Towards a Texture Naming System: Identifying Relevant Dimensions of Texture

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Abstract

Recently, researchers have started using texture for data visualization. The rationale behind this is to exploit the sensitivity of the human visual system to texture in order to overcome the limitations inherent in the display of multidimensional data.

A fundamental issue that must be addressed is what textural features are important in texture perception, and how they are used. We designed an experiment to help identify the relevant higher order features of texture perceived by humans. We used twenty subjects, who were asked to rate 56 pictures from Brodatz's album [1] on 12 nine-point Likert scales. We applied the techniques of hierarchical cluster analysis, non-parametric multidimensional scaling (MDS), Classification and Regression Tree Analysis (CART), discriminant analysis, and principal component analysis to data gathered from the subjects.

Based on these techniques, we identified three orthogonal dimensions for texture to be repetitive *vs.* non-repetitive; high-contrast and non-directional *vs.* low-contrast and directional; granular, coarse and low-complexity *vs.* non-granular, fine and high-complexity.

1 Introduction

Our research develops a classification scheme for visual texture. Classification lies at the heart of every scientific field. Classifications structure domains of systematic inquiry, provide concepts for developing theories, identify anomalies, and predict future research needs. Texture is an important visual cue, and has been studied by several researchers in psychophysics as well as computer vision [2, 3].

However, the understanding and use of texture is very limited when compared to other visual cues such as color. Color can be characterized by a variety of three dimensional representations (HLS/RGB etc). Interestingly, there is no comparable scheme for texture. This is due to a lack of a standardized taxonomy for texture, and the fact that the dimensions of texture have not been rigorously identified.

The use of color is standard in the presentation of multidimensional data. However, many artifacts could be introduced, such as the creation of false discontinuities [4]. Hence researchers have sought alternate ways of displaying multidimensional data, one of which is texture [5, 6, 7]. Furthermore, researchers are trying to harness the pre-attentive capabilities of human perception in order to aid visualization [4].

The Color Naming (CNS) [8] standardizes the specification of color by using simple, easily understood primitives from the English language. A parallel need is felt for a Texture Naming System, which would standardize the description and representation of texture. The standardization of vocabularies for features such as color, shape and texture would be useful for various kinds of applications, ranging from graphics to automatic defect classification.

Tamura *et. al.* [9], Amadasun and King [10], and Rao and Lohse [11] have tried to determine the relevant features used in texture perception. Some of the features identified include repetition, directionality, complexity, coarseness, contrast and granularity. However, the level of sophistication in characterizing shape and texture has not reached that of color, and much research still needs to be done. As a first step towards creating a Texture Naming System, we present those dimensions of texture along which variations can be captured and tweaked.

The goal of our research is to understand how people classify texture into meaningful, hierarchically structured categories. In [11] we began an exploratory research program aimed at classifying visual texture. Our classification was based on subjects' groupings of

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textures into categories that they themselves decided upon. We took the data from such an unsupervised classification, and analyzed it using multidimensional scaling and hierarchical cluster analysis. We tentatively identified three important dimensions for texture perception, namely repetitiveness *versus* irregularity, directional *versus* non-directional and structurally complex *versus* simple.

Once the potential dimensions have been identified, they can be validated by metric analysis. Our earlier study was lacking in that it did not use any quantitative data from the subjects: *only* non-metric grouping data were used. As a consequence, it is difficult to answer questions like what is the relative importance of these dimensions. Note that in order to properly design the metric part of the experiment, it was necessary to first hypothesize relevant dimensions. Hence we employed such a bootstrap technique, where the dimensions identified by the first experiment were used in the second.

In the current study we confirm the basic categories from our initial investigations and construct a classification of visual texture. Specifically, we identify features that characterize high-level categories of visual texture. The results describe the attributes that people may use to judge similarity among visual textures. Through an understanding of the taxonomic relationships among a broad range of textures, we hope to help users in graphics and visualization as well as computer vision construct effective algorithms for texture rendering and recognition.

This paper differs from our earlier paper [11] in two respects. Our earlier paper relied only on non-metric grouping data, whereas the current paper uses both metric data and non-metric data. Secondly, the earlier paper used 30 pictures from Brodatz's album, whereas the current paper uses 56 pictures. Thus, the results obtained from the current paper have better validity.

