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The Multivariate Rotation Method of Quantitative Grain Shape Analysis.

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The Multivariate Rotation Method of Quantitative Grain Shape Analysis

by

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CERTIFICATE OF APPROVAL

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ABSTRACT

The capacity of the multivariate rotation method of quantitative grain shape analysis (Parks, 1983a) to discriminate between sediments derived from different sources and environments is demonstrated using quartz grain shapes. In this procedure, digitized two-dimensional projection outlines are used to calculate thirty-six equally spaced radial lengths, radiating from the center of mass of the outline to the outline boundary, for each of several hundred quartz grains per sample. The set of radial lengths for each grain is rotated to a comparable orientation relative to an empirically derived reference shape. Upon rotation, the set of radial lengths serve as descriptors of the gross shape of the original grain outline. Comparison of these shape variables for each sample using multivariate statistical techniques allows discrimination between sediment samples.

Statistical analysis of estimated factor scores by Hotelling's T^2 test allowed determination of similarities and differences between samples. Significant differences were observed in shape signatures of quartz sand grains from the St. Peter sandstone, a New Jersey beach sand, a Lehigh River sand and a glacial till from Jackson Hole, Wyoming. Similar shape signatures were observed for samples of quartz sand derived from the Devonian age Montebello, Sherman Ridge and Catskill Formations of central Pennsylvania. Comparison of the results of this procedure and those obtained by

graphical and semi-quantitative analysis of Fourier shape descriptors for the same database are comparable. Based upon agreement of results with the Fourier procedure, the multivariate rotation method appears useful as an alternative quantitative grain shape analysis procedure for discrimination of sediments from different sources and environments.

INTRODUCTION

PURPOSE

Quantitative grain shape analysis of quartz sand grains is an accepted procedure for discrimination between sediments from different sources and environments (Ehrlich and Weinberg, 1970; Ehrlich et al., 1974; Yarus et al., 1976; Grothaus and Hage, 1978; Porter et al., 1979). In this investigation, the primary objective is to test the utility of the multivariate rotation method (Parks, 1981) as an alternate technique for quantitative grain shape analysis. Raw data, consisting of digitized projections of two-dimensional boundaries for approximately 400 quartz grains in each of seven samples, were processed using the multivariate rotation method. Most quantitative grain shape studies utilize Fourier shape data for analysis of shape variation. Initial studies (Ehrlich and Weinberg, 1970; Ehrlich et al., 1974) applied analysis techniques focusing on low order harmonics (2-10) carrying information on gross shape. Later investigations (Mrakovitch et al., 1976; Van Nieuwenhuise et al., 1978; Porter et al., 1979; Ehrlich et al., 1980; Mazzulo and Ehrlich, 1980) developed more sophisticated techniques for analysis of information carried by higher order harmonics (11-20), which are more descriptive of medium to fine scale grain shape features.

For purposes of this investigation, results of the multivariate rotation method are compared to those obtained by graphical and semi-quantitative methods described by Ehrlich and Weinberg (1970) on Fourier shape descriptors for the same data set. The rationale for such a comparison is two-fold. Shape analysis of Fourier data is well documented and accepted as a valid procedure. Use of early analysis techniques on the Fourier descriptors allows evaluation of the multivariate rotation method for discrimination of quartz grains on the basis of gross shape. Procedures described in this paper for processing rotated radial data sets reflect initial attempts to obtain information on shape variation in quartz grains and serve as a guide for defining problems for future study.

BACKGROUND

Meaningful characterization of sedimentary particle shape and the determination of its relation to sedimentary processes continue to be objectives of sedimentologists. Particle shape is influenced by a complex combination of factors which include parent rock type, mineral composition, physical properties, weathering processes, abrasion history, mode of transport and diagenetic effects (Blatt et al., 1972; Friedman and Sanders, 1978).

Many attempts have been made to describe particle shape in useful terms, but due to difficulties involved in defining and measuring shape parameters, especially for sand-size particles, most shape studies prior to the 1970's focused on the concepts of roundness and sphericity as originally described by Wentworth (1919) and Wadell (1932, 1935) (Russell and Taylor, 1937; Krumbein and Pettijohn, 1938; Krumbein, 1941; Pettijohn and Lundahl, 1943; Powers, 1953). Other problems with these concepts include the accuracy, precision and reproducibility of shape data, both within a given investigation and between independent studies, due to measurement variation and errors by human operators (Folk, 1972; Blatt et al., 1980). As a result, useful geologic information derived from shape studies based upon roundness and sphericity has been limited.

More recently, and primarily as a result of automated data collection methods that apply computer technology, several investigators (Schwarcz and Shane, 1969; Ehrlich and Weinberg, 1970; Boon et al., 1982; Parks et al., 1982) have proposed methods of quantitative shape analysis which obviate many problems associated with the concepts of roundness and sphericity. Clark (1981) summarizes and reviews several proposed approaches to quantitative shape analysis, stating important factors to be considered, and illustrating advantages and disadvantages of the various strategies discussed. The principal methods currently being applied utilize the digitized projections of two-dimensional grain boundaries as a basis for shape representation. Presently, the method using Fourier derived shape data for shape analysis as proposed by Schwarcz and Shane (1969), and initially applied by Ehrlich and Weinberg (1970), is the most widely developed and well-documented procedure. Results of several studies using the Fourier method on quartz sand samples indicate that populations of grains from a common source and with a similar transport history are characterized by an assemblage of shapes which constitute a unique shape signature (Ehrlich and Weinberg, 1970; Grothaus and Hage, 1978; Van Nieuwenhuise et al., 1978; Porter et al., 1979; Ehrlich and Chin, 1980; Hudson and Ehrlich, 1980; Wagoner and Younker, 1982). This signature can be used to distinguish the assemblage from another having a different source and transport history.

Parks (1981; 1982; 1983a) proposed a multivariate rotation method of quantitative shape analysis in which thirty-six radii spaced at equi-angular intervals, representing the two-dimensional grain boundary, are rotated to an orientation relative to a reference shape. Rotation of grains (i.e. sets of radial lengths) with respect to a reference shape is accomplished by a least-squares procedure to find the best fit. This rotation procedure may allow more meaningful comparisons between grains since grains with similar shapes have a common orientation relative to one another (Parks, 1981). The rotated radials are then used as shape descriptors for further multivariate analysis of the shape variation in quartz sand grains.

PREVIOUS WORK

Schwarcz and Shane (1969), and Ehrlich and Weinberg (1970) proposed and developed an objective procedure for grain shape analysis by which grain shape is quantitatively described. The method involves digitizing the projected two-dimensional boundary of a grain to obtain coordinates of peripheral points. These coordinates are used to determine the center of gravity of the grain outline and to calculate a harmonic Fourier series of the expansion of the radius as a function of the angle about the center of gravity. Such a mathematical model represents the shape as a linear equation, the terms of which represent contributions of known shape components to the overall two-dimensional shape (Ehrlich and Weinberg, 1970). This procedure is based upon evidence indicating that the two-dimensional outline of a grain is representative of a three-dimensional particle (Schwarcz and Shane, 1969; Tilmann, 1973). The harmonic coefficients of the Fourier series are analyzed by graphical and statistical techniques to determine variations in the two-dimensional projection of grain shapes (Ehrlich and Weinberg, 1970).

Limitations of the method have been discussed by several authors (Schwarcz and Shane, 1969; Ehrlich and Weinberg, 1970; Clark, 1981; Parks, 1981). Despite these limitations the method has demonstrated that differences between populations of quartz grains are the result of the geographic and stratigraphic source of the particles as well as the processes acting on the sediments. As currently applied by most investigators, the Fourier method focuses on higher order harmonics (17-20) which are descriptive of medium to fine scale shape variations, as opposed to lower order harmonics (2-10) characterizing overall gross shape (Mrakovitch et al., 1976).

Bokman (1952), using ratios of elongation for quartz grains in thin section, illustrated the usefulness of quartz grain shapes as a means for distinguishing two sandstone lithologies derived from different sources. Application of the Fourier shape analysis method has clearly demonstrated that quartz grain shapes yield meaningful information related to provenance, transportation and deposition of sediments. Several investigators (Ehrlich et al., 1974; Yarus et al., 1976; Van Nieuwenhuise et al., 1978; Porter et al., 1979; Brown et al., 1980; Riester et al., 1982) have shown that detrital quartz, due to its inherent characteristics and overall abundance, is useful both as a natural tracer of sediment transport and accumulation, especially for sand-size material, and as a means for distinguishing between sediment sources. Shape analysis has also been useful for determining relative contributions of sediments mixed together from several sources (Ehrlich et al., 1974; Grothaus and Hage, 1978; Van Nieuwenhuise et al., 1978; Porter et al., 1978; Ehrlich and Chin, 1980; Hudson and Ehrlich, 1980). Potential applications of shape analysis for stratigraphic analysis and correlation were illustrated by Mrakovitch (et al., 1976) and Mazzulo and Ehrlich (1980).

Investigations of the areal distribution and mixing of modern sediments off the Atlantic coast have successfully utilized shape analysis (Brown et al., 1980; Hudson and Ehrlich, 1980; Riester et al., 1982). Yarus (et al., 1976) distinguished between first cycle quartz grains from different igneous and metamorphic rock types. Modification of unique sand population shape signatures by abrasion and selective sorting during transport were observed by Van Nieuwenhuise (et al., 1978). Shape investigations utilizing the Fourier method have been conducted in a variety of sedimentary environments: fluvial (Ehrlich et al., 1974; Yarus et al., 1976; Kennedy and Ehrlich, 1981); beach (Ehrlich et al., 1974; Porter et al., 1979); estuarine (Van Nieuwenhuise et al., 1978); shelf and offshore (Mrakovitch et al., 1976; Hudson and Ehrlich, 1980; Brown et al., 1980; Riester et al., 1982); alluvial (Grothaus and Hage, 1978; Vander Zouwen and Younker, 1981; Wagoner and Younker, 1982); and glacial (Libert and Ridky, 1981).

Parks (1981; 1982; 1983a; 1983b) has proposed a multivariate rotation method of grain shape analysis which focuses on variations of gross shape. Digitized outlines of quartz grains are used to calculate thirty-six radials, spaced at equi-angular intervals, projecting from the center of mass to the boundary of the outline. Rotation of the radial set for each grain relative to an empirically derived reference shape provides a frame of reference for comparison of either large groups of grains or individual grains. The thirty-six radials per grain serve as measured variables descriptive of gross grain shape. Using linear combinations of the thirty-six rotated radials, data sets for each grain are reduced to produce the minimum number of new variables necessary to represent a large percentage of the shape variation observed. These new variables are analyzed by multivariate statistical methods to determine whether significant differences exist between groups of grains.

METHODS

SAMPLING

Quartz grains in the 0.35-0.50 mm (medium sand) size range were obtained from seven sediment samples covering a variety of sources and environments. Sources and localities for the samples (Figures 1 and 2) consist of the following: friable sandstone from the Saint Peter Sandstone, considered to be an ancient near-shore sand, Ottawa, Illinois; recent beach sand from Sandy Hook, New Jersey; a channel bar sample from the Lehigh River, Northampton County, Pennsylvania, which drains a variety of Devonian and Mississippian clastic lithologies in the Appalachian Mountains; pooled channel bar samples from two first-order streams, each isolated within the Montebello or Sherman Ridge Formations (Miller, 1961), both of which are stratigraphically adjacent Middle Devonian sandstones, Perry County, Pennsylvania; pooled channel bar samples from a stream isolated to the Duncannon Member of the Catskill Formation (Dyson, 1967), an Upper Devonian sandstone, Perry County, Pennsylvania; and pooled samples from glacial till in the Teton Mountains, Jackson Hole, Teton County, Wyoming (this sample will be referred to as the Jackson Hole till). Sample preparation is discussed in Appendix 1.

DATA COLLECTION

Two-dimensional projected outlines for approximately 400 grains per sample were digitized. Equipment used for collection of raw shape data is illustrated in Figure 3. The hardware included a

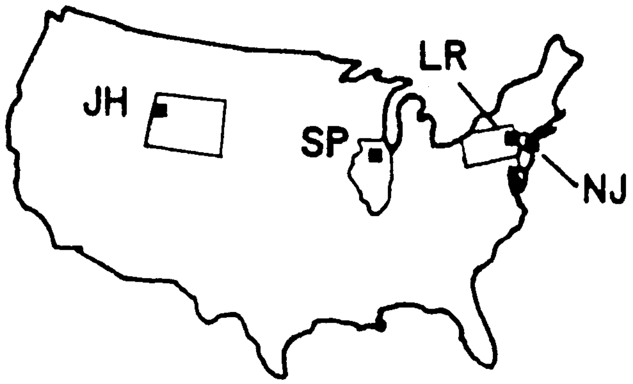

FIGURE 1. Location of samples: St. Peter sandstone (SP); New Jersey beach sand (NJ); Lehigh River sand (LR); and Jackson Hole till (JH).

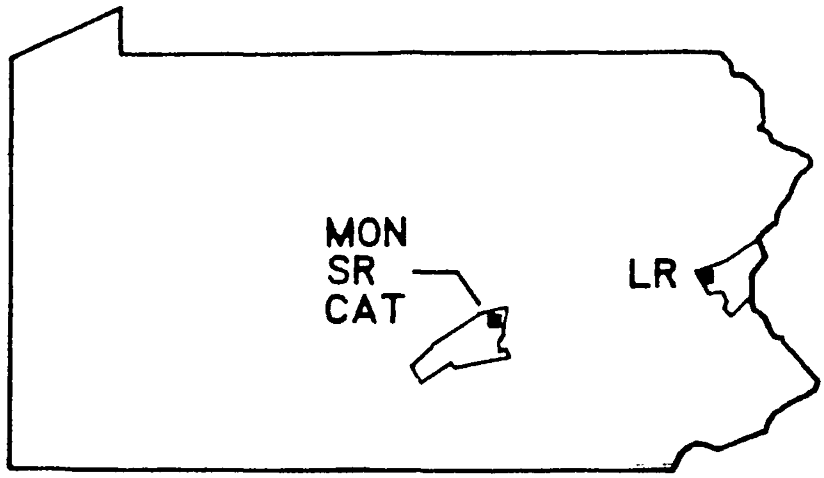

FIGURE 2. Location of samples: Lehigh River sand (LR); Sherman Ridge sand (SR); Montebello sand (MON); and Catskill sand (CAT).

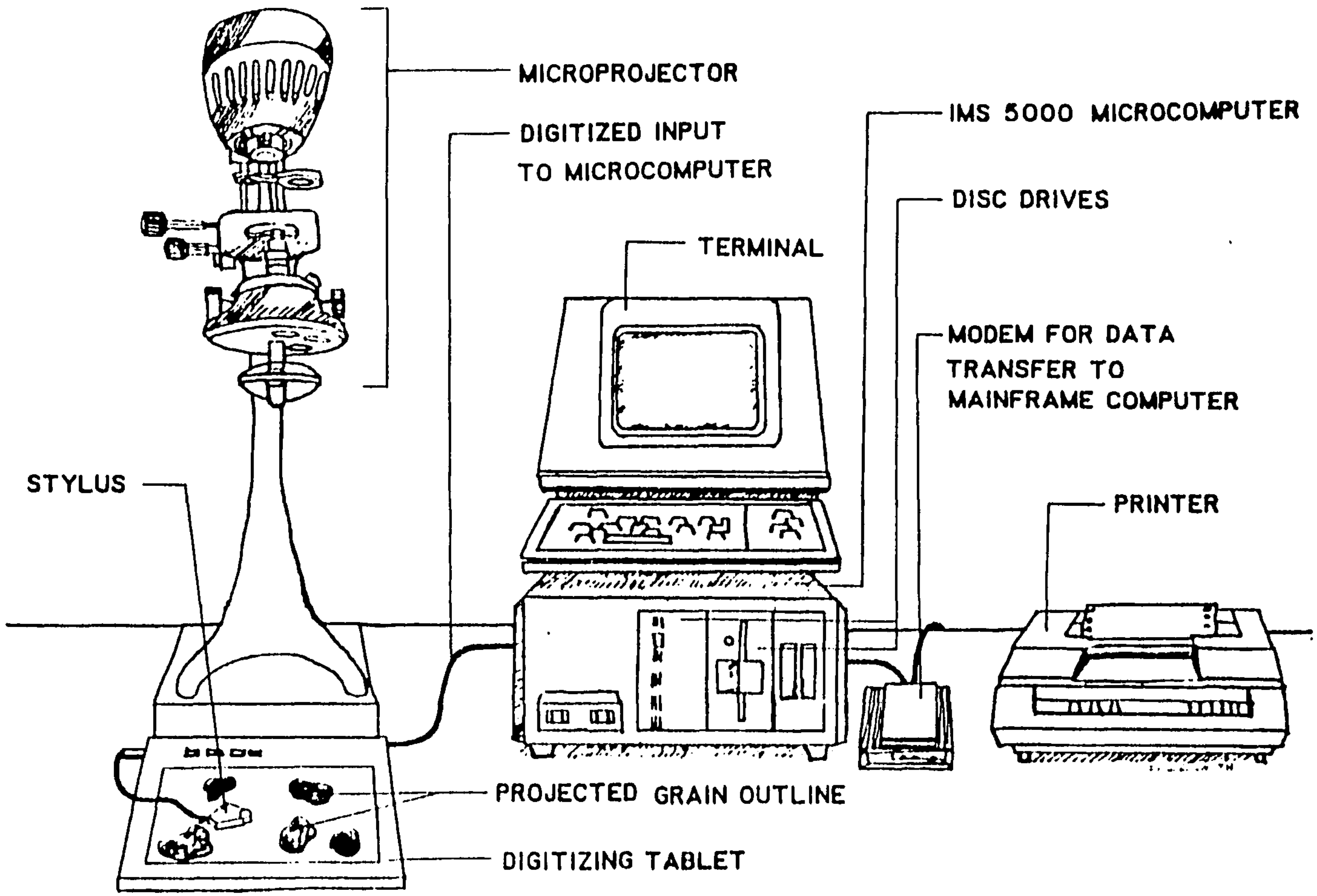

Figure 3. Equipment used for data collection and processing. (Illustration by Jessica Smith)

microprojector, Houston Hipad II electronic digitizing tablet with stylus, and an IMS 5000 microcomputer. The interface between the digitizing tablet and the microcomputer was implemented by FORTRAN programs.

Raw data for quantitative shape analysis was collected by digitizing (i.e. sampling) the projected two-dimensional continuous outline of each grain. Grains were placed loosely on a glass slide. The slide was tapped gently to allow perched grains to come to rest in a stable position. Grain orientation on the slide was not critical in terms of the shape information carried by the projected area of the grain. Tilmann (1973) demonstrated that shape information contained in the maximum projection plane of quartz grains was not significantly different from shape information carried by projection planes of grains in other orientations. Each slide was mounted on a mechanical stage on the microprojector. A 10 mm lens objective projected a two-dimensional darkened image, approximately 2-4 inches in diameter, onto the digitizing tablet. Coordinates for 150-200 points along the edge of the projected image were obtained by manually tracing the periphery of the outline in a few seconds with the stylus of the digitizing tablet. In the stream digitizing mode, the position of the stylus was automatically sampled at intervals of twenty-five milliseconds. The coordinates were stored on floppy disks.

DATA PROCESSING

Data processing utilized a series of FORTRAN programs by Parks (in preparation). These programs were modified to execute on an IMS 5000 microcomputer and to access data files stored on disk for the CDC CYBER 730 mainframe computer. Processing of X-Y coordinates which described the two-dimensional profiles began with calculation of the center of mass for the outline, using an algorithm by Hall (1976). Radial lengths from the center of mass to peripheral points on the outline were calculated for every third pair of X-Y coordinates, resulting in the calculation of fifty to sixty-five radial lengths on the average for each grain. Every third coordinate pair was used to calculate radial lengths that described the overall shape and to reduce computational time required for calculations. The fifty to sixty-five radial lengths were reduced to thirty-six radials equally spaced at ten degree intervals about the grain center of mass by a cubic interpolation procedure (Parks, in preparation). These thirty-six equally spaced radial lengths, considered as independent variables, defined the gross shape of the original outline portrayed by the X-Y coordinates (Figure 4).

