DESCRIPTIVE SENSORY ANALYSIS IN PRACTICE

Edited by

M.C. Gacula, Jr., Ph.D.

Gacula Associates
Scottsdale, Arizona

FOOD & NUTRITION PRESS, INC.
TRUMBULL, CONNECTICUT 06611 USA

DESCRIPTIVE SENSORY ANALYSIS IN PRACTICE

F N P

PUBLICATIONS IN FOOD SCIENCE AND NUTRITION

DESCRIPTIVE SENSORY ANALYSIS IN PRACTICE

Edited by

M.C. Gacula, Jr., Ph.D.

Gacula Associates
Scottsdale, Arizona

FOOD & NUTRITION PRESS, INC.
TRUMBULL, CONNECTICUT 06611 USA

FOOD & NUTRITION PRESS, INC.
6527 Main Street
Trumbull, Connecticut 06611 USA

Library of Congress Catalog Card Number: 97-060573
ISBN: 0-917678-37-0

Printed in the United States of America

DEDICATION

To my lovely daughters

Karen, Lisa, and Elena

PREFACE

In the last two decades, the need by Product Research and Development personnel to define what is in a product in terms of sensory impressions, rather than by instrumental measures, has been met by Descriptive Sensory Analysis techniques. This is an important development in sensory science because only human beings can accurately describe and identify the sensory properties of products and materials related to the basic senses of taste, smell, touch, and sight. By descriptive analysis, the senses that are perceived are quantified and related to product acceptance/preference, which is the ultimate goal in product development.

The motivation of this book comes from the need to collect in one document published materials dealing with the technical developments and applications of descriptive analysis to various types of products and materials, such as, dairy, meats, alcoholic beverages, textile materials, and other general applications. Each chapter in this book contains a wealth of materials on the various applications of descriptive analysis–its sensory philosophy, its statistical philosophy, and test execution which provides the readers a wide spectrum of the uses of descriptive analysis, and an opportunity to improve the current descriptive analysis techniques. Although there is no specific article in the book that deals with personal care products (soap, lotion, shampoo, conditioner, toothbrush, and shaving materials) and household products, it is an established fact that descriptive analysis has been widely and successfully used for these types of products.

The availability of many statistical software packages greatly enhanced the implementation of descriptive analysis techniques. In this book, the following packages were used to illustrate various techniques of data analyses:

SAS/STAT, a registered trademark of SAS Institute, Inc.
STATISTIX, a registered trademark of Analytical Software
DESIGN-EXPERT, a registered trademark of Stat-Ease, Inc.
DESIGN-EASE, a registered trademark of Stat-Ease, Inc.
Microsoft EXCEL, a registered trademark of the Microsoft Corporation

The author is indebted to all authors and publishers for their kind permission to reprint original papers in this book. The technical assistance of John Ose is gratefully acknowledged. I thank Food & Nutrition Press for publishing this book, and in particular, Jennifer Schuchman whose diligent work kept the publication process in order.

MAXIMO C. GACULA, JR.

CONTENTS

CHAPTER **PAGE**

INTRODUCTION

In the early 1950s, the Arthur D. Little company pioneered the Flavor Profile method (Cairncross *et al.* 1950; Caul *et al.* 1957, 1958; see Chapter 1.2) which became the foundation of the current descriptive sensory analysis techniques. Descriptive analysis is a sensory technique used to obtain an objective description of the sensory properties of various types of products and materials. Since the development of the Flavor Profile, new methods have evolved, such as the Quantitative Descriptive Analysis (Stone *et al.* 1992, see Chapters 1.3 and 1.6), the Spectrum Descriptive Analysis Method (Civille *et al.* 1991; Meilgaard *et al.* 1991), and the Free-Choice Profiling (see Chapter 6.7). The use of these methods in the sensory evaluation of various types of products is well-documented in both academic research and industrial work. A detailed discussion of the Flavor Profile, Quantitative Descriptive Analysis, and the Spectrum Descriptive Analysis Method is contained in an ASTM publication (Hootman 1992). Also discussed in this publication is the Texture Profile Method (Brandt *et al.* 1963) written by Munoz *et al.* (1992), which is not covered in this book because the documents pertaining to this subject could make a book by itself.