2 Background

Ware and Knight [5] present an interesting use of texture for visualization, where they use the dimensions of orientation, size and contrast for displaying data. The motivation for their work is similar to ours in that they seek appropriate dimensions of texture which are analogous to the dimensions of color, and that could aid in data display. Though their scheme was empirically tested, the fundamental question of the validity of the orientation-size-contrast texture space was not addressed. The results of our study shed light on this question.

Ware and Knight also bring up other questions such as which texture dimensions are perceptually orthogonal, and whether a uniform texture space can be developed (by analogy with uniform color spaces). Thus far these issues have not been well understood. Our work identifies the perceptually orthogonal dimensions of texture, and provides an insight into the organization of the texture space.

Van Wijk [6] presents a method that uses texture to visualize fields over surfaces. The texture is generated by randomly placing a spot over a surface. Spots of different size, shape and orientation could be used, giving rise to a variety of textures.

3 Methods

Our approach follows the methods used by Lohse et al. for developing a classification of graphics and images [12, 13].

Subjects

Twenty graduate and undergraduate students of the University of Pennsylvania participated in the study. The subjects' academic majors varied widely. Ages ranged from 20 to 35. Each subject was paid $20 for participating in the study.

Sample selection

We decided to use half the Brodatz album for our study, which amounts to 56 textures. Of these 56, we used 30 from our previous study [11] and randomly selected the remaining 26 textures.

The textures selected are shown in figure 4. These were presented in binders to subjects.

Selection of dimensions

We used a set of 12 dimensions which captured different aspects of texture description. We generated a list of texture terms based on the descriptions used by subjects in an earlier study [11], and descriptions from the literature on texture. This list can be found in [14].

Each unique word in the above list was tallied and we collapsed these data across similar word phrases, keywords, or synonyms. We selected twelve scale items from the final collapsed list of unique keywords.

Procedure

Subjects performed three tasks in a two hour session. These tasks were naming, rating, and sorting the 56 items. First, subjects examined all 56 items and named each one to insure familiarity with the entire range of items. This helped reduce the effects of order of presentation or anchoring effects on the subject's subsequent ratings. Next, subjects rated each of the 56 items on twelve 9-point Likert scales, shown in figure 1.

The final procedure was a bottom-up sorting task. For this task, the 56 items were placed randomly on a large table, and the subjects were asked to sort them into groups of similar items. Subjects were given no explicit criteria for judging similarity and could create any number of groups and any number of items per group. Once the subjects had completed their initial groupings, they described each group and explained why all the items in the group were similar. After the experimenter recorderd these descriptions, the subjects grouped their initial groupings into higher-order clusters of similar groups. Again, the experimenter recorded the subjects' explanations of why all the items within a cluster were similar. This process was repeated until all 56 items were placed in a single group.

4 Experimental Results

We used several techniques to analyze the data, including hierarchical cluster analysis, factor analysis and CART (Classification and regression trees) methodology.

4.1 Hierarchical cluster analysis

A matrix of similarities was constructed by counting the number of times each pair of textures was grouped together in the subjects' lowest level sorts. For example, textures d3 and d10 appeared in the same initial grouping for 10 of the 20 subjects, therefore the corresponding entry in the matrix is 10. This similarity matrix was then used as the basis for hierarchical clustering.

Hierarchical cluster analysis represents the objects of interest as leaves of a tree, whose non-terminal nodes are clusters. At each stage, the algorithm builds a tree by successively joining the most similar pair of items into a new cluster. The joining algorithm determines the method used to update the similarity matrix at each stage of the clustering process. We used the Ward linkage method [15]. Due to space limitations, the results of hierarchical cluster analysis cannot be shown graphically, and the reader is referred to [14].

The resulting tree had eight primary classes or clusters of textures. These classes are described in detail in section 5. We defer the discussion to a later section, as we combine the evidence gathered from different modes of analysis in order to arrive at a consistent interpretation.

4.2 Multidimensional scaling

After we had identified these major clusters of textures, we used multidimensional scaling, (MDS) to confirm the cluster analysis results. Multidimensional scaling helps identify properties that distinguish each cluster. It positions the items in n-dimensional space so that the inter-item distances in this space match as closely as possible (in a monotonic sense) the original distances [16]. This technique expresses the structure of the similarity data spatially rather than hierarchically.