The radial lengths were normalized to the mean radial length of each grain to reduce the size effect due to variations between grains within the size interval. Rotation of normalized radial lengths to a best fit relative to an empirically derived asymmetric reference shape (Figure 5) utilized a least-squares algorithm

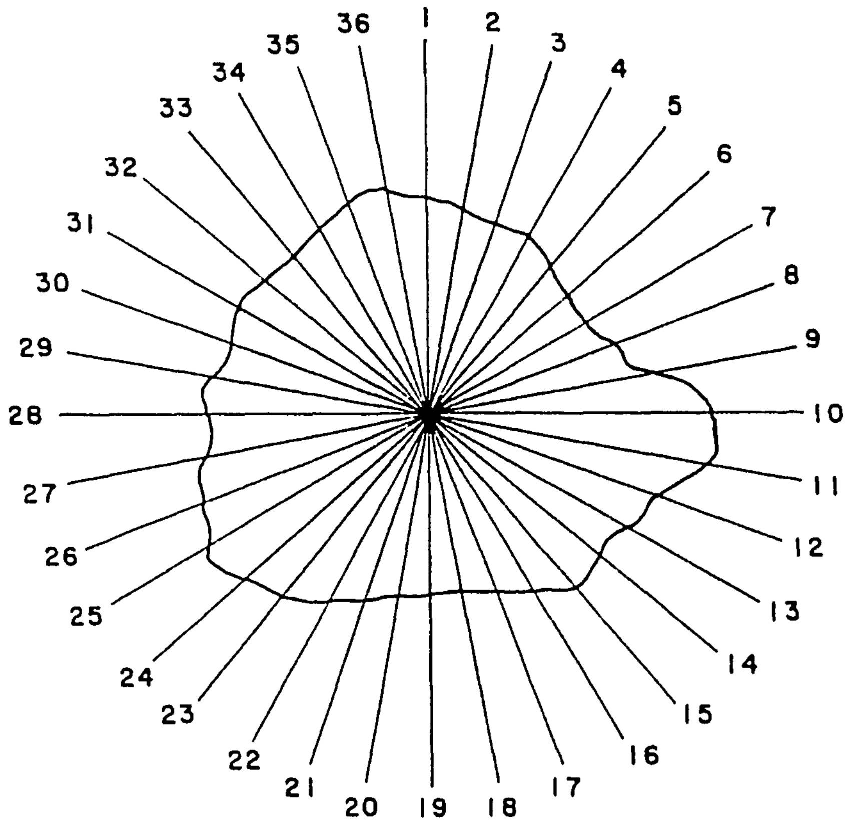

FIGURE 4. Example of grain outline defined by 36 radial lengths at equally spaced (10^{o}) intervals about the center of mass.

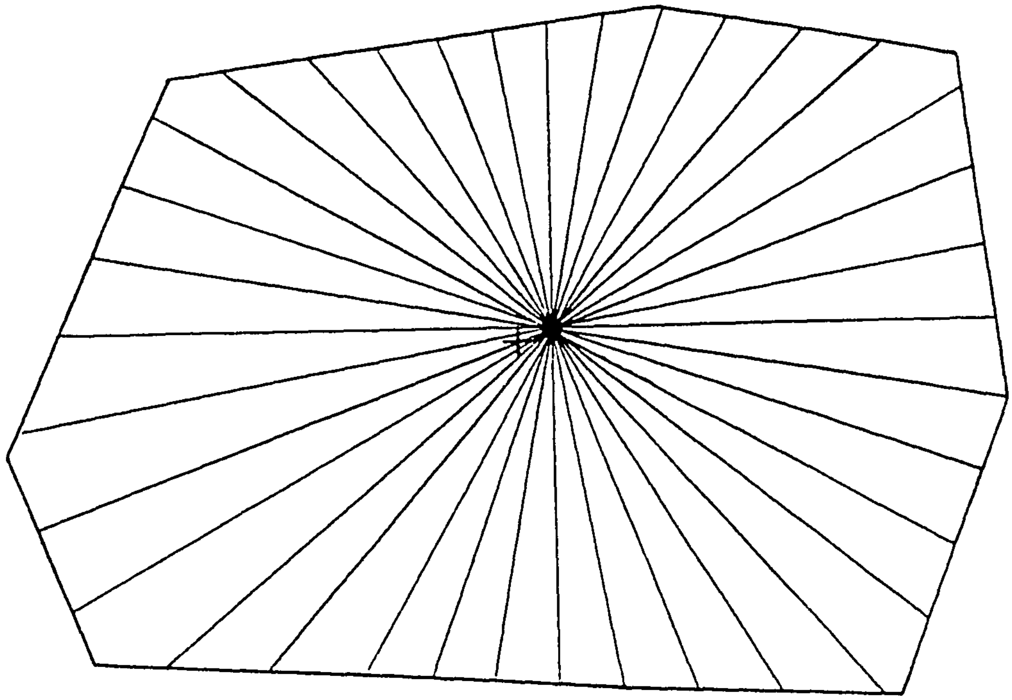

FIGURE 5. Reference shape for rotation of radial sets as defined by 36 equally spaced radial lengths. Note pivot point (●) for rotation is offset from center of mass (+).

(Parks, 1981; 1982). Upon rotation to the initial best fit position, a second rotation was executed after re-ordering the radials such that the grain was, in effect, flipped over. The rotation providing the best fit relative to the reference shape was used for further processing.

Rotation of all grains to a similar position with respect to the reference shape ensured that similarly shaped grains were oriented in the same manner, allowing more meaningful comparisons between either individual grains or groups of grains (Parks, 1981; 1983b). For example, grains with a rectangular shape rotated to a best fit position relative to the reference shape would all have a similar orientation. Pear-shaped grains rotated to a best fit position would have their own unique orientation relative to one another. However, it should be noted that the relationship between orientation of rectangular grains relative to pear-shaped grains was unrelated and arbitrary.

After rotation, the thirty-six radials, serving as shape descriptors for the projected outlines, were used as measured variables for further analysis with multivariate statistical tests.

DATA ANALYSIS

<u>FOURIER METHOD</u>. The rationale for quantitative shape measurement using a Fourier series is thoroughly discussed by several authors (Schwarcz and Shane, 1969; Ehrlich and Weinberg, 1970; Ehrlich et al., 1974; Clark, 1981). Briefly described, this

procedure uses the harmonic coefficients (amplitudes) of a closed Fourier series to characterize the projected two-dimensional outline of a grain. The number of terms calculated for the series is dependent on the precision desired. Each harmonic amplitude represents the contribution of a particular shape component to the overall shape of the grain outline. The set of amplitudes for a grain, referred to as the harmonic amplitude spectrum, are used as variables of shape for further analysis. A sample of quartz grains may be characterized by the mean harmonic amplitude spectrum, which consists of the mean amplitude value for each harmonic of all grains in the sample. Mean harmonic amplitude spectra are compared to discriminate between samples. A variety of graphical and statistical techniques have been applied to analysis of Fourier derived shape data (Ehrlich and Weinberg, 1970; Ehrlich et al., 1974; Mrakovitch et al., 1976; Van Nieuwenhuise et al., 1978; Ehrlich et al., 1980; Hudson and Ehrlich, 1980; Mazzulo and Ehrlich, 1980).

Analysis of Fourier derived shape data for samples in this study provided results of an accepted shape analysis method by which to evaluate the quality of results for sample discrimination using the multivariate rotation method. Fourier derived shape data from this investigation were analyzed using the basic procedure of Ehrlich and Weinberg (1970). Eighteen harmonic amplitudes per grain were calculated using thirty-six rotated radials per grain. Use of rotated rather than unrotated radials as input for Fourier analysis is immaterial, since harmonic amplitudes are rotation-invariant (Clark, 1981). Mean harmonic amplitude spectra graphs were constructed by plotting mean amplitude values against appropriate harmonic number. These graphs were compared by observing differences between corresponding mean amplitude values.

A stepwise discriminant function analysis was used to determine at which harmonics significant differences existed in harmonic amplitude spectra for all possible combinations of samples taken two at a time. This was done in order to verify differences observed in the graphical displays. Calculation of discriminant functions on Fourier amplitude values was executed using program P7M of the BMDP Statistical Software (Dixon, 1981) package. Significance of the comparisons performed by the stepwise discriminant function was determined from an approximate F statistic derived from Hotelling's T^2 and Mahalanobis D^2 statistics for the samples being compared. These results were used to verify conclusions based upon visual observations of graphically displayed mean harmonic amplitude spectra.

<u>MULTIVARIATE ROTATION METHOD</u>. R-mode factor analysis appears to be an obvious approach for reduction of multivariate rotation data consisting of thirty-six rotated radials (variables) for each of several hundred grains in a sample. The number of variables is reduced by using linear combinations of the original variables to

create a few hypothetical variables (factors) that contain 80 - 90 percent of the variance in the sample. The R-mode analysis procedure produces factor loadings which indicate the contribution of each original variable to each of the factors. The factor loadings are then used to calculate factor scores. Factor scores describe the entities (grains) of the original data set in terms of the new hypothetical variables (factors). The size of the original data set is subsequently reduced, since it can be characterized in terms of a few new variables rather than the original thirty-six variables.

Klovan (1975) concisely outlines details for the basic factor model of R-mode factor analysis. Summarized briefly, the procedure uses algebraic matrix manipulations to produce a new frame of reference for the variables of the data set. This is executed in such a manner that the new reference axes for the data coincide with the directions of maximum variance and are uncorrelated. To meet these two criteria, roots are calculated for sets of equations designed to maximize the variance and maintain orthogonality of the factors (Klovan, 1975). These roots are called eigenvalues. The number of axes is usually less than the original number of variables used to characterize the data. Factor scores are calculated from the matrix equation (Klovan, 1975):

$$F = ZAE^{-1}$$

where F is an n*p factor score matrix (n = no. of cases, p = no. of factors), Z is an n*v standardized data matrix (v = no. of original variables), A is the v*p factor loadings matrix, and E^{-1} is the inverse of the diagonal matrix of eigenvalues for the original correlation matrix.

The drawback to using straightforward R-mode factor analysis for comparisons between data sets is that the factor loadings matrix, A, changes for each data set and is automatically centered on the mean for that data set. Consequently, the reference axes also change for each data set. As a result, two different samples cannot be directly compared because data reduction for each sample is performed relative to different frames of reference. Specifically, for any two samples consisting of shape data for several hundred grains each to be compared, the second factor for a sample may not represent the same linear combination of original variables as the second factor for another sample, therefore making comparisons meaningless between the two (Parks, personal comm.). There is also a problem for comparisons if each of several samples is described by a different number of factors. In either case, data for the samples cannot be directly compared for purposes of discrimination.

Parks (1983a) suggested a procedure utilizing an R-mode factor analysis approach which produces a similar data reduction but allows direct comparison of different samples. The technique is a method of calculating "estimated factor scores" that can be directly compared between samples ("estimated" is used here to mean an approximation, not a statistical estimate). The product of the factor loadings matrix and the inverse of the diagonal matrix of eigenvalues is computed for one key or reference sample in the overall group of samples to be compared. This product matrix, referred to as the beta coefficients matrix (Parks, in preparation), is used as a constant in the matrix equation for calculating factor scores for all sets of grains (samples) comprising the study set for the problem under investigation. The standardized data matrix, Z, is post-multiplied by the beta coefficients matrix to calculate estimated factor score matrix for each sample. The new matrix equation is:

$$F = ZB$$

where B is the v x p beta coefficients matrix for the selected reference sample, and which is the product of the factor loadings matrix, A, and the eigenvalue matrix, E^{-1}.

This approach keeps the factor axes constant for the set of variables, therefore computing factor scores for each grain in all samples relative to the same set of factor axes or frame of reference. Comparison of any factor (for example the second factor), as represented by the factor scores, between any two samples is possible since the underlying variables for that factor do not change. Discrimination between samples is possible by determining significant differences between mean factor scores of each factor in the samples. The number of factors remains fixed for all samples because the factors are fixed for the beta coefficients matrix, B.

The beta coefficients matrix for this investigation (Appendix 3) was derived by an R-mode factor analysis (Parks, 1970) of the St. Peter sample. Factor analysis of this sample produced six factors accounting for 91% of the variance in the sample (see Appendix 4 for the factor loadings on variables of the St. Peter sample). The St. Peter sample was selected because the formation is a well-known and thoroughly described lithologic unit in the literature (Thiel, 1935) which has been used in past shape studies (Mazzulo and Ehrlich, 1980), and because the sample was expected to be distinctly different in its shape signature relative to the other samples examined in this study.

Initially, comparison of estimated factor scores was done visually (using factor score plots) to identify sample differences. In these diagrams factor scores for each sample are plotted relative to factor axes, for all possible pairs of factors. Comparison of diagrams for each pair of factors would allow visual identification of differences or similarities between samples. However, since overlap of sets of estimated factor scores was great, even for samples with extremely different shape characteristics, this procedure did not prove useful. Therefore, it was necessary to find another method of analysis.

Statistically significant differences between samples were detected for mean estimated factor scores of the factors using Hotelling's T^2 test. This is a test for equality of means for several variables simultaneously (Morris, 1967). The T^2 statistic is calculated from the Mahalanobis D^2 statistic of the group means. These statistics can be transformed to an F statistic, the significance of which can be determined for a specified level of significance using the appropriate degrees of freedom. These statistics were computed by the BMDP Statistical Software (Dixon, 1981) package, program P3D. Rotated radials were also used as input variables used to calculate T^2, D^2 and F statistics to determine if comparable results could be obtained without the calculation of estimated factor scores.

An overall view of the steps for collecting and analyzing shape data in this investigation using rotated radials as measured shape variables is illustrated in Figure 6. X-Y coordinates describing the projected grain boundary are used to determine the outline center of mass and to calculate the thirty-six radial lengths defining the gross shape of the outline. Radial lengths for each grain are rotated to a best fit with respect to the reference shape. Rotated radial lengths serve as variables for Fourier methods, direct multivariate statistical analysis (Hotelling's T^2 test), or reduction to estimated factor scores. Reduction to estimated factor scores initially requires factor analysis of the rotated radial set for a reference sample to produce the beta coefficients necessary for calculation of the scores.

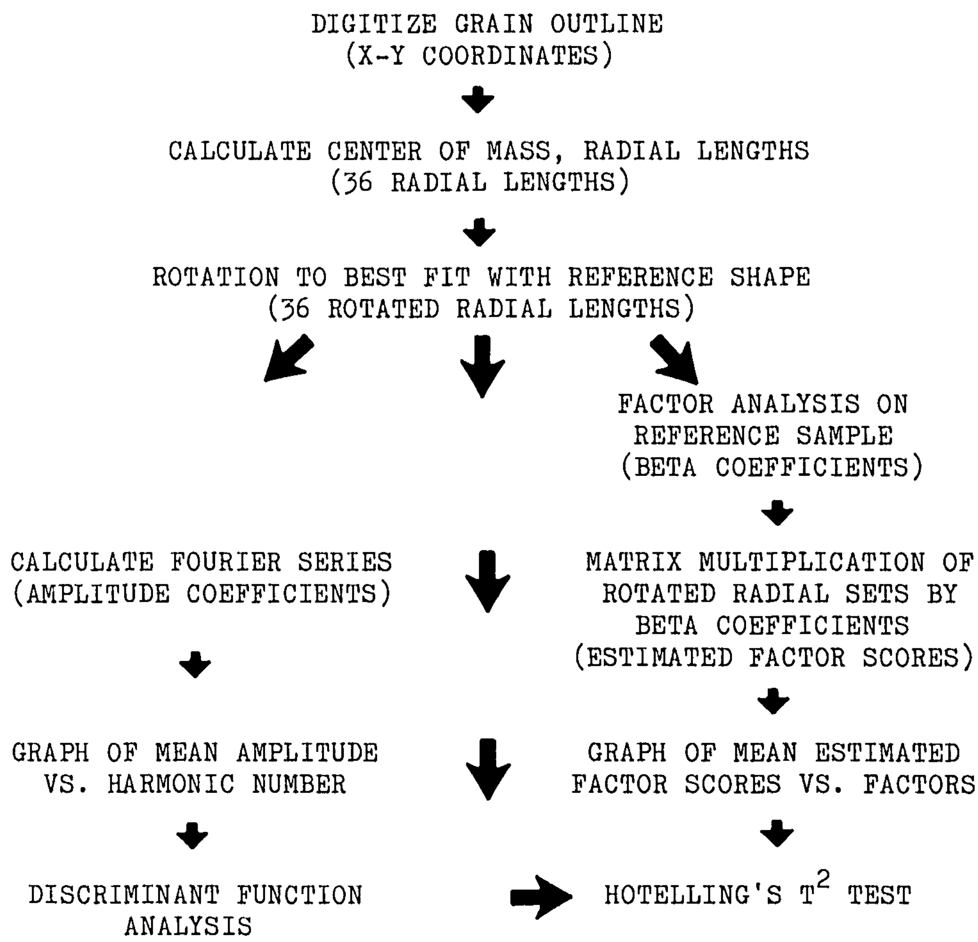

FIGURE 6. Flow diagram outlining steps of quantitative shape analysis used in this investigation.

RESULTS

FOURIER METHOD

Graphical Display. Graphical displays of mean harmonic amplitude spectra reveal differences and overall relationships between samples. Mean amplitude values are plotted against the appropriate harmonic number. The amplitude value for each harmonic is the mean value for all grains in a sample. Samples with relatively low values for mean harmonic amplitudes contain grains with two-dimensional projections which have less irregular shapes than samples with relatively higher mean amplitude values (Mrakovitch et al., 1976).

This relationship is clearly evident in Figure 7. The mean harmonic amplitude spectrum of the St. Peter sandstone sample displays the lowest mean amplitude values for harmonics two through fifteen, which indicates that projections of grains in this sample are less irregular in shape and have less angular surface texture relative to projections of grains in the other samples. This would be expected for sediments deposited in a nearshore environment which have undergone processes producing grains with smooth, rounded surfaces that approach sphericity such as those of the St. Peter sandstone. The New Jersey beach sample has a mean harmonic amplitude spectrum with values somewhat larger than the St. Peter, but consistently less than those of the Lehigh River sand and Jackson Hole till samples for harmonics three through fourteen.