Since its development, descriptive analysis has been successfully used in quality control to maintain sensory quality characteristics of products, in comparison of product prototypes, in understanding consumer responses in relation to product sensory attributes, in exploring the marketplace by sensory mapping so that gaps and opportunities in the map can be examined for possible development of new products, and in product matching, useful for claims substantiation and product improvement.

The success of the use of descriptive analysis depends on four factors: the training and experience of the judges, the panel leader, the sensory execution, and a long-term commitment by company management. Training is product-dependent because the sensory attributes vary among products, i.e., attributes for lotion products are different than those of wines. The length of training also depends on the product; some products require longer training than others. An experienced judge, by virtue of product exposure and product usage, should not be considered a trained judge, because they were not taught in scaling procedures, attribute definition, and other aspects of product-related training. The ideal situation is the existence of experienced and trained judges in an organization. The panel leader or program administrator has a critical role in the establishment and maintenance of a descriptive analysis panel, particularly in maintaining motivation of panel members. Sensory execution would include the choice of reference standards, conduct of the test, and test design. These factors are exemplified in several chapters of the book as applied to various types of products and experimental conditions. The last factor, management commitment, is the prime mover for a successful sensory program in both academia and industry. Development of a descriptive analysis program, as everyone knows, requires time and a special physical facility that requires capital investment.

Consumer testing is generally expensive compared to a descriptive analysis, hence, in product development, descriptive analysis is done first to screen and eliminate prototypes that do not meet the prescribed sensory criteria. A research guidance panel type of study is conducted to determine consumer liking for these prototypes, and the resulting data are correlated with the data from descriptive analysis.

The product development process is more effective when prototypes have undergone thorough descriptive analyses before subjecting the product to a marketing consumer test, such as a central location test (CLT). It is important in this type of application that results from descriptive analysis must be predictive of consumer test results, hence, the development of descriptive analysis must be consumer-oriented. However, there are products that cannot be packaged for laboratory testing because of the expense involved. In this case a surrogate package is used during sensory evaluation that simulates consumer use of the product. Remember that the ultimate goal is to produce a robust prototype from descriptive analysis.

An important application of descriptive analysis is in sensory evaluation of samples from formula optimization studies that utilize the principles of design of experiments (DOE). The use of DOE in product development is highly recommended because it is more efficient and in the long run, less costly than the traditional one-variable at a time approach. Although, the initial number of samples (design points) to be evaluated is larger than the traditional approach, the repetition of the study would be unlikely; it is more efficient in the sense that the effects of more than one ingredient in the formulation can be studied simultaneously. Tables 1.0.1 and 1.0.2 show the number of samples in a mixture experimental design according to the number of ingredients to be studied in the formula. In using mixture designs, it is important to know that the response to be measured is dependent on ingredient proportion rather than amount, otherwise the mixture design will not apply and the response surface design should be used. Examples of responses that depend on the amount of ingredient in the formula are fertilizer experiments and the level of salts in an antiperspirant formula. In sensory optimization studies it is highly recommended that a control sample should be included in the experiment.

With a properly designed study, sensory attributes from descriptive analysis can be simultaneously optimized to obtain a number of optimal formulas for testing by the research guidance panel. Several DOE useful in formula optimization work are given in Gacula and Singh (1984) and Gacula (1993). DESIGN-EXPERT and DESIGN-EASE (Stat-Ease, Inc) are software packages that can generate experimental designs based on the objectives and types of studies. These are illustrated in Chapter 7.

TABLE 1.0.1
A THREE-INGREDIENT MIXTURE DESIGN

Design points	Ingredient A	Ingredient B	Ingredient C
1	1	0	0
2	0	1	0
3	0	0	1
4	.5	.5	0
5	.5	0	.5
6	0	.5	.5
7	.33	.33	.33

Total number of samples = 7 + Control = 8. Coded ingredient levels are shown.

