To the Graduate Council:

I am submitting herewith a thesis written by Christopher Michael Heaps entitled "Similarity and Features of Natural Textures." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Arts, with a major in Psychology.

Stephen Handel

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We have read this thesis
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SIMILARITY AND FEATURES OF NATURAL TEXTURES

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ABSTRACT

Several features responsible for attentive texture similarity have been proposed, but exactly which ones are important for attentive texture perception and classification is unclear. The purpose of the present investigation was to determine if features are used to judge the attentive similarity of natural textures, and if so to identify these features and establish what type of model is best for conceptualizing them. Subjects in two experiments placed pictures into groups however they wished. Other groups of subjects described the resulting clusters and MDS dimensions, identified the objects/surfaces depicted in the pictures, and ranked the pictures along several hypothesized attribute-based dimensions. Results indicated that similarity is context-dependent and that a dimensional model is inappropriate for conceptualizing natural textures.

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CHAPTER I

INTRODUCTION

Gestalt psychologists were the first to discuss the organization of the visual image into discrete and coherent regions that maximized Prägnanz (Wertheimer, 1958). Since then, modern perceptual research has attempted to define how the visual image is segregated perceptually into objects and surfaces, and how structure in the visual image is created from certain visual primitives. Much of this research has centered on the role of texture segregation in perception. Texture segregation results from dividing the visual field into distinct regions, a process that occurs prior to the focusing of attention (Beck, 1972; Treisman, Sykes, & Gelade, 1977; Treisman, 1985). The work of Julesz (e.g., 1975; 1981), for example, has led to the identification of features, termed "textons" responsible for preattentive texture segmentation. The set of textons implicated in preattentive texture segmentation has been subject to subsequent revision (e.g., Julesz 1986; Bergen & Adelson, 1988). Following this segregation, a set of attentive texture features is assumed to be responsible for judgments of texture similarity (Tamura, Mori, and Yamawaki., 1978).

An understanding of attentive texture perception is important for a variety of perceptual tasks, including those relevant to machine vision, and could inform models of preattentive texture segmentation (Treisman, 1982). The present investigation assesses the presence of attentive visual primitives, or texture features, that emerge across sets of natural textures. Three tasks were used as converging operations to determine if such generalizable features exist. Results show that the similarity between pairs of textures is based on the unique characteristics of the two textures (cf. Tversky, 1977; Tversky & Gati, 1987), and that perceptually salient features are dependent on characteristics of all the textures in the set in accord with Tversky's (1977) *diagnosticity principle*. It is concluded that a dimensional model of natural texture features is inappropriate, and that similarity is better represented by a family resemblance model of pictorial categorization.

The Definition Problem

Any rigorous study of texture requires a precise definition of what is meant by the term "texture." Despite its intuitive meaning, it is difficult to define texture exactly. This difficulty is at least in part due to the fact that all surfaces, however different from one another, can be said to have texture. That is, objects or materials that do not look or feel alike all have texture, just as all objects have "shape." We can just as easily talk about the texture of a piece of carpet or of a shirt as we can the texture of the side of a brick building, the surface of water, or clouds in the sky. Accounting for texture in its many and varied forms requires a quite inclusive definition. The lack of such a comprehensive definition applicable to all instantiations of texture is widely recognized (Essock, 1992), and has been referred to as "the definition problem," (Gorea, 1995, p. 55).

We can gain a working understanding of texture by inspecting texture stimuli. Figure 1* shows some typical stimuli taken from both the human and artificial vision literature. Figures 1a and b show stimuli from Beck (1966; 1982), an originator of modern texture perception research. Figures 1c and d show stimuli from Julesz (1981;1986), a major investigator in the psychophysics of texture perception. These textures are considered representative of those found in the human visual literature, and are referred to as abstract textures. Figures 1e is taken from Tamura, Mori, and Yamawaki (1978), and Figure 1f is taken from Rao and Lohse (1993); both are from the same original source, Brodatz (1966). These textures are considered representative of those found in the artificial vision literature, and are referred to as natural textures.

A major common theme in formal definitions of texture is that of elements, constituents, or particles (cf. Amadasun and King, 1989; Beck, 1982; Bergen, 1991). Individual parts of the object, material, or perceived surface are repeated spatially, as with the grains of sand in a beach, or the indentions in a ceiling tile. Besides the obvious term "texture elements," these simple constituents of texture have been referred to as "texture features," "texture primitives," and by the widely-recognized term "textons," (Julesz, 1981). The frequency and regularity of the repetition of these elements, often called periodicity, are assumed to be responsible for perceptual differences in texture. At the most basic level, the periodicity of a texture is represented by invariant repetition of differentially intense areas of light. Viewing texture as varying patterns of light is the simplest and most visually primitive conceptualization of texture.

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* All tables and figures may be found in the Appendix.

At a slightly less primitive level, a host of other variables come into play. As Beck (1982) notes, in viewing a texture "the pattern as a whole is perceived to have a characteristic lightness, directionality, coarseness, and so on" (p. 285). Stereoscopic depth, apparent motion, color, and a number of other characteristics also may or may not emerge at some point in the process of perceiving texture. How these variables influence the way textures are perceived is not well understood, although some computational models of texture perception based primarily on quantifying texture periodicity have enjoyed restricted success (e.g., Caelli, 1988; Harvey & Gervais, 1981; Julesz, 1981). Such models, however, have often employed as stimuli abstract textures differing systematically along a set of pre-defined dimensions.

The focus on texture elements has lead to two primary levels of analysis for texture and to two contrasting approaches for modeling texture. The two levels of analysis reflect the imposition of successively greater levels of structure or organization in the process of visual perception. Texture elements are referred to as microtexture, and the organization of those elements is referred to as macrotexture (Van Gool, Dewaele, & Oosterlinck, 1983). For example, in Figure 1a microtexture is represented by the L and T elements themselves, whereas the macrotexture here is defined by the predominant orientations of the elements. As Beck (1966) points out, the differing orientation of the "tilted T" elements to the rest of the L and T elements produces perceptual segregation. In Figure 1e, microtexture is represented by what appears to be tiny circles. Macrotexture arises from the distribution of these elements throughout the texture. Here, the elements are distributed evenly, and appear to be slightly more organized horizontally than vertically. It is this pattern created by the texture elements that gives rise to macrotexture (Gagalowicz & Ma, 1985). Thus, the more microtexture elements of a texture allow themselves to be segregated, or grouped, the more macrotexture, and consequently structure, is present in the texture. When a great deal of structure is present in a texture, it is sometimes the case that aspects of the macrotexture can themselves be seen as elements. At this point, the texture may take on characteristics that make them identifiable as particular objects, materials, or surfaces (Treisman & Gelade, 1980; Treisman, 1985).

The two major contrasting approaches for modeling texture also make use of the microtexture-macrotexture distinction. Statistical approaches focus on specifying relationships among microtexture elements, whereas structural approaches focus on the importance of various kinds of macrotexture structure emergent in the texture (e.g., predominant orientation). Many models, however, can be thought of hybrid statistical-structural approaches (Haralick, 1979) in that they attempt to unify the two levels of analysis by identifying what types of relationships between microtexture elements give rise to what kinds of macrotexture structure. Perhaps the best-known statistical model of texture, that of Julesz (1975; 1981), began with the assertion that the human visual system could not discriminate textures that did not differ in their first-order statistics (the "Julesz conjecture") and has subsequently incorporated structural considerations (Julesz' "textons"). By connecting and attempting to explain the relationship between these two levels of analysis, texture models seek to explain how structure is characterized at different levels, how structure and organization are created in the visual image, and which aspects of structure are important in visual perception.

The Importance of Texture

Texture is an integral characteristic of the objects and materials of the visual world, and important information contained in the visual images of objects and surfaces can be described as a function of the qualities or characteristics of texture (Gibson, 1950a). Texture as represented in real-world scenes contains information used to impose structure on, and to give form to, the visual image. Specifically, texture is implicated in the process of segregating the visual image into discrete regions (e.g., separating the sidewalk from the grass), and is then used to make basic perceptual decisions about the nature of the segregated objects and surfaces (Marr, 1982; Gibson, 1979). For example, when walking across uneven outdoor terrain the hiker quickly learns to identify and make use of surface areas that afford good footing and to avoid those that do not (Watt, 1995). The tilt or direction of the surface extracted from textural information (Marr, 1982) indicates that some surfaces should not be stepped upon. Also, dangerous objects such as snakes that have textures similar to the textures of surrounding objects or surfaces can provide effective camouflage. Indeed, the design of camouflage can be seen as a task of effectively matching or imitating texture (Köhler, 1947).

Texture Segregation and Attention

Beck (1966) showed that texture segregation occurs without focused attention, or preattentively, ,and that attentive similarity judgments of abstract texture did not predict how abstract texture was preattentively segregated. Since this demonstration, evidence for two relatively independent visual analyses, one preattentive and one arising from directed attention (i.e., attentive), has mounted (e.g., Julesz, 1980; Treisman & Gelade, 1980; Treisman, Sykes, & Gelade, 1977). Up to the present, however, preattentive texture segregation has been the focus of most subsequent work on texture perception. But both preattentive and attentive levels, as well as the interactions between them, are relevant for specifying how structure and organization are imposed visually (Palmer & Rock, 1994), and attentive perception is critical for object perception/recognition (Marr, 1982; Northdurft, 1992; Treisman & Gelade, 1980).

Attentive Texture Features

Rao and Lohse (1993) conducted the most thorough investigation of attentive texture features in visual perception. They used 30 pictures from the Brodatz (1966) album of textures (see Figure 2), asking a heterogeneous group of 20 subjects, including IBM professionals and undergraduate students, to organize the pictures into groups in any way they wished. The resulting similarity matrix was used in hierarchical cluster analysis and multidimensional scaling (MDS) analyses to identify features that led to the judgments of similarity. Rao & Lohse identified six major clusters (see Table 1) and reported that a three-dimensional MDS solution fit the data best (see Table 2).

Perhaps the most important finding from this study is simply that some variables responsible for producing similarity grouping in abstract textures (Beck, 1966; Landy & Bergen, 1991; Olson & Attneave, 1970), including line orientation, linearity of elements and spatial frequency, were of limited use in explaining similarity grouping in natural textures. Many of the similarity judgments made of natural textures in the Rao & Lohse study could not be explained by variables found to be responsible for abstract texture similarity, since no corresponding textures or texture elements exist in abstract textures. Thus, the lack of a comprehensive understanding of the role of texture in vision, could in part be due to the fact that attempts at developing such an understanding have made use of a narrow range of textures; that is, only those representable as highly abstract patterns with dichotomous elements (see Figure 1).

Given the truly inclusive presence of texture, is a comprehensive taxonomy of attentive texture features (or, for that matter, a successful model of preattentive-attentive texture segregation), generalizable to all textures? Rao & Lohse concluded that three attribute-based dimensions could be used to identify and classify textures. These dimensions were termed Repetitiveness, Orientation, and Complexity, respectively (see Table 2 and Table 3). The Repetitiveness of a texture was defined as the frequency with which the elements or lines of the texture are repeated. This description of repetitiveness corresponds to the most widely-used texture descriptor, "periodicity," which is generally a measure of the spatial frequency of microtexture elements composing the larger texture pattern, or macrotexture. Repetitiveness is also operationalized by the authors as representing the amount of "structure" present in the texture (Garner, 1974). Examples of a highly structured texture include d1(wire) and d26 (brick) in the Brodatz album, and examples of unstructured textures include d37 (water) and d107 (rice paper) in the Brodatz album (see Figure 2). Note that while wire and brick are both highly structured, wire can be said to be much more periodic than brick since there are many more texture elements (i.e., squares or rectangles) created by the weaving of the wire than are created by the spaces between the bricks. Also, water and rice paper are both unstructured, yet the repetition of randomly placed lines in rice paper makes the image much more periodic than the figure-less flow of water.

The Orientation of a texture was defined as the degree to which the lines or elements of a texture are oriented, or directed, toward a particular direction. Orientation can be seen as separate from Repetitiveness, since how often a texture's elements are repeated need not correspond to how directed they are to a particular direction (e.g., see d74). The role of structure, however is somewhat implicit in orientation, since more structured textures are likely to produce a uniform orientation (i.e., be highly oriented). The Complexity of a texture was defined as the degree of difficulty in providing a verbal description of the texture. Obviously, some textures are much easier to describe than others (e.g., compare d26 and d5). Once again, however, the role of structure is implicit in complexity, as it is often much easier to define and explain textures that are highly structured and less easy to define unstructured, or random textures.

The Rao & Lohse study and the resulting solution are more parsimonious than prior efforts directed toward the same goal (Amadasun & King, 1989; Tamura et al., 1989), yet the solution shows limited correspondence with prior proposed classification schemes (see Table 3). Moreover, the stimulus configuration derived from a MDS analysis is not necessarily interpretable. That is, although the space created by the analysis may be interpretable in terms of semantically definable, attribute scales (i.e., dimensions), the axes created by MDS need not correspond to readily-interpretable concepts. Corroborating the existence of attribute-based scales that can be used to describe the configuration of stimuli in the perceptual space created by the MDS analysis requires independent confirmation. Direct measures of the hypothesized scales must be obtained and compared to the stimulus configuration before conclusions about what properties are responsible for the configuration are made.

Exactly what features are important for attentive texture perception and classification is still unclear, and the proposed three-attribute dimensional model proposed by Rao & Lohse (1993) has yet to be tested. Also, no studies identifying attentive texture features have attempted to demonstrate the presence of the same features in textures other than in those tested. The purpose of the present investigation was (1) to determine if features are used to judge the similarity of natural texture, (2) if so, to identify these features and establish what type of model is best for conceptualizing them, and (3) to determine the generalizability of these features across natural textures. To meet these goals, subjects in two experiments made similarity judgments of two separate sets of natural textures by placing pictures into groups however they wished. Other groups of subjects described aspects or attributes common to derived groups of pictures and to derived MDS dimensions, identified the objects or materials depicted in each member of the two picture sets, and rank ordered pictures according to hypothesized attributes.

CHAPTER II

EXPERIMENT 1: BRODATZ TEXTURES

The purpose of Experiment 1 was to determine the attributes used to perceive and organize visual textures. Several kinds of tasks were performed by different groups of subjects, although each task utilized the same set of 30 textures from Brodatz (1966). In the first task subjects grouped textures according to perceived similarity. The derived similarities were then analyzed using hierarchical clustering and multidimensional scaling (MDS) techniques to create a set of disjoint groups that maximize within-group similarity and a three-dimensional representation of the similarities. Thus, the first task is a replication of Rao & Lohse (1993).

Judgments of similarity may be based on the similarity of objects or surfaces represented in the pictures, on the black-white textures themselves, or on superordinate attributes or dimensions created by the set of pictures. Given the multiplicity of possibilities, other tasks served as converging operations. To investigate the utility of objects or surfaces to determine judgments, subjects identified the pictures. To investigate the textural properties, subjects described the resulting clusters. Finally, to investigate the possible use of superordinate dimensions, subjects named the obtained dimensions and also rank-ordered the pictures along a set of plausible defined dimensions. The results indicated that all three types of similarity are used simultaneously in a context, so that models of similarity based on family resemblances most closely mirror the emergence of attentive organization. That is, the similarity between two stimuli or among groups of stimuli may utilize different bases. The dimensional structure was not perceptually meaningful.

Method

Participants

The grouping, description, and ranking tasks involved 20, 20, and 120 subjects respectively. All subjects were college students naive to the purposes of the experiment and all subjects received extra course credit in exchange for volunteering to participate.

Materials

Thirty pictures were reproduced from Brodatz (1966) on a high-resolution photocopier. The pictures themselves measured 6 x 6" and were printed on standard 8½ x 11" paper. They were the same ones used by Rao & Lohse (1993). See Figure 2 for each of the pictures.

Procedure

Groups

Method. The pictures were laid out randomly for each subject approximately 2" from one another in three rows of 10. Subjects were shown the pictures on the table and given the following instructions: "This is a set of 30 pictures. Take a moment to familiarize yourself with them. Once you have done so, organize them into groups on the basis of similarity. Put the pictures that are most similar to one another in the same group. You may create a minimum of three groups and a maximum of six groups." The restriction concerning number of groups was imposed because a pilot study indicated that subjects tended to create so many groups that relative similarity between stimuli was difficult to judge. With the exception of this restriction, the grouping task is identical to the procedure reported by Rao & Lohse (1993).

Analyses. Hierarchical clustering and MDS were performed on the grouping data. In both procedures, similarity judgments are seen as distances between the stimuli. Similarity and distance are opposite scales, with high similarity corresponding to small distance, and vice versa. For this reason, groupings are most intuitively coded as dissimilarities (rather than similarities), such that high values indicate both greater dissimilarity and more distance between stimuli, and low values indicate smaller dissimilarity and less distance between stimuli. Hierarchical cluster analysis groups a set of stimuli together based on judged similarity until all stimuli are members of clusters (i.e., groups of two or more) and all clusters have been joined together. Clustering proceeds from highly similar to less similar stimuli. Highly similar stimuli are grouped together first, until eventually the furthest distance between groups is calculated and all stimuli are grouped together. The choice of what to regard as meaningful levels of grouping or clusters is a decision made by the researcher, and depends on the nature of the stimuli. MDS places the stimuli into a spatial configuration (a "perceptual space") of one or more dimensions based on judged similarity. The exact number of dimensions necessary to represent the relative similarity of all of the stimuli is also based on researcher decision after considering several "goodness-of-fit" criteria.

From the group memberships noted by the experimenter, a symmetric 30 x 30 dissimilarity matrix was constructed for each subject. Pairs of pictures placed in the same group were given a score of zero, and pairs of pictures not placed in the same group were given a score of one. Dissimilarity matrices from all 20 subjects were averaged to create a pooled dissimilarity matrix with scores ranging from zero (maximally similar, always in same group) to one (maximally dissimilar, always in different groups). The pooled matrix is seen in Table 4.

Descriptions

The stimuli were identical to those used in the grouping task. The describing task consisted of three sub-tasks that took place in the following order for all subjects.

1. Clusters. Subjects were first shown the pictures in each group recovered from the cluster analysis performed on the dissimilarities from the grouping task. Recovered groups were presented in random order sequentially, and subjects were asked to provide as many descriptive terms (i.e., adjectives) as they could for the group as a whole.

2. Dimensions. Next, subjects were shown a large conference table on which 3 x 5" index cards labeled 1-30 were arranged in three rows of 10, allowing enough space for one 8½ x 11" picture to be placed directly below each index card with a 2" separation. Subjects were told that the cards on the table represented the rank order of the pictures along some dimension that would be explained. The cards labeled 1 and 30 represented the two extremes or end-points of the dimensions, and intermediate numbers represented the "middle" of the dimension. After the subject understood the layout the pictures were placed in their appropriate ranked slot one after the other for each of the three recovered dimensions from the MDS. Subjects were asked to provide a descriptive name for each dimension. Dimensions were presented in random sequence.

3. Objects Surfaces. Finally, the entire set of pictures was laid out in three rows on another table. Subjects named the object or surface depicted in each picture sequentially. Picture lay out was randomized for each subject. The naming task was done last so that subjects' judgments about the nature of the picture would not influence the cluster and dimension naming tasks.

In each of the three sub-tasks, semantically similar terms were combined (e.g., "random" and "disorganized," as well as "not man-made" and "natural," "wood" and "tree").

Rankings

Subjects were handed the 30 8½ x 11" pictures in a stack, and were given the following instructions: "This is a set of 30 pictures. Take a moment to familiarize yourself with them. Once you have done so, let the experimenter know that you are ready and we will begin." Once subjects indicated they were ready, they were then told, "Previous research indicates that the pictures in this set can be organized by their attributes. You are to put the pictures in their rank order as best you can according to the attribute given by placing each texture beneath the index card that best corresponds to its position in the set." One of the attributes was then explained to the subjects, and they completed the ranking task. A description of the relevant attribute was written on a nearby chalkboard as a reminder.

The subjects ranked the pictures according to 12 attributes. These attribute names were came from the three dimensions hypothesized by Rao & Lohse (1993; Repetitiveness, Orientation, and Complexity), results of the description task described above, and from previously suggested attributes representing attentive texture similarity. The 12 attributes were explained as follows: (1) "The Repetitiveness (REP) of a texture means how frequently the elements or lines in the texture are repeated." (2) "The Orientation (ORT) of a texture means how much the lines or elements in the texture are oriented in a particular direction." (3) "The Complexity (CPX) of a texture means how difficult it would be to give a verbal description of the texture." (4) "The Structure (STR) of a texture is how much organization vs. how much randomness there is in the lines or elements in the texture." (5) "The Shape (SHP) of a texture is how round, circular, or spherical vs. how angular, square, or rectangular the lines or elements in the texture are." (6) "The Size (SIZ) of a texture is how large vs. small the lines or elements in the texture are." (7) "The Connectedness (CNT) of a texture is how joined vs. separate the lines of elements in the texture are" (8) "The Hardness (HRD) of a texture is how hard vs. soft the objects or materials in the texture are." (9) "The Roughness

(RGH) of a texture is how rough vs. smooth the objects or materials in the texture are." (10) "The Depth (DPT) of a texture is how bumpy vs. flat the objects or materials in the texture are." (11) "The Linearity (LIN) of a texture is how line-like vs. unline-like the lines or elements in the texture are." (12) "The Naturalness (NAT) of a texture is how naturally existing vs. man-made the objects or materials in the texture are." The order of the attributes was randomized across subjects.