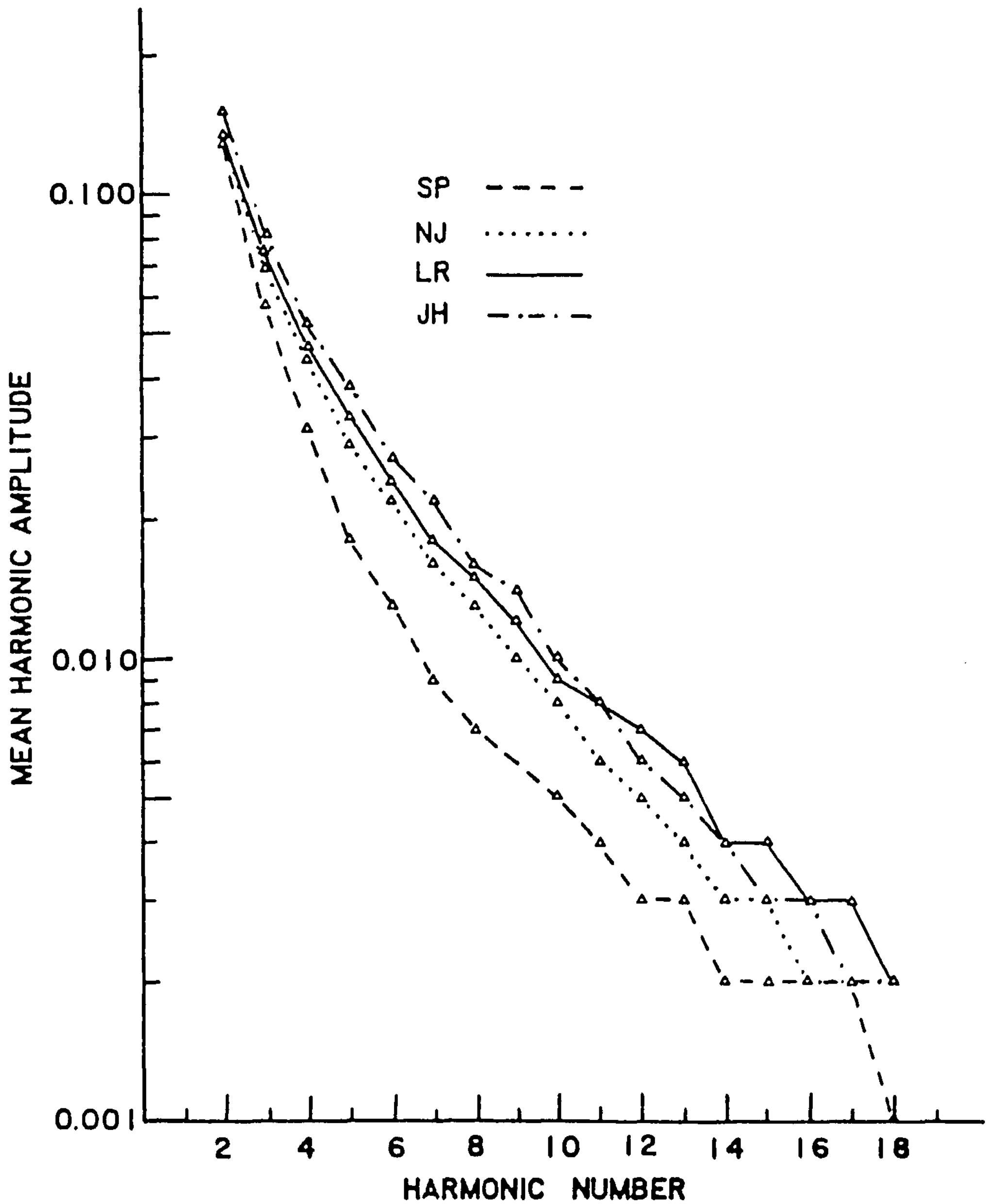

FIGURE 7. Graph of mean harmonic amplitude vs. harmonic number for the St. Peter sandstone (SP), New Jersey beach sand (NJ), Lehigh River sand (LR), and Jackson Hole till (JH) samples. (See Appendix 2 for confidence intervals).

Values of the Lehigh River mean amplitude spectrum are intermediate between those of the New Jersey beach and Jackson Hole till samples for harmonics three through ten. For harmonics eleven through eighteen of the Lehigh sample values remain higher than those of the New Jersey sample, but equal to or higher than the mean values for the till.

The gradation of mean values from the lower values for the St. Peter to higher values for the Jackson Hole sample, as shown in Figure 7, illustrates the departure of grain projections for these samples from smooth, less angular to more angular and irregular shapes. Using conventional terminology of the roundness and sphericity concepts, the St. Peter would be described as having rounded and more spherical grains, while the till would be considered more angular and less spherical. The New Jersey beach and Lehigh River samples would be intermediate between these extremes in terms of roundness and sphericity, with the grains of the New Jersey sample closer to those of the St. Peter in shape characteristics. As for discrimination of the samples represented in Figure 7, based upon observable differences between values of the mean harmonic amplitude spectra, it appears that the samples may be unique and distinctly different.

Figure 8 is a graph of mean harmonic amplitude spectra for fluvial sediments of the Lehigh River and sediments derived from particular Devonian sandstone lithologies, which themselves were

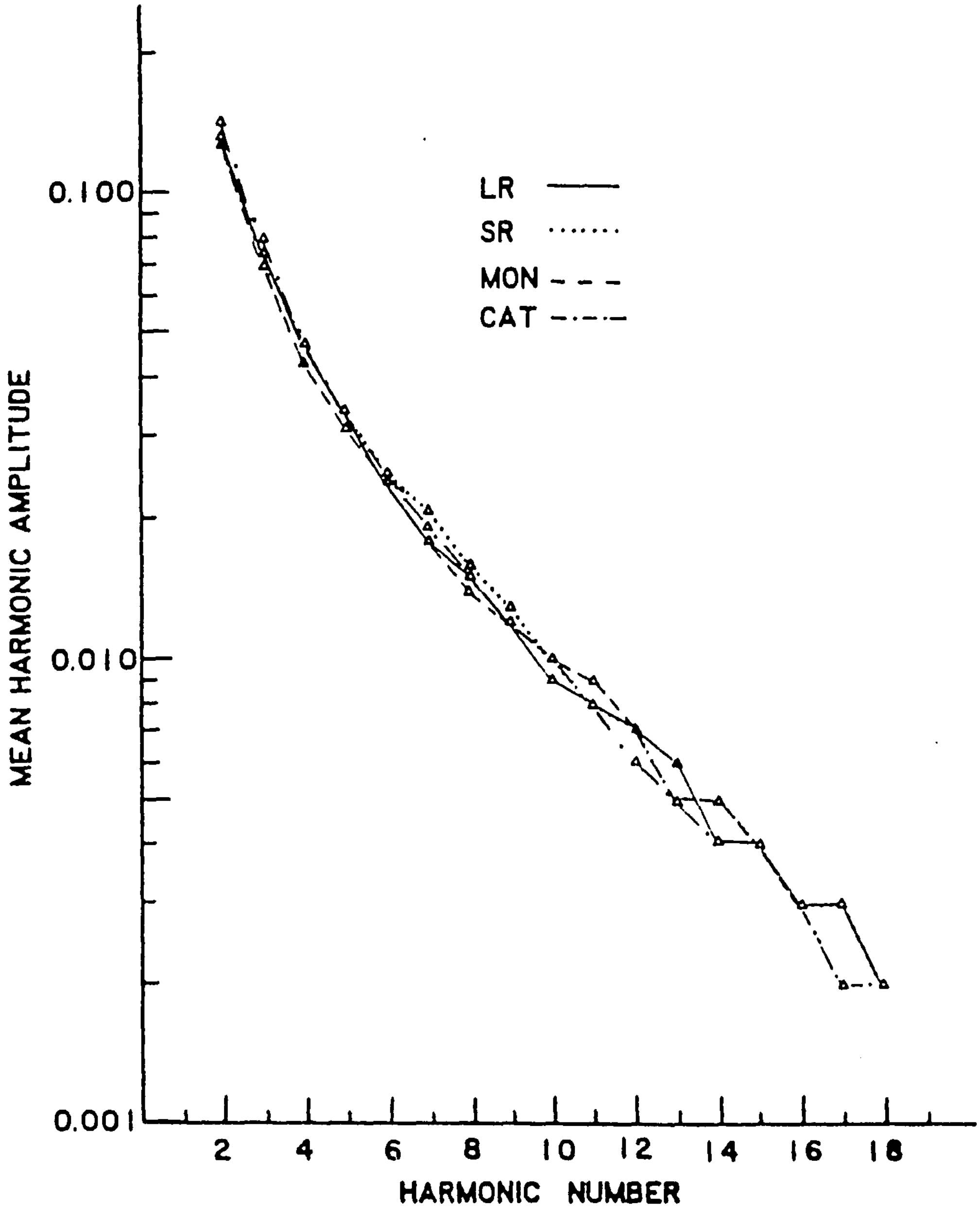

FIGURE 8. Graph of mean harmonic amplitude vs. harmonic number for the Lehigh River sand (LR), Sherman Ridge sand (SR), Montebello sand (MON), and Catskill sand (CAT) samples. (See Appendix 2 for confidence intervals).

presumably derived from a common source, based upon the areal proximity of the units. Mean amplitude values for sediments from the Lehigh River and streams draining the Montebello, Sherman Ridge and Catskill Formations overlap closely for almost all harmonics, especially harmonics two through sixteen. Based upon the observed overlap of the spectra, these samples are almost indistinguishable, especially in terms of gross shape as represented by harmonics two through ten.

Discriminant Functions. Ehrlich and Weinberg (1970) used harmonic amplitudes as independent variables for a discriminant function analysis in order to verify conclusions based upon observations of graphical displays for mean harmonic amplitude spectra. Although this procedure does not allow definitive discrimination between samples, it provides statistical evidence that indicates at which harmonics significant differences exist.

In this study, amplitude values for harmonics two through eighteen were used as independent variables in a stepwise discriminant function analysis. Computation of linear classification functions was based upon stepwise selection of variables. The variable selected at each step was the one which added the most to the separation of the groups in the discriminant function (Dixon, 1981). Using the Mahalanobis D^2 statistic for the groups an approximate F statistic was calculated for the variables entered into the discriminant function. Significance of the F statistic was determined at the 5% significance level (using appropriate degrees of freedom) to demonstrate that the variables entered into the discriminant function displayed significant differences between the samples being compared. This information was used to determine whether or not observed similarities and differences in the graphical displays (Figures 7 and 8) were statistically significant.

Harmonic amplitudes for the Lehigh River, Montebello, Sherman Ridge and Catskill samples were analyzed using all possible combinations of pairs, and also for all four simultaneously. Results of these comparisons are summarized in Table 1. For each pair of samples only two to four harmonics out of seventeen were entered into the discriminant function. This indicates that for most harmonics there was no significant difference between mean amplitude values for any two samples. For the Montebello - Sherman Ridge comparison, the two harmonics entered into the discriminant function were not significantly different at the 5% level. Comparing all four samples simultaneously, only one harmonic out of seventeen showed a significant difference between the samples. Due to the apparent lack of significant shape variation as expressed in terms of mean harmonic amplitude spectra, it was difficult to discriminate between these samples conclusively. These results corroborate the similarity of the four samples observed in Figure 8.

Sample Comparison	Harmonic No. Entered into Function	F Statistic	D. F.	Critical F Statistic*
LR-MON	4,11	8.07	2, 788	3.01
LR-SR	7,11,15	8.70	3, 817	2.61
LR-CAT	2,7,16	4.78	3, 791	2.61
MON-SR	7,8	2.77	2, 771	3.01
MON-CAT	2,3,4,12	9.46	4, 743	2.38
SR-CAT	2,3,7,8	4.67	4, 773	2.38
LR-SR-MON-CAT	7	6.12	3, 1565	2.60

* At 5% significance level

H_o: No significant difference between samples for harmonics entered into discriminant function.

F - Approximate F Statistic from Mahalanobis D^2
D. F. - Degrees of Freedom
Critical F - Interpolated value for D. F.

TABLE 1. Results of stepwise discriminant function analysis on harmonic amplitude spectra for the Lehigh River (LR), Sherman Ridge (SR), Montebello (MON), and Catskill (CAT) sand samples.

Table 2 displays results of discriminant functions using harmonic amplitudes for samples from the St. Peter sandstone, New Jersey beach, Lehigh River and Jackson Hole till. The Lehigh River sample was selected to represent the fluvial sediments derived from Devonian sandstones since there was no apparent difference between those samples, and since it contained sediments from more than one sandstone unit. Samples again were compared two at a time for all possible combinations, as well as all four simultaneously. Results for the discriminant function on each pair showed that for every case, from seven to eleven harmonics adding most to the separation of the groups were entered into the function. On the average, at least half of the total number of variables were entered into the discriminant function. Most of the harmonics entered were low order harmonics (2-10) descriptive of gross shape, although for each pair several higher order harmonics were also entered. Comparison of all four samples simultaneously resulted in eleven harmonics entering into the discriminant function, seven of which were low order harmonics (2-10). The large F values for the sample pairs in Table 2 show a greater separation between samples than is the case for Table 1. Samples in Table 1 have greater similarity to each other, based upon the smaller F values, than those in Table 2. The observed differences between mean harmonic amplitude spectra in Figure 7 are supported by the results of the discriminant function analyses at the 5% significance level. Shape variation as

Sample Comparison	Harmonic No. Entered into Function	F Statistic	D. F.	Critical F Statistic*
SP-NJ	2,5,6,7,8, 9,10,11,17	53.06	9, 884	1.89
SP-LR	2,5,6,7,8, 9,11,14,15	114.68	9, 831	1.89
SP-JH	2,4,5,6,7,8, 9,10,11,13,17	103.85	11, 807	1.80
NJ-LR	2,5,9,12, 13,14,15	17.42	7, 843	2.02
NJ-JH	3,5,7,9, 10,11,18	24.89	7, 821	2.02
LR-JH	2,4,5,6,7, 11,13,15,16	11.62	9, 806	1.89
SP-NJ-LR-JH	2,5,6,7,8,9, 10,11,13,14,15	34.71	33, 4870	1.66

* At 5% significance level

H_o: No significant difference between samples for harmonics entered into discriminant function.

F - Approximate F Statistic from Mahalanobis D^2
D. F. - Degrees of Freedom
Critical F - Interpolated value for D. F.

TABLE 2. Results of stepwise discriminant function analysis on harmonic amplitude spectra for the St. Peter sandstone (SP), New Jersey beach (NJ), Lehigh River (LR), and Jackson Hole till (JH) samples.

characterized by eighteen harmonic amplitudes per grain is sufficient for discrimination of these samples by this procedure.

MULTIVARIATE ROTATION METHOD

Analysis of multivariate rotation data included both graphic and statistical methods. Statistical analysis of multivariate rotation data involved application of Hotelling's T^2 test, with rotated radials serving as measured shape variables for each grain. The T^2 statistic in combination with the Mahalanobis D^2 statistic enables testing of the equality of group means for several variables simultaneously (Morris, 1967; Dixon, 1981). These statistics are related and can be transformed to an F statistic (Morris, 1967). In order to discriminate between samples, the F statistic is tested at a specified level of significance to determine significant differences. These statistics were computed using both estimated factor scores and rotated radials as variables for each grain. The purpose for using both sets of variables was to determine if both would yield similar results. The initial expectation was that the estimated factor scores would provide somewhat better results, since they represent the essential information carried by the original variables.

Rotated Radials. Results utilizing rotated radials as variables for Hotelling's T^2 test on data from the sand samples of the Devonian units are summarized in Table 3. It is noted that in the analysis, with radials as variables for testing equality of

Sample Comparison	D^2	T^2	F	DF	P Value
LR-MON	0.23	45.67	1.25	35, 755	0.16
LR-SR	0.24	49.02	1.34	35, 785	0.09
LR-CAT	0.27	52.54	1.44	35, 759	0.05
MON-SR	0.17	33.58	0.92	35, 738	0.61
MON-CAT	0.31	57.59	* 1.57	35, 712	0.02
SR-CAT	0.23	45.51	1.24	35, 742	0.16

*Significant at 5% level   Critical F value = 1.45

H_o: No difference in mean radial lengths between samples

D^2 - Mahalanobis D^2 statistic
T^2 - Hotelling's T^2 statistic
DF - Degrees of Freedom
P Value - Probability of rejecting H_o if H_o is true

TABLE 3. Results of two-sample Hotelling's T^2 test using rotated radial lengths for the Lehigh River (LR), Sherman Ridge (SR), Montebello (MON), and Catskill (CAT) sand samples.

means for each sample pair, one variable was omitted for each comparison. The omission occurred because the particular variable (radial length) was a linear combination of the other variables, as determined by the statistical software. This appeared to be an artifact of the program in the statistical package. Specifically, rotated radial number eight was omitted in every case except the Lehigh River - Catskill and Montebello - Catskill pairs, for which radials number two and seven, respectively, were omitted . As a result, calculation of the statistics was based upon thirty-five variables.

At the 5% significance level, results show a significant value of the F statistic for only the Montebello - Catskill pair (Table 3). A significant difference between these samples is not entirely unexpected since results of the discriminant function analysis using Fourier data (Table 1) showed significant differences at four harmonics, three of which (2,3,4) characterize gross shape. It is also noted that in Table 1, four harmonics were significantly different for the Sherman Ridge - Catskill samples. However, for the Hotelling's T^2 test on rotated radial lengths, no difference (5% significance level) was detected between this sample pair.

The difference detected between the Montebello - Catskill pair appears to be anomolous since the sample from the Sherman Ridge Formation, which is stratigraphically adjacent to the Montebello but below the Catskill, is statistically indistinguishable from both the Montebello and Catskill as shown by this test in Table 3. Although there is no obvious reason for the results of the comparisons between these samples in view of their apparent similarity as determined by results from Fourier data, this procedure indicated that there is significant shape variation between some of the samples. It may be that the differences between only two to four harmonics for each sample pair shown in Table 1, are enough to consider the samples as distinctly different. However, this would not resolve the inconsistency which exists since only two of these samples showed significant differences on the basis of rotated radials.

Table 4 contains results of the Hotelling's T^2 test for the St. Peter sandstone, New Jersey beach, Lehigh River and Jackson Hole till samples, using rotated radials as variables. Again the Lehigh River sample is used as the fluvial sample for these comparisons since it is composed of sediments from a variety of sandstone sources, and also to allow straightforward comparison of results with those of the Fourier method.

For all possible combinations of sample pairs between this group of samples, significant differences existed at the 5% significance level. These samples, derived from very diverse sources and environments, are distinguishable from one another on the basis of gross shape variation. However, the magnitude of the F values is not much greater than the magnitude of the F values shown

Sample Comparison	D^2	T^2	F	DF	P Value
SP-NJ	0.66	141.41	* 3.88	35, 818	0.00
SP-LR	1.39	292.84	* 8.03	35, 805	0.00
SP-JH	1.49	304.19	* 8.33	35, 783	0.00
NJ-LR	0.40	84.82	* 2.33	35, 815	0.00
NJ-JH	0.46	94.41	* 2.59	35, 793	0.00
LR-JH	0.28	56.26	* 1.54	35, 780	0.03

*Significant at 5% level   Critical F value = 1.45

H_o: No difference in mean radial lengths between samples

D^2 - Mahalanobis D^2 statistic
T^2 - Hotelling's T^2 statistic
DF - Degrees of Freedom
P Value - Probability of rejecting H_o if H_o is true

TABLE 4. Results of two-sample Hotelling's T^2 test using rotated radial lengths for the St. Peter sandstone (SP), New Jersey beach (NJ), Lehigh River (LR) and Jackson Hole till (JH) samples.

in Table 3. These results also agree with those obtained by semi-quantitative methods using Fourier derived data for the same samples.

Estimated Factor Scores. Plotting mean values of estimated factor scores versus the appropriate factor permits visual inspection of mean differences between samples. Figure 9 illustrates such a graph for the Devonian sandstone sediments. The most obvious relationship is the similar trend of changes in mean factor scores from one factor to another. Mean factor scores decrease from Factor 1 to Factor 2, and then increase to a maximum value for Factor 5 in each case. For Factor 6 all samples have mean values near zero. The similarity of the changes in mean values of factor scores is a qualitative indication that these samples are similar in their shape characteristics.

In Figure 9, the Montebello sample exhibits the smallest range of mean values, and the Catskill sample shows the largest range of mean values. Of the samples displayed, these two have the largest differences. This observation lends support to the significant differences determined between these two samples (Table 3) for results of Hotelling's T^2 test using rotated radials as variables.

Figure 10 is a graph of mean estimated factor scores versus factors for the St. Peter - Jackson Hole suite of samples. In this illustration, trends of mean values are quite different for each sample. Qualitatively, these four samples appear to be different on

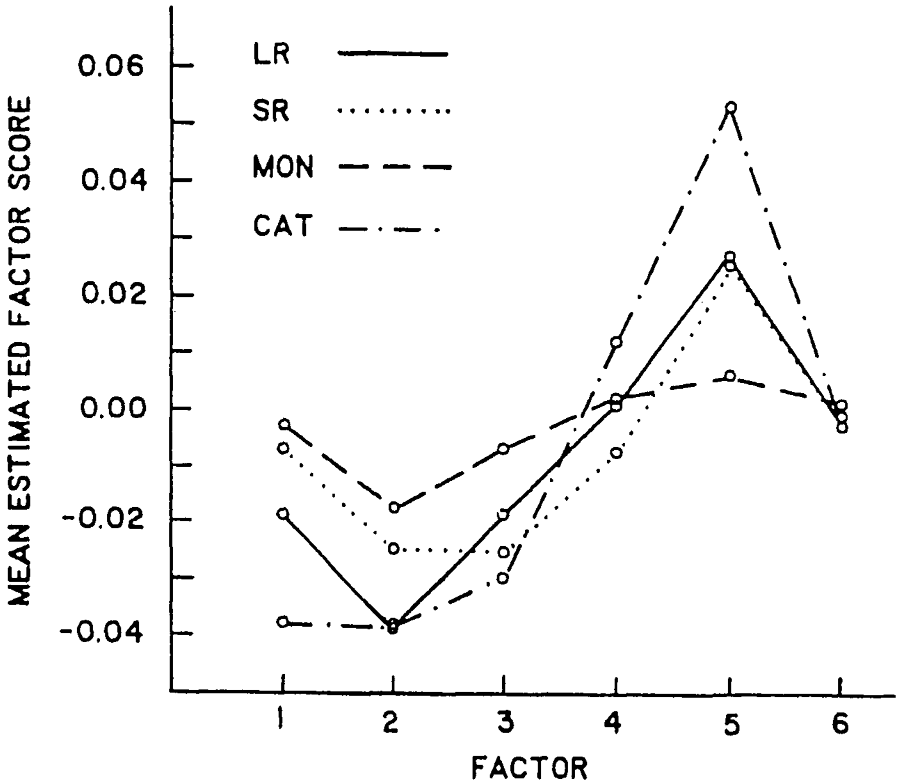

FIGURE 9. Graph of mean estimated factor score vs. factor for the Lehigh River sand (LR), Sherman Ridge sand (SR), Montebello sand (MON), and Catskill sand (CAT) samples. (See Appendix 6 for confidence intervals).