We used three dimensions to perform multidimensional scaling. Figures 3a shows the plots of the output from multidimensional scaling in the $x-y$ plane. Similar plots for the $x-z$ and $y-z$ planes can be found in [14]. The Kruskal stress (form 1) in three dimensions is 0.12 which is considered a good fit [16][p 54]. (In our earlier experiment [11], the stress was 0.045). The eight clusters remain basically intact. Thus, the multidimensional scaling solution lends further credence to the reality of the categories found through hierarchical clustering.

We found that the x MDS coordinate is strongly correlated with the scale variables of repetitive, random, directional, regular, oriented and uniform; the y coordinate with contrast and directional and the z coordinate with granular, complexity and fine.

4.3 Principal component analysis

A principal components analysis of the data revealed that only one scale, granularity, explained less than five percent of the total variance. No single scale explained more than 10 percent of the total variance. The analysis suggests that the twelve scales are relatively independent (i.e., nonredundant) and of approximately equal importance (in terms of variance explanation), so we therefore make use of all twelve in the analyses described below.

4.4 Analysis using Classification and Regression Trees

The CART (Classification and Regression Trees) methodology [17] was next used to construct a binary classification tree (figure 4) in order to determine if the ratings on the 12 scales were predictive of membership in the clusters yielded by the hierarchical clustering analysis. Each terminal node of such a tree is associated with a single texture class. The simplest type of classification tree is one in which each internal node of the tree corresponds to a single independent variable, called the splitting variable for that node. Associated with the splitting variable is a threshold value which determines whether a to-be-classified item is sent left or right in the subsequent branching. Items are classified by running them down the tree and sending them right or left at each node depending on whether or not they exceed the threshold value for the corresponding splitting variable at that node. When an item reaches a terminal node, it is assigned to the class associated with that node.

In order to apply the CART program, ratings on the 12 scales were averaged across all 20 subjects. The analysis yielded the classification tree shown in Figure 4. This tree correctly classifies 50 of 56 or 89% of the textures. The "true" classification rate is estimated at 70% using a cross-validation estimate [17]. This is considered a good classification rate. For the sake of comparison we note that in the study of Lohse et al. [13] the tree correctly classified 84% of the graphics and the true classification rate was 53%.

This result strongly suggests that the ratings on the 12 scales can be used to predict group membership derived from the sorting data.

4.5 Discriminant analysis

The purpose of the discriminant analysis was to determine the relationship between the rating scales and the sort-derived classes.

Discriminant analysis is a technique whereby linear combinations of a set of independent variables are constructed so as to maximally discriminate among the classes of interest. Discriminant analysis was applied to the same data used in the CART analysis described above. In order to provide clearer interpretation, the resulting discriminant functions were first rotated. Based on both the rotated coefficients for the discriminant functions and the discriminant loadings (i.e., the correlations between the scales and the discriminant functions), the first three functions correspond most strongly to the random, repetitive, and granular scales, respectively. Note that these are the same scales that comprise the first three splitting variables in the classification tree.

The discriminant analysis correctly classified 48 of 56 or 86% of the textures. The "true" classification rate is estimated at 49%. These classification rates are nearly identical to those found using the CART methodology. These results, when combined with those of the CART analysis, provide confirmation for our belief that the rating scales are predictive of class membership in sorting and may have served as the basis on which subjects made their sorting decisions.

Overall, our analyses all provide confirmatory evidence of the taxonomic structure of the items found through hierarchical clustering. In addition, both the results of the CART analysis and the discriminant analysis suggest that the 12 rating scales can be used as predictors of class membership in the classification.

5 Discussion: nature of items in the classes

Eight categories of visual texture emerged from the classification. This section describes the characteristics of these major groups. These groups are color coded in figure 4.

The cluster A, comprising of **granular textures** is encoded through red. Such textures contain an average shape (which may be thought of as a grain), which is randomly distributed across a plane. The CART diagram (figure 4) supports this interpretation as the cluster A is described by the terms random and granular.

Cluster B, encoded through pink consists of **"marble-like"** textures, which can be considered random, non-granular, non-repetitive textures (as can be seen from the CART diagram). In figure 3 cluster B falls at the extreme positive end of the X axis, which represents randomness. Interestingly, clouds (d91 and d90) are considered similar to marble, and fall in class B even though they are semantically different.

Cluster C, encoded through white consists of **lace-like** textures, and can be considered non-random, non-repetitive textures (from the CART diagram). Another property of cluster C, that of non-directionality, can be inferred from MDS plot 3, where it occurs in the opposite end of the Y axis from cluster F, which represents directional textures.