Ranking at 1 was always from the first extreme mentioned in the attribute description (e.g., "round, circular, or spherical" in the case of shape), and from "most" to "least" (e.g., most repetitive picture at rank 1 and least repetitive at rank 30). A ranking procedure was used rather than a rating scale procedure because subjects reported that it was easier for them to make comparisons between pictures when all of them were simultaneously visible. The order of the stimuli was recorded for each dimension, and ranks were averaged across subjects.

Results

Groups

Hierarchical Cluster Analysis

Initial Analysis. Hierarchical cluster analysis was performed on the pooled dissimilarity matrix generated from the grouping task. The Complete Linkage Method for determining cluster membership was used (*SPSS for Windows*). This method begins by joining the two stimuli (pictures) closest in distance to create an initial cluster. Next, individual stimuli are joined to either the initial cluster or to other stimuli to create new clusters. For each unclustered stimulus, both (1) distance to all other unclustered stimuli and (2) distance to the farthest member of already existing clusters are computed. Individual stimuli are then joined to other unclustered stimuli or to already existing clusters based on the smaller of the two distances. Distance between clusters is determined by computing the distance between the two furthest stimuli in each cluster. Because the distance between a to-be-clustered stimulus and the furthest member of a cluster may be less than the distance between the to-be-clustered stimulus and other unclustered stimuli, individual stimuli may remain unclustered while some clusters have been joined with others. This process continues until all stimuli are clustered together. Well-defined groups may emerge at several points during the clustering process, and the ability to interpret the clusters usually determines the stopping point.

The dendrogram for the cluster analysis is seen in Figure 3. The cluster analysis yields 10 basic groups labeled Groups A through G-2 in Figure 2. Later in the clustering process, some of these groups combine to form more general groups, referred to as Clusters. Clusters E, F, and G are each made up of two more basic groups that are not joined together until relatively late in the clustering process, labeled "1" and "2" for each clusters. In contrast, Clusters A, B, C, and D are formed early in the analysis, indicating that all of the textures within each group are highly similar. Thus, the cluster analysis can be seen as yielding either seven or 10 clusters, depending on the level of analysis. Intuitively, clusters or groups with fewer members are more homogeneous than clusters or groups with more members. Seeing the stimulus set as composed of 10 groups presumably allows a more definite identification of which features are important in judging individual pairs of pictures as similar. Thus, analysis of similarity and grouping will take place at the finer level except where noted.

Pictures in Group A appear to be similar in that they are all marked by rounded, or at least "closed" shaped elements that are frequently repeated. All of the pictures are made up of naturally occurring objects, and four of the five are rock (the other is d74, beans). Pictures in Group D appear to share a lack of oriented elements and a "grainy" quality. Each of the pictures are made up of man-made materials (d32, d57, and d86) that are similar in appearance. Pictures in Group E-1 share their constituent material (marble), and both appear as "blotchy" patterns with highly irregular elements. Thus, texture pattern and object/surface type are both possible bases for similarity in Groups A, D, and E-1.

Pictures in Group B are all marked by what can be described as "web" patterns. Although the materials making up each of the pictures are quite different, all three share frequently repeated lines that cross at various orientations, forming frequently repeated small elements with many sides. Pictures in Group C all appear to have square or rectangular elements. As with those in Group B, lines of pictures in Group C cross to form elements. Despite the fact that the materials of d18 (raffia-1) and d64 (rattan) are similar in appearance, these pictures are grouped with two pictures each with different materials (d1, wire and d26, brick). Pictures in Group F-1 all have long, thin elements that are relatively well-oriented. Two of the three are wood (d69, d71), while the third is fur (d93). Thus, texture pattern appears to be primarily responsible for similarity in Groups B, C, and F-1.

It is difficult to isolate what is responsible for the similarity of pictures in Group E-2, F-2, G-1, and G-2. Pictures in Group E-2 all have somewhat large shapes, although d41 (lace) appears to have a smaller microtexture not unlike those in Group B. Their materials are obviously all quite different. Pictures in Group F-2 do not share pattern similarity, as d50 (raffia-2) and d78 (cloth) both have long, thin, strongly vertically oriented lines and are similar in material composition to one another. Such a pattern appears more similar to the textures of Group F-1 than to d37 (water). Water, by contrast, has primarily horizontally oriented lines and is not similar in material composition to either raffia-2 or cloth. Both members of Group G-1 posses strong figure-ground contrast, but the elements of d107 (rice paper) are randomly oriented, whereas those of d43 (lightbulb) vary from vertically oriented curvilinear lines, to circular lines. Similarity in Group G-2 is perhaps due to the hierarchical nature of both texture patterns. Small elements are connected to larger elements in both d10 (crocodile skin) and d87 (sea fan).

The judged similarity of pictures in Group B, Group C, Group F-1, Group F-2, and Group G-2 appears to support the idea that line orientation is not primary in similarity judgments of natural texture. If predominant line orientation were important in similarity, several of the clusters recovered here would not have been created, as predominant line orientation differs substantially in all of these groups. Linearity of elements appears of some importance, as generally "lined" pictures were often grouped together. The same can be said of spatial frequency. Several of the created groups contain pictures with elements of similar spatial frequency. However, there are several pictures in the set that can be described as generally lined, and several that can be described as fairly periodic (or having high spatial frequency) that were not grouped together. Again, linearity and spatial frequency do not appear to be primary in judging similarity in natural texture. However, it is difficult to say exactly what variables were important for judging similarity in the grouping task. Many of the similarity judgments appeared to be group-specific. Determining the variables or features responsible for similarity judgments in the grouping task was the goal of the describing and ranking tasks.

Comparison with Rao & Lohse (1993). Rao & Lohse identify six major clusters in their cluster analysis solution, labeled Cluster A-F in Table 1, and the six major clusters can be broken down into 11 "finer" sub-clusters. Two dissimilarity matrices for the Rao & Lohse results were computed based on six and 11 clusters and compared to the two dissimilarity matrices for the present results based on seven and 10 clusters. The dissimilarity matrices were computed by giving texture pairs in the same cluster a score of zero and texture pairs in different clusters a score of one. The correlation was found to be moderate ($r = .318$, $p < .01$; $N = 450$) for the more inclusive clusters, but was much higher between clusters found when only the most similar stimuli were grouped together ($r = .738$, $p < .01$; $N = 450$). Thus, it appears that the results of the two cluster analyses are substantially similar at the early stages of the process, and that it is not until several groups have been joined that the two solutions begin to differ in any measure.

Multidimensional Scaling

Initial Analysis. Non-metric MDS was also performed on the pooled dissimilarity matrix. The matrix was treated as interval-level data, and distance was computed using a squared Euclidean distance measure (*SPSS for Windows*). A scree plot of S-Stress, Stress, and 1- R^2 measures for the one through six dimensional solutions is seen in Figure 4. These three measures have all been proposed as descriptive of the amount of deviation from monotonicity (difference between the distances in the MDS solution and the distances in the original dissimilarity matrix) in the MDS solution (Shiffman, Reynolds, & Young, 1981). S-Stress is a measure of this deviation in squared distance (Takane, Young & de Leeuw, 1977), stress is a measure of deviation in distance (Kruskal, 1964a, 1964b, Kruskal & Wish, 1978), and 1-R^2 is a measure of the proportion of variation in the dissimilarities not accounted for by the MDS solution. Young and Lewychyj (1979) view the 1-R^2 measure as the most straightforward guide to determining dimensionality. The scree plot was used heuristically to determine the appropriate dimensionality of the solution, following the suggestion of Cattell (1978). Cattell indicates that the point at which a sharp "elbow" occurs in the curve of the measures is the appropriate dimensional choice for a solution. While no sharp elbow exists for the S-Stress measure, the smallest angle in the curve of the Stress measure and the 1-R^2 measure is at the three-dimensional point.

How well the inter-stimulus distances in the original dissimilarity matrix were preserved in the inter-stimulus distances found in each of the MDS solutions (varying according to dimensionality) was also used as a method for determining the appropriate solution dimensionality. Distance preservation is poorest in the one- and two-dimensional solutions, best in the three- and four-dimensional solutions, and poor in the five- and six-dimensional solutions. Because the four-dimensional solution also preserved inter-stimulus distances well while providing a slightly better fit to the data in terms of 1-R^2, correlations between the dimensions in the three- and four-dimensional solutions were computed. These correlations are seen in Table 5. Each of the first three corresponding dimensions are substantially correlated with one another.

Dimension three of the three-dimensional solution is also somewhat correlated with dimension four of the four-dimension solution. Thus, it appears that the variance accounted for by dimension three in the three-dimensional solution is primarily accounted for by dimension three in the four-dimensional solution. As the four-dimensional solution offers only a .08 improvement in R^2, the three-dimensional solution is considered a better fit to the data. Also, results of the Rao & Lohse (1993) MDS solution provide prior evidence that the stimuli can be fit into a three-dimensional space. Thus, based on the location of the elbow in the scree plot, the preservation of inter-stimulus distances along the various dimensions, and the number of dimensions deemed appropriate in previous analysis, the three-dimensional solution was determined to be optimal. Stimulus coordinates for the three-dimensional solution can be seen in Table 6. Plots of the stimuli in each of the two-dimensional combinations (dimension one vs. two, one vs. three, and two vs. three, respectively) can be seen in Figure 5. Viewing the arrangement of the stimuli in the three dimensional space shows that they are arranged in disjoint groups that are scattered differently along each dimension. With rare exception, the pictures within each cluster are tightly packed on all dimensions. The dimensional structure reflects the ways that the clusters can be organized, and a comparison of the dimensions shows that each one represents possible bases of similarity among the clusters.

Dimension one separates pictures in Groups B, C, D, and F-2 on the positive side of the X-axis from Groups A, E-1, E-2, and G-1 on the negative side of the X-axis. Group F-1 straddles the center of the X-axis. Such a distinction could perhaps be based on structure, with more organized pictures (e.g., reptile skin, brick) falling on the positive side of the X-axis and more random pictures (e.g., marble-2, mica) falling on the negative side. Another possible attribute varying along dimension one is linearity. Pictures on the positive side of the X-axis appear to have more line-like elements, and more straight lines (e.g., raffia-cotton, rattan), and pictures on the negative side appear to have less line-like elements, and less straight lines (e.g., hops, clouds).

Dimension two separates pictures in Groups G-1, F-1, and F-2 on the positive side of the Y-axis from Groups A, B, and C on the negative side of the Y-axis. Group D straddles the Y-axis. This ordering of the stimuli appears to move from pictures with large lines or linear units (e.g., rice paper, raffia-2) on the positive side of the Y-axis to pictures with units that are difficult to define (e.g., marble-2, crocodile skin) in the center of the axis, to pictures that have small and less linear units (e.g., pebbles-1, cloth-1) on the negative side of the axis. Roughness also appears to increase as stimulus values on the Y-axis decrease. Dimension three separates Groups D, E-1, E-2, B, and G-1 on the positive side of the Z-axis from Groups F-1, F-2, and C on the negative side. Group A straddles the Z-axis. In comparison to dimension two, dimension three contrasts Groups B and C and Groups F and G, but makes Groups F and C and Groups G and B equivalent. Pictures with positive values on the Z-axis appear to have little or no directionality, and appear generally random (e.g., ceiling tile, paper). Pictures with moderate or near-zero values on the Z-axis have circular elements and are two-directional in orientation (e.g., lightbulb, marble-3), whereas pictures with negative values appear to have linear elements and have a single directionality (e.g., raffia-2, wood-1). These trends are supported by comparing Groups B, C, F, and G, groups that most clearly illustrate the differences between dimensions two and three. Despite these general trends in stimulus differences, no abstract dimensional structures are readily apparent, and no other rotations appear to represent a more compelling rendering of the perceptual space than the unrotated solution.

Comparison with Rao & Lohse (1993). Because Rao & Lohse (1993) do not report their original data matrix, a direct comparison between the two matrices cannot be made. However, a basic measure of the similarity between the data collected in the two analyses was obtained by converting the inter-stimulus distances recovered in each of the MDS solutions into pairwise inter-stimulus distances in the 3-dimensional Euclidean space to yield a matrix of ideal pairwise distances based on the MDS solutions. The correlation between the off-diagonal elements of these matrices indicates substantial similarity between the data matrices as scaled by the respective MDS algorithms ($r = .663$, $p < .01$; $N = 450$). The correlation matrix between each of the dimensions of the Rao & Lohse solution and each of the dimensions of the Experiment 1 solution is seen in Table 7. Direct comparison of each of the corresponding dimensions in the two solutions shows that each of the first dimensions in both solutions are strongly related, as are each of the second dimensions in both solutions. Only the respective third dimensions are not significantly correlated, with dimension three of the Experiment 1 solution more closely related to dimension one of the Rao and Lohse solution. Overall, the two MDS solutions are substantially similar.

Descriptions

Groups

Frequencies for Group descriptors are seen in Figure 2. The most frequently mentioned descriptor for pictures in Group A was "roughness." Mention was also made of the common shape and separateness of the elements in each of the pictures, as well as a common hardness. Pictures in Group B were also described as "rough," and mention was made of the connectedness and common shape of the elements in these pictures. Pattern symmetry was also mentioned as characteristic of these pictures. By far the most frequent observation made about the pictures in Group C was that all of them shared the same pattern, although subjects seemed at a loss to find an exact term for that property. Such a description is particularly interesting given the differing orientation of the line elements in raffia-1 (d18) from the others in the group. Subjects also noted that the patterns were all "regular." Pictures in Group D were also described primarily as "rough," but also as having some sort of "porosity," most often explained as having "spaces" in the texture or between elements. Pictures in Group D were also described as standing out in three dimensions

(3d), or as having some depth between figure and ground. Pictures in Group E-1 were described as "random," and as being made up of the same material. Subjects were unable to find an adequate verbal descriptor to capture the shared properties of the pictures in Group E-2, although the singular mention of "complex shapes" seems appropriate. These pictures were also described as having depth. Pictures in Group F-1 were described as having "wavy lines," and as appearing "grainy," in addition to appearing "rough." Pictures in Group F-2 were described as having lines that had a single prominent directionality. Pictures in Group G-1 were described by their "random lines" and strong figure-ground "contrast." Pictures in Group G-2 were also described as having lines that had a single prominent directionality, and also as having "intricate" patterns.

Dimensions

Frequencies for dimension descriptors are seen in Table 8. Subjects most often indicated that dimension one varied from very little to a great amount of structure or organization in texture pattern, although six also said they could find no systematic variation in the rank ordered pictures. Dimension two was most frequently described as varying in orientation, from unoriented in the positive values to equally vertically and horizontally oriented in the negative values. Six subjects also thought structure/organization varied systematically. Most subjects could not identify any systematic variation in pictures rank ordered along dimension three, although those that reported they could identify systematic variation most often saw differences also due to structure/organization. Such a description explains the correlation of dimension one from the Rao & Lohse solution with dimension three from the Experiment 1 solution (see Table 7).

The term structure/organization was used to describe dimensional variation in fully one-third of the judgments across the three dimensions. Despite the fact that structure/organization was best represented by the rank ordering of the pictures along dimension one, structure/organization was also seen as important in explaining rank orders along all three dimensions. There were no mentions of the repetitiveness or the complexity of the pictures along any of the dimensions, indicating that the interpretation made by Rao & Lohse (1993) was not as salient an explanation of the variation along dimension one as the that of structure/organization. A clearly modal response emerged for dimension two as well, this one corresponding to the dimensional attribute of Orientation hypothesized by Rao & Lohse. Ten subjects indicated that dimension two varied according to texture orientation. Thus, it appears that the attribute hypothesized by Rao & Lohse was supported as the most salient explanation of the variance along dimension two. It is also worthy of note that across the three dimensions "don't know" was as common a response as structure/organization, making up nearly one-third of the responses.

Objects/Surfaces

Frequencies for objects/surfaces supplied for each of the pictures can be found in Figure 2. These can be compared with descriptive terms given by Brodatz (1966). A few of the pictures were always correctly identified (d23, d26, d64, d69, d91). Many of the modal names can be described as generally accurate (d1, d3, d5, d10, d18, d30, d58, d62, d71, d74, d93), while others are generally inaccurate (d32, d34, d37, d41, d78, d86, d87, d88). Others, subjects often could not identify (d43, d50, d52, d57, d61, d107). Breaking the modal responses into categories of pictures that were generally accurately named vs. those that were generally inaccurately named shows 16 generally accurate identifications, and 14 generally inaccurate identifications. Some textures were always or almost always correctly identified (e.g., d26), and an equal number were never or almost never correctly identified (e.g., d43). Generally then, the set was evenly split between identifiable and unidentifiable objects/surfaces.

The ability of subjects to generally correctly identify picture objects/surfaces may have some influence on similarity grouping (Nosofsky, 1986). Table 9 breaks down each of the 10 groups according to how many of the member pictures of each group were generally correctly identified or generally incorrectly identified. Of those groups whose members were all generally correctly identified (Group A, Group C, and Group F-1), the members of each group were not all identified as the same, or even necessarily similar, objects/surfaces. Thus, it appears that when picture objects/surfaces can be correctly identified, pattern variables are more primary than the nature of the depicted objects/materials in grouping. Those groups whose members were all generally incorrectly identified (Group D, Group F-2, Group G-1, Group G-2) fell into two categories. When members of these groups were incorrectly identified as being made up of objects/surfaces, the objects/surfaces as identified tended to be similar in nature (e.g., all materials for floor surfaces in Group D). However, these pictures were also generally similar in pattern, and so this finding may be an artifact of the pictures in the present set. When picture objects/surfaces were generally not identified (that is, when the most frequent response was "don't know"), these textures tended to be grouped together as a remainder group (e.g., Group G-1).

Rankings

Attribute Dimensions

Ranks for the pictures on each attribute dimension can be seen in Table 10. Correlations of the attribute dimensions with one another can be seen in Table 11. Rankings of Repetitiveness, Orientation, Structure, and Linearity were highly intercorrelated with an average correlation of .870 (N = 30). Size and Connectedness were highly correlated, and Complexity, Naturalness, Shape, Size and Connectedness were correlated with one or more attributes of the above cluster. Rankings of Roughness, Hardness, and Depth were intercorrelated less strongly. These attributes are not related to any of those above, appear to form a cluster based on expected tactile percepts.

Correlation with MDS Solution

Correlations between the ranked dimensions and the dimensions derived from the MDS solution from Experiment 1 are found in Table 12. Rankings of Repetitiveness and Structure are associated with all three of the derived MDS solution dimensions from Experiment 1. Rankings of Orientation, Complexity, and Depth, Connectedness, and Linearity are associated with two of the derived dimensions. Rankings of Shape, Size, Roughness, Hardness, and Naturalness are associated with only one of the derived dimensions.

Regression onto MDS Space

Davison (1983) indicates that multiple regression can be used to determine whether attributes hypothesized to underlie similarity judgments represent relevant aspects of the MDS solution space. Attributes can be considered to represent similarity in perceptual space if attributes are not substantially correlated with one another and if they have large multiple correlations with the unrotated MDS solution dimensions. Stimulus coordinates for the three unrotated dimensions were used as independent variables in twelve separate regression equations to predict each of the ranked dimensions. In the regression equations, the multiple R^2 value represents how much of the variance in the multidimensional space was captured by each of the individual ranked dimensions. Standardized regression coefficients and R^2 values for each of the equations are found in Table 13. Davison (1983) recommends that attributes only be considered to explain a significant amount of variance in the multidimensional space when $R^2 > .7$.

Rankings for Repetitiveness, Orientation, Structure, Connectedness, and Linearity all meet the criteria of having multiple R^2 values above .7. As can be seen from Table 12, only two of these attributes, Structure and Connectedness, are not significantly correlated with each other. Another attribute not significantly correlated with Structure and Connectedness that comes close to the $R^2 > .7$ requirement is Depth ($R^2 = .635$). Together, the combination of Structure, Connectedness, and Depth explain a substantial proportion of the variance in the MDS solution space.