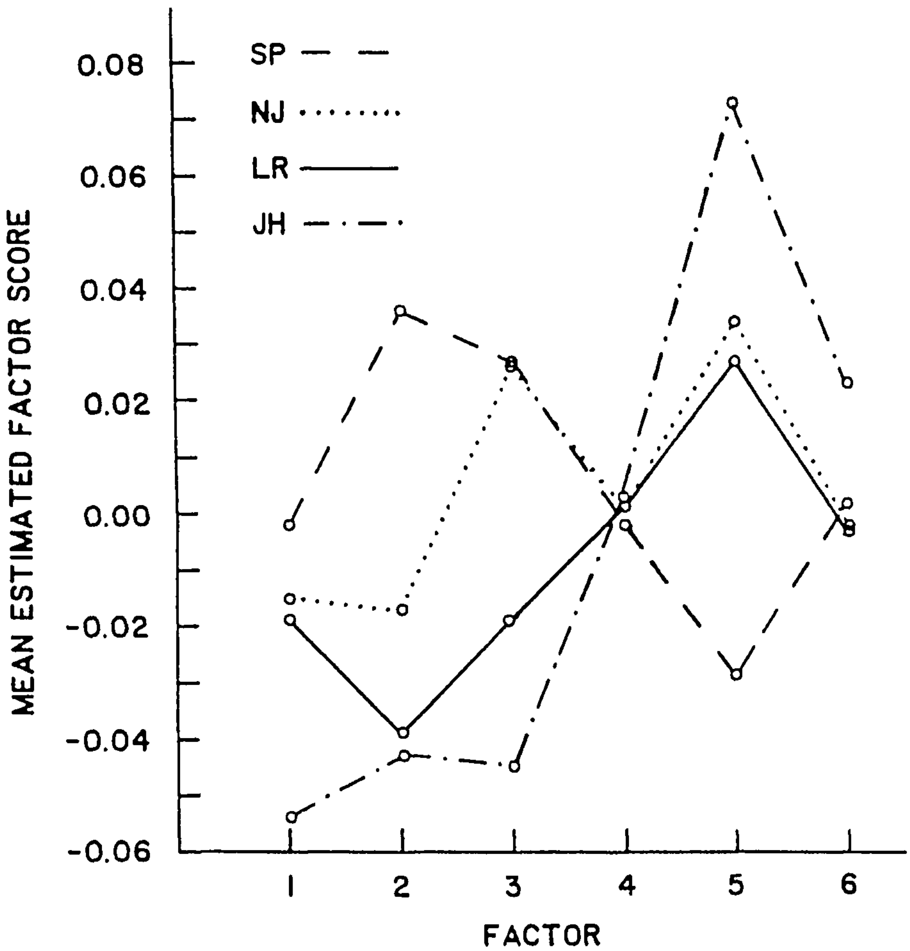

FIGURE 10. Graph of mean estimated factor score vs. factor for the St. Peter sandstone (SP), New Jersey beach sand (NJ), Lehigh River sand (LR), and Jackson Hole till (JH) samples. (See Appendix 6 for confidence intervals).

the basis of observed differences for mean estimated factor scores, and the difference in the distribution of these means from one factor to another.

The differences of values for the St. Peter and Jackson Hole samples are the largest of the four samples. The New Jersey beach and Lehigh River samples have intermediate mean values between these extremes. A similar relationship was observed for these samples in Figure 7 for mean harmonic amplitudes of the low order harmonics two through ten.

Another interesting feature of Figures 9 and 10 is that, in both instances, most if not all the samples have very similar mean values of estimated factor scores for Factors 4 and 6. The reason for this similarity is unclear, however, it may reflect some underlying shape feature or component which is common to all the samples. Overall, graphs of mean values for estimated factor scores plotted against the corresponding factors confirmed expected similarities and differences between groups of samples.

Use of estimated factor scores as variables for Hotelling's T^2 test on samples from the Devonian sandstones produced results shown in Table 5. At the 5% level of significance there was no difference between pairs of samples with two exceptions, the Montebello - Catskill and Sherman Ridge - Catskill pairs. It seems reasonable that the shape signatures of samples from the stratigraphically adjacent Montebello and Sherman Ridge formations would be similar to

Sample Comparison	D^2	T^2	F	DF	P Value
LR-MON	0.04	7.77	1.29	6, 784	0.26
LR-SR	0.01	2.17	0.36	6, 814	0.91
LR-CAT	0.05	9.52	1.58	6, 788	0.15
MON-SR	0.03	5.40	0.89	6, 767	0.50
MON-CAT	0.16	29.89	* 4.95	6, 741	0.00
SR-CAT	0.08	14.82	* 2.45	6, 771	0.02

*Significant at 5% level Critical F value = 2.11

H_o: No difference in mean factor scores between samples

D^2 - Mahalanobis D^2 statistic
T^2 - Hotelling's T^2 statistic
DF - Degrees of Freedom
P Value - Probability of rejecting H_o if H_o is true

TABLE 5. Results of two-sample Hotelling's T^2 test using estimated factor scores for the Lehigh River (LR), Sherman Ridge (SR), Montebello (MON), and Catskill (CAT) sand samples.

each other, yet different from that of the Catskill sample, which is stratigraphically higher. The fact that the adjacent Montebello and Sherman Ridge Formations have been defined as separate and distinct formations (Miller, 1961) does not necessarily mean that they are, in fact, different lithologic units. Therefore, it is possible these formations could have the same shape signature. The Catskill Formation, which is higher in the stratigraphic section and not adjacent to either the Montebello or Sherman Ridge, could reasonably be expected to have a different shape signature. In any case, a conflict exists with the results of the T^2 test using radials as variables, in which no significant difference was detected between the Sherman Ridge - Catskill samples (5% significance level). This conflict may indicate that the factor scores produce better resolution than the rotated radials. Results from Fourier data showed significant differences between the Sherman Ridge - Catskill and Montebello - Catskill pairs for four harmonics in each case.

Results for estimated factor scores as variables for the T^2 test, shown in Table 6, are quite conclusive for the St. Peter sandstone, New Jersey beach, Lehigh River and Jackson Hole till samples. Pairwise comparisons of all samples at the 5% significance level displayed differences between samples in every case. These results are in agreement with those obtained using radial lengths as variables, as well as with the outcome for Fourier derived shape variables. However, it should be noted that when analyzing

Sample Comparison	D^2	T^2	F	DF	P Value
SP-NJ	0.25	53.37	* 8.84	6, 847	0.00
SP-LR	0.36	75.17	* 12.45	6, 834	0.00
SP-JH	0.68	138.31	* 22.91	6, 812	0.00
NJ-LR	0.06	13.65	* 2.26	6, 844	0.04
NJ-JH	0.19	38.91	* 6.45	6, 822	0.00
LR-JH	0.12	23.64	* 3.92	6, 809	0.00

*Significant at 5% level   Critical F value = 2.11

H_o: No difference in mean factor scores between samples

D^2 - Mahalanobis D^2 statistic
T^2 - Hotelling's T^2 statistic
DF - Degrees of Freedom
P Value - Probability of rejecting H_o if H_o is true

TABLE 6. Results of two-sample Hotelling's T^2 test using estimated factor scores for the St. Peter sandstone (SP), New Jersey beach (NJ), Lehigh River (LR), and Jackson Hole till (JH) samples.

estimated factor scores (Table 6), calculated F values for each sample pair are larger than the F values for the same sample pair when using rotated radial lengths (Table 4). This is strong evidence to suggest that estimated factor scores provide better resolution, and accordingly, are more useful for discriminating between samples.

DISCUSSION

Although results for quantitative shape analysis of quartz grains with the multivariate rotation method indicate the usefulness of the technique, there are several issues which must be addressed. Although the method produced comparable results to the Fourier procedure for the St. Peter - Jackson Hole suite of samples representing diverse sediment sources, some discrepancies existed between results of the two methods when analyzing sediments derived from the Devonian sandstones, which have a more narrow spectrum of shape variation. One of several explanations may account for the disagreement of these results utilizing the same database.

For the multivariate rotation method, results of the shape analysis on fluvial sediments from the proximate Devonian sandstones varied slightly depending upon whether radial lengths or factor scores were used for statistical tests (Tables 3 and 5). It is not completely clear why this is the case, however, several possibilities are suggested. The differences between some of these samples detected by analysis of both sets of variables indicates that there are subtle but discernible variations in shape signatures of samples which reasonably could be expected to be somewhat similar in view of the common age and proximity of the sandstone sources.

It would appear that the problem is related to the choice between rotated radials or factor scores as variables for the statistical analysis. Intuitively, it seems that the use of thirty-six radials as input for the analysis may be the cause of the discrepancies between results for these two variable sets. Aside from the fact that such a large number of variables is cumbersome to handle and expensive in terms of computer time, there is an inordinate amount of redundancy using so many variables. This is supported by the fact that for the St. Peter sample six factors accounted for 91 percent of the variance in the data. This redundancy would be likely to create noise in the data, adding to the complexity of subtle shape variations that must be differentiated. If redundancy is indeed a source of noise, then the R-mode factor analysis approach for computing estimated factor scores to use as variables for analysis seems justified, since it eliminates redundancy and the resulting noise.

The estimated factor scores appear to be more sensitive for detecting variations in shape signatures. For the sediment samples derived from the Devonian sandstones, a significant difference was detected between the Sherman Ridge - Catskill pair for estimated factor scores (Table 5), but not for rotated radials (Table 3). Although a significant difference was detected between the Montebello - Catskill pair using both sets of variables, the F value for the estimated factor scores (Table 5) is approximately three times larger than the F value for rotated radial lengths (Table 3).

It appears, therefore, that estimated factor scores are best suited for analysis of shape variation. The factor scores eliminate redundant information carried by rotated radial lengths, and seem to be more sensitive to shape variations based upon initial evidence. Conclusive determination of which variable set is best for analysis will require a more detailed and sophisticated investigation specifically designed to verify this preliminary finding.

Results obtained by use of rotated radials as variables (Table 4) for statistical analysis of the St. Peter - Jackson Hole suite of samples lends support to the concept that radials contain noise and are less sensitive to shape variations. For these samples, results of discrimination between sample pairs were the same as the results using estimated scores (Table 6). Since the shape variation in this suite of samples is so evident, the redundancy of information carried by the radials is not as critical because the intensity of the variations is discernible despite any associated noise. The estimated factor scores appear to be more sensitive to the shape variation in these samples. For the St. Peter - Jackson Hole sample group, the F values obtained from estimated factor scores were larger for any given sample pair than the F value obtained from rotated radial lengths for the same sample pair (Tables 4 and 6). The larger F value for each sample pair indicates greater separation of the samples than a smaller value even though the F values are significant in both cases.

As for shape analysis results of the fluvial samples using the Fourier (Figure 8 and Table 1) and multivariate rotation methods (Figure 9 and Tables 3 and 5), the slight differences between results probably reflect the type of data analysis. For the pairwise analyses of the fluvial samples significant differences between some samples (Montebello - Catskill and Sherman Ridge - Catskill) were detected by the multivariate rotation method using estimated factor scores. From Fourier derived shape data, using discriminant function analysis, minor differences were observed for four of the harmonics. The small number of harmonics exhibiting significant differences is considered insufficient evidence that the samples are distinctly different. It appears, however, that the differences between samples detected at these few harmonics may have been enough to be responsible for the difference detected by the multivariate rotation method. The conclusion of no difference between samples, based upon Fourier results, was somewhat subjective since there is no standard procedure for deciding how many harmonics must be significantly different to reveal a "real" difference in the grain shape signature. Use of a more sophisticated analysis method on the Fourier derived data, such as chi-square analysis of shape frequency distributions (Ehrlich et al., 1980), might produce more objective results.

Application of the various procedures outlined reveals distinct differences in the shape signatures of quartz grains for the St.

Peter sandstone, New Jersey beach, Lehigh River, and Jackson Hole till samples. In general, results for the sediment samples derived from Devonian sandstones showed no differences between most samples. Agreement of results on the same database for the procedures applied demonstrates the capacity of the multivariate rotation method for discrimination of samples on the basis of variations in shape signatures of quartz sand grains from diverse sediment sources.

Thirty-six equally spaced radial lengths from the center of mass to the peripheral outline for projected two-dimensional quartz grain shapes, rotated to a common orientation, serve as useful measured shape variables. Estimated factor scores, as computed from the rotated radials for each grain using the multivariate rotation method of Parks (in preparation) are adequate as variables for statistical analysis to discriminate differences in shape signatures of quartz grains.

Limitations of the method. Despite the apparent utility of the multivariate rotation method for shape discrimination of sediments from different sources there are limitations and drawbacks. Use of Hotelling's T^2 test, to determine the equality of means for the estimated factor scores between two samples, is quite adequate for circumstances involving comparisons of a small number of samples. However, for investigations requiring analysis of large numbers of samples, use of this test may be cumbersome since only paired comparisons are possible.

Another limitation at the present time is that the resolving power of the method is not well-defined. Preliminary results suggest that the method may have potential beyond that which was originally anticipated. This is evidenced by the detection of shape differences in the fluvial samples derived from the Devonian sandstones for which analysis of Fourier derived data suggested a common origin. However, modifications of either the method or statistical procedures may be required to increase the sensitivity of the method.

Factors (hypothetical variables) derived by R-mode factor analysis of the St. Peter sample are assumed to represent specific components of shape which contribute to the overall two-dimensional representation of each grain. It is nct known, however, what these components are or how they are related to one another. Knowledge of the shape components represented by the factors would allow insight into the structure of raw data (rotated radials) and permit evaluation of the ability of the estimated factor scores to characterize the shape of a unique grain.

Future Research. On the basis of information produced by this investigation, several subjects for future study may be defined. A detailed analysis of the resolving power of the multivariate rotation method would provide information useful in choosing problems for which this type of procedure is best suited. A combination of carefully designed experiments on synthetic data sets as well as selected geologic investigations should provide the necessary information.

Estimated factor scores derived from rotated radial lengths appear to be better suited than rotated radials alone for discriminating between samples by application of Hotelling's T^2 test. However, this test only allows pairwise comparison of samples. Further research is necessary to determine a statistical procedure for multivariate analysis of estimated factor scores which will allow more efficient comparison of large numbers of samples simultaneously. The current approach only verifies whether or not significant differences exist for means of factor scores.

While evidence supports the use of estimated factor scores as variables for statistical analysis of shape data, further work is required to understand the meaning of the underlying factors and beta coefficients from which these scores are derived. Insights into the structure of raw data (rotated radials) would be facilitated if the meaning of the factors can be determined. More information is also needed on the beta coefficients. Several beta coefficients matrices derived from different samples should be tested on the same database to determine what impact a particular set of coefficients will have on the results for a given data set.

Finally, a procedure capable of sorting out mixtures of sediments derived from multiple sources would greatly enhance the applicability of the multivariate rotation method for a large number of sedimentation problems. Such a procedure would require the capacity to discriminate shape variations of quartz sand grains within a sample, and to determine the proportions of sediments contributed by each source to mixed samples.

CONCLUSIONS

This investigation has demonstrated the usefulness of the multivariate rotation method of quantitative grain shape analysis for discrimination of shape variation in sediment samples from several diverse sources and environments. Preliminary results indicate that rotated radial lengths serve as adequate shape variables descriptive of projected two-dimensional grain outlines. Estimated factor scores, as calculated by the procedure outlined, allow data reduction and enhance shape information necessary for sample discrimination. These scores, characterizing the gross shape of each grain, serve as variables for statistical analysis to determine significant differences between samples.

Shape analysis of quartz grains in sediments derived from Devonian sandstones of central Pennsylvania indicates that the grains, derived from lithologies of similar age, geographic location, and presumably a common source, have similar shape signatures. Quartz grains in sediment samples from the widely different sources and environments sampled have unique shape signatures which permit discrimination between these sediments.

The multivariate rotation method produces results comparable to those obtained by semi-quantitative analysis of Fourier derived shape data for discrimination of sediments from the diverse sources and environments sampled. Overall results verify conclusions of previous investigators that projected two-dimensional outlines of quartz sand grains carry information on particle shape which is useful for distinguishing sediments derived from unique sources.

