73	13.14	0.000*	-0.93	0.355	-0.98	0.327
HD	159.12						
PDFD5							
HU	6459.17	1.19	0.372	-2.11	0.036*	-2.10	0.037*
HD	72.44						
PDFD6							
HU	421.43	1.09	0.644	0.38	0.707	0.37	0.708
HD	395.92						
PDFD7							
HU	1.27	281.48	0.000	-0.88	0.380	-0.94	0.348
HD	20.12						
PDFD8							
HU	2613.84	1.12	0.555	2.24	0.026*	2.24	0.020*
HD	1769.56						
PDFD9							
HU	1.86	1.54	0.025	0.54	0.592	0.53	0.597
HD	1.25						

*Significant at $\alpha = 0.05$

Table 9. Heads up (HU) vs. heads down (HD), magnification = 0.8.

Variable	Mean	F Value	2-Tail Prob.	Pooled Variance Estimate T Value	Pooled Variance Estimate 2-Tail Prob.	Separate Variance Estimate T Value	Separate Variance Estimate 2-Tail Prob.
RUDPOS							
HU	0.75	1.35	0.122	-2.47	0.014*	-2.49	0.013*
HD	1.21						
THROTT							
HU	0.598	1.01	0.948	-2.06	0.040*	-2.06	0.041*
HD	0.821						
PITCH							
HU	2.775	1.17	0.410	-2.83	0.005*	-2.85	0.005*
HD	3.658						
ROLL							
HU	1.578	1.07	0.735	-1.10	0.274	-1.10	0.273
HD	1.880						
VSI							
HU	-596.09	1.08	0.698	-2.95	0.004*	-2.94	0.004*
HD	-494.98						
ASER							
HU	-1.90	1.43	0.065	1.28	0.202	1.26	0.208
HD	-2.70						
RANGE							
HU	181.14	1.24	0.275	2.00	0.047*	2.01	0.045*
HD	-13.58						
ERLOC							
HU	0.991	1.30	0.172	3.16	0.002*	3.13	0.002*
HD	-2.73						

*Significant at $\alpha = 0.05$

Table 10. Magnification = 0.8 vs. magnification = 0.32, heads down.

Variable	Mean	F Value	2-Tail Prob.	Pooled Variance Estimate T Value	Pooled Variance Estimate 2-Tail Prob.	Separate Variance Estimate T Value	Separate Variance Estimate 2-Tail Prob.
PITCH							
mag 0.8	3.13	2.17	0.000*	2.66	0.008*	2.59	0.010*
mag 0.32	2.44						
ROLL							
mag 0.8	1.771	2.18	0.000*	1.80	0.074	1.75	0.082
mag 0.32	1.333						
VSI							
mag 0.8	-539.02	1.10	0.628	1.77	0.078	1.78	0.077
mag 0.32	-595.75						
ASER							
mag 0.8	-1.74	1.56	0.016*	-2.85	0.005*	-2.81	0.005*
mag 0.32	0.029						
RANGE							
mag 0.8	51.85	1.17	0.401	0.45	0.653	0.45	0.651
mag 0.32	8.74						
ERLOC							
mag 0.8	0.164	1.27	0.200	-3.95	0.000*	-3.92	0.000*
mag 0.32	4.149						

*Significant at $\alpha = 0.05$

Table 11. Magnification = 0.43 vs. magnification = 0.8, heads up.

Variable	Mean	F Value	2-Tail Prob.	Pooled Variance Estimate T Value	Pooled Variance Estimate 2-Tail Prob.	Separate Variance Estimate T Value	Separate Variance Estimate 2-Tail Prob.
PITCH							
mag 0.8	3.658	2.58	0.000*	3.78	0.000*	3.80	0.000*
mag 0.43	2.667						
ROLL							
mag 0.8	1.88	2.24	0.000*	2.89	0.004*	2.91	0.004*
mag 0.43	1.211						
VSI							
mag 0.8	-494.98	1.08	0.673	0.70	0.485	0.70	0.485
mag 0.43	-517.43						
ASER							
mag 0.8	-2.70	1.57	0.016*	-1.07	0.284	-1.07	0.285
mag 0.43	-2.03						
RANGE							
mag 0.8	-13.58	1.11	0.564	-1.21	0.227	-1.21	0.227
mag 0.43	109.95						
ERLOC							
mag 0.8	-2.732	1.22	0.288	-2.27	0.024*	-2.27	0.024*
mag 0.43	-0.164						

*Significant at α = 0.05

Table 12. Factors obtained with PA2.

Variable	Communality	Factor	Eigenvalue	Pct of Variance	Cumulative Pct
IN1	0.93970	1	3.79105	24.2	24.2
IN2	0.75108	2	2.80917	18.0	42.2
IN3	0.94751	3	2.25288	14.4	56.6
IN7	0.86659	4	1.54189	9.9	66.5
IN8	0.90732	5	1.17486	7.5	74.0
IN9	0.88118	6	1.06442	6.8	80.8
IN13	0.81981	7	0.86647	5.5	86.3
IN14	0.80563	8	0.82340	5.3	91.6
IN15	0.75343	9	0.75262	4.8	96.4
PDFD1	0.00528	10	0.56421	3.6	100.0
PDFD2	0.57848				
PDFD3	0.24121				
PDFD4	0.72263				
PDFD5	1.00276				
PDFD6	0.76271				
PDFD7	0.38158				
PDFD8	1.00947				
PDFD9	0.02292				
PITCH	0.52975				
ROLL	0.42217				
RUDPOS	0.25025				
THROTT	0.23549				
VSI	0.29899				
ASER	0.38563				
RANGE	0.60283				
ERLOC	0.51656				