Cluster D, encoded through magenta, is formed of **random** textures with fine detail, but possessing no obvious structuring elements. From the CART diagram of figure 4, the description is random, granular, with low contrast. From an examination of the elements of cluster D, we see that they are homogeneous and lack directionality.

According to the CART diagram, cluster E, encoded through green may be described as random, non-granular and somewhat repetitive. The repetitive aspect probably derives from the fact that there primitives, such as lines in d15, d107, and d108; bubbles in d110, and d112; and cones in d88 that serve as repetitive elements. However, the repetition is random and not regular. From the MDS plots of figure 3, cluster E occurs towards the random end of the X axis, is neutral in the Y axis, and occurs towards the end of the Z axis that corresponds to non-granular, fine and high complexity.

Cluster F, encoded through blue is formed of **directional, locally oriented** textures. According to the CART diagram, it is non-random and non-repetitive. In the MDS plots of figure 3, it falls on the positive Y and positive Z axes and is neutral to X. Such textures are characterized by a dominant local orientation within each portion of the texture.

Cluster G, encoded through yellow, and cluster H, encoded through orange consist of **repetitive** textures. Repetitive textures are modeled by a primitive element that is replicated according to geometric placement rules. For instance, the brick wall (texture d26) is created by taking a single rectangular brick and repeating it along the 0^0 and 45^0 directions. In the MDS plots of figure 3, these clusters remain intact. The negative x axis in the MDS plot correlates strongly to the labels repetitive, non-random, regular and uniform. This interpretation is further preserved in the CART diagram of figure 4. The CART methodology provides the interpretation that the clusters G and H are non-random and repetitive. Note that multiple descriptors (e.g. repetitive, uniform and regular) apply to these clusters.

The quality that separates G from H is that of directionality. From figure 3 we see that the elements of H have smaller Y coordinates than the elements of G. The CART diagram (figure 4) also lends credence to this interpretation as G is considered more oriented than H. The items in G and H reflect this interpretation – e.g. d50 and d11 possess the dominant direction of vertical, and d26 and d94 possess the dominant direction of horizontal. On the other hand, the items in H, such as d101 and d102 have no *single* preferred direction. They are equally repetitive in the x and y directions.

5.1 The dimensions of texture

From an examination of the above descriptions of the clusters, the MDS plots, and the correlation between scale ratings and MDS coordinates, we arrived at the following interpretation for the MDS axes. Further confirmatory analysis may be found in [14].

The X axis represents repetitiveness in texture. This appears to be the most important feature used by humans in distinguishing textures. The feature of repetitiveness is also significantly correlated with that of regularity, uniformity and non-randomness.

The Y axis represents a combination of directionality and contrast.

The Z axis represents a combination of granularity, coarseness and complexity.

It is interesting to observe the similarity between the MDS plots in this paper and the MDS plots from our previous work [11], in spite of the fact that the subjects used in the two studies were different. Furthermore, the cluster analysis diagrams from the two studies are also in correspondence. Thus, our findings are strongly suggestive of the nature of the texture space.

Figure 2 summarizes the orthogonal dimensions of texture that we have uncovered in this study.

6 Conclusion

In this paper we have identified the three most significant dimensions of texture, based on a study of twenty subjects over 56 texture images. The orthogonal dimensions we identified are repetitive *vs.* non-repetitive; high-contrast and non-directional *vs.* low-contrast and directional; granular, coarse and low-complexity *vs.* non-granular, fine and high-complexity. This interpretation fits the data well, and refines the results we presented earlier [11].

The combinations of features such as low-contrast and directional, occurring in the Y axis, can be given any name, but they constitute the quantitites which can be interpreted as a dimension of texture.

Through an understanding of the taxonomic relationships among the broad range of textures used in this paper, we hope to help users in graphics, visualization as well as computer vision construct effective algorithms for texture rendering and recognition. Finally, a quantization of the values along each of the three dimensions we have identified will lead to a Texture Naming System, in the spirit of the Color Naming System.

In order to complement the study of visual texture, we are also undertaking a study of the categorization of texture words. This verbal categorization will aid in the design of an appropriate quantization scheme for the dimensions of texture that we identified.

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References

[1] P. Brodatz, *Textures: A Photographic Album for Artists and Designers.* New York: Dover Publications, 1966.