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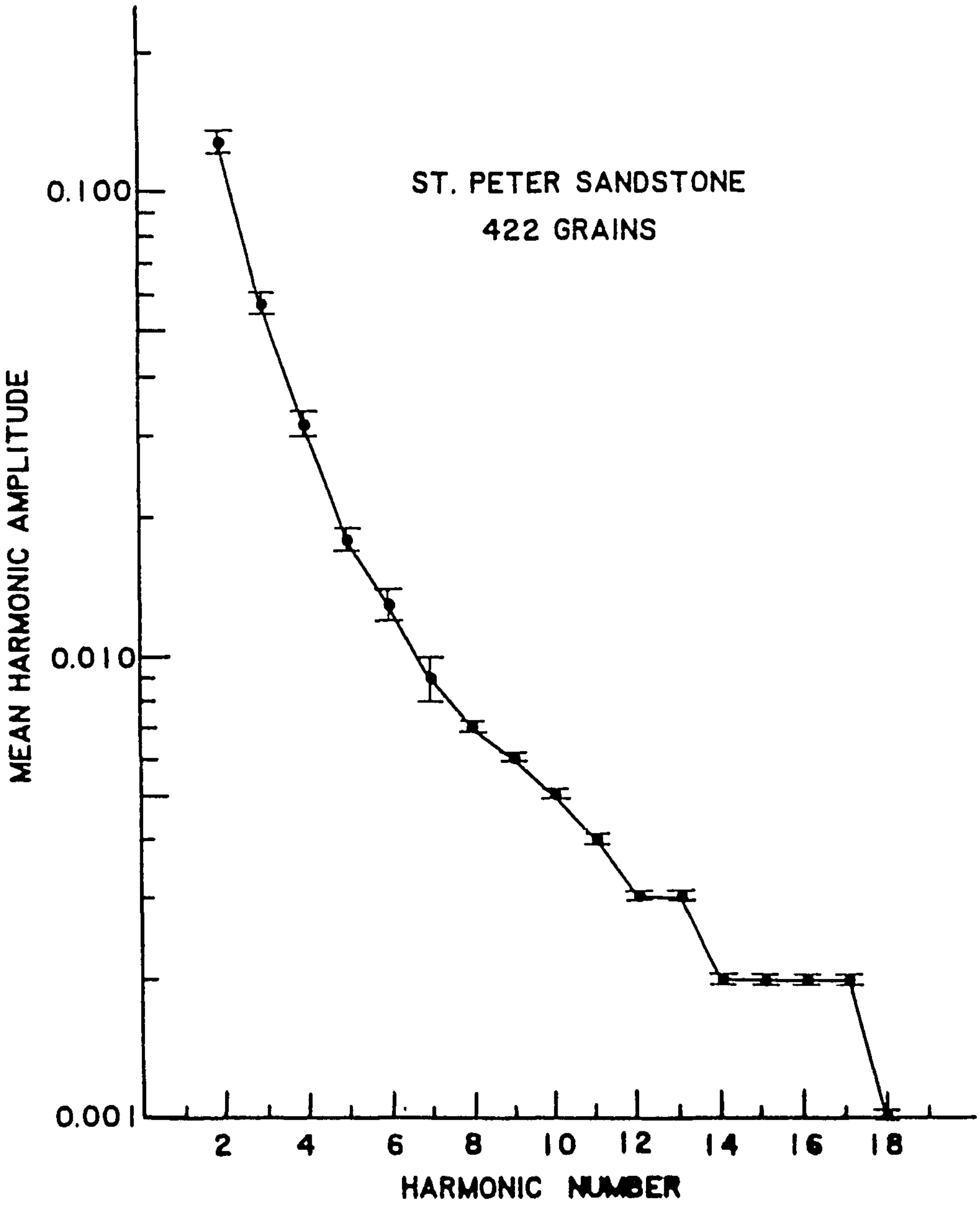
APPENDIX 1

SAMPLE PREPARATION

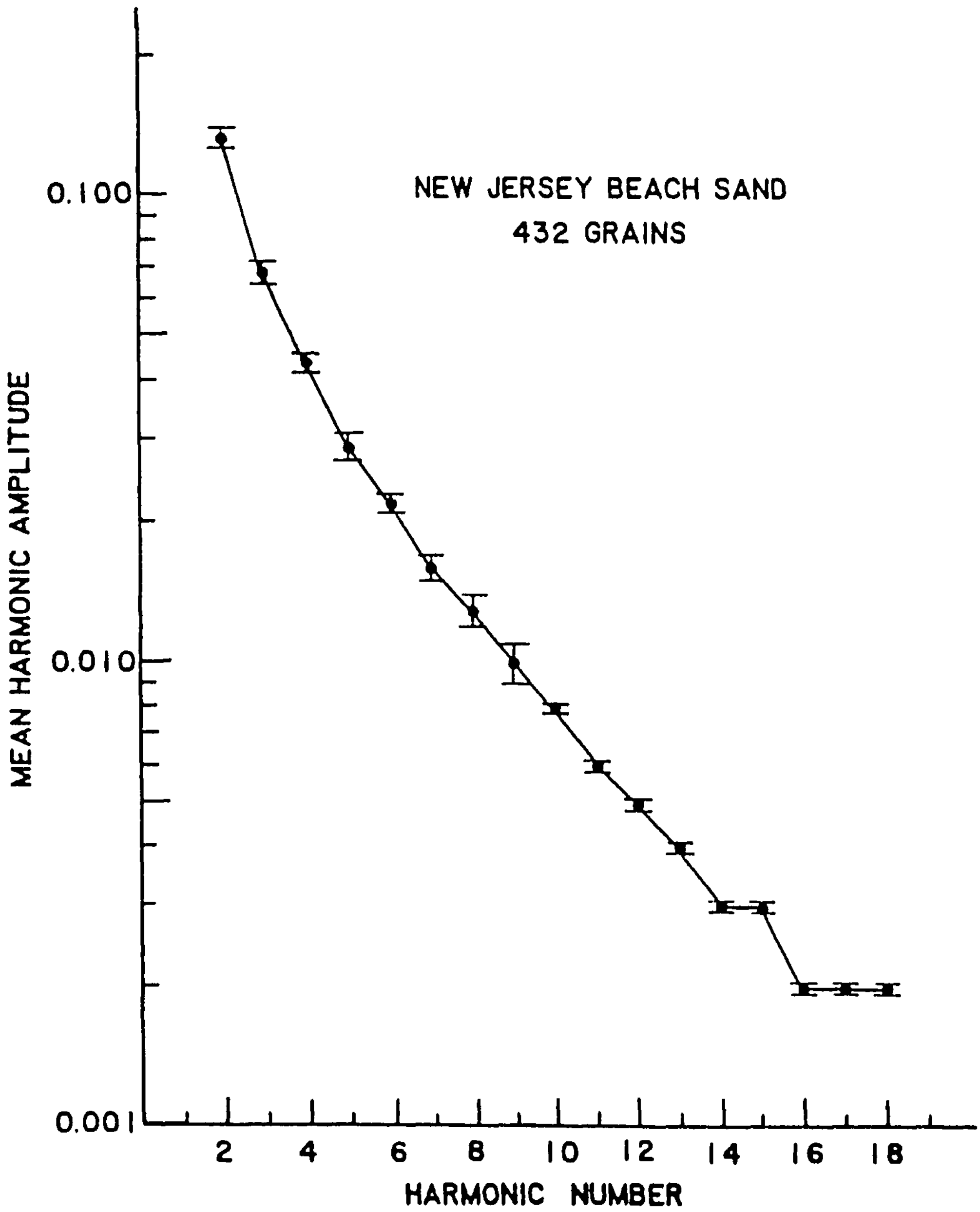
Fluvial and till samples contained significant amounts of mud, therefore a 10 ml. volume of sodium metaphosphate solution (50 grams per liter distilled water) was added to each. Samples were shaken for ten minutes in a wrist action shaker to disperse the clay fraction and facilitate removal of sediments less than the 0.063 size fraction by wet sieving.

All samples were dry sieved to isolate the 0.35-0.50 mm size fraction to be used for shape analysis. For each sample this size fraction was treated with hydrochloric acid to remove iron oxide coatings from the grains. Samples were warmed on a hot plate in a 10 percent hydrochloric acid solution for several minutes to speed up the reaction. Some samples required repeated treatments, washing the sample with distilled water between each treatment, before all the iron oxide was removed. Treatment was considered complete when freshly added hydrochloric acid solution ceased turning pale green to pale yellow in color. Upon rinsing and drying, samples were ready to be digitized.

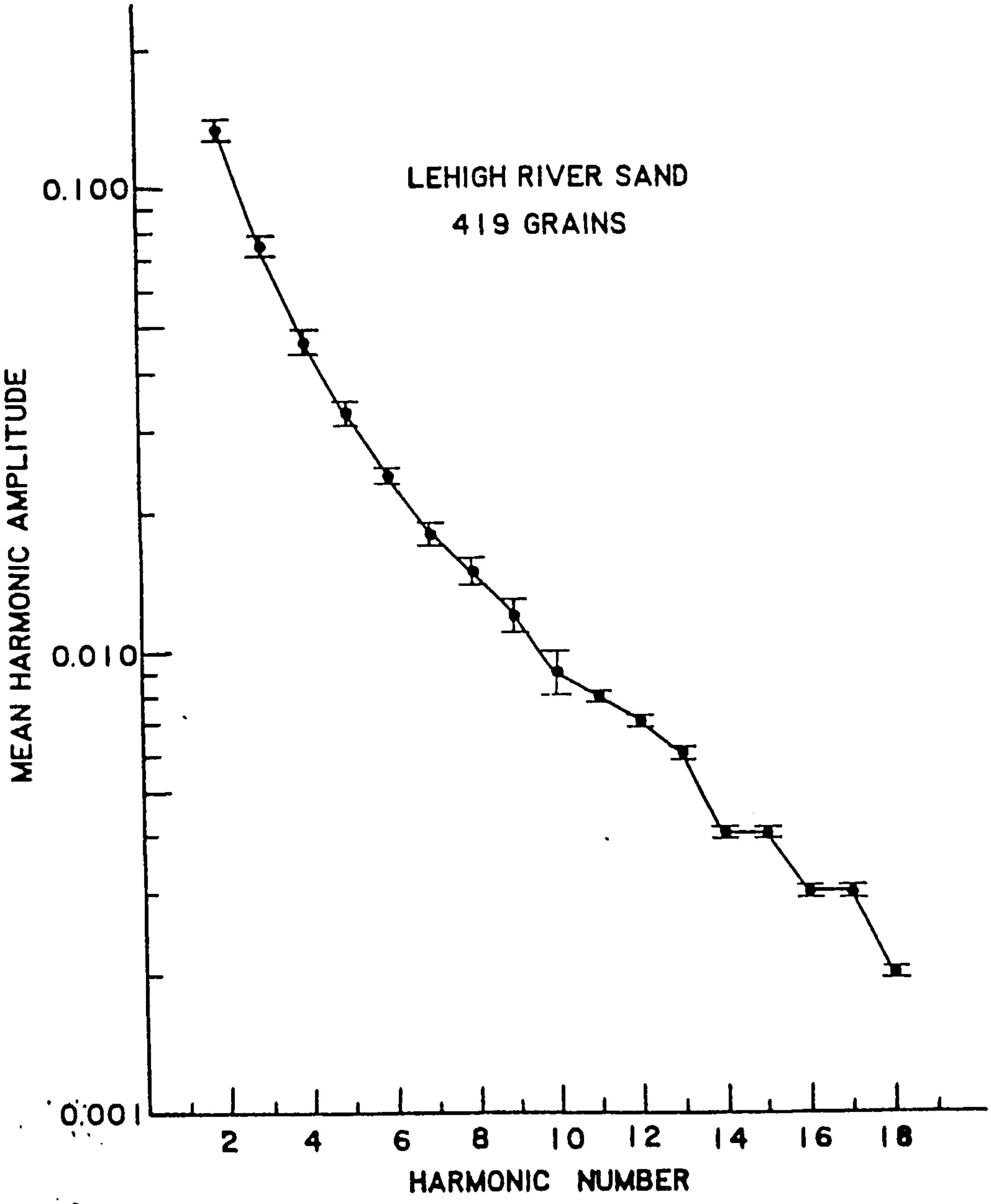
Prior to digitizing, each sample was viewed through a binocular microscope. Approximately 400 quartz grains were randomly selected from each sample. Grains were placed loosely on a glass slide, approximately 100 at a time, and digitized by tracing the projected two-dimensional grain boundary.



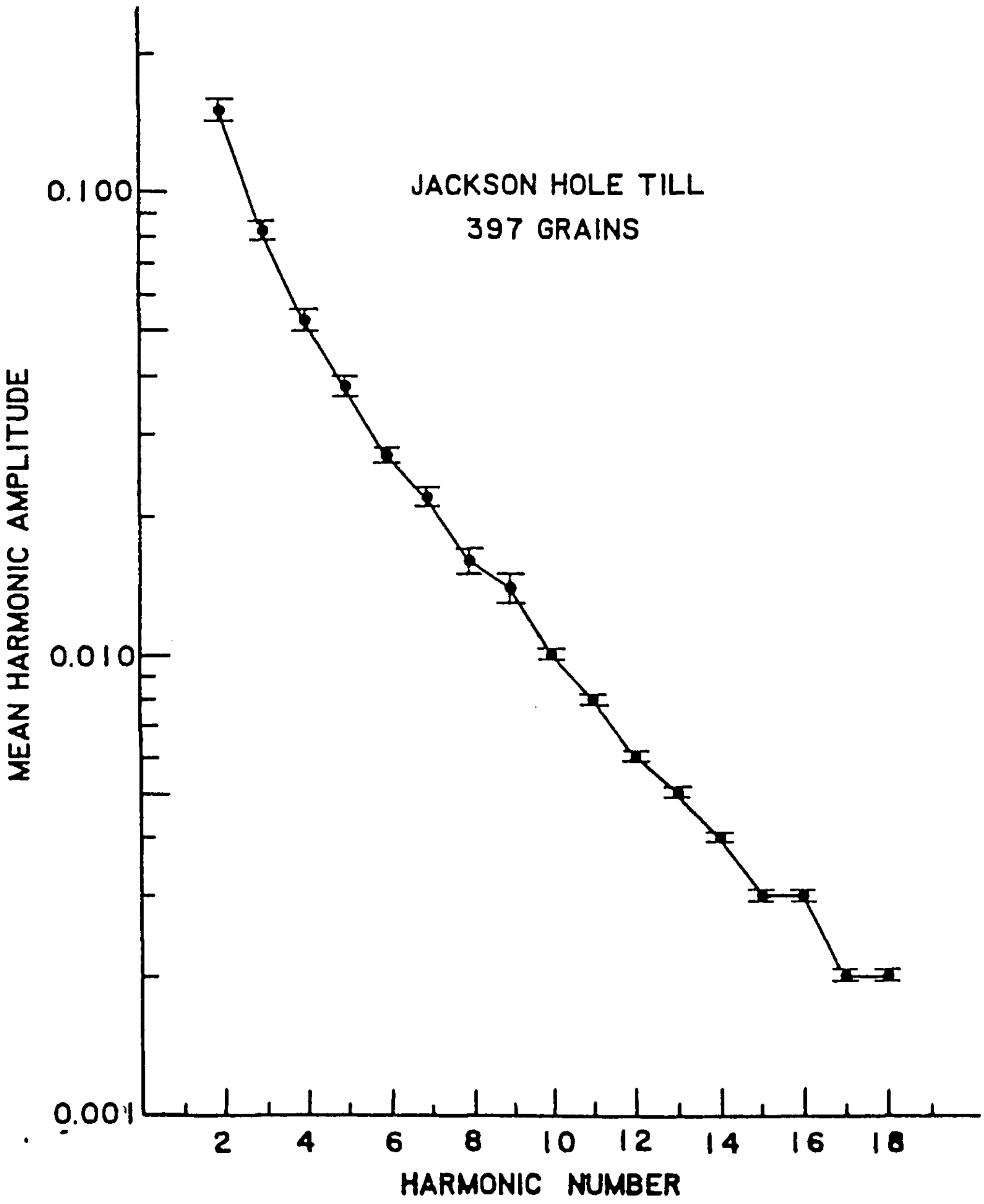
APPENDIX 2A. Graph of mean harmonic amplitude vs. harmonic number for the St. Peter sandstone sample. Error bars define the 95% confidence interval.



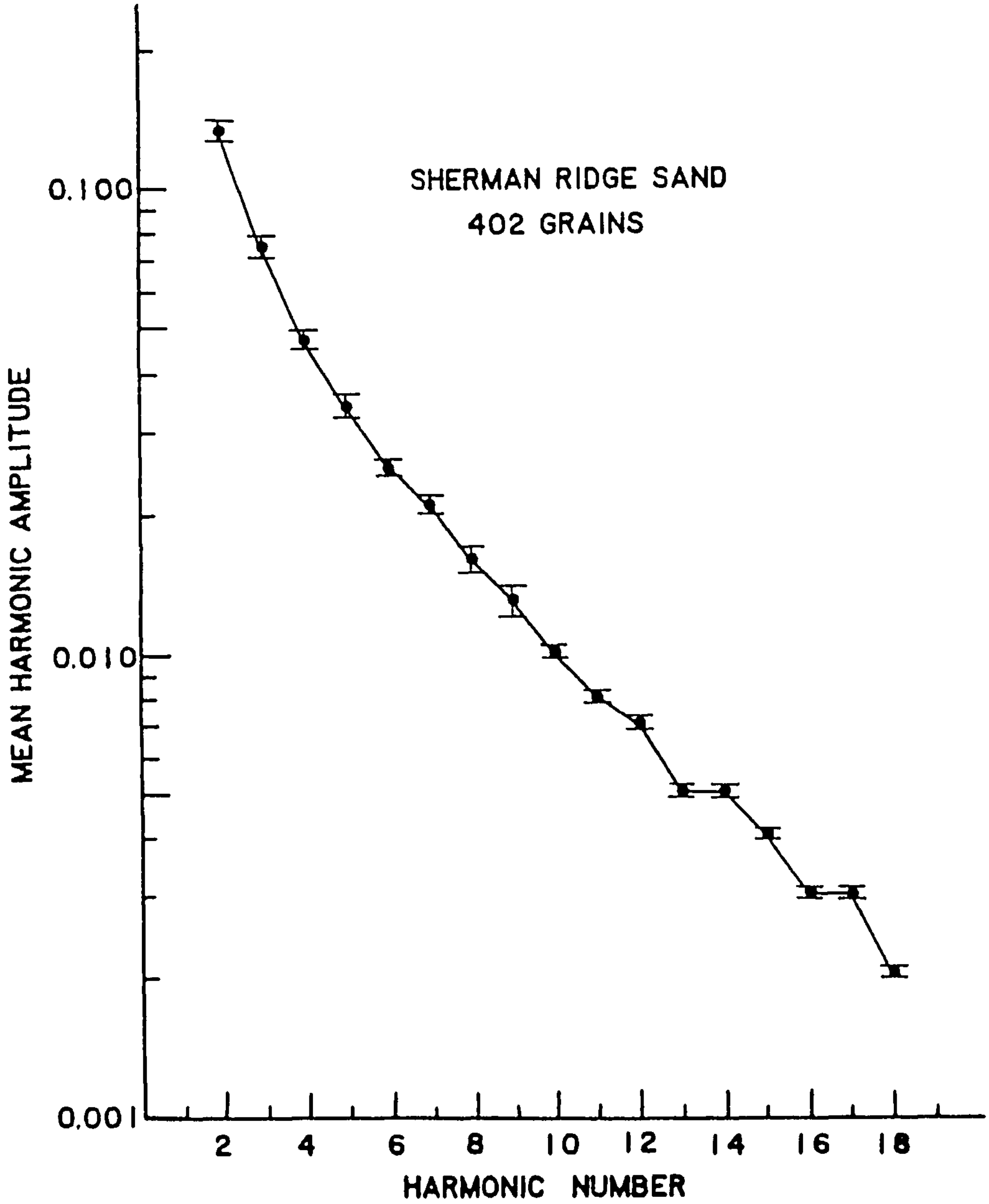
APPENDIX 2B. Graph of mean harmonic amplitude vs. harmonic number for the New Jersey beach sand sample. Error bars define the 95% confidence interval.



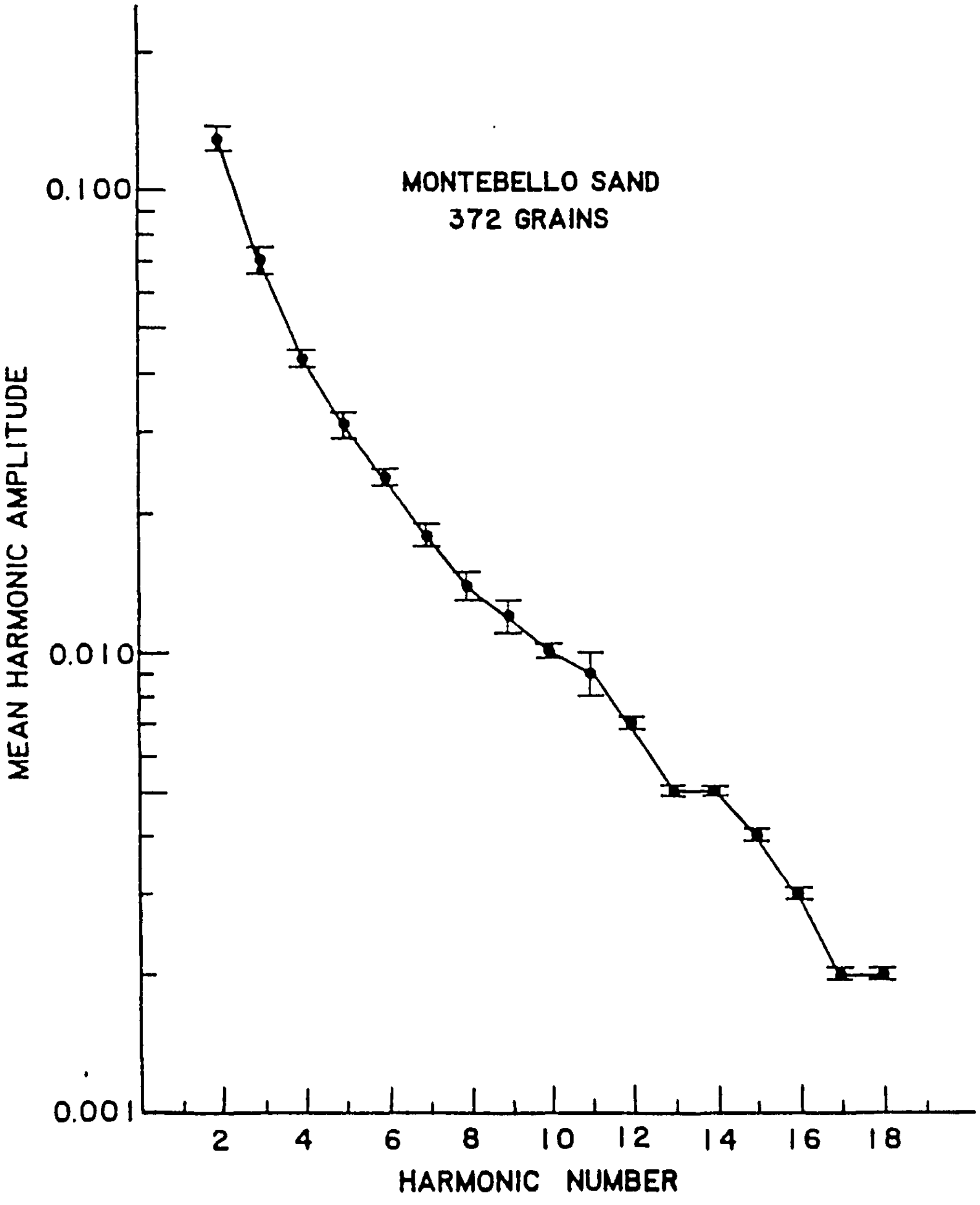
APPENDIX 2C. Graph of mean harmonic amplitude vs. harmonic number for the Lehigh River sand sample. Error bars define the 95% confidence interval.