TABLE 1.0.2
A TWO-INGREDIENT MIXTURE DESIGN

Design points	Ingredient A	Ingredient B
1	1	0
2	.67	.33
3	.5	.5
4	.33	.67
5	0	1

Total number of samples = 5 + Control = 6. Coded ingredient levels are shown.

REFERENCES

BRANDT, M.A., SKINNER, E.Z. and COLEMAN, J.A. 1963. Texture Profile Method. J. Food Sci. *28*, 404-409.

CAIRNCROSS, S.E. and SJÖSTROM, L.B. 1950. Flavor Profiles—A new approach to flavor problems. Food Technol. *4*, 308-311.

CAUL, J.F. 1957. The Profile Method of flavor analysis. Advances in Food Research *7*, 1-40.

CAUL, J.F., CAIRNCROSS, S.E. and SJÖSTROM, L.B. 1958. The Flavor Profile in review. Flavor Research and Food Acceptance, Arthur D. Little, Inc., Reinhold Publishing Co., New York.

CIVILLE, G.V. and DUS, C.A. 1991. Evaluating tactile properties of skincare products: A descriptive analysis technique. Cosmetic and Toiletries *106,* 83-88.

GACULA, JR., M.C. and SINGH, J. 1984. *Statistical Methods in Food and Consumer Research.* Academic Press, San Diego, CA.

GACULA, JR., M.C. 1993. *Design and Analysis of Sensory Optimization.* Food & Nutrition Press, Trumbull, CT.

HOOTMAN, R.C. (ed.). Manual on Descriptive Analysis Testing for Sensory Evaluation. ASTM Manual Series: MNL 13, ASTM, Philadelphia, PA.

MUNOZ, A.M., SZCZESNIAK, A., EINSTEIN, M.A. and SCHWARTZ, N.O. 1992. The Texture Profile. In *Manual on Descriptive Analysis Testing for Sensory Evaluation,* (R.C. Hootman, ed.), ASTM Manual Series: MNL 13. ASTM, Philadelphia, PA.

MEILGAARD, M., CIVILLE, G.V. and CARR, B.T. 1991. Sensory Evaluation Techniques. CRC Press, Boca Raton, FL.

STAT-EASE, Inc. Minneapolis, MN.

STONE, H. 1992. Quantitative Descriptive Analysis (QDA). In *Manual on Descriptive Analysis Testing for Sensory Evaluation,* (R.C. Hootman, ed.), ASTM Manual Series: MNL 13. ASTM, Philadelphia, PA.

DESCRIPTIVE SENSORY ANALYSIS METHODS

In this book, three methods will be briefly presented because several works have already been published describing the details and use of these methods. There are similarities among the methods, but they differ in sensory philosophy, length of training, presentation of results, and sensory scales. The three methods are thoroughly described in a publication edited by Hootman (1992) and in other publications by Heymann *et al.* (1993), Powers (1988), and Einstein (1991). Unlike the cited publications, detailed applications of these methods in various experimental situations are reported in various chapters of the book.

Flavor Profile and Profile Attribute Analysis

The Flavor Profile Method (FP), developed by the Arthur D. Little, Inc., in 1949, was the first technique to assess the flavor and aroma impressions of food products. An extension of the Flavor Profile is the Profile Attribute Analysis (PAA), which incorporates numerical aspects of sensory description. As a result, standard statistical methods, such as analysis of variance, factor analysis, principal component analysis, and others are used to analyze the data. A detailed discussion of both FP and PAA are given by Neilson *et al.* (1988).

Quantitative Descriptive Analysis

The Quantitative Descriptive Analysis (QDA) was developed by the Tragon Corporation in the mid-1970s to address the problem of quantifying sensory description. As a means of quantifying sensory perception, an unstructured line scale is used that approaches a continuous scale, an important property that permits the use of standard statistical procedures. The spider plot, that characterizes QDA, is used as a graphical tool for presenting the results. Plotting can be accomplished by using the Microsoft Excel. See Chapters 1.3 and 1.6 for the original articles pertaining to QDA and that by Zook and Pearce (1988).