[2] B. Julesz and J. R. Bergen, "Textons: The fundamental elements in preattentive vision and perception of textures," *Bell System Technical Journal*, vol. 62, no. 6, pp. 1619–1645, 1983.

[3] A. R. Rao, *A taxonomy for texture description and identification.* Springer Verlag, 1990.

[4] B. Rogowitz, D. Ling, and W. Kellogg, "Task dependence, veridicality and pre-attentive vision: taking advantage of perceptually-rich computer environments,"

in *Human Vision, Visual Processing and Digital Display III*, vol. SPIE Vol. 1666, pp. 504–513, Feb 1992.

[5] C. Ware and W. Knight, "Orderable dimensions of visual texture for data display: orientation, size and contrast," in *ACM Conference on Human Factors in Computing Systems (CHI)* (P. Bauersfeld, J. Bennett, and G. Lynch, eds.), pp. 203–209, 1992.

[6] J. V. Wijk, "Spot noise texture synthesis for data visualization," *Computer Graphics*, vol. 25, no. 4, pp. 309–318, 1991.

[7] R.M.Pickett and H.Levkowitz, "Iconographic displays of multiparameter and multimodality images," in *IEEE Conference on Visualization in Biomedical Computing*, May 1990. Atlanta.

[8] T. Berk, L. Brownston, and A. Kaufman, "A new color naming system for graphics languages," *IEEE Computer Graphics and Applications*, vol. 2, pp. 37–44, May 1982.

[9] H. Tamura, S. Mori, and T. Yamawaki, "Textural features corresponding to visual perception," *IEEE Trans. Systems, Man, and Cybernetics*, vol. 8, pp. 460–473, June 1978.

[10] M. Amadasun and R. King, "Textural features corresponding to textural properties," *SMC*, vol. 19, pp. 1264–74, Sept 1989.

[11] A. Rao and G. Lohse, "Identifying high level features of texture perception," *CVGIP: Graphical Models and Image Processing*, vol. 55, pp. 218–233, May 1993.

[12] G. Lohse, H. Rueter, K. Biolsi, and N. Walker, "Classifying visual knowledge representations: A foundation for visualization research," in *Visualization '90: Proceedings of the First Conference on Visualization*, pp. 131–138, IEEE Computer Society Press, 1990. San Francisco, CA.

[13] G. Lohse, N. Walker, K. Biolsi, and H.Rueter, "Classifying graphical information," *Behaviour and Information Technology*, vol. 10, pp. 419–436, 1991.

[14] A. Rao and G. Lohse, "Towards a texture naming system: identifying relevant dimensions of texture perception," *IBM Research Technical Report*, 1993. forthcoming.

[15] J. Ward, "Hierarchical grouping to optimize an objective function," *Journal of the American Statistical Association*, vol. 58, pp. 236–244, 1963.

[16] J. Kruskal and M. Wish, *Multidimensional scaling.* Sage Publications, 1978.

[17] L. Breiman, J. Friedman, R. Olshen, and C. Stone, *Classification and Regression Trees.* Wadsworth and Brooks, 1984. Pacific Grove, CA.

Low contrast (diffuse edges)	1	2	3	4	5	6	7	8	9	High contrast (sharp edges)
Non–repetitive	1	2	3	4	5	6	7	8	9	Repetitive
Non–granular	1	2	3	4	5	6	7	8	9	Granular
Non–random	1	2	3	4	5	6	7	8	9	Random
Rough	1	2	3	4	5	6	7	8	9	Smooth
Low feature density	1	2	3	4	5	6	7	8	9	High feature density
Non–directional	1	2	3	4	5	6	7	8	9	Directional
Low structural complexity	1	2	3	4	5	6	7	8	9	High structural complexity
Coarse	1	2	3	4	5	6	7	8	9	Fine
irregular	1	2	3	4	5	6	7	8	9	regular
non–oriented	1	2	3	4	5	6	7	8	9	locally oriented
Non–uniform	1	2	3	4	5	6	7	8	9	Uniform

Figure 1: The twelve rating scales used in the experiment.