Discussion

When subjects are faced with the task of placing pictorial stimuli into a small number of groups based on similarity, they have a variety of options (Torgerson, 1965). Subjects can group the picture on the basis of the objects represented in the pictures (e.g., mica can go with pebbles), on the basis of the surface characteristics represented in the pictures (e.g., rough surfaces grouped with other rough surfaces, perforated surfaces such as nets grouped with reptile skin), on the basis of texture characteristics (e.g., similar orientations of lines or fissures, similar frequency of small elements), or on the basis of abstract dimensions that theoretically could rank order all the pictures (e.g., a structure dimension, such that one end of the continuum is made up of repeating units and the other end is simply a random pattern of white and black). At times these aspects are correlated across the levels of similarity so that the decision to group or not group a pair of pictures is simple. In other cases, these aspects conflict. For example, two pictures of marble (e.g., marble-1 and marble-3) could be grouped together on the basis of material identity. But, marble-1 is made up of disorganized light blobs and swirls throughout the picture, whereas marble-3 is made up of well-defined white shapes of various sizes bordered on all sides by dark background. Thus, marble-1 can be grouped with other pictures without well-defined elements and marble-3 can be grouped with other pictures with isolated, well-formed elements of similar shape.

In working through the grouping task, subjects began by placing very similar pictures into groups, leaving a large number of pictures that are not obviously related. The pictures that are grouped share many characteristics and they are placed in the same group by nearly all subjects. We would hypothesize that the object and surface properties dominate this part of the task, but not completely. Next, subjects begin to group previously ungrouped pictures into separate groups, to place ungrouped pictures into previously formed groups, or to combine two groups. At this stage, the pictorial properties of the texture appear most important. It is critical to note that each grouping decision may have a different rationale (Medin & Schaffer, 1978). A picture of coffee beans may be joined to a picture of marble due to the repetition of circular elements while at the same time a picture of woven rattan is joined to a picture of bricks due to the square elements and linear, highly oriented vertical texture pattern. Together the locally judged bases for similarity and the hierarchical completion of the grouping task suggest that similarity is being judged first by texture pattern or, where possible, object/surface identity and later by a "best fit" criterion. Subjects are making use of the context generated by the entire set of pictures and are being serendipitous in allocating pictures to various groups. Finally, and there is little evidence for this, subjects might utilize dimensions to arrive at the final grouping. In sum, we are arguing that the grouping task and resulting dissimilarity matrix be understood as the outcome of several perceptual realities based on different "levels of grain" of the pictures. Although the MDS techniques produce a spatial array, we do not believe that dimensions have an important perceptual role. The evidence for this is summarized below.

Salient aspects of the picture often gave a general indication of the object/surface depicted, but did not often lead to a completely accurate identification. Thus, it would seem that the salient aspects of the picture serve to narrow the object/surface possibilities by eliminating numerous types of objects or surfaces from consideration. For example, the salient aspects of d26 (brick) mean that it is highly unlikely that it would be identified as raffia weave (d18) or handwoven oriental rattan (d64), despite the fact that these pictures are judged as substantially similar. Despite the impossibility of mistaking brick for raffia weave, both textures are similar in overall structure. The class of objects or materials excluded by the salient aspects of a particular texture, however, is not always intuitive. This point is illustrated particularly well by the identification of d37 (water) as sand by 12 subjects! Despite the fact that water and sand are not similar objects/surfaces, they have a similar overall visual appearance, perhaps due to the fact that both surfaces are shaped by wind.

A second important finding from the describing task appears to be that one of the major differences between natural textures and abstract textures is the presence of tactile descriptors for natural texture. Intuitively, it would seem that no such descriptions would be likely, or are even possible, for abstract textures. The possibility that both visual and tactile attributes interact in real-world evaluations of texture seems plausible (Amadasun & King, 1989; Tamura, et al., 1978). The relevance of tactile attributes in visual perception is easily explained by the Gibsonian notion of affordance (cf. Gibson, 1979). For example, subjects' evaluation of the pictures in Group D as being porous, or as having the property of "fillability with liquid" was made entirely visually, without direct experience of the surface's actual porosity or any tactile characteristics. Moreover, descriptions of roughness and hardness correspond to attributes found to mediate similarity judgments of tactile texture by Hollins and his colleagues (Hollins, Faldowski, Rao & Young, 1993). This correspondence raises the possibility that such tactile attributes can be assessed with some degree of accuracy by virtue of visual perception alone, another plausible possibility given the importance of texture in real-world perceptual tasks (Marr, 1982; Watt, 1985).

The fact that unidentifiable objects/surfaces tended to be grouped together suggests that some groups may have been created by subjects simply as "other" groups, or as groups of stimuli whose similarity in relation to others in the set was difficult to assess. In observing subjects' performance on the grouping task, the creation of numerous groups (often containing one, two, or three stimuli) on the part of subjects was frequently observed. Because such grouping made similarity between the entire set difficult to assess, the three-to-six group restriction was placed on subsequent grouping tasks. This restriction appears to have acted as a forced-choice requirement, making subjects find "best fit" judgments between small, low-level groups of stimuli. These stimuli are also perhaps extreme with regard to one or more of the bases of judgment used to group the stimuli in the present set, and could have acted as outliers in influencing grouping.

The pattern of responses given in the description task seems to indicate that general properties such as pattern structure/organization, orientation, interconnectedness, shape, and roughness are important in describing natural textures. Also, perception of these properties of natural textures is largely independent of object/surface identification. The attributes of Repetitiveness and Orientation hypothesized by Rao & Lohse to represent abstract texture dimensions are both able to explain a substantial amount of the MDS solution space. Unfortunately, the amount of variance explained by each attribute appears to overlap substantially, demonstrating that these attributes are not independent of one another. Complexity does not appear to be substantially related to the configuration of the stimuli in the MDS solution. Thus, the names given by Rao & Lohse to the derived dimensions are not informative for purposes of illustrating what psychological constructs are represented by the perceptual space. Moreover, these attributes cannot be considered useful for the purpose of identifying and classifying textures since they do not correspond to more basic similarity judgements made by a comparable group of subjects. Other attributes (e.g., Structure, Shape, Size, Linearity, and Naturalness) were substantially intercorrelated with one another and with the attributes hypothesized by Rao & Lohse, suggesting the possibility that all of these attributes capture aspects of another, superordinate attribute. If a dimensional model were appropriate for specifying texture features, such a hypothetical superordinate attribute would be orthogonal to other attributes in explaining the stimulus grouping and MDS dimensions in the present analysis. Evidence from the description task indicates that this superordinate attribute is best termed "structure."

In general, however, subjects had some difficulty identifying continuous, abstract dimensions of texture. Even after collecting grouping and naming data and analyzing clustering and MDS results, the author found interpretation of the recovered MDS dimensions difficult. The most common term given to explain dimensional variation fit the general category of structure/organization. Most often, subjects whose responses were categorized as meaning structure/organization said something to the effect of, "They appear to be more organized toward this end, and to be very random patterns at the other end." While structure/organization is a fairly abstract descriptor, even when subjects were prompted with other possible attributes after giving their final response almost all reported that they could not see any evidence of variation according to other attributes. For example, after some subjects described the order of the textures along dimension one, they were asked, "Do you think the pictures become more repetitious in either direction?" or, "Does it seem as if the parts of the pattern become more frequent toward either end?" Only two subjects reported "seeing" the attribute suggested by the experimenter.

Collectively, these findings suggest that the present set of stimuli cannot be reliably ordered along abstract dimensions but are judged similar or different by virtue of attributes specific to the members of each individual cluster and not present across clusters. The idea of stimulus categorization according to family resemblance (Wittgenstein, 1953) is supported by the judgments of subjects in the describing task who used different types of adjectives to describe the commonalities found among stimuli within each of the clusters recovered from the grouping task. This distinctiveness of the clusters, and thus the inappropriateness of a dimensional model for portraying the features in the present texture set, may also be indicative of the 'inclusiveness' characteristic of texture mentioned above. Also, the stimuli in the present set may not be adequately representative of real-world textures (Rao & Lohse, 1993). The purpose of Experiment 2 was to answer the question of whether the findings characteristic of the Brodatz set used in the first experiment would generalize to other stimulus sets. That is, are there texture features or dimensions not represented in the Brodatz set that are relevant for an understanding of attentive texture perception? To provide an answer to this question, an entirely novel set of textures was used, and analyses were performed using the same methods as before.

CHAPTER III

EXPERIMENT 2: MIT TEXTURES

The purpose of Experiment 2 was to assess the generalizability of the findings established in Experiment 1 using a novel set of 24 textures from the Massachusetts Institute of Technology's World Wide Web site.

Method

Participants

As in Experiment 1, both the grouping and the describing task each involved 20 subjects. The ranking task involved 60 subjects. All subjects were college students naive to the purposes of the experiment and all subjects received extra course credit in exchange for volunteering to participate.

Materials

Twenty-four pictures from the Massachusetts Institute of Technology's World Wide Web site were printed using a HP LaserJet Series II black-and-white printer on standard 8½ x 11" paper. The pictures themselves measured 7 x 7" and are seen in Figure 6. Some stimuli were selected to resemble those in the Brodatz set (see Figure 7).

Procedure

Groups, Descriptions, and Rankings

The grouping and describing tasks as well as the conversion of the grouping data into a dissimilarity matrix was identical to that in Experiment 1. The only difference between Experiment 1 and the present experiment was the fact that 24 instead of 30 pictures were used. The pooled dissimilarity matrix is seen in Table 14. The ranking task was also identical. Based on the outcomes from Experiment 1, however, only six dimensions were evaluated. The dimensions were Repetitiveness, Orientation, Complexity, Structure, Connectedness, and Depth. In Experiment 1, Structure, Connectedness, and Depth were found to be relatively independent of one another and to explain a large amount of the variance of the recovered MDS space.

Results

Grouping

Hierarchical Cluster Analysis

Initial analysis. Hierarchical cluster analysis was performed on the pooled dissimilarity matrix. The Complete Linkage Method for determining cluster membership was again used (*SPSS for Windows*). The dendrogram for the cluster analysis is seen in Figure 8. The cluster analysis yields eight basic groups, labeled Group A-H in Figure 7.

Members of Group A are highly periodic, or repetitive, textures. Rattan, straw, and rope are all woven, and it is likely that fabric is as well. Also, the materials all have a similar general appearance. Members of Group C are also periodic, and have a common material composition of brick. Bricks (01) and tile bricks (02) share a common horizontal orientation, whereas stone (03) is less oriented. Members of Group D are highly periodic and share a common lack of orientation as well as a general similarity in material. All are plant material, and the "stringy" appearance of straw-2 (14) connects it easily to pine needles (17) and evergreen leaves (16). Particle board (20) appears to join the other members of Group C relatively late, and could be considered to represent its own group. Members of Group G have tiny dot-like elements similar to those found in Group F; here, however, both are metal. Both texture pattern and material similarity are potentially responsible for grouping in Groups A, C, D, and G.

Members of Group B are highly periodic, and share a general roundness to their elements. Their respective materials, however, are quite different. Thus, it is likely that texture pattern is responsible for similarity in Group B. Bark-1 (04), bark-3 (06), and wood (23) make up Group E, and share a common material composition. Whereas bark-1 is both horizontally and vertically oriented, bark-3 is primarily vertically oriented. Conversely, wood has a circular orientation. Thus, it is likely that material identity is responsible for similarity in Group E. Members of Group F are similar in the respect that each appears to have tiny blob-like elements, and have a rough appearance. Interestingly, bark-2 (05) does not group with other bark/wood stimuli, as it perhaps has lost certain "wood" properties through its low definition. Overall, the two pictures are not very similar in appearance, and their material compositions are not similar.

Members of Group H can be said to have predominantly horizontal lines, but their respective texture patterns are not very similar. Their materials are also very different. Fur (10) also seems to form somewhat of a group if its own, but eventually joins with the members of Group H. It is difficult to isolate exactly what variables are responsible for similarity among the members of both Groups F.

Comparison with Experiment 1. The smaller set of pictures used in the present experiment (24 vs. 30) yielded fewer groups (8 vs. 10) than in the larger Brodatz set used in Experiment 1. Comparisons of similar pictures and derived groups from the Brodatz and MIT sets can be seen in Figure 7. In short, the derived groups differ across picture sets; the equivalent pictures from each set are grouped with different types of pictures so that the descriptions of the derived groups in each set varies. In each instance, despite the similarity of one or more pictures across sets, other group members of the compared pictures in one set show little or no similarity to corresponding group members in the other set. For example, Figure 7a shows a comparison between the members of the MIT Group A with raffia-1 (d18) and rattan (d64) from the Brodatz set. While these pictures show general similarity across sets, raffia-1 and rattan are grouped with d1 (wire) and d26 (brick) in the Brodatz set. Now consider bricks (01) and tile bricks (02) of the MIT set as analogues of brick of the Brodatz set (Figure 7b). In the MIT set, the fact that bricks and tile bricks do not group with the members of Group A in a similar manner to the grouping of brick with raffia-1 and rattan in the Brodatz set illustrates that similarity across sets does not exist above pairwise comparisons. Groups across sets generally are not comparable. The possible exception to this is the relationship between Group B of the MIT set and Group A of the Brodatz set. Both groups appear to have been created on the basis of the circular, round, or spherical elements characteristic of all members of both groups (Figure 7c). Across sets, beans (8) of the MIT set is very similar in general appearance to beans (d74) from the Brodatz set (Figure 7c).

Multidimensional Scaling Analysis

Non-metric multidimensional scaling (MDS) analysis was also performed on the pooled dissimilarity matrix. The matrix was treated as interval-level data, and distance was computed using a squared Euclidean distance measure. A scree plot of S-Stress, Stress, and 1- R^2 measures for the one through six dimensional solutions is seen in Figure 9. Examination of the scree plot shows a somewhat sharper elbow at the three-dimensional point than was seen in the corresponding scree plot in Experiment 1, and the four-dimensional solution offers only a .08 improvement in R^2. Also, the results of Experiment 1, as well as those of Rao & Lohse (1993) provide ample evidence that the stimuli can be fit into a three-dimensional space. Thus, based on the location of the elbow of the scree plot, the preservation of inter-stimulus distances along the various dimensions, and the number of dimensions deemed appropriate in previous analyses, the three-dimensional solution was determined to be optimal. Stimulus coordinates for the three-dimensional solution can be seen in Table 15. Plots of the stimuli in each of the two-dimensional combinations (dimensions one vs. two, one vs. three, and two vs. three) can be seen in Figure 10.

The dimensional space contains disjoint groups that mainly occur on the extremes of the dimensions. This is particularly noticeable in the plot of dimension one vs. dimension three. Each dimension represents several possible bases of similarity among the clusters. Dimension one separates Groups A, B, and C from Groups G, H, E, F, and D along the X-axis. Pictures on the positive side of the X-axis appear (a) more compact and repetitious in structure (e.g., fabric, 13), (b) made up of artificial (man-made) objects/surfaces (e.g., pegboard, 22) , and (c) have more articulated linearity and interconnected elements (e.g., rope, 12) than pictures on the negative side of the X-axis. Conversely, pictures on the negative side of the X-axis appear to have (a) more stringy and less organized structure (e.g., straw-2, 14), (b) made up of more natural, or biological, objects/surfaces (e.g., bark-1, 04), and (c) have less well articulated and generally unconnected elements (e.g., sand, 21). Dimension two separates pictures in Group E, F, and H from pictures in Group D and G along the Y-axis. Pictures in Group C and A have values near zero on the Y-axis. Pictures with positive values on the Y-axis appear to be oriented predominantly in one direction (e.g., bark-3, 06), whereas those with near-zero values on the Y-axis appear to be oriented predominantly in two directions (e.g., bricks, 01). Pictures with positive values on the Y-axis appear to generally lack orientation (e.g., pine needles, 17). Dimension three separates pictures in Groups B and E from those in Groups G and H along the Z-axis. Textures in Groups D, F, A, and B have values near-zero on the Z-axis. Pictures with positive values on the Z-axis appear to (a) have more organized elements (e.g., tile bricks, 02), and (b) appear harder than textures with negative values on the Z-axis, which appear to (a) have more random structure, appearing directionless and unit-less, and (b) seem to be softer (e.g., water, 24).

Descriptions

Groups

Frequencies for Group descriptors are seen in Figure 6. Pictures in Group A were most frequently described as rough, and also as having regular patterns. It was unanimously decided that pictures in Group B shared element shape, as did members of Groups A and C in Experiment 1. Pictures in Group C were frequently described as being hard and regular in pattern, as well as being man-made. Pictures in Group D were most frequently described as being random, and as being made up of common materials. Pictures in Group E were frequently described as being rough, hard, and as composed of common materials. The similarities between the two members of Group F were unclear to most subjects. Pictures in Group G were frequently seen as random, but also as having similarly sized elements. The predominance of horizontal lines was most descriptive of pictures in Group H. Generally, commonalities among members of groups were easier to describe for pictures in the MIT set than for pictures in the Brodatz set. Subjects tended to give a narrower range of descriptors in the present experiment , but those descriptors were similar to those given in Experiment 1.

Dimensions

Frequencies for dimension descriptors are seen in Table 16. Subjects most often indicated that dimension one varied from very little to a great amount of structure or organization in texture pattern, but almost as frequently could not identify any attribute varying across pictures rank ordered along dimension one. Dimension two was most frequently described as varying in roughness, although an equal number of subjects could find no systematic difference in pictures rank ordered along dimension two. Most subjects could not identify any systematic variation in pictures rank ordered along dimension three, although roughness, orientation, and structure/organization were all mentioned.

Objects/Surfaces

Frequencies for objects/surfaces supplied for each of the pictures can be found in Figure 6. These can be compared with descriptive terms generated by the author. Several of the pictures were always correctly identified (bricks, tile bricks, stone, bark-3, straw-2, pine needles, wood, water). Many other identifications can be described as generally accurate (bark-1, clouds, beans, rattan, fur, straw-1, rope, evergreen leaves, pegboard), while the rest are considered generally incorrectly identified (bark-2, fabric, leaves, metal-1, metal-2, particle board, sand).

Generally, pictures in the MIT set were easier to identify than those in the Brodatz set. Fewer descriptors were usually used in identifying pictures from the MIT set, and responses were usually more strongly modal than those used to identify pictures from the Brodatz set. Three or fewer object/surface names were given for most of the pictures, and many had strongly modal responses. Whereas roughly half of the Brodatz pictures (16 of 30) were generally correctly identified, 17 of the 24 textures in the MIT set were generally correctly identified. Also, eight of the pictures in the MIT set were unanimously correctly identified and another six were considered highly identifiable. Only five pictures in the Brodatz set were considered highly correctly identifiable. An equal number from both sets (5) are considered highly unidentifiable. Also, there does not appear to be any influence of identifiability on grouping.

Rankings

Attribute Dimensions

Ranks of the pictures on each attribute dimension can be seen in Table 17. Intercorrelations of the ranked attribute dimensions can be seen in Table 18. Rankings of Repetitiveness were again significantly associated with rankings of Orientation. Unlike the results of Experiment 1, rankings of Repetitiveness and Orientation were not significantly associated with rankings of Complexity. Also unlike Experiment 1, rankings of Repetitiveness were not significantly associated with rankings of Structure. Instead, rankings of Structure were associated with rankings of Orientation and Connectedness. Also, rankings of Depth are associated with rankings of Connectedness. Repetitiveness, Structure, and Depth represent one set of three uncorrelated attributes, Orientation, Complexity, and Depth represent a second set, and Connectedness, Repetitiveness, and Complexity represent a third. Because of the lack of intercorrelation within each of these sets, they could potentially be used to explain the MDS solution space if each has a high enough R^2 value.

Correlations and vector angles between the ranked dimensions and the dimensions derived from the MDS solution from Experiment 2 are found in Table 19. Structure is significantly correlated with both dimension one and dimension three. Repetitiveness, Orientation and Complexity are all significantly correlated with dimension one. Connectedness is significantly correlated with dimension two. Depth is not correlated with any of the dimensions of the derived MDS solution. As in Experiment 1, stimulus coordinates for the three unrotated MDS dimensions were used as independent variables in six separate regression equations to predict each of the ranked attribute dimensions. Standardized regression coefficients and R^2 values for each of the three equations are found in Table 20. Only the attribute Structure meets the $R^2 > .7$ criterion ($R^2 = .746$). Thus, it does not appear that the MDS space is explainable with any of the other attributes tested.

Discussion

While several of the Groups recovered from the cluster analysis in Experiment 2 appear to have one or more generally similar analog textures in groups recovered from the cluster analysis in Experiment 1, general group membership does not appear comparable across sets. Other members of such groups appear dissimilar in general appearance, and comparison across solutions indicates that grouping is dependent to some degree on both the texture pattern and material properties of the other members of the set. For example, it appears that because there were other stimuli like bricks (01) in the MIT set, these stimuli were grouped together (forming Cluster B), whereas in the Brodatz set the lack of stimuli with great similarity to brick (d26) meant that this stimulus was grouped with others that shared pattern similarity (e.g., wire; forming Cluster C). The relationship between Group B in the MIT set and Group A in the Brodatz set may be the exception, however. Members of both groups have circular, round, or spherical elements and appear to be analogous to one another. However, it was again the case that correctly identified similar or identical objects/surfaces were grouped together.