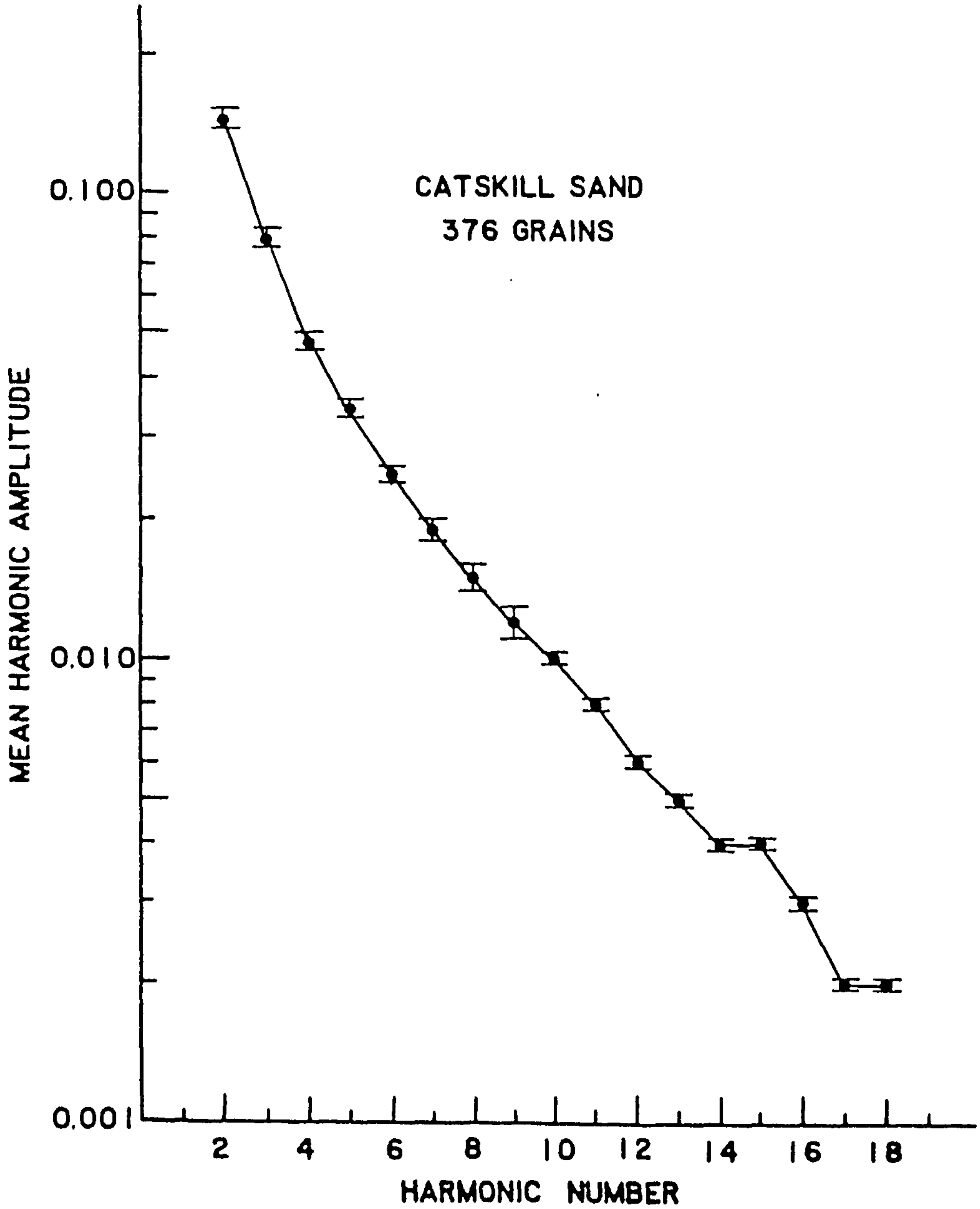
APPENDIX 2D. Graph of mean harmonic amplitude vs. harmonic number for the Jackson Hole till sample. Error bars define the 95% confidence interval.



APPENDIX 2E. Graph of mean harmonic amplitude vs. harmonic number for the Sherman Ridge sand sample. Error bars define the 95% confidence interval.



APPENDIX 2F. Graph of mean harmonic amplitude vs. harmonic number for the Montebello sand sample. Error bars define the 95% confidence interval.



APPENDIX 2G. Graph of mean harmonic amplitude vs. harmonic number for the Catskill sand sample. Error bars define the 95% confidence interval.

		FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5	FACTOR 6
	1	.09878822	.02639567	-.11474554	.02400774	-.03884165	.02504508
	2	.08656073	.00841302	-.09993747	.04130196	-.04222548	-.04517755
	3	.06195823	-.03317698	-.03419502	-03113719	-.01730447	-.14797466
V	4	-.00120460	-.11876115	.06873072	-.00805730	.04853157	-.23832981
	5	-.08666814	-.15380552	.08965660	-.02404855	.06656054	-.13741836
	6	-.11425098	-.11877151	.01104548	-.01743438	.04643127	.05402984
	7	-.09226297	-.06328971	-.03775069	-.04611443	.03617799	.13672574
A	8	-.05218341	-.00116587	-.06496248	-.08066425	.02404691	.13101346
	9	-.00942718	.06580802	-.05445745	-.09819629	.00607178	.06311027
	10	.03253746	.12658838	-.00455990	-.09326960	-.00275403	-.04727605
	11	.05205535	.16036218	.04657979	-.03162001	-.01451396	-.13838514
R	12	.04085097	.14769764	.06624041	.08666036	-.02829664	-.15773946
	13	.00322088	.07677342	.05391067	.23085146	-.02401262	-.08608175
	14	-.04282191	-.03750417	-.00611303	.32829959	-.01151384	.05660261
	15	-.05437333	-.15216503	-.06435825	.25262229	.04403111	.17745995
I	16	-.03012094	-.18052390	-.04972782	.07377065	.07442121	.14336598
	17	-.00000250	-.13191132	.02345018	-.07743536	.05020092	-.00557947
	18	.02259046	-.05727323	.06256268	-.14676139	-.01353100	-.12362972
	19	.03142082	.01963074	.05124089	-.14062108	-.09911174	-.15868359
A	20	.01895051	.06612953	.00706754	-.07808532	-.17447586	-.11079618
	21	-.00856129	.07207030	-.05102773	.00983062	-.21059194	.02929641
	22	-.02579728	.05136252	-.08472383	.06004236	-.17753007	.20675303
	23	-.04650542	-.04577798	-.04152402	.05112203	.02628690	.43476971
B	24	.03114924	-.11107273	.13153168	-.15417291	.33445587	.19469342
	25	.06314782	-.03352858	.08148046	-.17662697	.24181783	-.09182047
	26	.04372504	.01489833	-.04430026	-.10702521	.10319239	-.10758926
	27	.00538386	.03151894	-.13707173	-.01624469	.00487399	-.03683995
L	28	-.05391130	.02536813	-.16538390	.08549123	-.06155872	.04684392
	29	-.11418243	.01802569	-.11410578	.17170524	-.10998029	.08041164
	30	-.14819020	.00647202	.03494017	.18532036	-.09984481	.02981125
	31	-.13360284	.00031236	.27186497	.11796970	-.03065816	-.08319823
E	32	-.04110270	.00441268	.36267088	-.01217140	.05762708	-.10873343
	33	.04707575	.01182146	.23770792	-.06562430	.08416703	-.02924147
	34	.08609841	.01494034	.09165354	-.08776739	.06517858	.04223337
	35	.10036903	.02476201	-.02689479	-.04940530	.02102136	.08219724
	36	.10287381	.03031380	-.09238081	-.00857061	-.01642791	.07284682

APPENDIX 3. Beta ceofficients matrix for the St. Peter sandstone sample (0.35-0.50 mm size interval). Variables are rotated radial lengths.

		FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5	FACTOR 6
	1	.09878822	.02639567	-.11474554	.02400774	-.03884165	.02504508
	2	.08656073	.00841302	-.09993747	.04130196	-.04222548	-.04517755
	3	.06195823	-.03317698	-.03419502	-03113719	-.01730447	-.14797466
V	4	-.00120460	-.11876115	.06873072	-.00805730	.04853157	-.23832981
	5	-.08666814	-.15380552	.08965660	-.02404855	.06656054	-.13741836
	6	-.11425098	-.11877151	.01104548	-.01743438	.04643127	.05402984
	7	-.09226297	-.06328971	-.03775069	-.04611443	.03617799	.13672574
A	8	-.05218341	-.00116587	-.06496248	-.08066425	.02404691	.13101346
	9	-.00942718	.06580802	-.05445745	-.09819629	.00607178	.06311027
	10	.03253746	.12658838	-.00455990	-.09326960	-.00275403	-.04727605
	11	.05205535	.16036218	.04657979	-.03162001	-.01451396	-.13838514
R	12	.04085097	.14769764	.06624041	.08666036	-.02829664	-.15773946
	13	.00322088	.07677342	.05391067	.23085146	-.02401262	-.08608175
	14	-.04282191	-.03750417	-.00611303	.32829959	-.01151384	.05660261
	15	-.05437333	-.15216503	-.06435825	.25262229	.04403111	.17745995
I	16	-.03012094	-.18052390	-.04972782	.07377065	.07442121	.14336598
	17	-.00000250	-.13191132	.02345018	-.07743536	.05020092	-.00557947
	18	.02259046	-.05727323	.06256268	-.14676139	-.01353100	-.12362972
	19	.03142082	.01963074	.05124089	-.14062108	-.09911174	-.15868359
A	20	.01895051	.06612953	.00706754	-.07808532	-.17447586	-.11079618
	21	-.00856129	.07207030	-.05102773	.00983062	-.21059194	.02929641
	22	-.02579728	.05136252	-.08472383	.06004236	-.17753007	.20675305
	23	-.04050542	-.04577798	-.04152402	.05112203	.02628690	.43476971
B	24	.03114924	-.11107273	.13153168	-.15417291	.33445587	.19469342
	25	.06314782	-.03352858	.08148046	-.17662697	.24181783	-.09182047
	26	.04372304	.01489833	-.04430026	-.10702521	.10319239	-.10758926
	27	.00538386	.03151894	-.13707173	-.01624469	.00487399	-.03683995
L	28	-.05391130	.02536813	-.16538390	.08549123	-.06155872	.04684392
	29	-.11418243	.01802569	-.11410578	.17170524	-.10998029	.08041164
	30	-.14819020	.00647202	.03494017	.18532036	-.09984481	.02981125
	31	-.13360284	.00031236	.27186497	.11796970	-.03065816	-.08319823
E	32	-.04110270	.00441268	.36267088	-.01217140	.05762708	-.10873343
	33	.04707575	.01182146	.23770792	-.08562430	.08416703	-.02924147
	34	.08609641	.01494034	.09165354	-.08776739	.06517858	.04223337
	35	.10036903	.02476201	-.02689479	-.04940530	.02102136	.08219724
	36	.10267381	.03031380	-.09238081	-.00857061	-.01642791	.07284682

APPENDIX 3. Beta ceofficients matrix for the St. Peter sandstone sample (0.35-0.50 mm size interval). Variables are rotated radial lengths.

		FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5	FACTOR 6
	1	0.820	0.416	-0.163	-0.236	-0.074	0.085
	2	0.796	0.340	-0.329	-0.159	-0.137	0.036
	3	0.740	0.150	-0.506	-0.011	-0.155	-0.086
V	4	0.454	-0.270	-0.700	0.217	-0.067	-0.235
	5	-0.129	-0.678	-0.517	0.303	0.075	-0.161
	6	-0.554	-0.688	-0.196	0.166	0.180	0.044
	7	-0.752	-0.537	0.032	-0.012	0.215	0.115
A	8	-0.863	-0.336	0.150	-0.173	0.176	0.098
	9	-0.889	-0.094	0.241	-0.255	0.070	0.021
	10	-0.837	0.213	0.297	-0.237	-0.064	-0.100
	11	-0.711	0.514	0.285	-0.107	-0.203	-0.169
R	12	-0.487	0.731	0.181	0.101	-0.296	-0.123
	13	-0.154	0.827	-0.008	0.351	-0.279	0.030
	14	0.277	0.665	-0.254	0.496	-0.147	0.242
	15	0.618	0.265	-0.460	0.391	0.121	0.323
I	16	0.750	-0.159	-0.461	0.175	0.255	0.179
	17	0.747	-0.458	-0.299	0.026	0.181	-0.064
	18	0.716	-0.592	-0.106	-0.084	0.019	-0.209
	19	0.681	-0.604	0.105	-0.169	-0.153	-0.212
A	20	0.650	-0.572	0.268	-0.194	-0.266	-0.097
	21	0.641	-0.494	0.409	-0.168	-0.252	0.108
	22	0.618	-0.327	0.558	-0.136	-0.088	0.290
	23	0.402	0.029	0.625	0.010	0.397	0.398
B	24	-0.325	0.496	0.124	0.082	0.711	-0.087
	25	-0.690	0.421	-0.271	-0.073	0.318	-0.286
	26	-0.810	0.231	-0.370	-0.203	0.059	-0.155
	27	-0.861	0.085	-0.352	-0.226	-0.069	0.032
L	28	-0.901	-0.072	-0.247	-0.106	-0.130	0.198
	29	-0.859	-0.236	-0.054	0.116	-0.188	0.268
	30	-0.718	-0.346	0.181	0.386	-0.190	0.159
	31	-0.308	-0.307	0.505	0.647	-0.117	-0.116
E	32	0.314	-0.029	0.672	0.544	0.053	-0.298
	33	0.677	0.232	0.541	0.189	0.164	-0.231
	34	0.788	0.345	0.339	-0.064	0.173	-0.099
	35	0.819	0.409	0.164	-0.211	0.105	0.027
	36	0.825	0.431	0.003	-0.259	0.014	0.086
% VARIANCE		45.89	18.56	12.77	6.21	4.52	3.20
CUMULATIVE % VARIANCE		45.89	64.55	77.33	83.54	88.07	91.27

APPENDIX 4A. Principal components analysis factor loadings on variables for rotated radial lengths of the St. Peter sandstone sample.

		FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5	FACTOR 6
	1	0.900	-0.223	-0.094	0.184	-0.185	0.064
	2	0.824	-0.335	-0.133	0.228	-0.179	-0.092
	3	0.646	-0.522	-0.102	0.215	-0.160	-0.291
V	4	0.148	-0.768	-0.057	0.088	-0.071	-0.496
	5	-0.551	-0.641	-0.051	-0.127	-0.003	-0.367
	6	-0.852	-0.263	-0.135	-0.244	0.073	-0.057
	7	-0.859	0.068	-0.189	-0.322	0.144	0.113
A	8	-0.763	0.342	-0.245	-0.355	0.212	0.141
	9	-0.603	0.584	-0.230	-0.314	0.257	0.083
	10	-0.376	0.780	-0.140	-0.180	0.319	-0.034
	11	-0.149	0.864	-0.027	0.065	0.369	-0.150
R	12	0.057	0.764	0.057	0.381	0.377	-0.203
	13	0.240	0.446	0.110	0.700	0.355	-0.156
	14	0.374	-0.086	0.081	0.840	0.223	-0.021
	15	0.417	-0.627	-0.015	0.591	0.075	0.119
I	16	0.364	-0.864	-0.024	0.156	-0.111	0.112
	17	0.274	-0.820	0.085	-0.188	-0.325	-0.016
	18	0.228	-0.654	0.167	-0.361	-0.524	-0.113
	19	0.217	-0.433	0.205	-0.397	-0.701	-0.108
A	20	0.198	-0.268	0.205	-0.332	-0.822	-0.016
	21	0.189	-0.173	0.204	-0.216	-0.856	0.197
	22	0.226	-0.083	0.239	-0.128	-0.741	0.480
	23	0.213	-0.007	0.330	-0.039	-0.187	0.823
B	24	0.046	0.171	0.183	-0.085	0.829	0.355
	25	-0.155	0.298	-0.188	-0.105	0.844	-0.209
	26	-0.324	0.344	-0.451	-0.097	0.618	-0.314
	27	-0.469	0.357	-0.572	-0.044	0.434	-0.254
L	28	-0.664	0.345	-0.535	0.042	0.280	-0.143
	29	-0.830	0.313	-0.319	0.130	0.099	-0.055
	30	-0.884	0.255	0.065	0.161	-0.028	-0.030
	31	-0.634	0.166	0.649	0.145	-0.137	-0.002
E	32	0.030	0.052	0.940	0.056	-0.178	0.128
	33	0.563	-0.028	0.719	-0.015	-0.155	0.249
	34	0.786	-0.085	0.414	-0.020	-0.141	0.286
	35	0.885	-0.111	0.163	0.037	-0.160	0.271
	36	0.915	-0.151	0.002	0.111	-0.179	0.193
% VARIANCE		30.20	20.46	9.97	8.07	16.34	6.21
CUMULATIVE % VARIANCE		30.20	50.67	60.64	68.71	85.05	91.27

APPENDIX 4B. Varimax factor loadings on variables for rotated radial lengths of St. Peter sandstone sample.

FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5	FACTOR 6
-0.28634	-0.45674	-0.07539	-0.18071	-0.02849	0.12270
0.27816	-0.12407	0.05555	-0.28543	-0.02775	0.02318
0.05653	0.16653	-0.01064	-0.14023	-0.19682	-0.02829
0.20129	0.27642	0.18712	0.05007	-0.08516	-0.32233
-0.01252	-0.27832	-0.15842	0.07638	0.06019	-0.05230
0.27726	-0.01225	0.17201	-0.22502	0.02364	-0.11718
0.06096	-0.02159	0.29569	-0.02408	-0.00192	-0.36374
-0.28589	-0.16816	-0.17641	-0.12468	-0.01027	0.18294
-0.24659	0.07309	0.07390	-0.05639	-0.17743	-0.19089
0.01113	-0.03699	0.26230	0.24147	0.03707	0.19609
0.19658	0.24693	0.12914	-0.08647	0.18253	-0.12727
-0.20307	0.22321	-0.07731	-0.28104	0.09567	-0.07964
0.00242	0.10004	-0.00394	-0.01743	-0.14982	-0.33435
-0.35476	-0.03328	-0.03542	0.05229	0.04901	0.05808
0.10912	0.10960	0.06415	-0.15897	0.16220	0.01283
0.06788	0.03572	0.11761	0.12167	0.08545	0.29458
-0.52747	-0.01715	0.17402	-0.19973	-0.01149	-0.11432
0.02309	-0.20451	-0.32271	0.22792	-0.05334	-0.38762
-0.60433	0.26621	-0.19267	-0.15847	-0.09803	0.67869
0.02530	0.28782	-0.13410	0.28422	0.29563	-0.07449

APPENDIX 5. Example of estimated factor scores for twenty grains from the New Jersey beach sand sample.