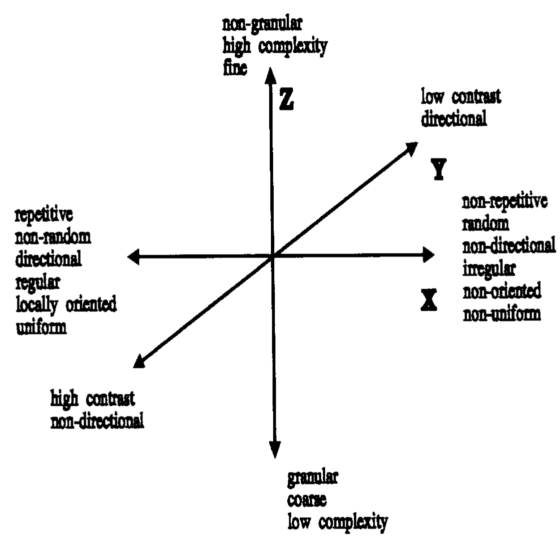

Figure 2: The three dimensions of texture.

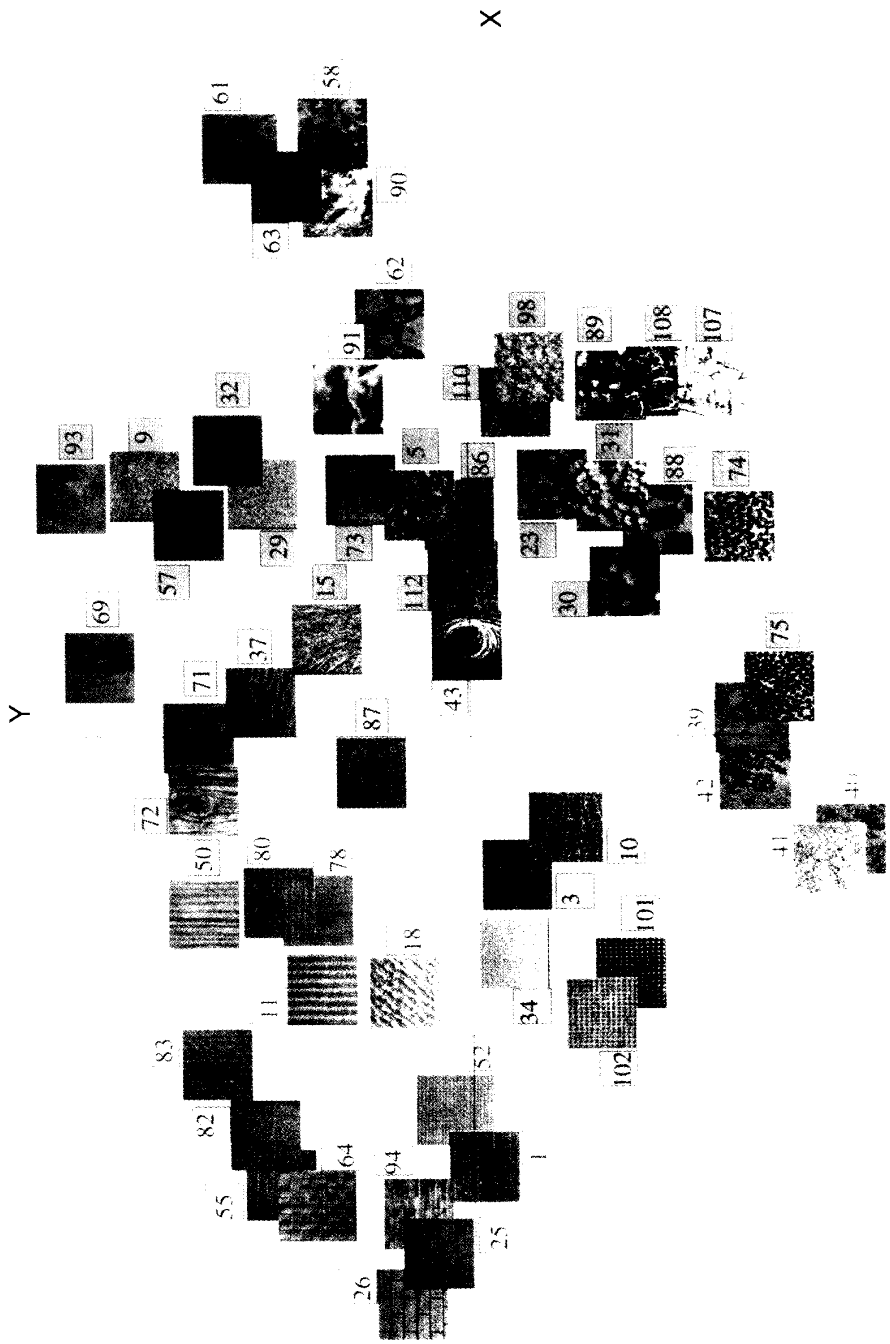

Figure 3: The result of performing multidimensional scaling using three dimensions. The projection into the $x - y$ plane is shown.