In terms of attributes, Structure again appears to be playing a large role in the recovered MDS solution. In general, subjects had some difficulty identifying any attribute or feature responsible for the pictures presented as dimensions. Again, nearly one-third (19) of the responses provided by subjects were "don't know." Also, it is difficult to identify definite continua of abstract features in evaluating rankings along each of the recovered dimensions, and attributes that were able to account for substantial portions of the variance in Experiment 1 (e.g., Repetitiveness) were not able to do so in Experiment 2. It appears that of all the attributes tested in Experiment 1, only Structure is relevant to both sets. This lack of association between ranked attribute dimensions from Experiment 1 and Experiment 2, suggests that either one or both of the sets are unrepresentative of natural textures, that there are no identifiable abstract features represented in either set, or that the basis for similarity judgments cannot be generalized across texture sets. Just as with the pictures described in Experiment 1, however, descriptors for pictures in the present experiment were tactile in nature, further supporting the idea that primarily tactile attributes are important in the perception of natural textures. Attributes primarily associated with visual pattern were also provided in the present experiment. Visual pattern attributes are highly similar to those provided in Experiment 1, suggesting that the pictures share some basic similarity. Thus, findings of the description task suggest that the third alternative above is correct and that the bases for similarity cannot be generalized across sets. Such a conclusion is in accord with Tversky's (1977) diagnosticity principle which states that subjects will attend to and base similarity judgments on stimulus features that are salient and thus relevant bases for classification and discrimination in tasks such as the grouping task. This conclusion also extends the finding of Tversky (e.g., Tversky & Gati, 1978) and of Medin and his colleagues (Medin, 1983; Medin, Dewey & Murphy, 1983; Medin & Schaffer, 1978) who have demonstrated the context-dependence of similarity with other types of stimuli.

CHAPTER IV

GENERAL DISCUSSION

The strategy of subjects in both grouping tasks appeared to involve three stages. After surveying all of the pictures on the table, subjects began by putting only a few pictures (usually two or three) together in each group. At this first-order level, grouping was most often completed by material or pattern similarity or identity. Once subjects had again surveyed the set, they would then combine some or all of the first-order groups. Also, pictures with little or no apparent similarity to the remaining pictures were grouped either together with groups in which they were considered a best fit or in a general "other" group consisting of pictures with no clear relations to any pictures either within- or between-groups. If this first-order combining step did not provide a number of groups within the limits of the instructions, subjects proceeded to combine second-order groups. Each group appeared to have uniquely characteristic within-group similarities that were not found across groups. Substantial differences in grouping of similar pictures across sets suggests that the bases for similarity judgments and created groups were context-dependent in both sets (Tversky, 1977; Tversky & Gati, 1978). Only in the case of Group A of the Brodatz set and Group B of the MIT set, was grouping across sets substantially similar. Usually, similar pictures from each set were spread across very different groups, indicating the differences between the members of both sets as a whole.

The uniqueness of each group was confirmed by the descriptions for each group. The descriptors for each group were based on the characteristics of the pictures within each group, so that the descriptors were often not applicable to other groups. Moreover, about one-third of the subjects described recovered MDS dimensions in both experiments could not identify any systematic variation among the rank-ordered pictures. Those who reported systematic variation along the rank-ordered pictures often gave vague explanations for the variation such as "organization." The results of each of these tasks suggest that natural textures are organized hierarchically, rather than by orthogonal features or attributes. Similarity appears to be categorical, rather than continuous. Although stimuli are representable within a perceptual space, that space does not necessarily reflect the hierarchical process used by subjects to create the space, and the created perceptual space as a whole is not meaningful to subjects. Only isolated parts of the perceptual space, or strong similarities among stimuli, seemed meaningful to subjects.

Several attributes or features appear to be of some importance in judging the similarity of natural textures, including those previously hypothesized such as Repetitiveness, Orientation, Structure, and Linearity. Other attributes not often considered in judging texture visually, primarily tactile attributes, also accounted for variance in the perceptual space and were supplied by subjects describing stimulus groups and dimensions. The inclusion of tactile features within visual perception is reasonable within an ecological view of perception (Gibson, 1979). However, many of the attributes judged were not independent of one another, indicating that at least some similarity judgments were not captured by the attributes. Again, hierarchical rather than continuous organization appears to render the use of continuous features problematic in explaining the similarity judgments made by subjects in both experiments. Moreover, the differential importance and explanatory power of attributes used in the ranking tasks of both experiments appears to reflect the context dependence of the similarity judgments. Thus, although abstract feature-based attributes can be used to explain the organization of the stimuli in the recovered perceptual space, the particular attributes important and their relationships to one another are dependent upon the members of the set. Such a situation is perhaps analogous to textural segregation taking place in a visual array, whereby the salience and contrast of visible textures is dependent upon which other textures are also visible. For example, textural differences may be visible between two adjacent pieces of carpet that have been differentially worn; however, such differences are minor in comparison to the textural differences between carpets and the adjacent concrete.

The categorical structure reflected in the grouping process may have been influenced by identification of many of the stimuli as known objects and/or surfaces. A key basis for similarity judgments was object/surface similarity or identity. Using objects/surfaces as a basis for similarity judgments would make a categorical organization likely, since similar or identical objects/surfaces are bound to be judged as more similar to one another than to objects/surfaces that are different. The fact that many different objects/surfaces were represented in both sets and were occasionally duplicated one or more times meant that the category structure was created on the basis of family resemblance. For example, woods shared a great deal of similarity with one another. The woods in turn shared some aspect of pattern similarity with water, and water shared some aspect of pattern similarity with fur. Thus, both object/surfaces relationships and pattern relationships served simultaneously as bases for similarity. However, this synchrony was not always the case, and sometimes similarities and differences between object/surface relationships and pattern relationships served as a confounding factor in evaluating judgments of similarity. If object/surface and texture pattern characteristics are the variables relevant for similarity judgments of natural textures, it will be necessary to determine what predicts object/material identification (or misidentification), and what aspects of pattern are salient within the perceptual context.

Variables that Beck (1966) and others showed were responsible for similarity judgments in abstract textures were not found to be of primary importance for natural textures. Natural textures often do not posses strongly defined linear elements, or even strongly defined elements, and so textural differences among natural surfaces cannot possibly be due to line orientation, linearity of elements, or spatial frequency. However, these variables do appear to play some role in textural differences. Pattern similarity or identity, one major basis of similarity judgments in the present study, can in many cases be explained as a function of each of the variables of line orientation, linearity of elements, and spatial frequency. Given the characteristics of the recovered groups in the present study, it is unclear whether attentive similarity judgments of natural textures will predict preattentive segregation.

REFERENCES

REFERENCES

Amadasun, M., & King, R. (1989). Textural features corresponding to textural properties. *IEEE Transactions on Systems, Man, and Cybernetics, 19,* 1264-1274.

Beck, J. (1966). Effect of orientation and of shape similarity on perceptual grouping. *Perception and Psychophysics, 1,* 300-302.

Beck, J. (1967). Perceptual grouping produced by line figures. *Perception and Psychophysics, 2,* 491-495.

Beck, J. (1972). Similarity grouping and peripheral discriminability under uncertainty. *American Journal of Psychology, 85,* 1-19.

Beck, J. (1982). Textural segmentation. In J. Beck (Ed.), *Organization and representation in perception* (p. 285-317). Hillsdale, NJ: Lawrence Erlbaum Associates.

Bergen, J.R. (1991). Theories of visual texture perception. In D. Regan (Ed.), *Spatial Vision* (p. 114-139). NY: CRC Press.

Bergen, J.R., & Adelson, E.H. (1988). Visual texture segmentation and early vision. *Nature, 333,* 363-364.

Brodatz, P. (1966). *Textures: A photographic album for artists and designers.* NY: Dover.

Caelli, T.M. (1988). An adaptive computational model for texture segmentation. *IEEE Transactions on Systems, Man, and Cybernetics, 18(1),* 9-17.

Cattell, R.B. (1978). *The scientific use of factor analysis in behavioral and life sciences.* NY: Plenum.

Davison, M.L. (1983). *Multidimensional scaling.* New York: John Wiley & Sons.

Essock, E.A. (1992). An essay on texture: The extraction of stimulus structure from the visual image. In B. Burns (Ed.), *Percepts, concepts, and categories* (p. 3-36). NJ: Elsevier.

Gagalowicz, A., & Ma, S.D. (1985). Sequential synthesis of natural textures. *Computer Vision, Graphics and Image Processing, 30,* 289-315.

Garner, W.R. (1974). *The processing of information and structure.* NY: John Wiley.

Gibson, J.J. (1950a). The perception of visual surfaces. *American Journal of Psychology, 63,* 367-384.

Gibson, J.J. (1979). *The ecological approach to visual perception.* Boston: Houghton Mifflin.

Gorea, A. (1995). Visual texture. In T.V. Papathomas, C. Chubb, A. Gorea, & E. Kowler (Eds.), *Early vision and beyond* (p. 55-57). Cambridge, MA: The MIT Press.

Haralick, R.M. (1979). Statistical and structural approaches to texture. *Proceedings of the IEEE, 67,* 786-804.

Harvey, L.O., & Gervais, M.J. (1981). Internal representation of visual texture as the basis for the judgment of similarity. *Journal of Experimental Psychology: Human Perception and Performance, 7,* 741-753.

Hollins, M., Faldowski, R., Rao, S., & Young, F. (1993). Perceptual dimensions of tactile surface texture: A multidimensional scaling analysis. *Perception & Psychophysics, 54,* 697-705.

Julesz, B. (1975). Experiments in the visual perception of texture. *Scientific American, 232,* 34-43.

Julesz, B. (1980). Spatial nonlinearities in the instantaneous perception of textures with identical power spectra. *Philosophical Transactions of the Royal Society of London,* Series B, *290,* 83-94.

Julesz, B. (1981). Textons, the elements of texture perception, and their interactions. *Nature, 290,* p. 91-97.

Julesz, B. (1986). Texton Gradients: The texton theory revisited. *Biological Cybernetics, 54,* 245-251.

Köhler, W. (1947). *Gestalt Psychology.* NY: Liveright.

Kruskal, J.B. (1964a). Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. *Psychometrika, 29,* 1-27.

Kruskal, J. B. (1964b). Nonmetric multidimensional scaling: A numerical method. *Psychometrika, 29,* 15-129.

Kruskal, J.B. & Wish, M. (1978). *Multidimensional scaling.* Beverly Hills, CA: Sage.

Landy, M.S., & Bergen, J. (1991). Textural segregation and orientation gradient. *Vision Research, 31,* 679-691.

Marr, D. (1982). Vision: A computational investigation into the human representation and processing of visual information. San Francisco: W.H. Freeman.

Medin, D.L. (1983). Structural principles in categorization. In T.J. Tighe & B.E. Shepp (Eds.), *Perception, cognition, and development: Interactional analysis* (p. 203-230). Hillsdale, NJ: Earlbaum.

Medin, D.L., Dewey, G.I., & Murphy, T.D. (1983). Relationships between item and category learning: Evidence that abstraction is not automatic. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 9,* 607-625.

Medin, D.L., & Schaffer, M.M. (1978). Context theory of classification learning. *Psychological Review, 85,* 207-238.

Northdurft, H. (1992). Feature analysis and the role of similarity in preattentive vision. *Perception & Psychophysics, 52(4),* 355-375.

Nosofsky, R.M. (1986). Attention, Similarity, and the Identification-Categorization Relationship. *Journal of Experimental Psychology: General, 115(1),* 39-57.

Olson, R.K., & Attneave, F. (1970). What variables produce similarity grouping? *American Journal of Psychology, 83, 1-21.*

Palmer, S., & Rock, I. (1994). Rethinking perceptual organization: The role of uniform connectedness. *Psychonomic Bulletin & Review, 1(1),* 29-55.

Rao, A.R., & Lohse, G.L. (1993). Identifying high level features of texture perception. *CVGIP: Graphical Models and Image Processing, 55,* 218-233.

Shiffman, S.S., Reynolds,M.L., & Young, F.W. (1981). *Handbook of multidimensional scaling.* NY: Academic Press.

Takane, Y., Young, F.W., & de Leeuw, J. (1977). Nonmetric individual differences multidimensional scaling: An alternating least squares method with optimal scaling features. *Psychometrika, 41,* 505-529.

Tamura, H., Mori, S., Yamawaki, T. (1978). Textural features corresponding to visual perception. *IEEE Transactions on Systems, Man, and Cybernetics, 8,* 460-473.

Torgerson, W.S. (1965). Multidimensional scaling of similarity. *Psychometrika, 30(4),* 379-393.

Treisman, A. (1982). Illusory conjunctions in the perception of objects. *Cognitive Psychology, 14,* 107-141.

Treisman, A. (1985). Preattentive processing in vision. *Computer Vision, Graphics, and Image Processing, 31,* 156-177.

Treisman, A., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12,* 97-136.

Treisman, A., Sykes, M., & Gelade, G. (1977). Selective attention and stimulus integration. In S. Dornic (Ed.), *Attention and performance, VI* (p. 333-361). Hillsdale, NJ: Erlbaum.

Tversky, A. (1977). Features of similarity. *Psychological Review, 84,* 327-352.

Tversky, A., & Gati, I. (1978). Studies of similarity. In E. Rosch & B.B. Lloyd (Eds.), *Cognition and categorization.* Hillsdale, NJ: Erlbaum.

Van Gool, L., Dewaele, P., & Oosterlinck, A. (1983). Texture analysis annotated. *Computer Vision, Graphics, and Image Processing, 29,* 336-357.

Watt, R.J. (1995). Some speculations on the role of texture processing in visual perception. In T.V. Papathomas, C. Chubb, A. Gorea, & E. Kowler (Eds.), *Early vision and beyond* (p. 59-66). Cambridge, MA: The MIT Press.

Wertheimer, M. (1958). Principles of perceptual organization. In D.C. Beardslee & M. Wertheimer (Eds.), *Readings in Perception.* Princeton, NJ: Van Nostrand-Reinhold. (Originally published in German, 1923).

Wittgenstein, J. (1953). *Philosophical investigations.* Oxford: Blackwell.

Young, F.W., & Lewychyj, R. (1979). *ALSCAL-4 user's guide (2nd ed.).* Carrboro, NC: Data Analysis and Theory Associates.

APPENDIX

Table 1
Cluster and Group Membership for Broadatz Pictures from Rao and Lohse (1993)

Cluster	Group	Pictures
A	1	d10
	2	d3
		d34
		d52
	3	d87
B	1	d18
		d64
		d26
		d1
	2	d50
		d78
C	1	d32
		d57
		d86
C	2	d37
		d71
		d93
		d69
D	1	d58
		d61
		d62
	2	d5
		d30
		d23
		d74
E		d91
		d88
F		d43
		d41
		d107

Table 2
Stimulus Coordinates for 30 Brodatz Pictures in Three-Dimensional Space from Rao and Lohse (1993)

Picture	Dimension 1 Repetitiveness	Dimension 2 Orientation	Dimension 3 Complexity
d1	-1.04	0.61	0.18
d3	-0.40	0.45	0.46
d5	0.67	0.59	-0.42
d10	0.11	0.55	0.38
d18	-0.51	0.59	0.03
d23	0.74	0.96	-0.29
d26	-1.01	0.59	0.18
d30	0.81	0.92	-0.20
d32	-0.04	-0.12	-0.73
d34	-0.73	0.27	0.46
d37	0.01	-0.78	-0.48
d41	0.29	-0.67	0.89
d43	-0.01	-0.86	0.55
d50	-0.78	0.03	-0.36
d52	-0.67	0.16	0.34
d57	0.06	-0.17	-0.78
d58	1.13	-0.03	0.03
d61	1.13	0.09	-0.01
d62	1.04	0.14	0.05
d64	-1.00	0.63	0.01
d69	-0.45	-0.98	-0.14
d71	-0.60	-0.89	-0.54
d74	0.66	0.89	-0.05
d78	-0.73	-0.15	-0.21
d86	0.37	-0.26	-0.69
d87	-0.24	0.05	0.45
d88	0.57	-0.83	0.55
d91	0.80	-0.78	0.14
d93	-0.62	-0.67	-0.50
d107	0.43	-0.33	0.69

Table 3
Comparison of Texture Attributes Identified by Various Authors from Rao & Lohse (1993)

Rao and Lohse	Tamura et al.	Amadasun and King
repetitiveness	regularity/irregularity	
orientation	directionality linelikeness vs. bloblikeness	
complexity		complexity
	coarseness contrast roughness/smoothness strength	coarseness contrast busyness

Table 4
Pooled Dissimilarity Matrix from Experiment 1

Picture	d1	d3	d5	d10	d18	d23	d26	d30	d32	d34	d37	d41	d43	d50	d52	d57	d58	d61	d62	d64	d69	d71	d74	d78	d86	d87	d88	d91	d93	d107
d1	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d3	.70	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d5	1.0	1.0	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d10	.75	.70	.80	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d18	.20	.65	.95	.80	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d23	1.0	1.0	.00	.80	.95	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d26	.00	.70	1.0	.75	.20	1.0	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d30	1.0	1.0	.00	.80	.95	.00	1.0	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d32	.95	.55	1.0	.85	.95	1.0	.95	1.0	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d34	.75	.20	1.0	.85	.70	1.0	.75	1.0	.50	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d37	.95	.95	1.0	.65	.95	1.0	.95	1.0	.95	1.0	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d41	.95	.75	.95	.90	.90	.95	.95	.95	.95	.70	.85	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d43	1.0	.90	1.0	.90	1.0	1.0	1.0	1.0	.95	.90	.85	.75	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d50	.90	.90	1.0	.70	.85	1.0	.90	1.0	.90	.90	.55	.90	.90	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d52	.70	.20	1.0	.80	.65	1.0	.70	1.0	.50	.10	.95	.80	1.0	.90	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d57	.95	.60	1.0	.90	.95	1.0	.95	1.0	.10	.60	.85	1.0	.95	.95	.60	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--
d58	.95	1.0	.90	1.0	.95	.90	.95	.90	.85	.95	.90	.70	.85	.85	.95	.90	.00	--	--	--	--	--	--	--	--	--	--	--	--	--
d61	.95	1.0	.85	1.0	.95	.85	.95	.85	.90	.95	.90	.75	.90	.85	.95	.95	.10	.00	--	--	--	--	--	--	--	--	--	--	--	--
d62	1.0	1.0	.25	.90	.95	.25	1.0	.25	1.0	1.0	1.0	.80	1.0	1.0	1.0	1.0	.65	.60	.00	--	--	--	--	--	--	--	--	--	--	--
d64	.20	.65	.95	.80	.00	.95	.20	.95	.95	.70	.95	.90	1.0	.85	.65	.95	.95	.95	.95	.00	--	--	--	--	--	--	--	--	--	--
d69	1.0	1.0	.95	.90	.95	.95	1.0	.95	1.0	1.0	.65	.85	.70	.45	.95	1.0	.85	.90	.95	.95	.00	--	--	--	--	--	--	--	--	--
d71	1.0	1.0	.95	.85	.95	.95	1.0	.95	1.0	1.0	.60	.95	.85	.35	1.0	1.0	.85	.80	.95	.95	.30	.00	--	--	--	--	--	--	--	--
d74	1.0	1.0	.00	.80	.95	.00	1.0	.00	1.0	1.0	1.0	.95	1.0	1.0	1.0	1.0	.90	.85	.25	.95	.95	.95	.00	--	--	--	--	--	--	--
d78	.90	.75	1.0	.65	.90	1.0	.90	1.0	.75	.80	.50	.95	.75	.30	.75	.80	.95	.95	1.0	.90	.60	.65	1.0	.00	--	--	--	--	--	--
d86	1.0	.85	.95	.85	1.0	.95	1.0	.95	.50	.90	.80	.85	.90	.90	.90	.40	.70	.80	.80	1.0	.95	.95	.95	.95	.00	--	--	--	--	--
d87	.90	.80	1.0	.65	.95	1.0	.90	1.0	.85	.85	.65	.65	.90	.60	.85	.80	.90	.90	1.0	.95	.70	.75	1.0	.70	.85	.00	--	--	--	--
d88	1.0	.95	.80	.95	.95	.80	1.0	.80	.95	.90	.85	.35	.80	1.0	.95	1.0	.65	.65	.65	.95	.90	.95	.80	1.0	.90	.70	.00	--	--	--
d91	1.0	.95	.90	1.0	.95	.90	1.0	.90	.95	.95	.65	.60	.70	1.0	1.0	.90	.60	.60	.80	.95	.90	.85	.90	1.0	.80	.85	.40	.00	--	--
d93	.95	.95	1.0	.85	.95	1.0	.95	1.0	.90	1.0	.55	1.0	.65	.65	.95	.90	.90	.85	1.0	.95	.55	.35	1.0	.60	.90	.95	1.0	.85	.00	--
d107	1.0	.95	1.0	.80	1.0	1.0	1.0	1.0	1.0	.90	.70	.55	.50	.85	1.0	.95	.85	.90	.90	1.0	.85	.80	1.0	.85	.75	.70	.55	.75	.70	.00

Table 5
Intercorrelations of Derived MDS Dimensions For Three- and Four-Dimensional Solutions from Experiment 1

Three Dimensional Solution	Four Dimensional Solution			
	D1	D2	D3	D4
D1	**.985**	.011	-.004	.260
D2	-.036	**.993**	-.073	-.108
D3	-.035	-.016	**.960**	-.345

Note. Correlations in bold type are significant at the .05 level.