SAMPLE	FACTOR	MEAN ESTIMATED FACTOR SCORE	STANDARD DEVIATION	95% CONFIDENCE INTERVAL	
SP	1	-0.002	0.193	-0.012	0.008
	2	0.036	0.017	0.028	0.044
	3	0.027	0.165	0.019	0.035
	4	-0.002	0.158	-0.010	0.006
	5	-0.029	0.138	-0.036	-0.022
	6	0.002	0.132	-0.004	0.008
NJ	1	-0.015	0.206	-0.035	0.005
	2	-0.017	0.204	-0.037	0.003
	3	0.026	0.207	0.006	0.046
	4	0.000	0.223	-0.011	0.011
	5	0.034	0.166	0.026	0.042
	6	-0.002	0.197	-0.012	0.008
LR	1	-0.019	0.209	-0.030	-0.009
	2	-0.039	0.214	-0.050	-0.029
	3	-0.019	0.215	-0.030	-0.009
	4	0.001	0.258	-0.012	0.014
	5	0.027	0.173	0.019	0.035
	6	-0.003	0.215	-0.014	0.008
JH	1	-0.054	0.247	-0.066	-0.042
	2	-0.043	0.213	-0.054	-0.033
	3	-0.045	0.245	-0.057	-0.033
	4	0.003	0.283	-0.011	0.017
	5	0.073	0.201	0.063	0.083
	6	0.023	0.243	0.011	0.035
SR	1	-0.007	0.224	-0.018	0.004
	2	-0.025	0.210	-0.035	-0.015
	3	-0.026	0.226	-0.037	-0.015
	4	-0.008	0.256	-0.021	0.005
	5	0.025	0.168	0.017	0.033
	6	-0.002	0.211	-0.012	0.008
MON	1	-0.003	0.217	-0.014	0.008
	2	-0.018	0.213	-0.029	-0.007
	3	-0.007	0.192	-0.017	0.003
	4	0.002	0.237	-0.010	0.014
	5	0.006	0.155	-0.002	0.014
	6	0.001	0.196	-0.009	0.011
CAT	1	-0.038	0.221	-0.049	-0.027
	2	-0.038	0.225	-0.049	-0.027
	3	-0.030	0.217	-0.041	-0.019
	4	0.012	0.230	0.000	0.024
	5	0.053	0.169	0.011	0.013
	6	-0.001	0.229	-0.024	0.022

APPENDIX 6. 95% confidence intervals for mean values of estimated factor scores of the St. Peter sandstone (SP), New Jersey beach (NJ), Lehigh River (LR), Jackson Hole till (JH), Sherman Ridge sand (SR), Montebello sand (MON) and Catskill sand (CAT) samples.

VITA

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TRAITS AS PROTOTYPES
IN
HUMAN MEMORY

by

Elizabeth Howlett Creyer

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Aug. 8, 1983
(date)

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This thesis is dedicated to my family whose love has been a constant source of support and encouragement.

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Abstract

The purpose of this study was to demonstrate the functioning of the concepts of likeableness and dislikeableness as prototypes. Thirty-two (32) males selected from the Lehigh University subject pool served as subjects. An acquisition set of 42 items describing a likeable and dislikeable character was presented to subjects. Subjects were then administered a recognition test containing 20 old items (i.e. members of the acquisition set) and 30 new items (10 likeableable, 10 control, 10 dislikeable). For each item on the recognition test, a subject both identified the character described by that item and rated how certain he was about his decision. Only the 30 new items in the recognition set were considered in the analysis. Data from the recognition test indicates that memory was biased towards recognizing nonpresented trait related items. This suggests that trait concepts are represented in memory as prototypes.

CHAPTER 1

TRAITS AS PROTOTYPES IN HUMAN MEMORY

STATEMENT OF THE PROBLEM

Scientists from both social and cognitive psychology are working towards a better understanding of the cognitive processes involved in perceiving, encoding, storing, and remembering social information. Much of this research has focused on person-memory, that is, memory for the characteristics and behavior of people. Numerous theorists (e.g., Mischel, 1979; Neisser, 1976;) have postulated that one's memory is influenced by one's stucture of prior knowledge called schemata. These thematic stuctures have been shown to influence both the encoding (e.g., Anderson, Reynold, Schallert, & Goetz, 1977; Rumelhart, 1977) and the retrieval (Cohen, 1983; Cantor & Mischel, 1979, 1977; Spiro, 1977) of information about other people. The schematic properties of traits (Cantor & Mischel, 1977), social attitudes (Judd & Kulik, 1980), occupations (Cohen, 1981), race (Taylor, Fiske, Etcoff, Ruderman, 1978), and sex (Taylor et al., 1978) have been demonstrated. However, the ability to generalize from the results of many of these studies is severly limited due to an inadequate analysis of the data, an improper experimental design, or both. The purpose of the present study was to test, using a proper experimental design and correct analysis of the data, whether the traits of likeableness and dislikeableness have schematic properties by examining whether recognition memory is biased towards information that is consistent with schematic expectations.

REVIEW OF THE LITERATURE

The notion of schema is appearing more and more frequently in the cognitive psychology literature which has long been dominated by two approaches to the study of memory - the information processing model and the levels of processing model. The information processing approach to memory (Simon, 1979; Shiffrin & Schneider, 1977; Atkinson & Shiffrin, 1968) identifies two distinct storage mechanisms - short term and long term memory. Incoming information is first stored in short term memory which is limited in both capacity (about 7 chunks, or units) and duration (lasting only a few seconds). If the information contained in short term memory is rehearsed, it may then be transferred to long term memory which is unlimited in both duration and capacity. However, the information processing model, as originally conceived (Waugh & Norman, 1965; Atkinson &

Shiffrin, 1968) has undergone a number of modifications and with each modification, the differences between the information processing model and the levels of processing model have become less distinct.

The levels of processing model (Craik, 1979; Colthart, 1977; Craik & Tulving, 1975; Craik & Lockhardt, 1972) has been viewed as extending, not replacing the information processing approach to memory (Craik, 1979). This model identifies memory as a by-product of various perceptual processes and analyses. That is, the result of various perceptual processes is a memory trace, the means by which we remember information. There is no need to postulate separate memory stores for the depth, or amount of processing is directly related to the task the subject is asked to perform. Hyde & Jenkins (1973) demonstrated this by presenting word lists to subjects who performed one of three types of orienting tasks on each of the items - semantic (i.e., attend to the meaning of the word), syntatic (i.e., identify the word's part of speech), or graphic (i.e., determine if the word contained specific letters). After the subjects completed their tasks, they were unexpectedly asked to recall the words. Subjects who performed the semantic task, that is, processed the information most deeply, recalled more words than subjects who performed nonsemantic rasks.

Although the information processing model and the depths of processing model have been commonly accepted approaches to the study of memory, a third approach - the schema model - is becoming increasingly popular among researchers (e.g., Cohen, 1983, 1981; Taylor et al., 1978; Tsujimoto, 1978). Schemata, a notion first developed by Bartlett (1932/1967), refer to cognitive structures - internal rule structures - that contain one's organized knowledge of the world. Each person has many schemata containing different types of information. For example, an avid baseball fan has a "baseball schema" containing the rules of play and these rules provide a cognitive framework through which the game is perceived and remembered. Current research in memory is moving in this new direction as more researchers are exploring how schemata influence the aquisition, storage, and retrieval of information (e.g., Cohen, 1983, 1981; Cantor and Mischel, 1979, 1977).

Theorists (e.g., Neiser, 1976) have postulated that schemata focus our attention on a particular aspect of the environment thereby making perception inherently selective. The perceived information is then actively processed or catagorized in terms of the appropriate schema. Research has shown that we use a number of different catagories to organize our perceptions of other people. For example, a study by Taylor, et al. (1978) in which subjects listened to a series of taped discussions supplemented by pictures of the participants, demonstrated that race can be used as the basis for the organization of information. Three of the participants were black and three were white (all particicpants were male). Each time a participant made a suggestion, his picture was presented. The task of the subject was to match, relying on their memories of the taped discussion, each of the suggestions with the man who offered it. If information is encoded in terms of race than one would expect a greater number of intraracial errors, i.e., black (white) suggestions erroneously attributed to other blacks because of the perceived similarity within groups. That is, blacks (whites) should be seen as similar to other blacks (whites) and different from whites (blacks). This was, in fact, the case - intraracial errors significantly exceeded interracial errors. A second study by Taylor et al. (1978) using male and female discussion participants was conducted and similar results were found, that is, intrasex errors far exceeded intersex errors. Thus the assumption that sex and race are catagories used to organize person information has been supported. As Taylor et al. stated, "Stereotypes can be thought of as attributes that are tagged to cataegory lables (e.g., sex, race) and imputed to individuals as a function of their being placed in that catagory, ...(p. 792".

Stereotypic knowledge about occupation has also been shown to influence memory in important ways (Cohen, 1981). Features that were truly typical of waitresses and features that were truly typical of librarians were identified by subjects who were asked to described their image of a typical librarian and a typical waitress. These attributes were rated by a different group of subjects according to how likely they were to be possessed by librarians and waitresses. Cohen then selected eighteen pairs of features - for each pair, one feature was highly likely of a waitress (e.g. does not wear glasses) and the other feature was highly likely of a librarian (e.g., wears glasses). Subjects viewed a videotape of the target character who was explicitly identified before hand as either a librarian or a waitress. The videotape contained nine features that were characteristic of librarians and nine features that were characteristic of waitresses.

After viewing the videotapes, subjects were presented a forced choice memory tests based on the eighteen pairs of features mentioned above. The results indicate that features that are consistent with one's stereotypes are better remembered. That is, when the target character was identified as a librarian, features characteristic of librarians were more accurately remembered than features that are characteristic of waitresses. These results suggest that subjects brought to mind occupational prototypes when recalling the information.

It has been hypothesized that most categories - concepts - are represented in memory by prototypes, that is, the example which allows us to best understand it (Rosch, 1975; Rosch & Mervis, 1975). Category prototypes may be determined neurophysiologically, as has been suggested in the case of color, or formed through the principles of learning (Rosch & Mervis, 1975). For example, many people share common person prototypes such as an "absent minded professor", a "dizzy blond", and an "all-American boy". A number of studies (e.g., Cohen, 1981; Cantor & Mischel, 1977) have shown that prototypes are, in fact, schemata, that is, they serve as the basis for the organization, or catagorization, of information. According to the schema model of memory, as incoming information about an individual is encoded in terms of a specific category (e.g. likeable), a comparison to prototype process occurs (Tsujimoto, 1978; Cantor & Mischel, 1977). Tsujimoto (1978) has shown that this categorization seems to be based on their prototypicality, the degree to which they share common characteristics of that category.

Tsjimoto presented subjects 14 lists of personality traits that varied in their similarity to the prototype list. The most similar list contained the greatest number of items in common with the prototype list. There were 3 prototype lists - positive (composed of positive traits), negative (composed of negative traits), and novel (composed of both negative and positive traits). Sixteen recognition lists were presented (including the prototype lists). Subjects were asked to rate how certain they were that they had heard the lists before. However, none of the 16 lists had ever been presented. Lists that had the most items in common with the prototype lists received the highest confidence ratings. Tsujimoto (1978) posits that during the recognition test, each new list was compared with the prototypes of the old lists.

The results obtained by Tsujimoto (1978) suggest that when information is organized in terms of prototypes, one's memory for that information is improved. Therefore if information is categorized in terms of prototypes, then category consistent information should be more memorable than category inconsistent information. A number of studies have, in fact, supported this interpretation (Cohen, 1981; Rothbart, Evans, & Fulero, 1979; Cantor & Mischel, 1977). One series of studies, however, by Hastie & Kumar (1979) has not.

Subjects formed impressions of 6 fictional characters, each described by eight synonymous trait adjectives (e.g., clever, bright). Hastie and Kumar (1979) then presented subjects lists describing the behaviors of each character which were congruent, incongruent, or neutral with respect to the given trait used to identify the character. The results indicate that behaviors that were inconsistent with the given trait were more likely to be recalled than behaviors that were consistent with the given trait.

The schema model of memory has great difficulty accounting for these results. Perhaps the inconsistent information is more salient and therefore more deeply processed than the consistent information. This study does differ from much of the current research in one important respect. Subjects anticipated a recall test as an intentional measure of memory. Even given this procedural difference, the question remains, why these results were found only by Hastie & Kumar (1979). A study by Spiro (1977) may help to shed some light on this matter.

Spiro (1977) has shown that subjects who anticipated an intentional measure of memory remembered information more accurately than subjects who did not expect a memory test. He presented a story about an engaged couple, Bob and Marge, in which Bob tells Marge he does not want children. In one condition, Marge is relieved because she does not want children either. In a second condition, Marge is very upset at Bob's revelation and argues bitterly. After the subjects had read the story, it was casually mentioned either that Bob and Marge were happily married, or that the engagement was broken. Several days later, the subjects were asked to recall the story about Bob and Marge. Subjects who anticipated an intentional measure of memory remembered the story more accurately than subjects who believed they were in a study of interpersonal relationships. For example, subjects believing they were in a study of interpersonal relationships who were told that Bob and Marge fought bitterly but were later married, often erroneously recalled that Bob and Marge ended their relationship. Likewise, many subjects told Bob and Marge agreed not to have children but later separated, erroneously recalled that Bob and Marge were married. Spiro suggests these errors occured because subjects who believed they were in a study of interpersonal relationships were more likely to assimilate the story into their pre-existing body of knowledge about interpersonal relationships than subjects who expected an intentional measure of memory. Thus, those subjects who did not anticipate a memory task were forced to rely on their 'interpersonal relationship' schema when recalling the details of the story. Spiro contends that this reliance on schemata when retrieving details of the story was responsible for the subjects' memory biases.

The biasing effects of schemata have been demonstrated in a number of other studies as well (e.g., Cantor & Mischel, 1979; Snyder & Uranowitz, 1979; Cantor & Mischel, 1977). Cantor & Mischel (1977) have suggested that when information about people is encoded in terms of a particular trait schema, memory is biased towards information that is consistent with that trait. That is, once an individual is assigned to a particular category (e.g., extravert), one tends to attribute characteristics to the individual that are consistent with that label.

Cantor & Mischel (1977) presented trait words describing four characters - an introvert, an extrovert, and two neutral (i.e., control) characters. After having formed an impression of the characters, subjects were asked to identify only those words actually used to describe the characters. This recogniton test contained both items used to describe the characters and new items (i.e., words that did not appear on the acquisition list) that were either consistent with the trait category or neutral with respect to the trait. For example, new trait-consistent words such as "assertive" and "outgoing" appeared on the recognition test that assessed the subjects' memory of the extravert character. Cantor and Mischel concluded from the results of this study, which indicated that subjects were more likely to falsely recognize words that were conceptually related to the trait category than neutral words, that traits function as prototypes. However, the biasing effects of prototypes on memory (i.e., the prototype effect) was not reliably demonstrated due to errors made in both the design of the study and in the analysis of the data.

DESIGN AND ANALYSIS ERRORS

There are several serious errors in the design and analysis of the Cantor & Mischel (1977) study, the first of which is known as the category confound effect (Kay & Richter, 1977). This error occurs when "only one sample from a population of possible samples is used to define a category of treatment factors (Kay & Richter, 1977)." As previously mentioned, subjects were presented trait items (the acquisition lists) describing four fictional characters. The extravert (introvert) character was described by 10 items - 6 moderately related to the trait of extraversion (introversion) and 4 unrelated (i.e., control) items. The two control characters were each described by ten items unrelated to either introversion or extraversion (e.g., tall). For all subjects, the same 10 items were always used to describe the extravert (introvert, control) character. The failure to use more than a single list of words to define a particular character results in the category confound effect.

The category confound is a serious problem in this case because the single set of items used to describe each character is confounded with that character, that is, the treatment category. A different set of acquisition items may have yielded differing results. The likelihood of this event cannot be estimated because there is no way to assess the effects of the individual items on the acquisition lists, that is, no way to estimate their variance. This confounding results in a serious interpretation problem - are the results of the study due to the treatment factor or the single list of acquisition items used to describe each character. Cantor & Mischel (1977) could have avoided this error by using a number of different randomly chosen acquisition lists to describe each character.

Cantor & Mischel not only failed to use a number of different randomly chosen acquisition lists, they also failed to use a number of different randomly chosen recognition lists for each character. There were four recognition lists, one for each of the four characters. New items (e.g., lively, timid) that were consistent with the trait categories (i.e., extraversion, introversion) were more likely to be erroneously recognized as having been used to described the characters than new neutral items (e.g., sensible, original). However, each of the four recognition lists were the same across subjects, that is, the same 15 items always appeared on the extravert (introvert) recognition list (16 items appeared on the control recognition list). Cantor & Mischel failed to assess the reliabilty across recognition words thus confounding the prototype effect with the single set of recognition items employed in the study.

Simply stated, in the analysis of their data, recognition word variance within catagories was simply ignored, that is, Cantor & Mischel implicitly treated it as a fixed effect. However, when a sample of words is chosen from a population of words, a words factor should be included as a random effect in the analysis of the data (Clark, 1973). Subsequently, recognition word variance within catagories should have represented a random effect in the analysis of the data. The pattern of results obtained by Cantor & Mischel could have resulted from word differences alone therefore, if the study were to be replicated using different recognition words, the same pattern of results may not emerge (Richter & Seay, 1983). The assumption that recognition word variance within categories represents a fixed effect means that the results obtained by Cantor & Mischel are not generalizable beyond the actual recognition words employed the study.

The errors mentioned above are by no means unique to the Cantor & Mischel (1977) study but have appeared frequently throughout the prototype literature. Catagory confound, that is, the failure to use a number of randomly chosen samples from a population of samples to define a treatment catagory, occurs in several studies (e.g., Cohen, 1981; Hartwick, 1979). However, the failure to include word variance as a random effect in the model is a much more common error, subsequently inadequate data analyses have been performed in many of the person prototype studies (e.g., Cohen, 1981; Hartwick, 1979; Taylor et al., 1978; Tsujimoto, 1978) Thus, although a number of studies seem to have demonstrated the prototype effect, there is some doubt as to whether it is, in fact, a reliable effect in the individual studies.

THE PRESENT STUDY

The purpose of this study was to demonstrate the prototype effect, using the concepts of likeableness and dislikeableness as prototypes, while avoiding the generalization problems found in much of the person prototype research. The likeable - dislikeable dimension was chosen because research has indicated that these conceptual categories are a basic - perhaps the most basic dimension of an individual's personality as perceived by others (Hartwick, 1979; Lott & Lott, 1970; Osgood, Suci, & Tannenbaum, 1957). There are number of important differences between the present study and the Cantor & Mischel (1977) study. To avoid the confounding of treatment categories (i.e., likeable, dislikeable) with the single acquisition list used to describe each of the characters, a different set of acquisition words were randomly chosen to describe each character for each subject. This allows for the generalization of the results across the total population of words that could have been randomly selected to define the likeable and dislikeable character. Recognition lists were also randomly selected for each subject. By confounding recognition lists with subjects, recognition word variance within treatment categories (i.e., likeable, dislikeable control) was properly treated as a random effect. Therefore, for each subject, a different set of recognition words and acquisition words were randomly chosen, incorporating all sources of random error into a single random factor - subjects. Subsequently, unlike the Cantor & Mischel (1977) study , the results of this study are generalizable beyond the actual recognition words used in the study.

Whereas Cantor & Mischel defined two prototype characters and two control characters, the present study defined only a likeable and dislikeable character. The elimination of the control characters meant that more words had to be used to describe each of the two characters in order to avoid a ceiling effect (i.e., subjects recognizing only those words actually used to describe the characters).

The likeable and dislikeable characters were explicitly identified as likeable and dislikeable, in addition to being described by 14 trait adjectives (e.g., happy, hostile) and 6 control adjectives (e.g., tall).