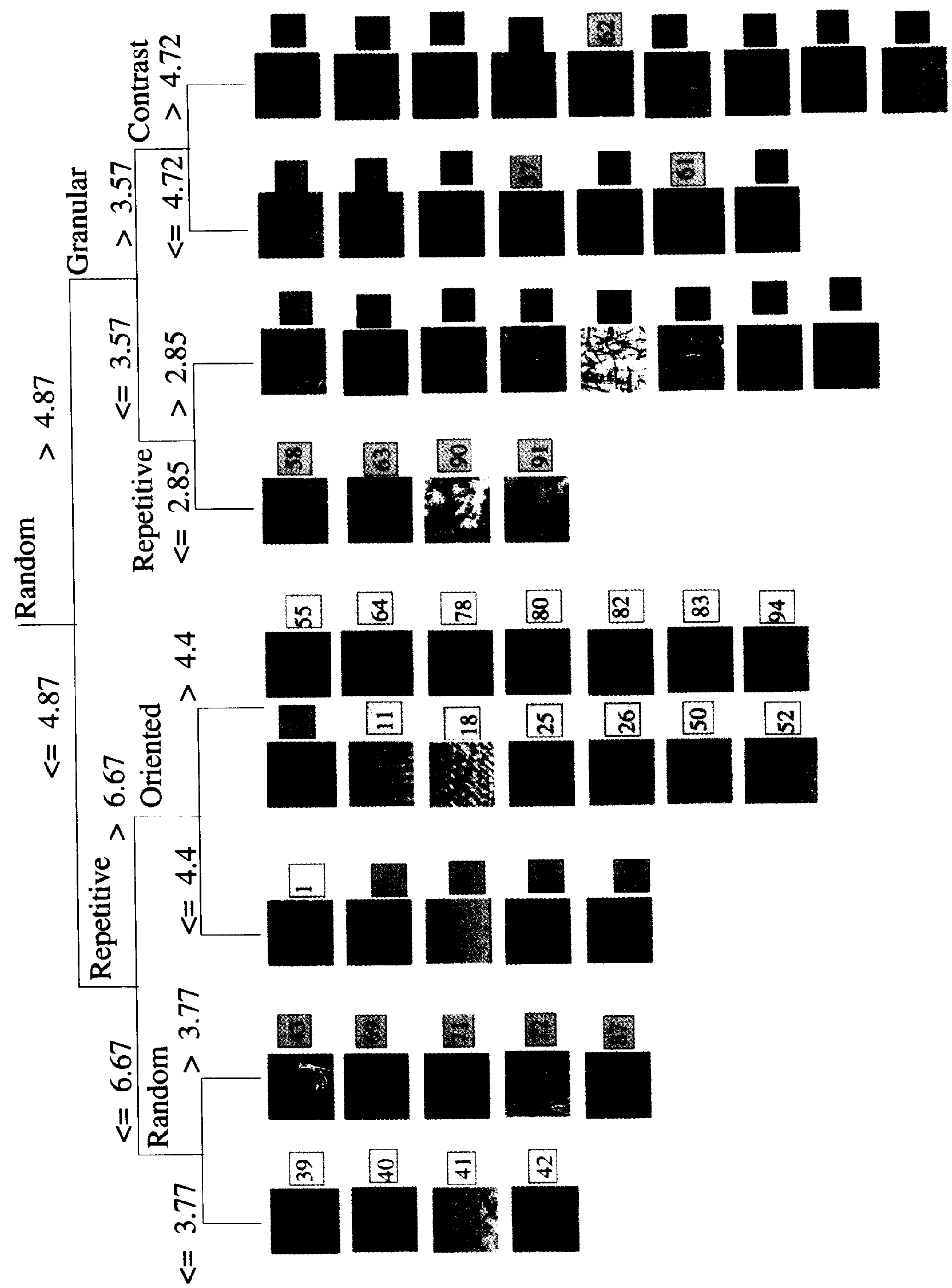

Figure 4: The result of performing CART analysis. Pictures go to the left if the cutoff value on the splitting variable is less than or equal to the cutoff value; otherwise they go right.