The Spectrum Descriptive Analysis Method

This method was developed by the Spectrum, Inc. in the late 1970s. Like the QDA and PAA, it also utilizes statistics to analyze the data obtained from a line scale anchored on both ends. Bar charts are used to portray the data, and again can be accomplished by the Microsoft Excel. See Meilgaard *et al.* (1991) for a thorough description and applications of the Spectrum Descriptive Analysis Method. Refer also to a paper by Civille *et al.* (1991).

Variants of Descriptive Analysis

The Free-Choice Profiling is a popular method which, unlike the traditional methods, uses untrained judges for evaluating products. A special type of statistical analysis is used known as Procrustes analysis that accounts for the effect of using untrained judges. See Chapters 6.1, 6.2, 6.7, and 6.11 for its application. Another variation is the Repertory Grid given in Chapter 6.11 and that for tobacco evaluation reported by Gordin (1987) given in Chapter 6.5.

Overview of Statistical Analyses

The most popular statistical methods are analysis of variance, factor analysis, principal component analysis, and regression analysis. The applications of these methods are described in various chapters of the book. The analysis of variance is a well-known method that breaks down the total variation into several sources. It is mainly used in hypothesis testing, i.e., test of significant difference between products, test of significant difference between panelists, etc. Another application of the analysis of variance is in the estimation of variance components. In this application, one desires to determine the percentage contribution of each source of variation to the total variability. This application is illustrated by Finkey *et al.* (1987) and in Gacula and Singh (1984). A comprehensive discussion of data relationships between descriptive analysis and consumer testing is given in an ASTM publication edited by Munoz (1997).

Regression and Correlation Analyses. The initial analyses in relating data obtained by descriptive analysis and consumer testing are regression and correlation analyses. Since different panels are used on both data sets, the input data are product means for each attribute. The data structure is shown in Table 1.1.1. It is desirable that many products with varying degrees of attribute intensities should be used. The variation in intensities will provide a better definition of attribute relationships. If the range of variation is not sufficient, misleading results may occur. The initial analysis is a simple linear regression,

$$Y_{ij} = B_o + B_1X_{ij} + E_{ijm} \qquad \begin{array}{l} i = 1,2, .., \text{kth product} \\ j = 1,2, .., \text{nth attribute} \\ m = 1,2, .., \text{lth rating} \end{array} \qquad \text{(Eq. 1.1.1)}$$

where Y_{i1} is the overall liking mean score, B_0 is the intercept, X_{ij} is the kth sensory attribute, and E_{ijm} is random error. The plot between Y_{ij} and X_{ij} provides an initial view of the relationship, how the products are positioned against attribute X_{ij}. The STATISTIX software, among others, can be used to provide the scatterplot of the mean scores with the regression line superimposed (Fig. 1.1.1). In this example, the overall liking for the product increases with increasing score intensity of attribute X8.

TABLE 1.1.1.
LAYOUT OF OBSERVATIONS FOR REGRESSION ANALYSIS
OF DATA OBTAINED FROM DESCRIPTIVE ANALYSIS AND CONSUMER TEST:
5 PRODUCTS, 6 ATTRIBUTES (X1-X6)

Products	X1	X2	X3	X4	X5	X6
1	y11	y12	y13	y14	y15	y16
2	y21	y22	y23	y24	y25	y26
3	y31	y32	y33	y34	y35	y36
4	y41	y42	y43	y44	y45	y46
5	y51	y52	y53	y54	y55	y56

Note: y11, . ., y56 are mean scores.