The elimination of the control characters also allowed for the employment of a single recognition list composed of likeable, dislikeable, and control words, unlike the Cantor & Mischel (1977) study which used four recognition lists, one for each character. Employing a single recognition list allowed for a simple analysis of the data which provided easily interpretable results. Although the recognition list contained both adjectives actually used to describe the characters and nonpresented, or new, adjectives (i.e., not used during the acquisition phase to identify the characters), only the new adjectives were considered in the analysis. This was done because we were not interested in comparing subjects' recognition of presented and nonpresented words: we were solely interested in those words falsely recognized as having been used to describe the characters. In addition, because the design is within subjects and words, the test of the prototype hypothesis was expected to be more powerful than the test used by Cantor & Mischel (1977).

Thus, the following hypothesis was proposed:

Subjects will use the trait concepts (likeable, dislikeable) as organizing prototypes for processing information, and will be biased towards recognizing nonpresented but trait-related adjectives.

That is, subjects are expected to erroneously identify nonpresented trait-related adjectives as being among the items originally used to describe the characters (acquisition set). For example, even though 'honest' was not among the acquisition list items, subjects are expected to erroneously identify 'honest' as being used to describe the likeable character more often than they erroneously identify 'honest' as being used to describe the dislikeable character. In sum, this study was conducted in order to demonstrate the prototype effect while properly including words in the ANOVA design as a random effect which permits the generalization of the results across both subjects and words.

CHAPTER 2

THE RESEARCH

EXPERIMENT 1

Method

Subjects. Eighty students enrolled in two introductory psychology courses served as subjects. The students were randomly selected from the Lehigh University subject pool and served in the study as part of the course requirement.

Procedure. Two hundred items were selected from Anderson's (1968) list of likeableness ratings of 555 personality trait words. These 200 items received the highest meaningfulness rating in Anderson's (1968) study. One hundred ninty-nine items were distributed across 8 pages (one of the items was inadvertently ommitted). Booklets, each containing 4 randomly selected pages of items were constructed. Therefore, each subject was required to rate either 99 or 100 items. The subjects were given the following instructions in writing:

"I am interested in determing how you describe the people you like and dislike. On the following pages there are 100 words commonly used to describe people. Think of a person as being described by each word. Then rate that word according to how much you would like that person. The scale on which to rate the person being described looks like this:

like dislike

1 2 3 4 5 6 7

Circle the most appropriate number. Work at your own pace, and please try to use the numbers 1-7 about equally often."

Results. The mean rating of the 199 items was 3.875, and the median was 3.975. The items were divided into three pools of approximately equal numbers words based on the frequency distribution shown if Figure 1. The 69 items with mean ratings between 1.00 and 2.99 composed the likeable pool of words. The 63 with mean ratings between 3.00 and 4.99 composed the control pool of words, and the 67 items with mean ratings between 5.00 and 7.00 composed the dislikeable pool of words.

EXPERIMENT 2

Method

Subjects. The subjects in this study were thirty-two (32)

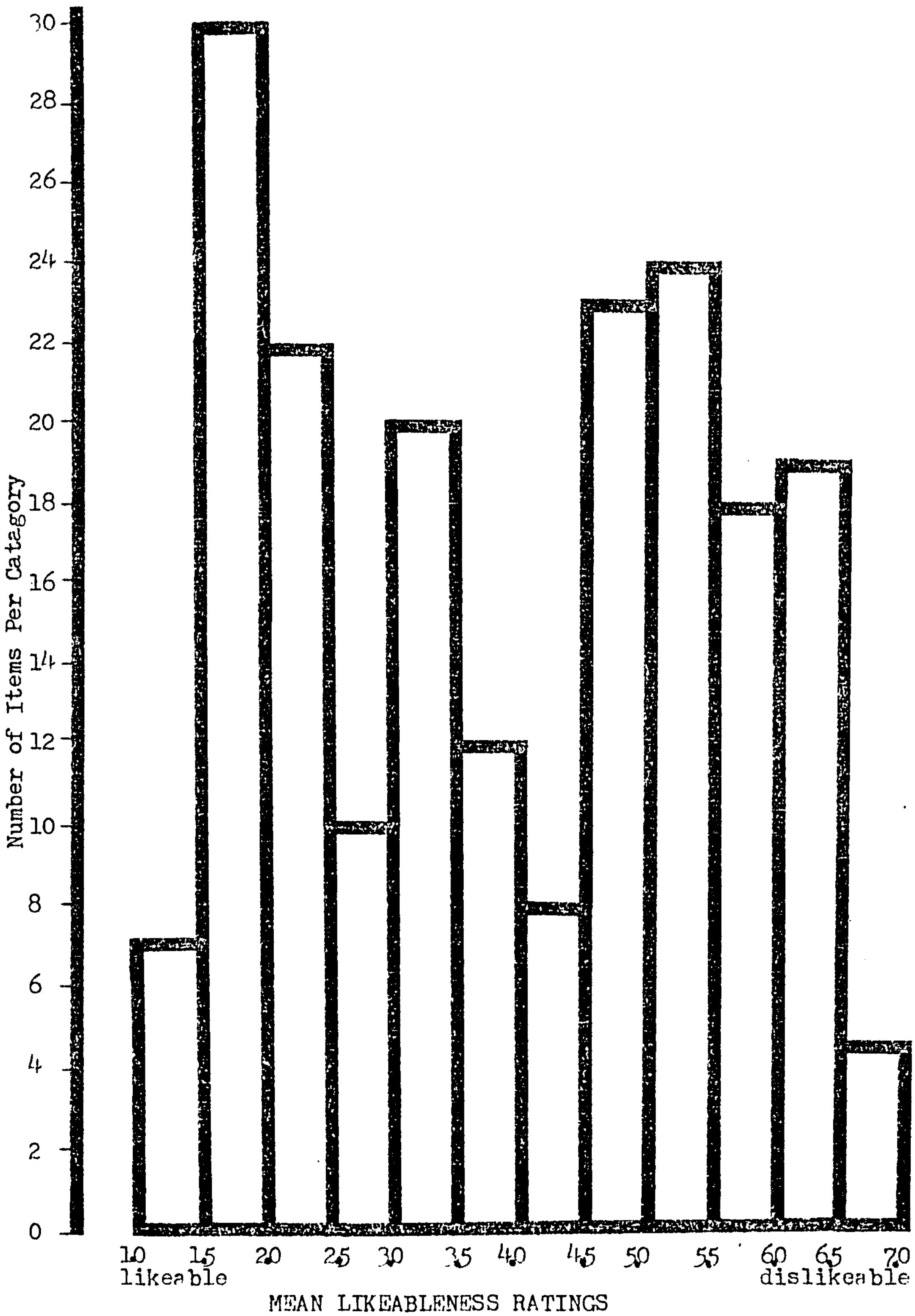

Figure 1: Frequency distribution of likeableness ratings.

male undergraduates randomly selected from the Lehigh University subject pool and served as part of a course requirement. Subjects were run in small groups; approximately 5 per session.

Stimuli. The pool of trait adjectives acquired from Study 1 was used to construct both the acquisition and recognition sets.

Acquisition set. The pool of adjectives rated as being likeable contained the 69 items that had mean ratings between 1.00 and 2.99. Trait adjectives rated as being dislikeable composed a pool of 67 items and obtained mean ratings of between 5.00 and 7.00. The remaining 63 adjectives obtained means between 3.00 and 4.99 which indicates that they were judged as not being particularily likeable nor particularily dislikeable. These items comprise the control pool.

Two characters, one likeable and one dislikeable, were created from these pools of words. Each character was described by 21 sentences in the form "X is friendly" (e.g. "Tom is friendly"). The likeable (or dislikeable) character was described by 14 sentences containing items randomly selected from the likeable (or dislikeable) pool of words. Six sentences contained items randomly selected from the control pool of words. The sentences "X is likeable" and "X is dislikeable", which explicitly identify the likeable character as likeable and the dislikeable character as dislikeable, were included in every acquisition set.

Thus, the acquisition set for each subject contained 21 sentences describing the likeable character and 21 sentences describing the dislikeable character. Since the items used to describe the characters were randomly selected for each subject, no two subjects received identical acquisition sets. The names of the characters, Jim and Bob, were randomized across subjects. For some subjects Jim was identified as likeable and Bob identified as dislikeable, while the reverse was true for other subjects.

Recognition set. A booklet containing fifty recognition set items was constructed. Thirty of those items were adjectives that were not among the acquisition set, ten each selected from the pools of likeable, dislikeable, and control adjectives. The remaining 20 items were selected from the acquisition set. Seven items used to describe the likeable character originally selected from the likeable pool of words were randomly chosen. Likewise, seven items used to describe the dislikeable character originally selected from the dislikeable pool of words were randomly chosen. Three control items used to describe the likeable character and three control items used to describe the dislikeable character were also randomly selected. As with the acquisition set, no two subjects were presented identical recognition sets. The order of the 50 recognition set items were then randomized for each subject.

Trait rating scale. Subjects were also asked to rate both characters as either high (1), moderate (2), low (3), or no information (4) on eight different traits. The following traits were included: extroverted, introverted, good, bad, likeable, dislikeable, flexible, and rigid. These scales were included so that in the event that nonsignificant results were obtained, it could be determined whether the subjects realized that the characters described to them were likeable and dislikeable. For example, the failure of a subject to rate the likeable character as likeable, would make the results extremely difficult to interpret since it would suggest that the expected prototype was not activated by exposure to the acquisition items.

Procedure

Acquisition set phase. During the acquisition set phase of this study, subjects viewed the 42 sentences describing the two characters. The order of the presentation of characters was randomized across subjects. That is, for some subjects the sentences describing the likeable character were presented first and the sentences describing the dislikeable character presented second while the reverse was true for other subjects. The following instructions were presented to the subjects both verbally and in writing:

"In this experiment you will be viewing a series of cards. Each card will describe a person. For example a card might say, 'Tom is thoughtless'. The cards will be describing two people - Jim and Bob. Each person will be described by a separate series of cards. When I tell you to begin I would like you to turn over the first card and read it. Each time the buzzer sounds, turn over the next card and read it. When you have gone through the entire deck of cards set them aside.

As you are viewing the cards try to form impressions of Bob and Jim. For example, would you like them to be your friends? After you have finished looking at all the cards I am going to ask you some questions about your impressions of Bob and Jim."

Subjects were given two seconds to view each card.

Impression formation task. This task was included to facilitate the formation of impressions of the two characters. By forming impressions of Bob and Jim, subjects were forced to actively process the information presented them. Additionally, since subjects were given five minutes to complete this task, they were forced to rely on long term memory during the recognition test phase. The following questions were asked the subjects in writing:

1. Would you like Bob to be your roommate? Briefly explain in one or two sentences why you would or would not want Bob as a roommate.

2. Would you like Jim to be your roommate? Briefly explain why you would or would not want Jim as a roommate

3. Would you like Bob to work with you on a project? Briefly explain why you feel that way about Bob.

4. Would you like Jim to work with you on a project? Briefly explain why you feel that way about Jim.

Recognition test phase. Subjects were presented booklets containing the recognition set items. These instruction were presented both verbally and in writing:

"In this part of the experiment you will be presented a list of 50 words. Alongside each of the words will be the names of the two people who were described to you and the item "No one". For each word, identify who was described by that word. If Bob was described by that word, place an X next to his name. If Jim was described by that word, place an X next to his name. If neither character was described by that word place an X next to "No one". The words will be arranged this way:

1. tall ____Jim

____Bob

____No one

1	2	3	4	5
very uncertain				very certain

After you indicate who was described by that word, then rate how certain you are about your decision on the scale provided. If you are very certain that the word 'tall' was used to describe Bob, place an X next to his name and circle 5. If you are very certain that the word 'tall' was not used to describe either character, then place an X next to "No one" and circle 5. The other numbers reflect intermediate levels of certainty. For example, if you are only moderately certain that a word was used to describe the person you indicated then you would circle 3.

When indicating who was described by a particular word, you may make only one choice. That is, you cannot indicate that one word was used to describe two people. Are there any questions?"

Results

Only the 30 new items in the recognition sets, (i.e. those that were not members of the acquisition set) were considered in the analysis. The following procedure was used to create an ordinal scale that reflected the confidence ratings of the subjcts. When a subject indicated that the likeable character was described by a particular item, his confidence rating on that item was multiplied by +1.00. When the dislikeable character was selected, the confidence rating was multiplied by -1.00. When subjects indicated that no one was described by the item, the number of zeros (0's) corresponding to the confidence rating was added to the sum of the confidence ratings for that catagory of words. For each subject, the mean of these signed ratings was calculated for each of three item catagories. For example, when a subject indicated that no one was described by a dislikeable item and was very certain about his decision, then 5 zeros were added to the sum of the confidence ratings for the dislikeable items. When a subject indicated that the likeable character was described by a likeable item and circled 3, then +3.00 was added to the sum of the confidence ratings of the likeable items. Thus, a +5 (-5) indicated that the subject was very certain that the item was used to describe the likeable (dislikeable) character during the acquisition phase of the study. Intermediate numbers represent intermediate levels of certainty. The mean ratings of the new likeable, dislikeable, and control items are given in Table 1. A one-way analysis of the data indicates that the group means are reliably different $\underline{F}$ (2, 62) = 42.313, $p < .001$.

TABLE 1: MEAN CONFIDENCE RATINGS

Word catagory

likeable	control	dislikeable
.4356	-.0773	-.3120

A second method was used to analyze the data because we were not certain that the scale on which the first analysis was based was free from distortion. That is, we were not sure whether the first method provided a valid measure of the subjects' recognition confidence. This second analysis ignored the confidence ratings: a confidence rating of 5 was treated the same as a confidence rating of 1. If the subject indicated that the likeable (dislikeable) character was described by an item, a +1.0 (-1.0) was added to the sum of the confidence ratings for that catagory of words. When a subject indicated that "no one" was described by a word in a particular word catagory (e.g. likeable), a 0 was added to the sum of the ratings for that word catagory. The mean ratings of the new likeable, dislikeable, and control items are given in Table 2. A one-way analysis of these data also indicates that the group means are reliably different $\underline{F}$ (2, 62) = 49.02, $p < .001$. It is clear from the data that the likeable (dislikeable) items were identified as having being used to describe the likeable (dislikeable) character significantly more often they were identified as having been used to describe "No one" or the dislikeable (likeable) character.

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TABLE 2: MEAN RATING OF ITEMS DISREGARDING CONFIDENCE RATINGS

Word catagory

likeable	control	dislikeable
.4400	-.1000	-.3240

Discussion

The research hypothesis which stated that subjects would use the trait concepts (likeable, dislikeable) as organizing prototypes for processing information and would be biased towards recognizing nonpresented, trait related items was confirmed. The biasing of memory towards recognizing nonpresented, trait related words supports the notion that the traits of likeableness and dislikeableness operate as prototypes for organizing information about personal attributes. Subjects were presented a description of two characters, one likeable and the other dislikeable, and seem to have used the traits of likeableness and dislikeableness to organize their impressions. Then, during the recognition phase, prototypes of these personality traits, that is, likeable and dislikeable, were activated as evidenced by memory biases consistent with the trait prototype. The prototype hypothesis has been supported by the results which indicated that subjects reported greater confidence that new likeable (dislikeable) items, as opposed to new dislikeable (likeable) and control items, had been used to describe the likeable (dislikeable) character during the acquisition phase of the study. The implication of this study is that the prototype effect is, in fact, a reliable effect.

Unlike many of the other prototype studies appearing in the literature, this study has been both a powerful and reliable demonstration of the prototype effect. The pattern of results obtained are generalizable beyond the actual set of words employed in the study because words were randomly selected and properly included in the ANOVA design as a random effect. That is, this study has provided statistical evidence that the same pattern of results would emerge if the study were to be replicated using a new selection of words in both the acquisition and recognition lists. Thus, the reliability of the prototype effect seems to have been established. In fact, the present study has provided statistical evidence that the prototype effect can be quite robust.

The experimental design used in this study, which allowed for a simple analysis of the data and the generalization of the results beyond the actual words used in this study, had one major drawback, that is, the preparation of the stimuli lists was a time consuming and tedious task. As stated in an earlier part of this paper, this study confounded words with subjects thus incorporating all sources of random error into a single factor - subjects. Because different acquisition lists and a different recognition list were randomly chosen for each subject, the lists had to be constructed by hand.

An alternative experimental design may have been a better solution to the generalization problems found in much of the prototype literature. Instead of preparing acquisition and recognition lists unique to each subject, subsets of lists could have been constructed introducing an additional factor, Lists, into the analysis. It would be desirable to construct as many lists as possible in order to maximize the power of the tests because the degrees of freedom for the error term used to test for the prototype effect is directly dependent on the number of lists (Richter & Seay, 1983). This method would reduce the time needed to prepare the study while still avoiding the generalization problems found in much of the prototype literature.

Although the results of this study are a reliable demonstration of the prototype effect and lend support to the prototype hypothesis, they do not conclusively demonstrate that personality traits operate as organizing prototypes for processing information. Richter & Seay (1983) have proposed an alternative to the prototype hypothesis, that is, the semantic similarity hypothesis. They have suggested that recognition responses in many prototype studies, such as the Cantor & Mischel (1977) study, may depend heavily upon the semantic similarity between the acquisition list words and the recognition list words. Some of the items on the acquisition lists may have been semantically similar to items on the recognition list. For example, the likeable character could have been described by the word "clever" during the acquisition phase and the word "witty", which is semantically similar to the word "clever", could have been appeared on the recognition list. Semantic generalization would occur if a subject, remembering that a word meaning clever was presented, erroneously recognized witty as being among the acquisition set items.

Further research is necessary to determine whether the semantic similarity hypothesis or the prototype hypothesis is the best explanation of the prototype effect. This problem could be studied using two conditions, in one condition trait-related items comprising the acquisition and recognition sets would be semantically similar (e.g., happy - cheerful)and in the second condition, the trait related items would not be semantically similar (e.g., friendly - daring). If memory was biased towards recognizing non-presented trait-related items in the first condition, but not in the second condition, then one could posit that subjects were responding to the meanings of the words and had not organized information in terms of prototypes. On the other hand, if memory is biased when the words were not semantically similar, then one could argue that prototypes were actually being used to organize incoming information.

Although the prototype hypothesis has been confirmed, it should be pointed out that the applicability of the results may be somewhat limited. Both Cohen (1981) and Gibbs (1979) note that because of an excess emphasis on objectivity and precision, much of the social science research lacks ecological validity. That is, because of the artificiality of the laboratory situation, the results of many studies are not generalizable to the real world. Unfortunately, the paradigm used in the present study, similar to paradigms typically used in prototype research, was very different from person-perception as it occurs in everyday life. Subjects were presented a list of trait adjectives describing fictional characters: the information presented about the characters related to only one dimension of their personality (i.e., whether they were likeable or dislikeable). Subjects were, in fact, given a list of personality attributes which is not the typical way of getting to know people. The paradigms of future person-memory research studies should be more similar to real-life person perception situations. For example, instead of simply presenting a list of adjectives describing a character, videotapes of people in every day situations could be presented thus increasing the complexity of the perceivers' tasks. However, such studies with more "natural" materials present even more formidable problems with regard to avoiding the category confound and other obstructions to establishing generalization across experimental materials.

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APPENDIX

AoV SUMMARY TABLE INCLUDING CONFIDENCE RATINGS

Source	SS	df	MS
Words	9.3571	2	4.6786
W*S	6.8554	62	.11057

F (2, 62)= 42.313   p<.001

AoV SUMMARY TABLE DISREGARDING CONFIDENCE RATINGS

Source	SS	df	MS
Words	9.8972	2	4.9486
W*S	6.2596	62	.10096

F (2, 62) = 49.015   p<.001

Vita

Elizabeth Howlett Creyer, nee Elizabeth Anne Howlett, the daughter of Anne and David Howlett, was born August 28, 1959. She is a native of Bethlehem and graduated with Honors from Liberty High School, Bethlehem, Pa. in 1977. She graduated with High Honors from Lehigh University in 1981 with a major in Psychology and a minor in International Relations. Elizabeth married Richard W. Creyer, Jr. in the spring of 1981.

During the 1981-1982 academic year Elizabeth held a Teaching Assistantship in the Department of Psychology at Lehigh University. While in this position, she team taught an introductory psychology course. She was awarded a Packard Fellowship for the 1982-1983 academic year which allowed her time to pursue her research interests. Elizabeth is currently enrolled in a doctoral program in Business Administration at Duke University, Durham, North Carolina.