(See color plates, p. CP-22.)

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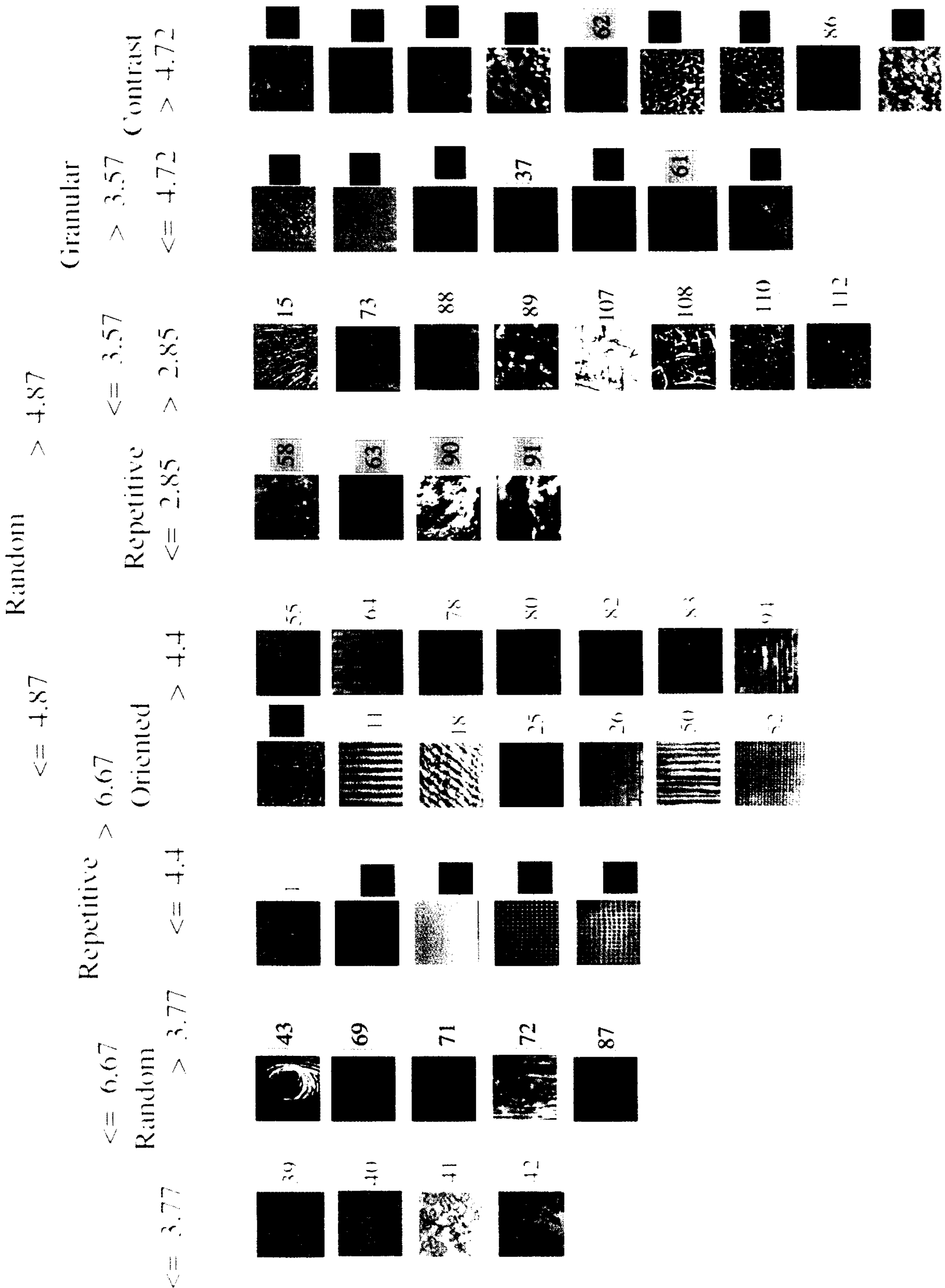

Figure 4: The result of performing CART analysis. Pictures go to the left if the cutoff value on the splitting variable is less than or equal to the cutoff value; otherwise they go right.