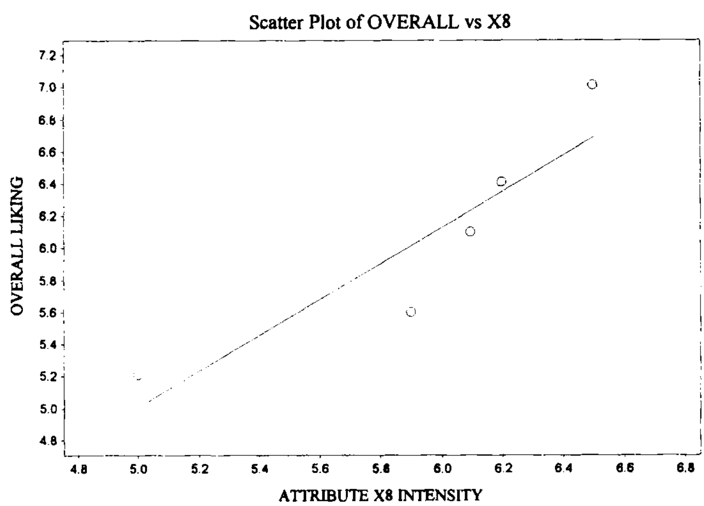

FIG. 1.1.1. SCATTERPLOT OF PRODUCT MEANS (○) USING THE STATISTIX SOFTWARE
Products plotted are with increasing amount of flavor additive.

The next step is to look at all the sensory attributes at the same time by running a stepwise regression analysis. The result of the analysis will provide the important attributes that predict overall liking. There are choices in the model to use in stepwise regression analysis. One must consult a statistician regarding the choice of the model. An example of a stepwise regression analysis is given in Chapter 7.

Factor Analysis and Principal Components. Descriptive sensory and consumer data are characterized by the presence of correlations among attributes in a given product. This correlation arises from the process of sensory evaluation which involves a "memory capacity," i.e., context effect, during evaluation of samples or products, as opposed to the use of a mechanical instrument. In addition, there is an intrinsic relationship in most sensory attributes of products due to synergistic or antagonistic effect of various ingredients used in product formulation.

To make use of the correlation among observations, multivariate statistical procedures are used in addition to univariate methods. Factor analysis and principal component analysis are the most common multivariate procedures used in the industry and academia for the analysis of this type of data. Another procedure gaining popularity is the Procrustes analysis described in Chapters 6.1, 6.2, 6.7, and 6.11. Multivariate methods have been known for a long time and books that vary in statistical complexity are widely available (Anderson 1958; Harman 1976; Morrison 1967; Afifi and Azen 1979). Briefly, let us discuss the methods of statistical analyses.

Factor analysis and principal component analysis are similar in many ways, the major similarities being that both methods make use of the correlation (variance-covariance) among attributes, and both methods have the objectives of reducing the number of attributes into a new set of attributes, the so-called factors or components. The reduction is expected to retain as much information in the original variables or attributes as possible. The resultant components, which are now a linear combination of the original attributes, are uncorrelated (statistically orthogonal). For example, there may be 20 original attributes used in rating the products; by using a principal component or factor analysis, the original number of attributes of 20 may be reduced, say, to five components. That is the data or the products can now be represented by these five components instead of 20, making the relationships among products and among attributes easily visualized and more manageable. Then the five components are given a hypothetical descriptive name in relation to the sensory and physical characteristics of the products.

The first principal component, PC1, accounts for the largest variance in the data; PC2, which is uncorrelated with PC1, the second largest; PC3, which is uncorrelated to PC1 and PC2, the third largest, and so on in a decreasing variance order. Suppose that PC1 consists of the following attributes: gentle to the gum, cleans teeth, bristle density, bristle stiffness. A descriptive name may be a mouthfeel component.

An important use of principal components is in the comparison of products based on principal component scores. This is accomplished by statistical conversion of the original ratings into principal component scores associated with each product. The PC scores can be used to correlate with consumer liking to aid product formulations and/or product improvements. Statistically, the use of PC scores in multiple regression analysis is not biased by collinearity because the principal components are uncorrelated. Furthermore, a multiple comparison tests of PC scores can be done to provide a separation of the products, the separation of which is based on the integrated sensory dimension—the principal components. This application is illustrated in Chapter 7.