Table 6

Stimulus Coordinates of Brodatz Pictures Along Three Derived MDS Dimensions From Experiment 1

	Dimension		
Picture	1	2	3
d1	1.0620	-1.3327	-0.6940
d3	1.4229	-0.7984	0.5059
d5	-1.6458	-0.9381	-0.5393
d10	0.4013	-0.3687	-1.4034
d18	0.8589	-1.3666	-0.6834
d23	-1.6381	-0.9317	-0.5409
d26	1.0437	-1.3385	-0.6936
d30	-1.6310	-0.9343	-0.5465
d32	1.1426	-0.3847	1.3124
d34	1.2772	-0.8366	0.7621
d37	0.2996	1.4572	-0.7380
d41	-0.2960	0.4291	1.4792
d43	-0.0113	1.7415	0.2578
d50	0.5703	1.0145	-1.2182
d52	1.3501	-0.9605	0.4491
d57	1.1674	-0.2840	1.3392
d58	-1.0544	0.2088	1.2307
d61	-1.3410	0.0389	0.9134
d62	-1.6728	-0.7507	0.0349
d64	0.8401	-1.3676	-0.6701
d69	-0.0565	1.3235	-1.1332
d71	-0.1154	1.2670	-1.2168
d74	-1.5911	-0.9475	-0.5095
d78	0.9298	0.8519	-0.9975
d86	0.1192	0.1991	1.6529
d87	0.8106	1.2242	-0.0050
d88	-1.2428	0.2177	1.0148
d91	-0.9976	0.6470	1.1274
d93	0.2023	1.3771	-1.0132
d107	-0.2041	1.5432	0.5227

Table 7

Intercorrelations Between Recovered MDS Dimensions From Rao & Lohse (1993) and Experiment 1

Rao & Lohse (1993) Dimensions	Experiment 1 Dimensions		
	1	2	3
1	**-.840**	.035	**.445**
2	-.034	**-.828**	-.242
3	.034	-.012	.178

Note. Correlations in bold type are significant at the .05 level.

Table 8
Descriptors Given in Experiment 1 for Recovered Texture Dimensions

Dimension	Descriptor	Frequency Mentioned
1	structure/organization	9
	don't know	6
	roughness	3
	brightness	2
2	orientation	10
	structure/organization	6
	depth	3
	hardness	1
3	don't know	12
	structure/organization	5
	depth	3

Table 9

Number of Generally Correctly Identifiable and Generally Incorrectly Identifiable Brodatz Pictures in 10 Recovered Groups from Experiment 1

Cluster	Number Generally Correctly Identified	Number Generally Incorrectly Identified
A	5	0
B	1	2
C	4	0
D	0	3
E-1	1	1
E-2	1	2
F-1	3	0
F-2	0	3
G-1	0	2
G-2	0	2

Table 10
Rank Order of Brodatz Pictures Along 12 Attribute Dimensions From Experiment 1

	Attribute Dimensions					
Rank	Repetitiveness	Orientation	Complexity	Structure	Shape	Size
1	d78	d26	d107	d64	d30	d58
2	d52	d1	d58	d34	d74	d88
3	d34	d64	d61	d1	d23	d62
4	d1	d50	d32	d26	d3	d91
5	d3	d52	d86	d52	d43	d26
6	d64	d78	d57	d18	d69	d30
7	d18	d34	d43	d78	d10	d43
8	d57	d3	d62	d3	d61	d41
9	d93	d18	d37	d57	d71	d61
10	d26	d37	d71	d32	d91	d107
11	d50	d10	d50	d10	d57	d86
12	d74	d93	d10	d50	d88	d74
13	d32	d87	d87	d74	d58	d64
14	d23	d69	d78	d87	d93	d23
15	d5	d71	d88	d93	d37	d18
16	d87	d43	d52	d69	d32	d10
17	d10	d57	d3	d5	d41	d71
18	d69	d41	d5	d71	d5	d1
19	d30	d74	d34	d37	d34	d37
20	d37	d32	d93	d41	d86	d50
21	d71	d86	d41	d88	d87	d69
22	d88	d23	d69	d30	d62	d5
23	d41	d30	d1	d23	d107	d87
24	d43	d88	d18	d86	d50	d34
25	d62	d5	d23	d61	d78	d52
26	d86	d107	d74	d62	d52	d3
27	d107	d61	d91	d91	d18	d93
28	d61	d91	d64	d43	d1	d32
29	d58	d62	d30	d58	d26	d57
30	d91	d58	d26	d107	d64	d78

Table 10 (continued)

	Attribute Dimensions					
Rank	Connectedness	Hardness	Roughness	Depth	Linearity	Natural.
1	d78	d26	d5	d30	d78	d30
2	d3	d86	d86	d5	d52	d62
3	d52	d1	d57	d74	d1	d58
4	d64	d62	d23	d23	d26	d5
5	d18	d69	d18	d18	d50	d23
6	d34	d57	d64	d62	d64	d88
7	d1	d5	d26	d64	d34	d107
8	d50	d23	d74	d1	d10	d91
9	d10	d30	d78	d87	d3	d69
10	d26	d71	d50	d88	d18	d10
11	d93	d74	d52	d57	d69	d74
12	d37	d58	d30	d86	d87	d61
13	d5	d61	d43	d58	d32	d37
14	d32	d52	d1	d26	d57	d71
15	d41	d50	d3	d10	d93	d93
16	d71	d34	d10	d52	d37	d3
17	d57	d10	d87	d50	d71	d34
18	d69	d64	d62	d3	d5	d78
19	d87	d3	d37	d37	d74	d86
20	d74	d18	d107	d78	d23	d87
21	d23	d78	d34	d91	d41	d50
22	d86	d93	d41	d32	d30	d1
23	d30	d32	d58	d61	d86	d32
24	d62	d43	d69	d43	d62	d57
25	d107	d87	d71	d107	d91	d52
26	d61	d88	d32	d41	d43	d41
27	d58	d107	d93	d34	d58	d26
28	d88	d37	d61	d71	d107	d18
29	d43	d41	d88	d93	d61	d64
30	d91	d91	d91	d69	d88	d43

Table 11

Intercorrelations of Ranked Attribute Dimensions for Brodatz Pictures from Experiment 1

Attribute	REP	ORT	CPX	STR	SHP	SIZ	CNT	HRD	RGH	DPT	LIN	NAT
REP	1.0	--	--	--	--	--	--	--	--	--	--	--
ORT	**.778**	1.0	--	--	--	--	--	--	--	--	--	--
CPX	**-.413**	-.343	1.0	--	--	--	--	--	--	--	--	--
STR	**.910**	**.845**	**-.457**	1.0	--	--	--	--	--	--	--	--
SHP	-.327	**-.492**	-.017	**-.483**	1.0	--	--	--	--	--	--	--
SIZ	**-.684**	**-.432**	-.102	-.228	.169	1.0	--	--	--	--	--	--
CNT	-.270	-.028	-.270	.259	**.444**	**-.670**	1.0	--	--	--	--	--
HRD	.217	.073	-.144	.169	-.028	.021	.172	1.0	--	--	--	--
RGH	**.429**	.246	-.286	.317	-.200	-.161	**.372**	**.523**	1.0	--	--	--
DPT	.149	-.146	**-.377**	.076	-.006	.270	.028	**.374**	**.665**	1.0	--	--
LIN	**.852**	**.922**	-.335	**.911**	**-.538**	**-.568**	.011	.165	.300	-.046	1.0	--
NAT	**-.405**	**-.633**	.133	**-.525**	**.473**	.256	.127	.124	-.222	.233	-.501	1.0

Note. Correlations in bold type are significant at the .05 level.

Table 12
Correlations and Vector Angles Between 12 Ranked Attribute Dimensions and Three Derived MDS Dimensions from Experiment 1

Attribute Dimension	Derived MDS Dimensions					
	Dimension One		Dimension Two		Dimension Three	
	r	Φ	r	Φ	r	Φ
Repetitiveness	**-.637**	130	**.453**	63	**.419**	65
Orientation	**-.794**	143	.179	80	**.502**	60
Complexity	-.006	90	**-.494**	60	**-.374**	112
Structure	**-.731**	43	**.514**	59	**.339**	70
Shape	**.524**	58	-.171	80	-.030	88
Size	**.631**	51	.064	86	-.152	99
Connectedness	**.672**	48	-.369	68	**.459**	63
Hardness	.090	85	**.456**	63	.209	78
Roughness	-.121	83	**.474**	62	.236	77
Depth	**.373**	68	**.674**	48	.134	82
Linearity	**-.779**	39	.310	72	**.470**	62
Naturalness	**.726**	43	-.055	93	.062	86

Note. Correlations in bold type are significant at the .05 level.

Table 13

Standardized Regression Coefficients and R^2 Values for 12 Ranked Attribute Dimensions Regressed onto Three Derived MDS Dimensions from Experiment 1

Attribute Dimension	Derived MDS Dimensions: Dimension One	Dimension Two	Dimension Three	R^2
Repetitiveness	-3.5520	2.6698	2.5862	.748
Orientation	-4.8441	1.0522	3.2886	.870
Complexity	-0.1549	-1.9504	-1.6134	.390
Structure	-5.3456	3.9129	2.6337	.871
Shape	3.7245	-1.1508	-0.0421	.298
Size	4.3714	0.5879	-0.9269	.420
Connectedness	3.7702	-2.0967	2.8409	.750
Hardness	0.7809	3.2288	1.6611	.267
Roughness	-0.6926	3.5626	1.8418	.287
Depth	2.5366	4.4913	1.1442	.635
Linearity	-5.4888	2.2203	3.5724	.877
Naturalness	4.1401	-0.1868	0.6270	.538

Table 14
Pooled Dissimilarity Matrix from Experiment 2

Picture	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
01	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
02	.00	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
03	.15	.15	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
04	.90	.90	.75	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
05	.95	.95	.95	.65	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
06	1.0	1.0	.85	.25	.70	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
07	1.0	1.0	1.0	.85	.60	.75	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
08	.95	.95	.95	1.0	.95	1.0	.90	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
09	.95	.95	1.0	1.0	1.0	1.0	1.0	.65	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
10	.95	.95	.90	.75	1.0	.75	.65	.90	1.0	.00	--	--	--	--	--	--	--	--	--	--	--	--	--	--
11	.95	.95	1.0	1.0	1.0	1.0	1.0	.65	.00	1.0	.00	--	--	--	--	--	--	--	--	--	--	--	--	--
12	.85	.85	.90	.95	.95	.95	1.0	.75	.20	1.0	.20	.00	--	--	--	--	--	--	--	--	--	--	--	--
13	.80	.80	.90	1.0	.95	.95	1.0	.75	.50	.85	.50	.55	.00	--	--	--	--	--	--	--	--	--	--	--
14	1.0	1.0	1.0	.95	.90	1.0	.90	.80	1.0	.85	1.0	.95	1.0	.00	--	--	--	--	--	--	--	--	--	--
15	1.0	1.0	1.0	.95	.70	.85	.90	.75	1.0	.95	1.0	.95	.90	.50	.00	--	--	--	--	--	--	--	--	--
16	1.0	1.0	1.0	.90	.65	.95	.70	.75	1.0	1.0	1.0	1.0	1.0	.35	.30	.00	--	--	--	--	--	--	--	--
17	1.0	1.0	1.0	.95	.85	1.0	.95	.75	.95	.85	.95	.95	1.0	.10	.45	.35	.00	--	--	--	--	--	--	--
18	.95	.95	.95	1.0	.70	.95	.90	.70	.95	.75	.95	.95	.55	.95	.65	.85	.95	.00	--	--	--	--	--	--
19	.95	.95	.95	.85	.60	.65	.90	.80	.95	.80	.95	.95	.90	.90	.60	.80	.85	.45	.00	--	--	--	--	--
20	.85	.85	.90	.80	.70	.70	.95	.95	1.0	.95	1.0	.95	.90	.50	.60	.65	.55	.80	.70	.00	--	--	--	--
21	1.0	1.0	.90	.45	.75	.45	.80	.90	.95	.80	.95	.95	.90	.80	.85	.65	.85	.90	.75	.80	.00	--	--	--
22	.65	.65	.80	1.0	1.0	1.0	1.0	.45	.50	.95	.50	.60	.55	1.0	1.0	1.0	1.0	.85	.85	.90	1.0	.00	--	--
23	.85	.85	.70	.20	.75	.30	.85	1.0	1.0	.70	1.0	1.0	.95	1.0	1.0	.95	1.0	1.0	.85	.85	.50	.95	.00	--
24	.95	.95	.90	.75	.85	.70	.25	.95	.95	.50	.95	1.0	1.0	.95	1.0	.90	1.0	.95	.90	1.0	.75	1.0	.65	.00

Table 15

Stimulus Coordinates of MIT Pictures Along Three Derived MDS Dimensions from Experiment 2

Picture	Dimension 1	Dimension 2	Dimension 3
01	0.8106	0.0635	1.7423
02	0.8106	0.0636	1.7423
03	0.6382	0.2375	1.7564
04	-1.0167	1.3417	0.5106
05	-1.2378	1.0529	0.3122
06	-1.0172	1.3380	0.4848
07	-0.3941	0.9963	-1.4259
08	1.1436	-0.9195	-0.2764
09	1.7667	0.0118	-0.5475
10	-0.5908	1.1149	-1.1043
11	1.7631	0.0135	-0.5535
12	1.7813	0.0198	-0.3807
13	1.6806	0.1406	-0.4678
14	-0.8262	-1.6371	0.1237
15	-0.7635	-1.6270	-0.0635
16	-0.8607	-1.5617	0.0848
17	-0.8197	-1.6457	0.1663
18	-0.0386	-0.6132	-1.4277
19	-0.5821	-0.6146	-1.2658
20	-1.0493	-0.7101	1.0085
21	-1.2560	0.4787	-0.3044
22	1.4293	0.2869	0.5733
23	-0.8763	1.2767	0.6886
24	-0.4948	0.8927	-1.3764

Table 16
Descriptors Given in Experiment 2 for Recovered Texture Dimensions

Dimension	Descriptor	Frequency Mentioned
1	structure/organization	9
	don't know	8
	roughness	3
2	roughness	6
	don't know	6
	distance from surface	4
	3d	4
3	don't know	5
	orientation	4
	roughness	3
	structure/organization	3
	3d	3
	natural/man-made	2

Table 17
Rank Order of MIT Pictures Along Six Attribute Dimensions

	Attribute Dimensions					
Rank	Repetitiveness	Orientation	Complexity	Structure	Connectedness	Depth
1	13	01	05	01	24	07
2	18	02	18	22	05	24
3	11	04	19	02	04	17
4	09	10	04	12	23	16
5	10	09	23	09	01	15
6	22	11	21	11	02	14
7	19	22	15	03	09	09
8	15	21	13	13	11	22
9	01	24	10	17	03	08
10	12	12	07	23	13	21
11	08	13	20	04	12	23
12	14	06	16	06	18	10
13	17	16	11	21	06	11
14	02	23	14	10	22	12
15	04	03	17	16	21	04
16	24	19	22	08	10	19
17	21	17	06	05	19	05
18	06	08	02	07	20	03
19	23	15	09	24	17	20
20	16	18	03	15	08	13
21	20	14	12	20	14	02
22	03	07	24	18	16	01
23	05	20	08	14	15	05
24	07	05	01	19	07	18

Table 18

Intercorrelations of Ranked Attribute Dimensions for MIT Pictures from Experiment 2

Attribute	REP	ORT	CPX	STR	CNT	DPT
REP	1.0	--	--	--	--	--
ORT	**.422**	1.0	--	--	--	--
CPX	.002	-.334	1.0	--	--	--
STR	.186	**.724**	**-.450**	1.0	--	--
CNT	.033	**.502**	.059	**.450**	1.0	--
DPT	-.200	-.183	-.267	-.224	**-.522**	1.0

Note. Correlations in bold type are significant at the .05 level.

Table 19

Correlations and Vector Angles Between 6 Ranked Attribute Dimensions and Three Derived MDS Dimensions from Experiment 2

Attribute Dimension	Derived MDS Dimensions					
	Dimension One		Dimension Two		Dimension Three	
	r	Φ	r	Φ	r	Φ
Repetitiveness	-.521	121	.252	75	.326	71
Orientation	-.469	118	-.403	114	-.173	100
Complexity	.500	60	-.157	99	.280	74
Structure	-.650	131	-.276	106	-.503	120
Connectedness	-.216	103	-.620	129	-.258	105
Depth	.296	73	.162	81	.309	72

Note. Correlations in bold type are significant at the .05 level.

Table 20

Standardized Regression Coefficients and R^2 Values for 6 Ranked Attribute Dimensions Regressed onto Three Derived MDS Dimensions from Experiment 2

Attribute Dimension	Derived MDS Dimensions			
	Dimension One	Dimension Two	Dimension Three	R^2
Repetitiveness	-2.1208	1.0657	1.5901	.445
Orientation	-2.3548	-2.3177	-0.8916	.422
Complexity	2.1448	-0.6861	1.3312	.339
Structure	-4.1266	-2.1603	-3.5330	.746
Connectedness	-1.4708	-4.5110	-1.8480	.504
Depth	1.8708	1.2476	2.1956	.208

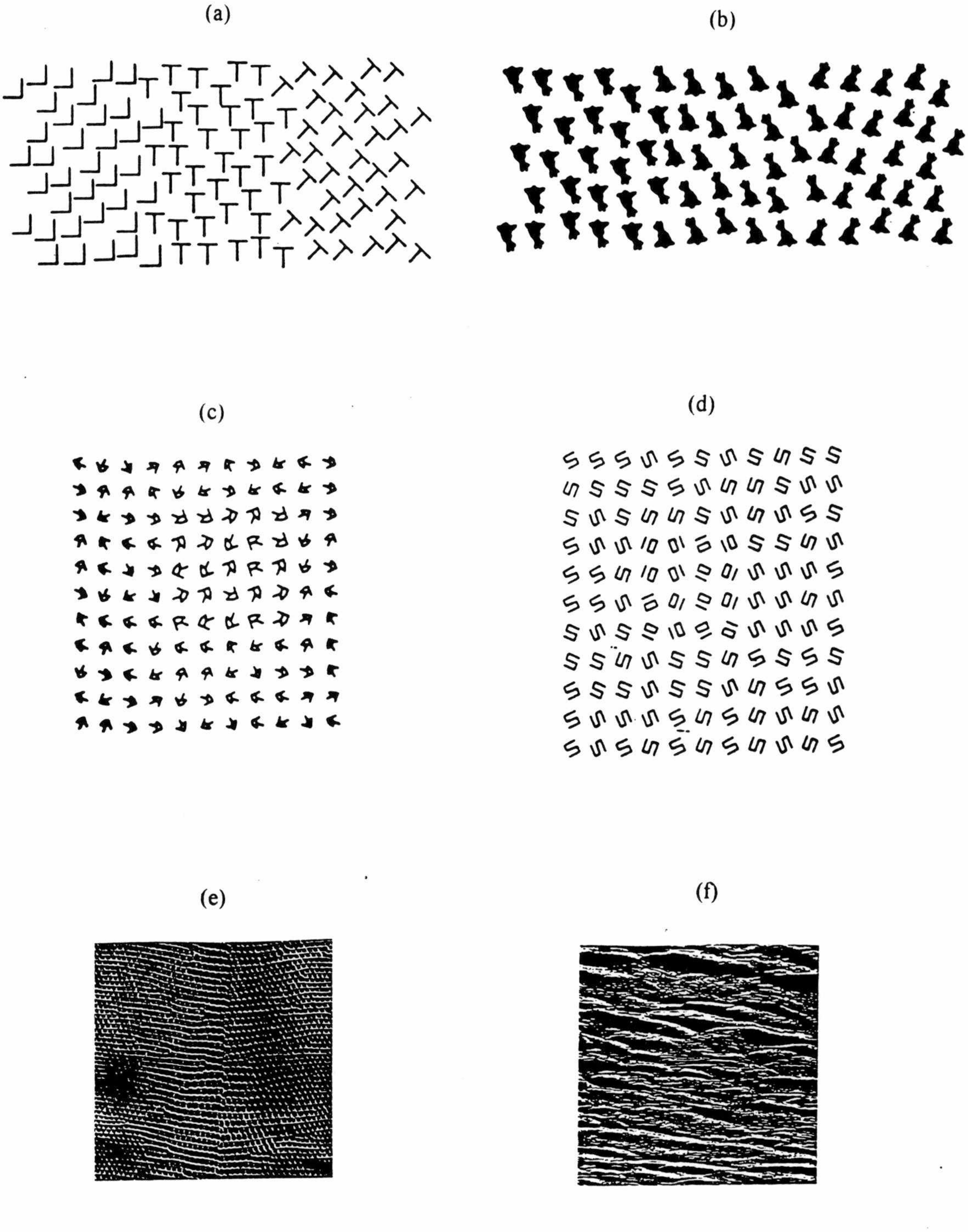


Figure 1. Common stimuli used in texture perception research. Abstract textures from the psychology literature include (a) L's, T's and tilted T's from Beck (1966); (b) Cat-like figures, upright, tilted, and their mirror images from Beck (1982); (c) R's at various orientations, from Julesz (1981); (d) S's and 10's at various orientations from Julesz (1985). Natural textures from the machine vision literature, taken from Brodatz (1966), include (e) Reptile skin, from Tamura, et al., (1978), and (f) Water, from Rao & Lohse (1993).