When there are no significant differences among product means, a principal component analysis defines the overall sensory dimensions of the data. When products are similar, the plot of the products, for example PC1 and PC2 would cluster around the (0,0) coordinate (Fig. 1.1.2). This type of analysis is useful in a study dealing with ingredient substitution and/or ingredient change in a formula; the analysis provides assurance that the overall sensory properties of the products did not change by the ingredient substitution. The traditional method of analysis has been the use of difference tests. The PC analysis is also useful in product matching studies. When products are dissimilar in many sensory characteristics, the products on the plot would scatter (Fig. 1.1.3), hence there is no match; on the contrary, the plot in Fig. 1.1.2 would indicate a reasonable match among products.

One of the differences between factor analysis and principal component analysis is in the model. For the principal component analysis, the model is

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \cdot \\ \cdot \\ \cdot \\ Y_p \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1p} \\ A_{21} & A_{22} & \cdots & A_{2p} \\ \cdot & & \cdot & \\ \cdot & & \cdot & \\ \cdot & & \cdot & \\ A_{p1} & & & A_{pp} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ \cdot \\ \cdot \\ \cdot \\ X_p \end{bmatrix} \qquad \text{(Eq. 1.1.2)}$$

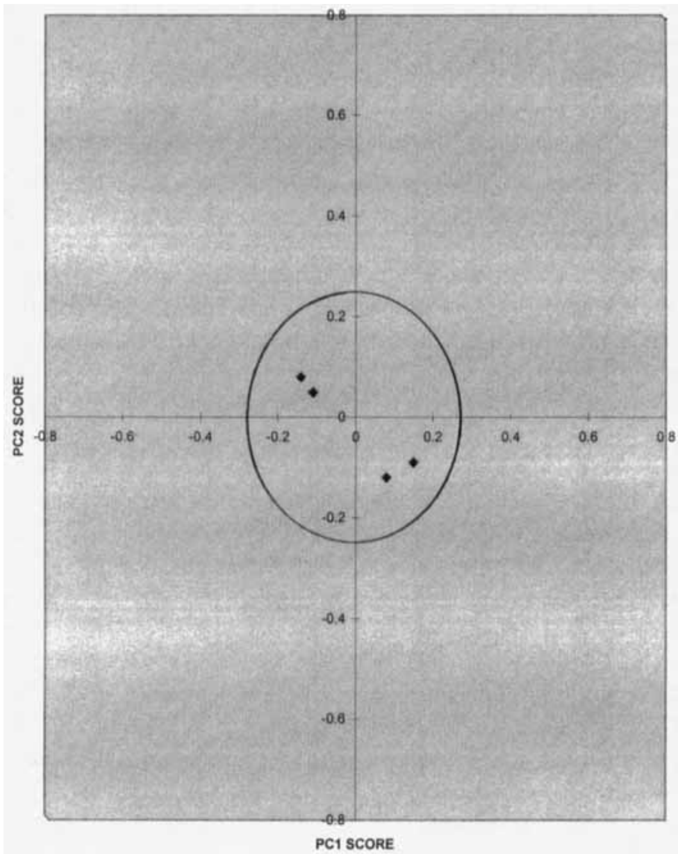

FIG. 1.1.2. PLOT OF PRINCIPAL COMPONENT SCORES PC1 AND PC2 FOR PRODUCTS (◆) WHICH SHOW NO SIGNIFICANT DIFFERENCES

where Y_i, i= 1,2, .., p, are the linear combinations of the original attributes; thus, Y_1 is the first principal component, Y_2 is the second principal component, and so on; the estimates of Y_i are uncorrelated; X_p is the observed sensory ratings of the attributes. The term A_{pp} is the coefficient (mathematically known as eigenvector) that needs to be obtained by solving Eq. (1.1.3). In matrix notation, the model is

$$Y = AX \qquad \text{(Eq. 1.1.3)}$$

where Y is a p × 1 matrix, A is a p × p matrix, and X is a p × 1 matrix. As one can see, principal components Y_i are statistical functions of the observed

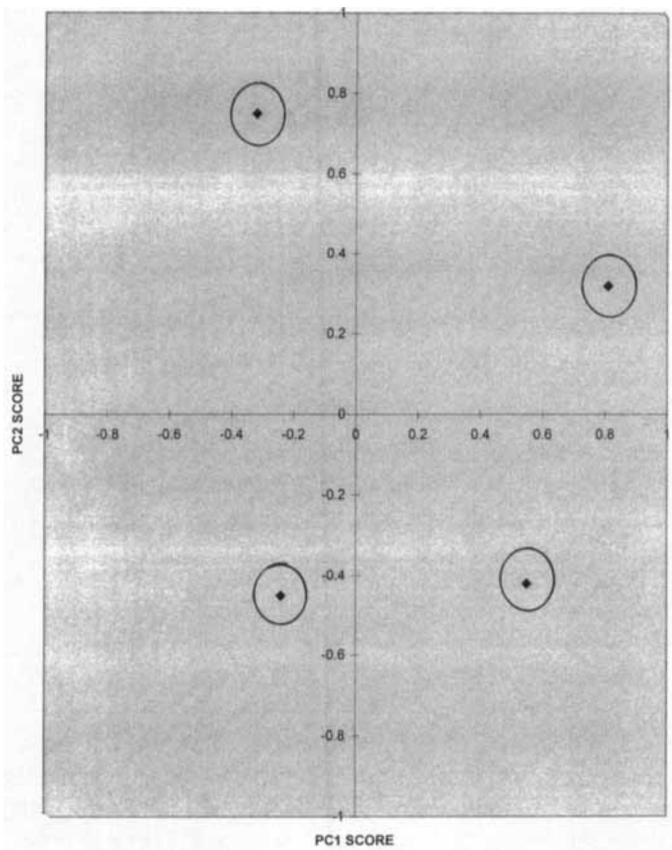

FIG. 1.1.3. PLOT OF PRINCIPAL COMPONENT SCORES PC1 AND PC2 FOR PRODUCTS (◆) WHICH SHOW SOME SIGNIFICANT DIFFERENCES

variables X_p. Thus, the equation for the first principal component is

$$Y_1 = A_{11}X_1 + A_{12}X_2 + \ldots + A_{1p}X_p \qquad \text{(Eq. 1.1.4)}$$

and for the second principal component,

$$Y_2 = A_{21}X_1 + A_{22}X_2 + \ldots + A_{2p}X_p$$

and so on for the remaining components. Substitution of standardized ratings into the above equations produces the principal component scores. There is software available to solve Eq. (1.1.3) and the SAS software (SAS 1990) is used in this book (see Chapter 7).

In factor analysis, the model is

$$\begin{bmatrix} X_1 \\ X_2 \\ \cdot \\ \cdot \\ \cdot \\ X_p \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1m} \\ A_{21} & A_{22} & \cdots & A_{2m} \\ \cdot & \cdot & & \\ \cdot & & \cdot & \\ \cdot & & & \cdot \\ A_{p1} & & & A_{pm} \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ \cdot \\ \cdot \\ \cdot \\ Y_m \end{bmatrix} + \begin{bmatrix} E_1 \\ E_2 \\ \cdot \\ \cdot \\ \cdot \\ E_p \end{bmatrix} \qquad \text{(Eq. 1.1.5)}$$

where X_p, i= 1,2, ..,p, are the observed ratings for p sensory attributes, Y_j, j= 1,2, .., m, are called the principal/common factors extracted from the original number of sensory attributes, given as rotated factor pattern in a SAS output. The term A_{pm}, is a coefficient that reflects the importance of the ith attribute on the jth factor; this coefficient is commonly known as factor loadings. The term E is the error component unaccounted for by the common factors. In matrix notation, the model is

$$X = AY + E \qquad \text{(Eq. 1.1.6)}$$

where X is a p × 1 matrix, A is a p × p matrix, Y is a p × 1 matrix, and E is also a p × 1 matrix. Factor scores are obtained by substituting the ratings into the resultant common factor equation given as standardized scoring coefficients in a SAS output. Again, the SAS software will be used to evaluate Eq. (1.1.6).