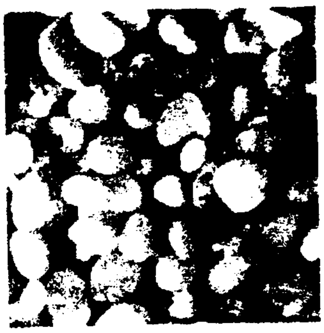
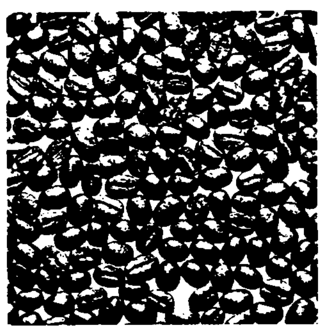
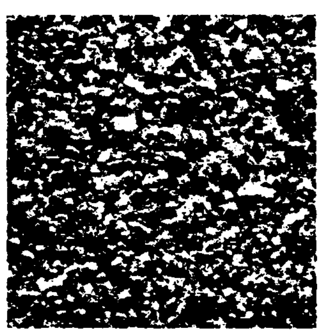
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d30	Beach pebbles (pebbles-2)	A	roughness	5	rocks	18
			don't know	4	insect eggs	1
			separate elem.	4	grapes	1
			shape of elem.	4		
			hardness	2		
			randomness	1		
d74	Coffee beans (beans)	A			coffee beans	15
					nuts	3
					potatoes	1
					insects	1
d5	Expanded mica (mica)	A			rock	11
					ashes	5
					cork	3
					granola	1

Figure 2. Brodatz pictures with group membership, subjects' group descriptors and frequencies, and subjects' object/surface names and frequencies (continued on next page).

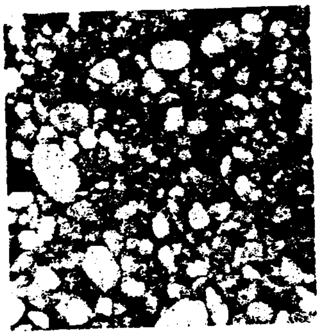
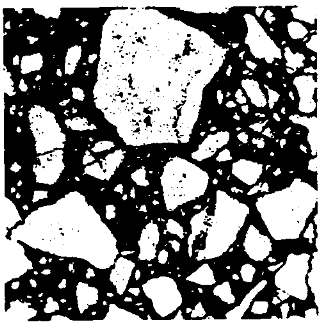
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d23	Beach pebbles (pebbles-1) 	A	roughness	5	rocks	20
			don't know	4		
			separate elem.	4		
			shape of elem.	4		
			hardness	2		
			randomness	1		
d62	European marble (marble-3) 	A			rock	6
					marble	5
					ice	4
					broken glass	4
					quartz	1

Figure 2 (continued)

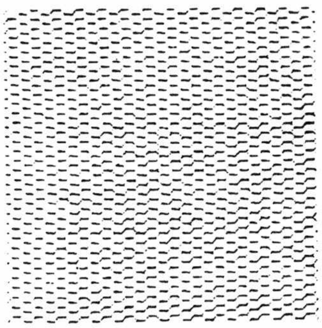
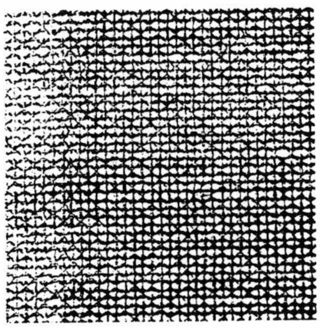
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d34	Netting	B	roughness	7	honeycomb	10
			connect. of elem.	3	mesh wire	4
			don't know	2	snake skin	2
			shape of elem.	2	don't know	2
			patt. symmetry	2	linoleum	1
			use for material	1	fishnet, nylon	1
			patt. smallness	1		
			simplicity	1		
			randomness	1		
d52	Oriental straw cloth (cloth-1)	B			don't know	10
					natural fiber	4
					string	3
					wicker	2
					wire	1
d3	Reptile skin	B			snake skin	14
					animal scales	3
					fishnet, rope	2
					honeycomb	1

Figure 2 (continued)

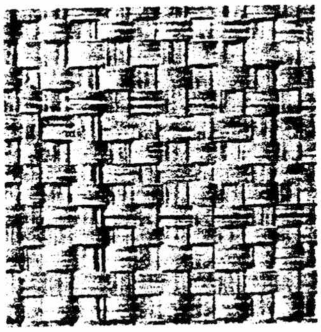
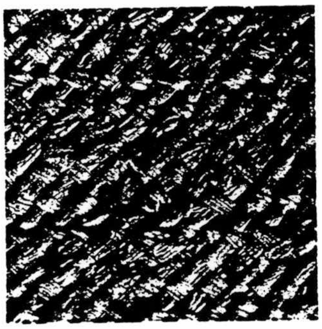
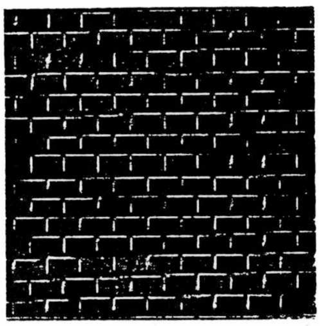
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d18	Raffia weave (raffia-1)	C	pattern identity	12	straw	17
			regularity	4	cloth	1
			don't know	1	corn husks	1
			roughness	1	silk	1
			simplicity	1		
			handmade	1		
d64	Handwoven rattan (rattan)	C			straw/wicker	20
						
d1	Woven aluminum wire (wire)	C			metal	9
					brick	9
					plastic	2

Figure 2 (continued)

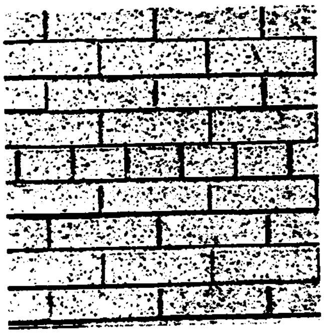
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d26	Ceramic-coated brick wall (brick)	C	pattern identity	12	brick	20
			regularity	4		
			don't know	1		
			roughness	1		
			simplicity	1		
			handmade	1		

Figure 2 (continued)

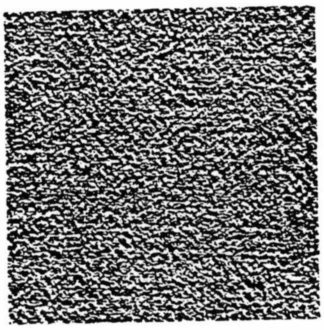
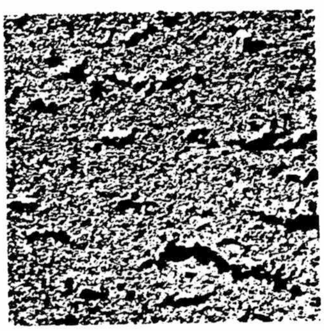
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d32	Pressed cork (cork)	D	roughness	5	floor tile	6
			porosity	4	rock	5
			3d	3	asphalt	4
			pattern identity	3	don't know	3
			use	2	counter top	1
			don't know	1	sand	1
			lightness	2		
			simplicity	1		
d57	Handmade paper (paper)	D			don't know	7
					carpet	5
					ceiling	3
					insulation	2
					concrete	2
					terry cloth	1
d86	Ceiling tile	D			brick	4
					concrete	4
					Lunar surface	4
					ceiling	4
					rock	3
					cork	1

Figure 2 (continued)

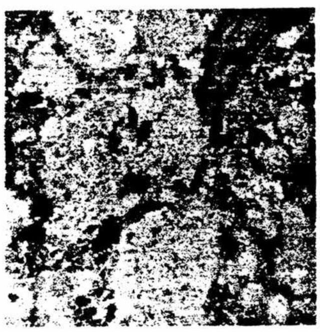
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d58	European marble (marble-1)	E-1	randomness	12	marble	10
			material identity	6	don't know	6
			pattern identity	2	leaves	1
					fungus	1
					water	1
					snow	1
d61	European marble (marble-2)	E-1			don't know	8
					marble	6
					water	2
					leaves in water	1
					rock	1
					Earth surface	1
					painting, canvas	1

Figure 2 (continued)

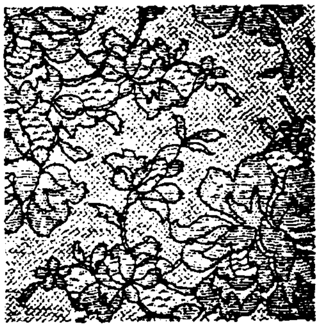
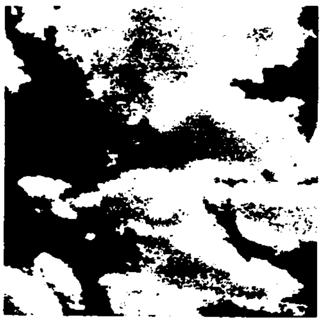
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d41	Lace	E-2	don't know	8	paper	9
			3d	5	lace	4
			randomness	3	don't know	4
			separable elem.	2	cloth	3
			lightness	1		
			complex shapes	1		
d88	Dried hop flowers (hops)	E-2			pine cones	10
					flowers	4
					don't know	4
					algae	2
d91	Clouds	E-2			clouds	20
						

Figure 2 (continued)

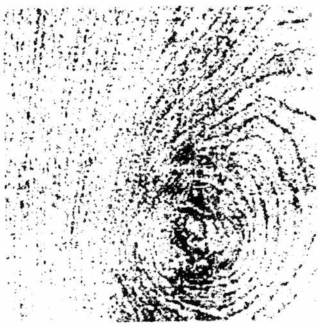
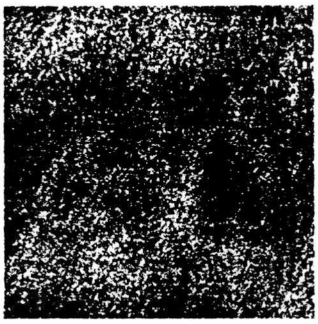
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d69	Wood grain (wood-1)	F-1	wavy lines	9	wood	20
			grainy	6		
			roughness	2		
			natural materials	1		
			use	1		
			don't know	1		
d71	Wood grain (wood-2)	F-1			wood	13
					don't know	4
					sky at night	1
					neurons	1
					oil	1
d93	Fur	F-1			animal fur	12
					don't know	7
					human hair	1

Figure 2 (continued)

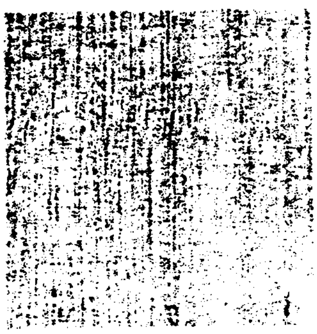
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d50	Raffia woven w/ cotton (raffia-2)	F-2	directionality	13	don't know	8
			don't know	7	man-made fiber	6
					straw	5
					plant cellulose	1
d78	Oriental straw cloth (cloth-2)	F-2			wallpaper	6
					textile	5
					wicker	3
					leaf	2
					don't know	2
					plant cellulose	1
					window screen	1
d37	Water	F-2			sand	12
					water	6
					don't know	2

Figure 2 (continued)

No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d107	Japanese rice paper (rice paper)	G-1	randomness	11	don't know	8
			don't know	5	paper	7
			lightness	4	grass	1
					spider web	1
					hair	1
					lens scratches	1
					cloth fiber	1
d43	Swinging lightbulb (lightbulb)	G-1			don't know	6
					wire	5
					string	5
					light	3
					etch-a-sketch	1

Figure 2 (continued)

No.	Description	Group	Group Descriptors	F	Object/ Surface	F
d10	Crocodile skin 	G-2	don't know	8	animal skin	12
			directionality	7	don't know	6
			intricate pattern	5	cells	1
					water bubbles	1
d87	Sea fan 	G-2			leaf	9
					tree limbs	5
					don't know	4
					coral	1
					lace	1

Figure 2 (continued)

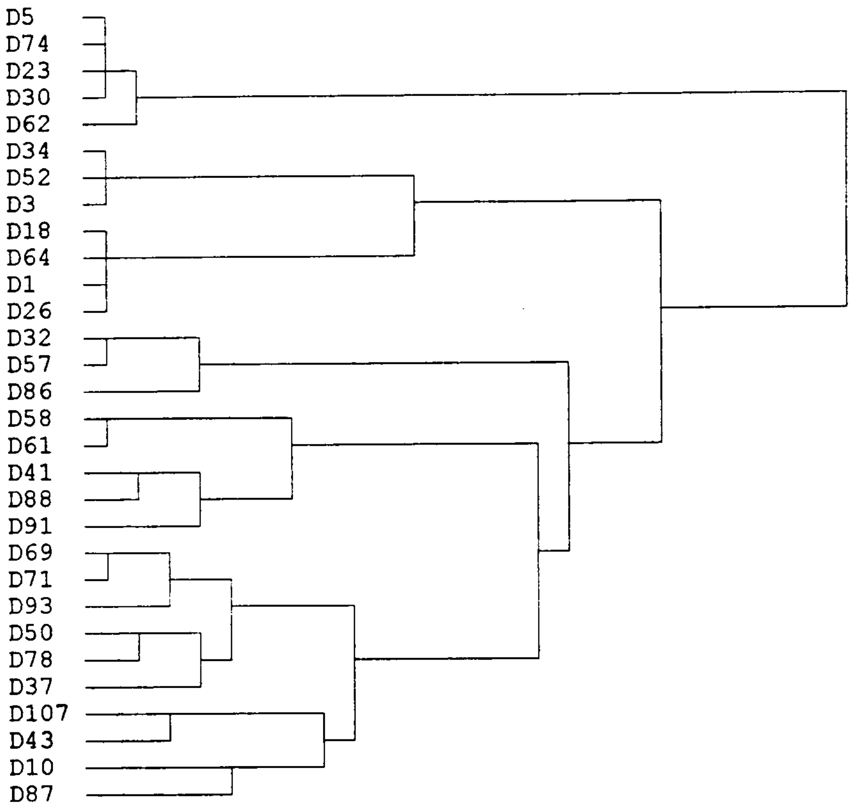


Figure 3. Dendrogram of hierarchical cluster analysis performed in Experiment 1.

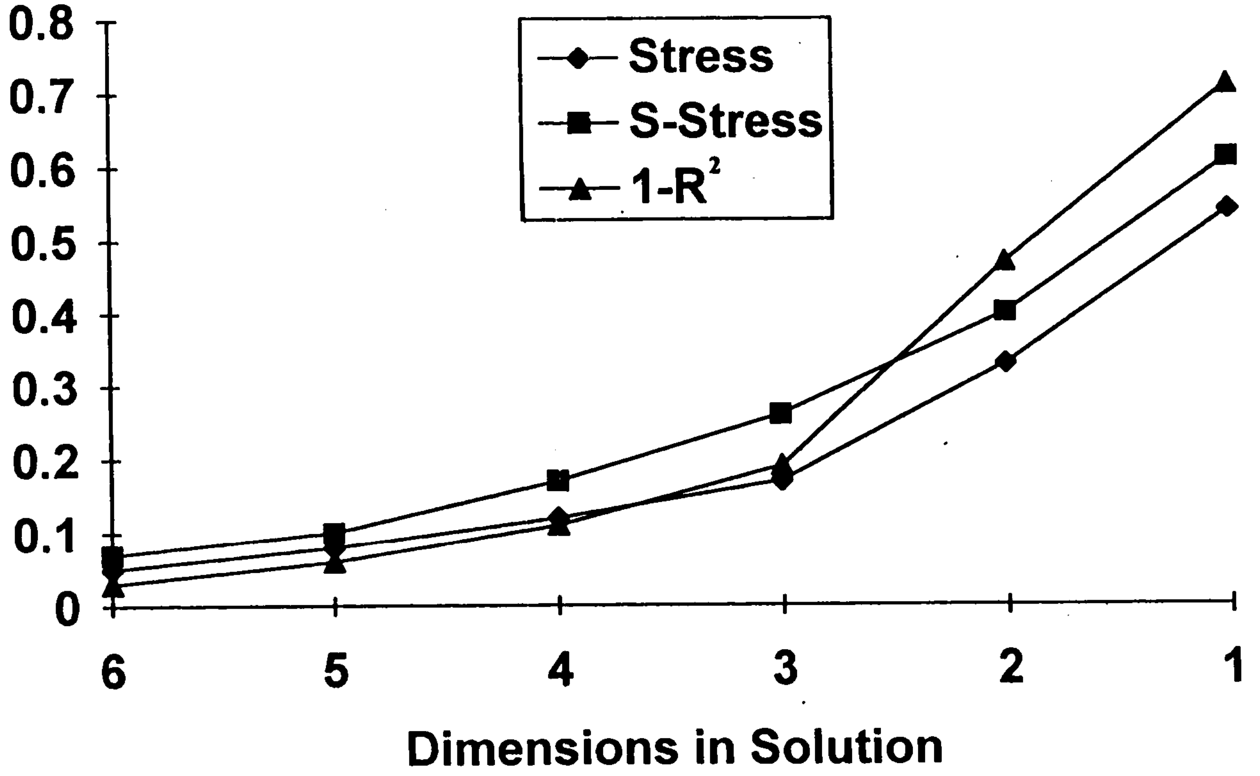


Figure 4. Scree plot of Stress, S-Stress, and $1\text{-}R^2$ for multidimensional scaling solutions from Experiment 1.

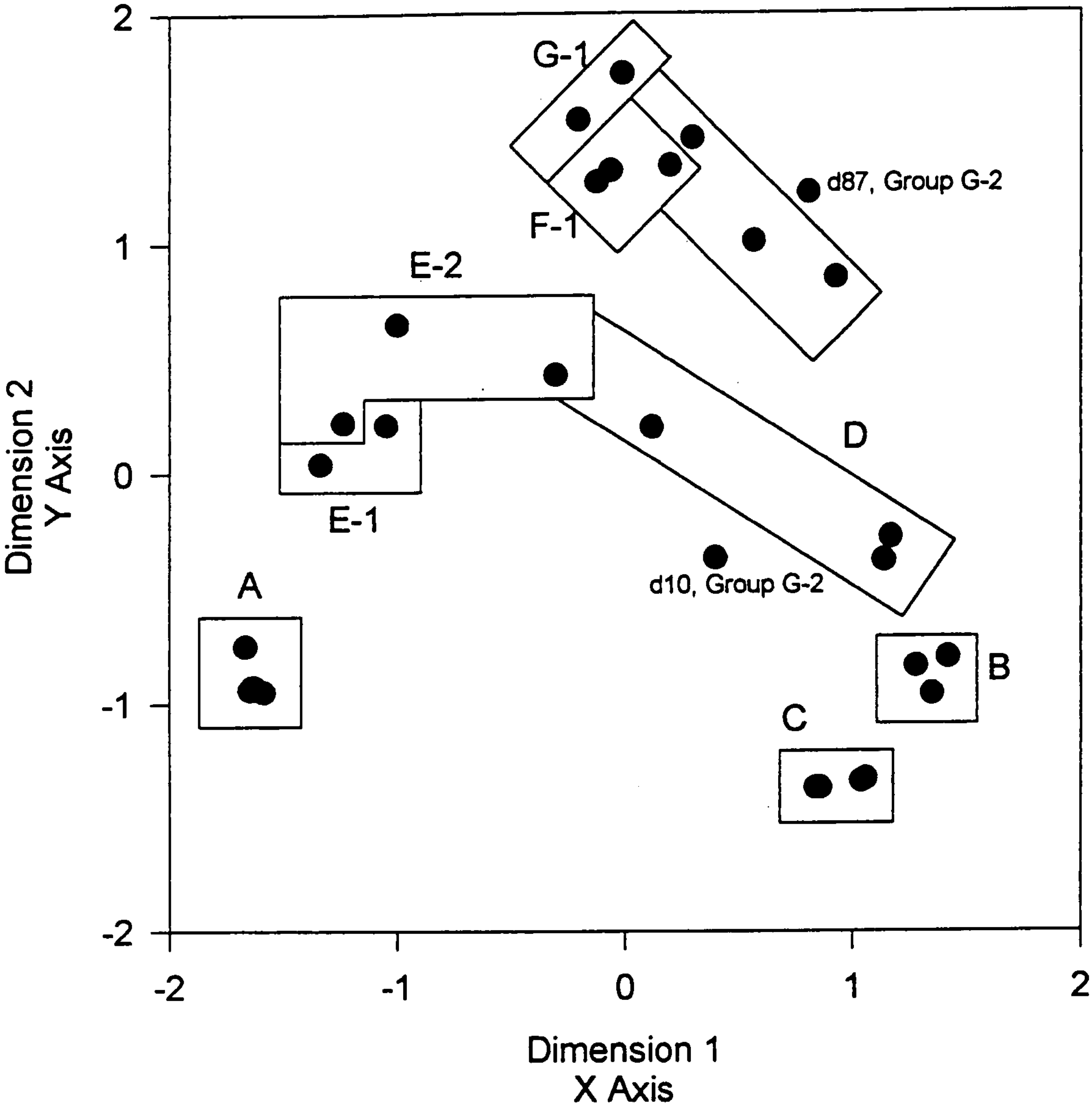


Figure 5. Pairwise plots of the 3-dimensional multidimensional scaling solution from Experiment 1 (continued on next page).

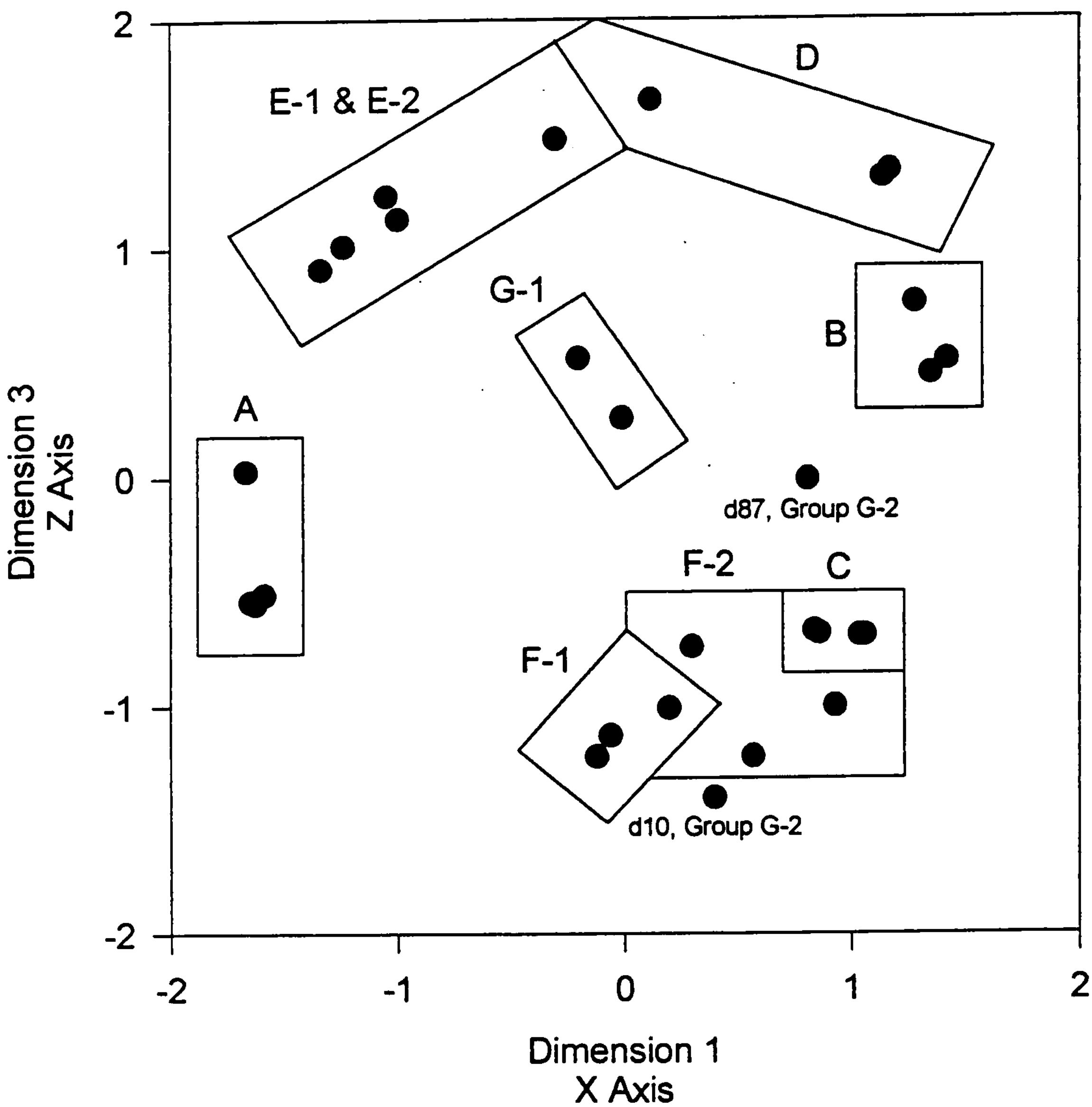


Figure 5 (continued)

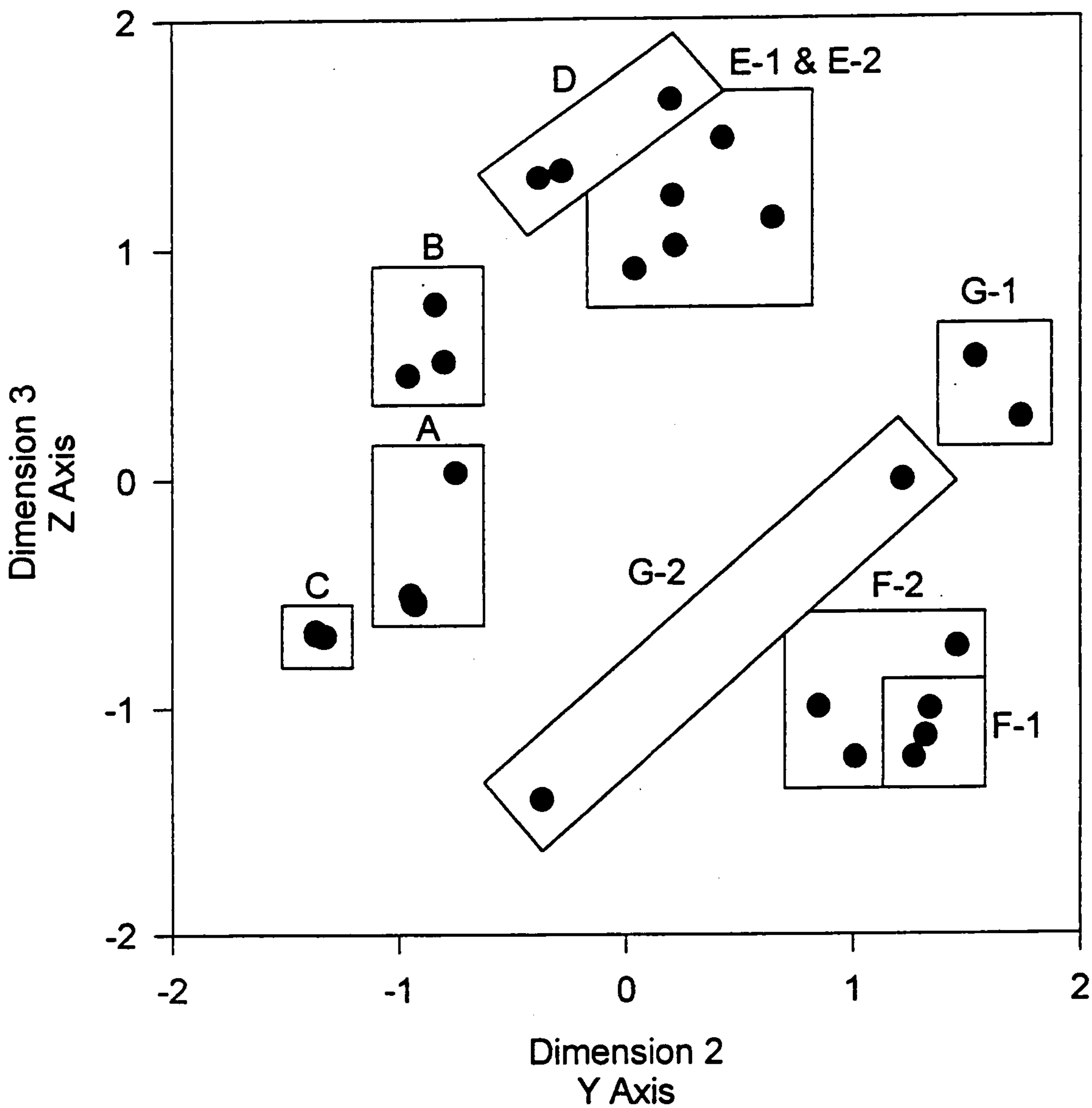


Figure 5 (continued)

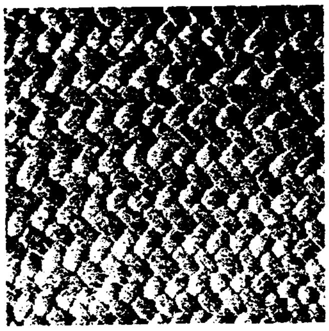
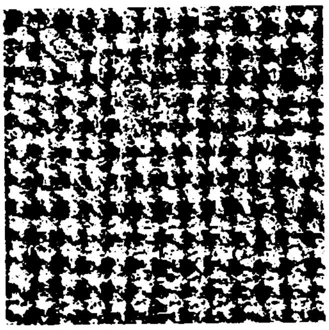
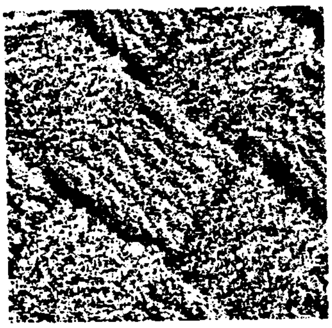
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
09	Woven rattan (rattan)	A	roughness	12	woven straw	17
			regularity	8	don't know	3
						
11	Tightly woven straw (straw-1)	A			doormat	9
					woven straw	8
					don't know	2
					rope	1
						
12	Woven rope (rope)	A			woven straw	16
					rug	3
					sweater	1
						

Figure 6. MIT pictures with group membership, subjects' group descriptors and frequencies, and subjects' object/surface names and frequencies (continued on next page).

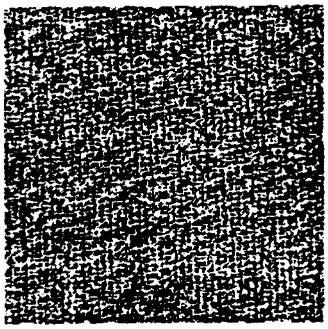
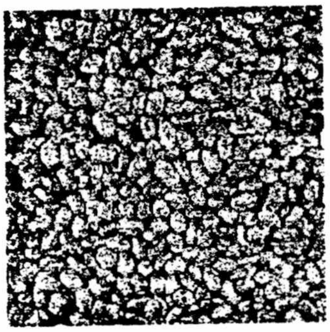
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
13	Fabric, high definition (fabric) 	A	roughness regularity	12 8	don't know wallpaper fabric screen	12 3 3 2

Figure 6 (continued)

No.	Description	Group	Group Descriptors	F	Object/ Surface	F
08	Beans	B	shape of elem.	20	beans	18
					nuts	2



No.	Description	Group	Group Descriptors	F	Object/ Surface	F
22	Pegboard	B			cardboard	15
					don't know	5

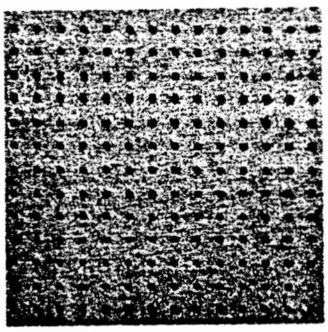


Figure 6 (continued)

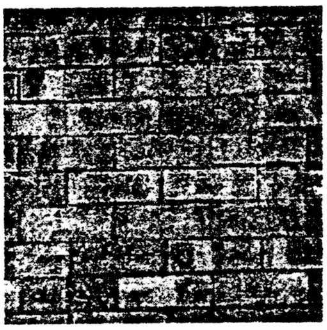
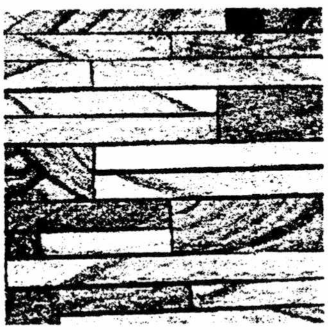
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
01	Bricks 	C	hardness regularity man-made	10 7 3	brick	20
02	Tile bricks 	C			brick	20
03	Stone blocks (stone) 	C			brick	20

Figure 6 (continued)

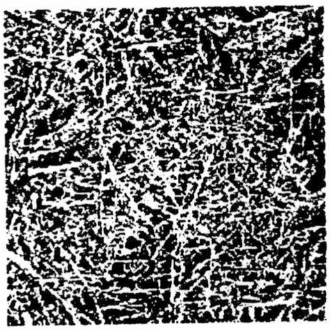
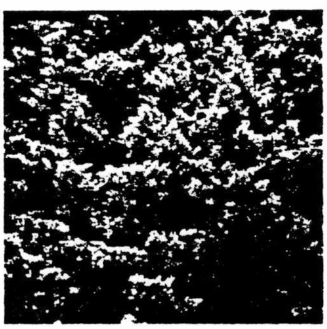
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
14	Loose straw (straw-2) 	D	randomness	14	straw	20
			material	5		
			don't know	1		
17	Pine needles 	D			pine needles	20
16	Evergreen leaves 	D			trees	9
					leaves	9
					don't know	2

Figure 6 (continued)

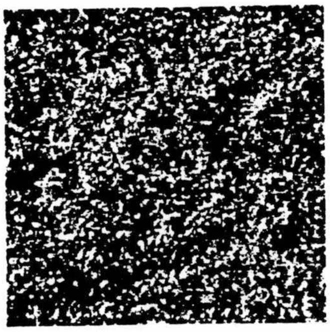
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
15	Leaves	D	randomness	14	don't know	8
			material	5	leaves	6
			don't know	1	grass	6
20	Particle board	D			don't know	10
					particle board	7
					sticks	2
					roof	1

Figure 6 (continued)

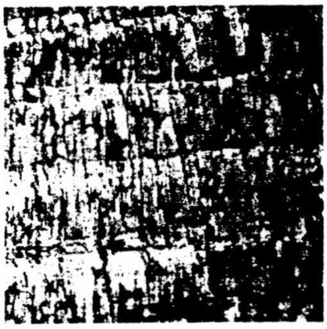
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
04	Tree trunk (bark-1) 	E	roughness material hardness randomness	8 6 4 2	wood don't know	16 4
06	Tree bark, high def. (bark-3) 	E			wood	20
23	Wood grain (wood) 	E			wood	20

Figure 6 (continued)

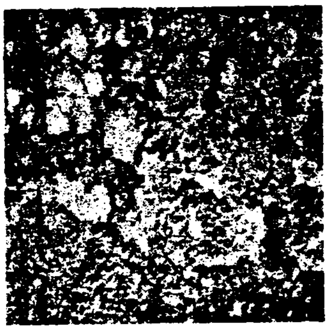
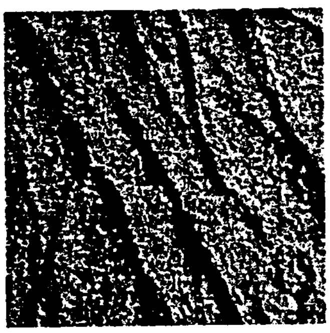
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
05	Tree bark, low def. (bark-2)	F	don't know	15	don't know	13
			size of elem.	3	mold	3
			randomness	2	concrete	1
					Lunar surface	1
					brick	1
					wood	1
21	Sand, high definition (sand)	F			don't know	19
					sand	1

Figure 6 (continued)

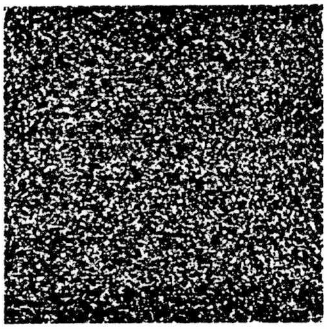
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
18	Metal, low definition (metal-1) 	G	randomness size of elements	11 9	static don't know plastic	14 5 1
19	Metal, high definition (metal-2) 	G			don't know worms	18 2

Figure 6 (continued)

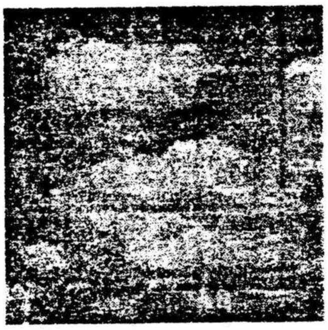
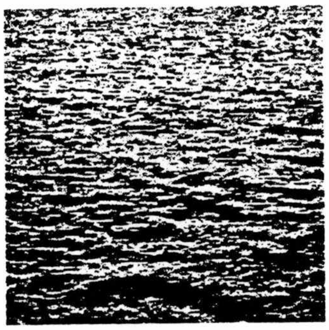
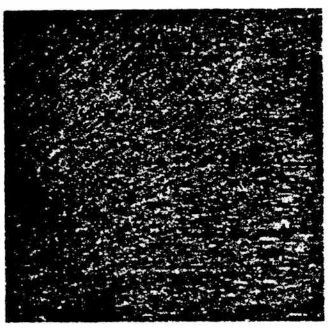
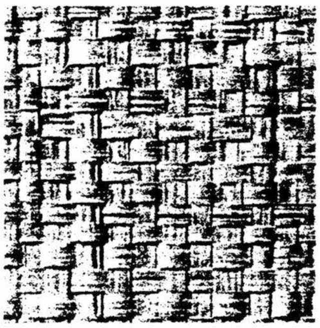
No.	Description	Group	Group Descriptors	F	Object/ Surface	F
07	Clouds	H	horizontal ort.	12	clouds	19
			don't know	8	don't know	1
						
24	Water	H			water	20
						
10	Animal fur (fur)	H			grass	13
					straw	4
					animal fur	2
					human hair	1
						

Figure 6 (continued)

(a)

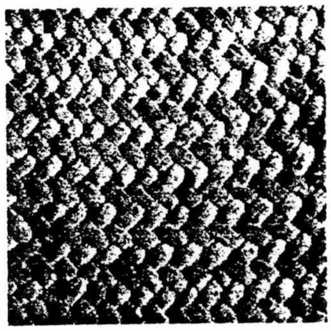
Brodatz Pictures		MIT Pictures	
No.	Description	No.	Description

d18 Raffia weave

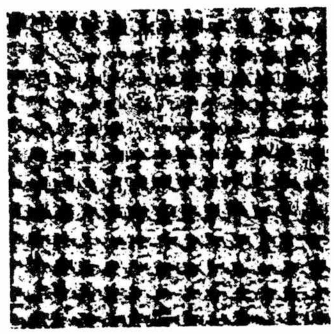


d64 Handwoven rattan

09 Woven rattan



11 Tightly woven straw



12 Woven rope

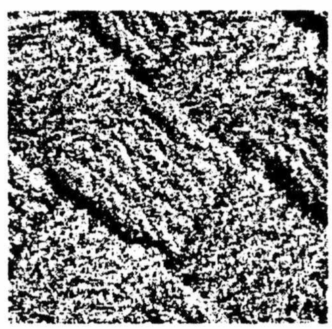
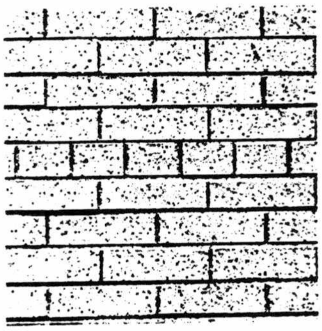


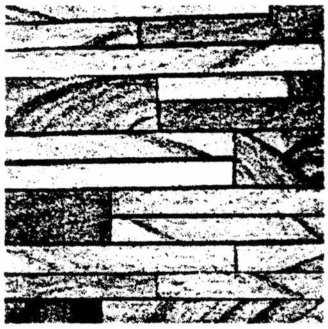
Figure 7. Comparisons of similar pictures from Brodatz and MIT Sets. (a) d18 and d64 from Brodatz compared to 09, 11, and 12 from MIT; (b) d26 from Brodatz compared to 01, 02, 03 from MIT; (c) d74, d30, d5, d23, d62 from Brodatz compared to 08 and 22 from MIT; (d) d74 from Brodatz compared to 08 from MIT (continued on next page).