Another difference is that in factor analysis it is assumed that some underlying factors which are smaller than the number of the observed variables ($m < p$), are responsible for the correlations among the observed variables. The SCREE plot in SAS provides the appropriate number of underlying factors for inclusion (see Chapter 7). In the principal component analysis, this assumption is not made, instead the total variation in the data is exhaustively divided into component parts; that is why the error term E is not shown in Eq. (1.1.3). The choice between principal component and factor analysis depends on the purpose of the statistical evaluation. It is not an easy choice because of their similarities; the results of statistical analyses by both methods may differ in some degree due to the type of mathematical rotations used in the analysis. In sensory evaluation, it is a common practice to combine sensory attributes into integrated or composite attributes (underlying factors), hence the factor analysis may be the appropriate choice. On the other hand, the principal component analysis can also be used by specifying in the SAS code the number of components to be included in the analysis.

REFERENCES

AFIFI, A.A. and AZEN, S.P. 1979. *Statistical Analysis: A Computer Oriented Approach*. Academic Press, San Diego, CA.

ANDERSON, T.W. 1958. *An Introduction to Multivariate Statistical Analysis*. John Wiley & Sons, New York.

CIVILLE, G.V. and DUS, C.A. 1991. Evaluating tactile properties of skincare products: A descriptive analysis technique. Cosmetic and Toiletries *106*, 83-88.

EINSTEIN, M.A. 1991. Descriptive Techniques and their Hybridization. In *Sensory Science Theory and Applications in Foods*, (H.T. Lawless and B.P. Klein, eds.), Marcel Dekker, New York.

FINKEY, M.B., GACULA, JR., M.C. and MILLER, J.K. 1987. Site to site variation in the soap chamber test. J. Sensory Studies *2*, 293-300.

GACULA, JR., M.C. and SINGH, J. 1984. *Statistical Methods in Food and Consumer Research*. Academic Press, San Diego, CA.

HARMAN, H.H. 1967. *Modern Factor Analysis*. The University of Chicago Press, Chicago, IL.

HEYMANN, H., HOLT, D.L. and CLIFF, M.A. 1993. Measurement of Flavor by Sensory Descriptive Techniques. In *Flavor Science — Sensible Principles and Techniques*, (T.E. Acree and R. Teranishi, eds.), ACS, Washington, DC.

HOOTMAN, R.C. (ed.). Manual on Descriptive Analysis Testing for Sensory Evaluation. ASTM Manual Series: MNL 13. ASTM, Philadelphia, PA.

MEILGAARD, M., CIVILLE, G.V. and CARR, B.T. 1991. *Sensory Evaluation Techniques*. CRC Press, Boca Raton, FL.

MORRISON, D.F. 1967. *Multivariate Statistical Methods*. McGraw-Hill, New York.

MUNOZ, A.M. (ed.). 1997. Relating Consumer, Descriptive, and Laboratory Data to Better Understand Consumer Responses. ASTM Manual 30. ASTM, West Conshohocken, PA.

NEILSON, A.J., FERGUSON, V.B. and KENDALL, D.A. 1988. Profile Methods: Flavor Profile and Profile Attribute Analysis. In *Applied Sensory Analysis of Foods*, (H. Moskowitz, ed.), CRC Press, Boca Raton, FL.

POWERS, J.J. 1988. Current Practices and Application of Descriptive Methods. In *Sensory Analysis of Foods*, (J.R. Piggott, ed.), Elsevier Applied Science, London.

SAS. 1990. SAS/STAT User's Guide, Ver. 6, 4th Ed. SAS Institute, Inc., Cary, NC.

ZOOK, K.L. and PEARCE, J.H. 1988. Quantitative Descriptive Analysis. In *Applied Sensory Analysis of Foods*, (H.R. Moskowitz, ed.), CRC Press, Boca Raton, FL.