(b)

Brodatz Pictures No.	Description	MIT Pictures No.	Description
d26	Ceramic-coated brick wall	01	Bricks



02 Tile bricks



03 Stone blocks

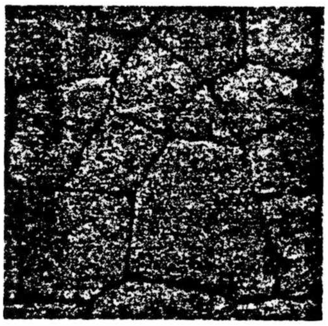
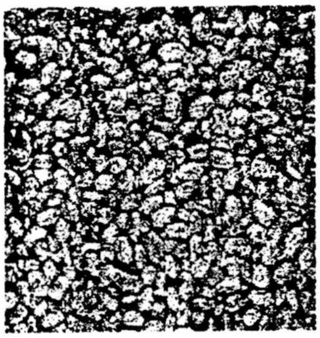


Figure 7 (continued)

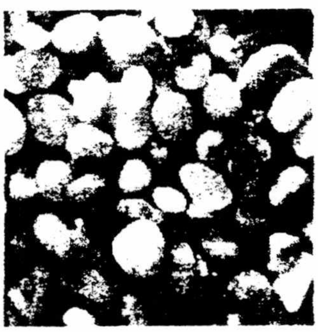
(c)

Brodatz Pictures

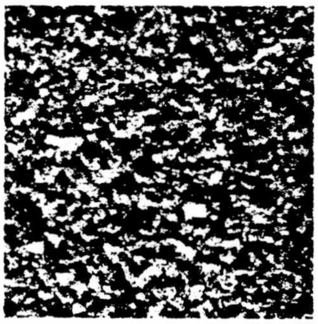
No.	Description
d74	Coffee beans



No.	Description
d30	Beach pebbles



No.	Description
d5	Expanded mica



MIT Pictures

No.	Description
08	Beans

No.	Description
22	Pegboard

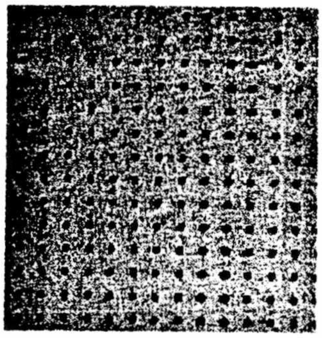
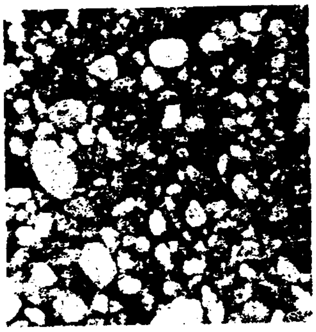


Figure 7 (continued)

(c)

Brodatz Pictures No.	Description	MIT Pictures No.	Description
d23	Beach pebbles		



d62	European marble		

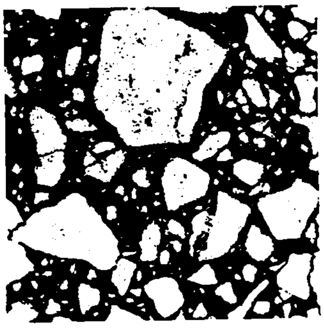


Figure 7 (continued)

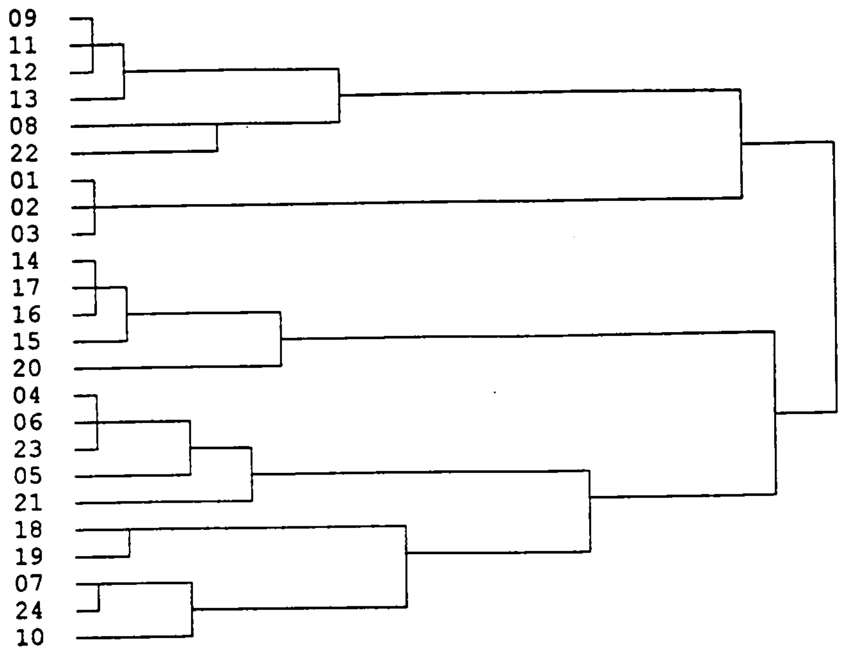


Figure 8. Dendrogram for cluster analysis performed in Experiment 2.

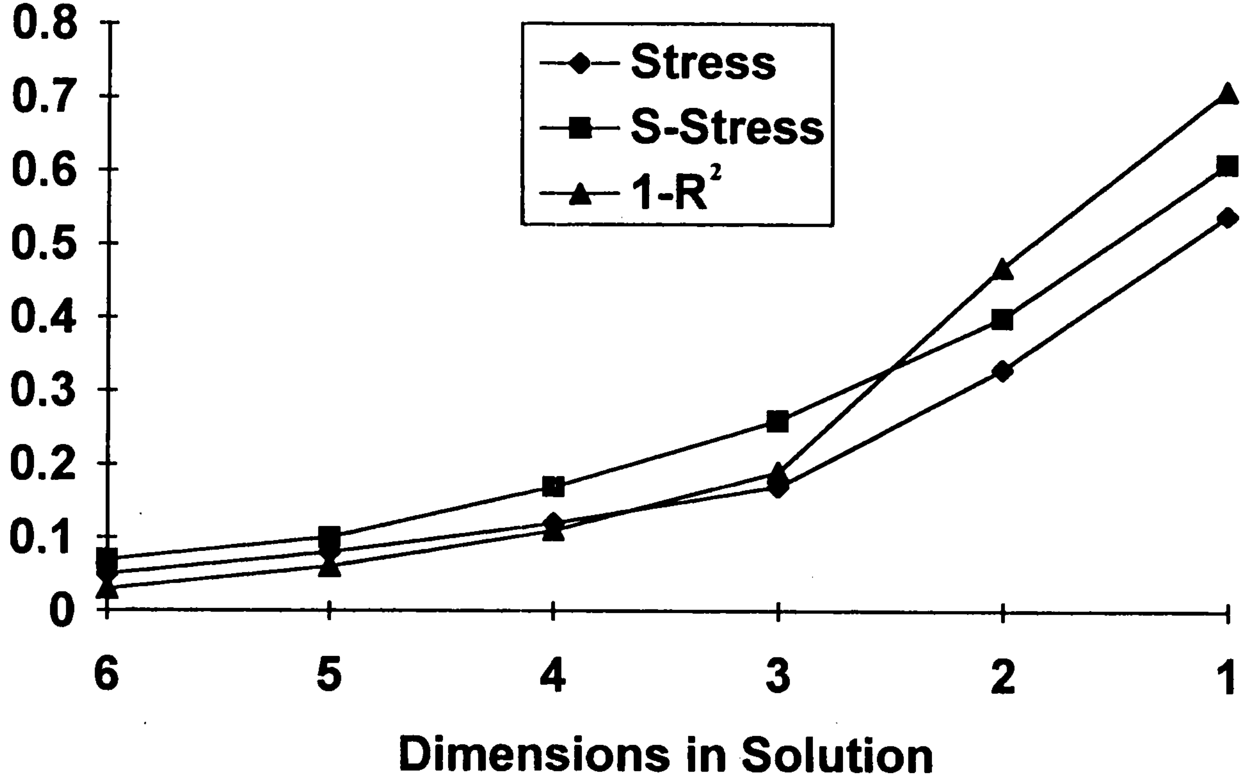


Figure 9. Scree plot of Stress, S-Stress, and 1-R^2 for multidimensional scaling solutions from 2 Experiment 2.

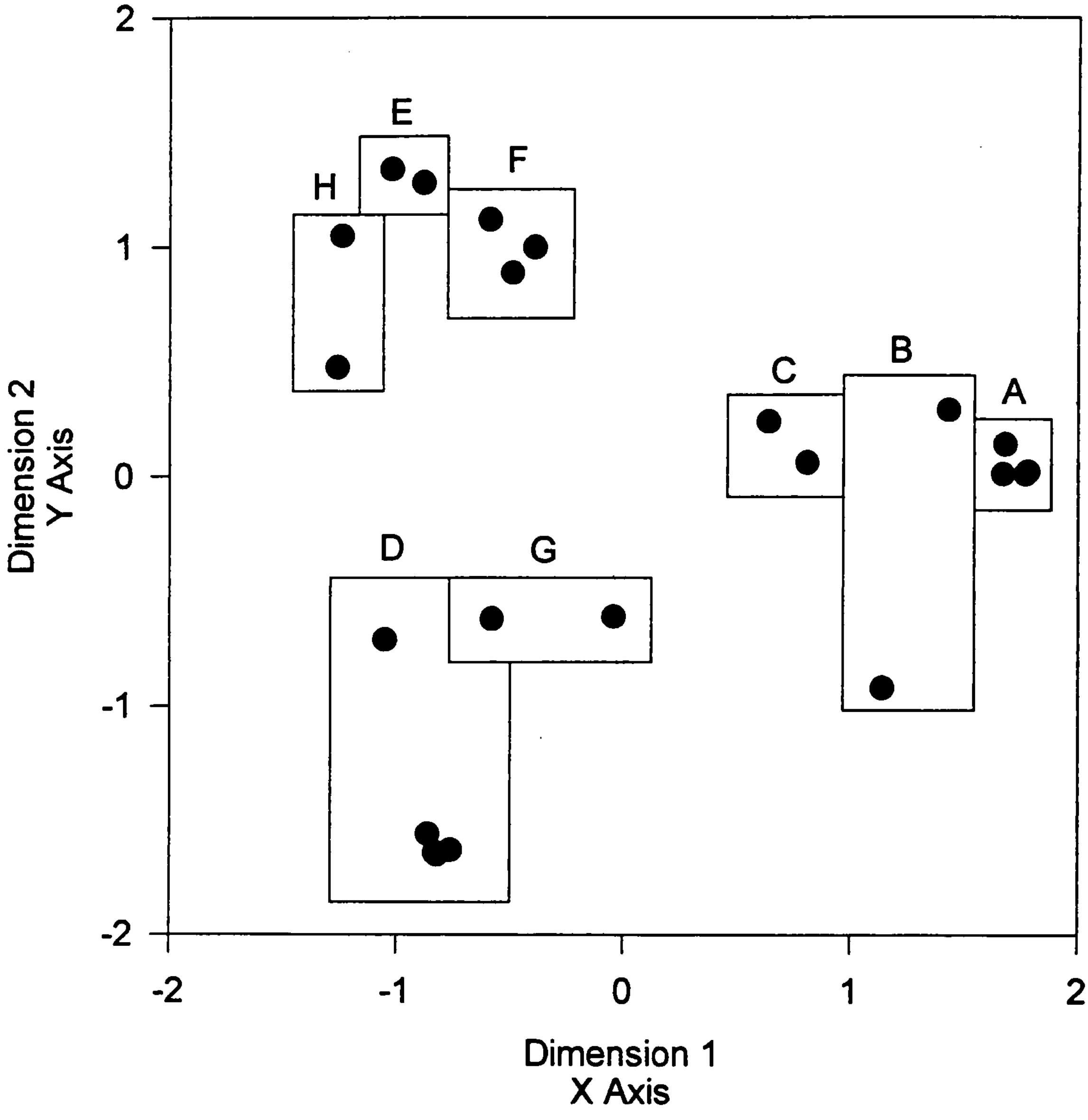


Figure 10. Pairwise plots of dimensions of the 3-dimensional multidimensional scaling solution from Experiment 2.

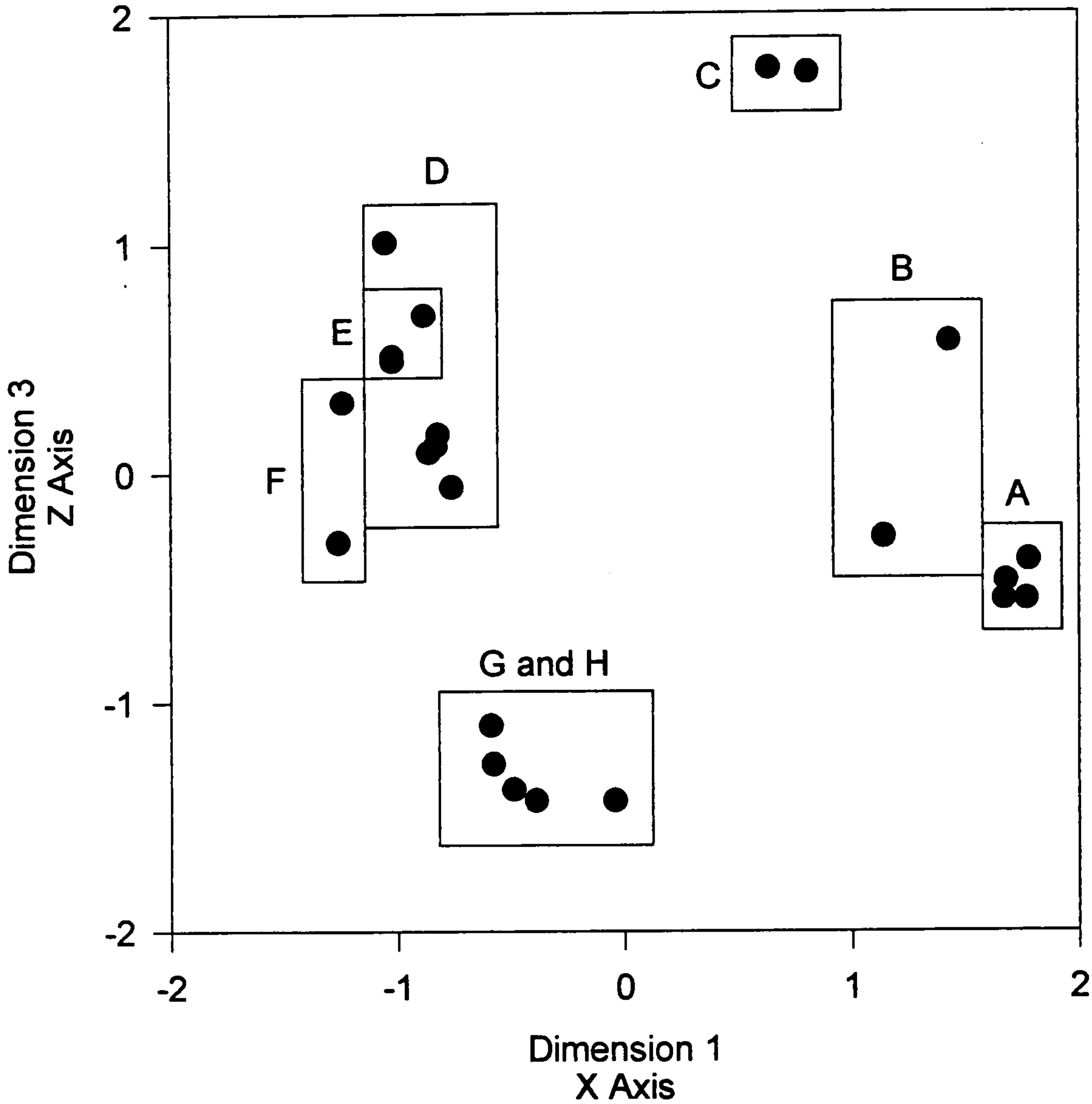


Figure 10. (continued)

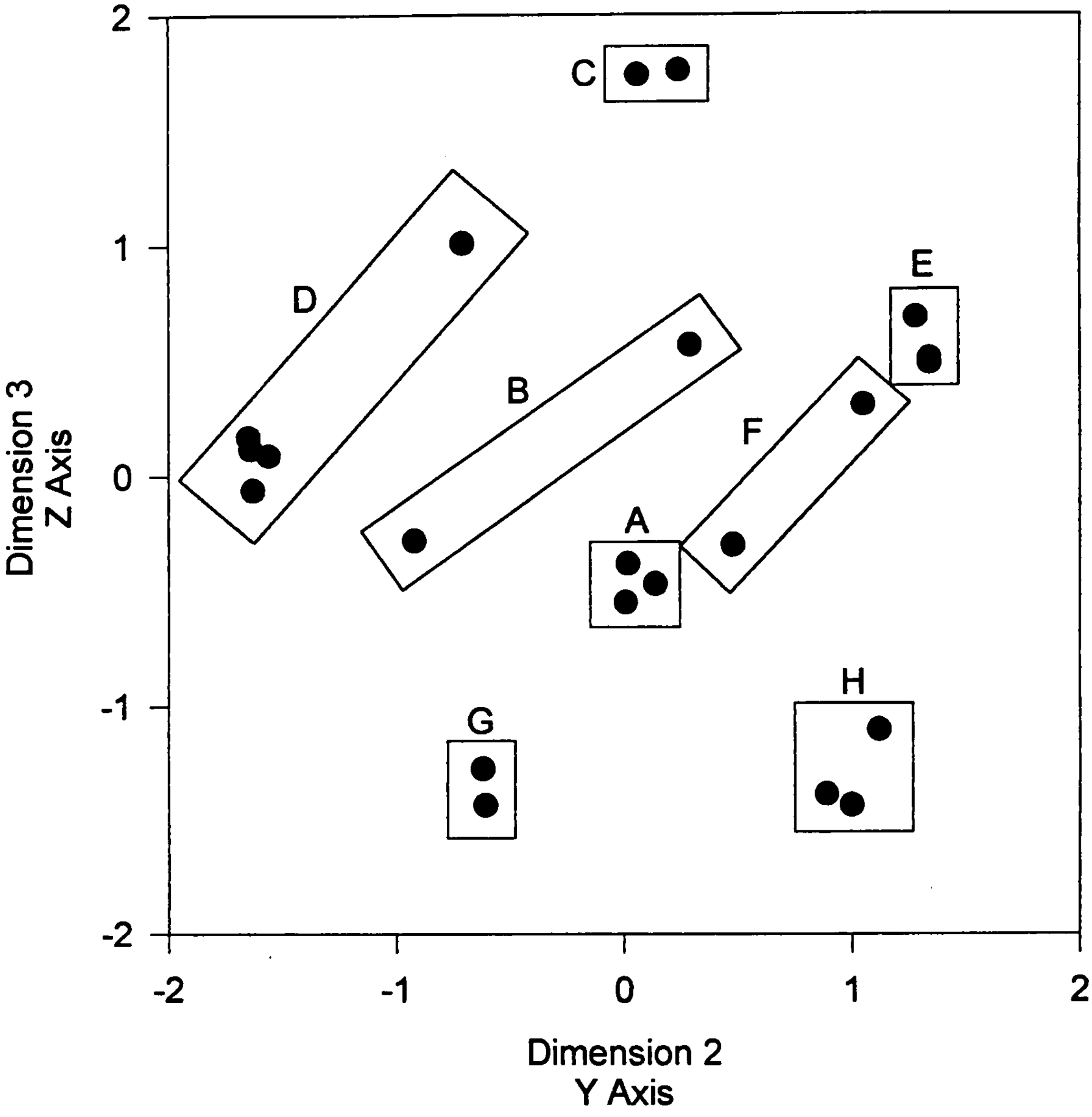


Figure 10. (continued)

VITA

Chris Heaps was born in Barrow-in-Furness, England on October 7, 1972. He and his family emigrated to the United States on April 14, 1975. He lived in Park Ridge, New Jersey until 1981, when he and his family moved to Bay St. Louis, Mississippi. He graduated from Bay High School in May, 1990 and entered Mississippi State University during August of the same year. In May, 1994 he received his Bachelor of Science degree in Psychology from Mississippi State University and began the Doctoral program in Experimental Psychology at The University of Tennessee, Knoxville in August, 1994. He received the Master of Arts degree in December of 1996, and is currently pursuing the Doctoral degree in Experimental Psychology.