1998 International Computer Symposium
Workshop on Computer Graphics and Virtual Reality
December 17-19, 1998, N.C.K.U., Tainan, Taiwan, R.O.C.

VIRTUAL PLANT RETRIEVAL BASED ON SUBJECTIVE MEASURES

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Abstract

Similarity retrieval is an important algorithm for database systems. To support the creation of good virtual world presentation, we need to retrieve polygonal objects from databases. In conventional database systems, retrieval of polygonal objects was based on only the features of the polygon. Unfortunately, such retrieval techniques do not consider the user's subjective measures. Some applications such as the creation of a virtual city can be done more effectively by applying designers' subjective measures to retrieval systems. This paper shows the creation of multidimensional spaces based on subjective measures by analyzing the correlation between the features of polygonal data using a multidimensional scaling and regression analysis. 3D polygonal tree objects are used as a data set to evaluate the effectiveness of our statistical approach. Our techniques enable users to retrieve objects more efficiently by considering subjective measures.

1. INTRODUCTION

There are several algorithms to retrieve 3D polygonal objects from a database. The text-based method uses labels and comments which are assigned by the person who designed the object. This kind of method requires much work for indexing. Super-quadratics or skeletons are effective indices to capture the structured abstract index of 3D objects. However, even if good indices are created, these algorithms are not enough to reflect personal subjective measures for similarity. These approaches have limited expressiveness for answering queries with different users. A statistics-based approach [7] [8] [9] [10] [11] was used to maximize users' subjective measures to solve this kind of problem for 2D images. We have extended this statistical approach to 3D object retrieval.

For 2D images, much research has been done to find good shape descriptors to interpolate missing dimensions. Although 3D objects contain precise shape information and shape descriptors compared to 2D images, this does not mean that retrieval can be done more easily, because still retrieval systems need to recognize which shape descriptors are important and more influential for similarity retrieval. Another problem is that different users use different shape descriptors to evaluate the similarity of 3D objects.

2. SIMILARITY RETRIEVAL FOR VIRTUAL TREES

In our statistics-based similarity retrieval, user behaviour is characterised by similarity preferences as shown in Figure 1. The behaviour can be represented by a user model to customise the query processing. Different users can be represented by different user profiles in the model. In this section we describe algorithms for similarity retrieval. We divide this process into four parts: (1) creating the parameter space, (2) creating the object feature space, (3) creating the user preference space, (4) and mapping the object feature

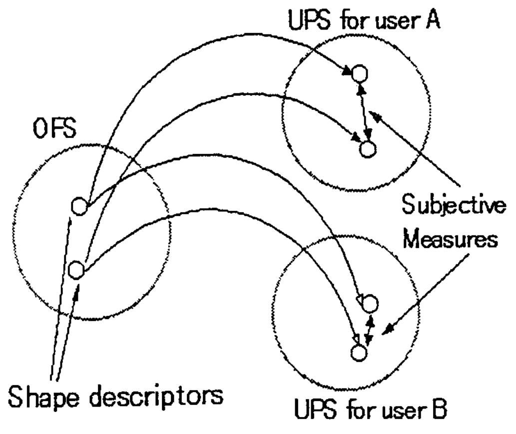

Figure 1. Object Feature Space and User Preference Space

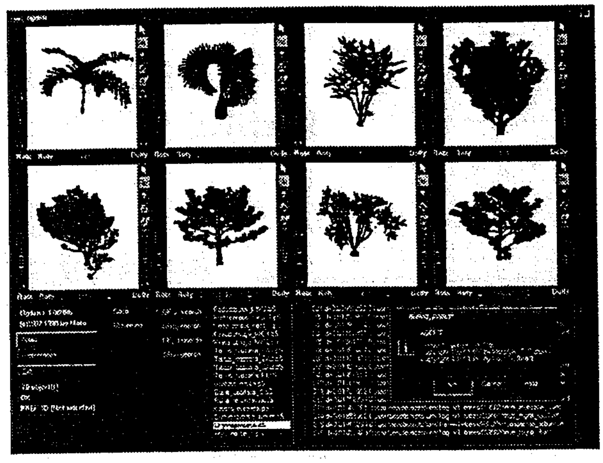

Figure 2. Subjective retrieval system

Table 1. Parameters

trunk height	branch length	twig length
trunk width	branch angle	twig angle
bottom height	winding step	twig curving
crown center	winding angle	twig density
bough length	winding twist	
bough curving		
bough twist		

space into the user preference space.

2.1. Parameter Space

Many modeling programs output a plant fractal based on Lindenmayer systems [1] [2] [3] [4]. These programs are being used to create natural materials, such as stones, terrain and trees. These fractal based programs use a set of rules and parameters. The rules tell the generation program how to manipulate parameters. The parameters (Table 1) such as the angles of branches, height of tree and many other parameters are used to control the shapes of trees. We have selected some of these parameters to create the parameter space.

2.2. Object Feature Space

It is very important to choose good shape descriptors to retrieve objects. The shape of an object can be described quantitatively using numeric shape descriptors such as roundness, curvature and compactness. The use of required shape descriptors depends on what kinds of objects are in the database. There are many ways to describe 3D objects, such as CSG, voxcel and polygon. If the 3D objects are described by polygons, polygon vertices can be good shape descriptors [23]. For the fractal generated polygonal trees, shapes of trees are determined by parameters. Therefore, we can use some of these parameters as shape descriptors.

2.3. User Preference Space

To support object retrieval based on users' subjective similarity measures, we need models of objects with similar relationships to be compared. Since we can not compare entire tree objects in the large database, we select some tree objects as a study data set to capture similarity preferences. We used multidimensional scaling (MDS) [15] [16] [17] [18] to create a user preference space using this study data set. MDS can analyse matrices of dissimilar or similar data. The analysis represents the rows and columns of the matrix as points in a Euclidean space. If a row and column are similar, then their points are close together, while if the row and column are dissimilar, their points are far apart.

Table 2. R^2 and Adjusted R^2

Axis	R^2	Adj. R^2	♯ of vars.
1	0.8387	0.8100	20
2	0.8120	0.8003	18
3	0.8110	0.8000	18
4	0.8303	0.8100	20
5	0.7998	0.7721	20

2.4. Mapping Object Feature Space into User Preference Space

When the object feature space and user preference space are created by using study objects, we need to find mapping functions to evaluate the relationships of these spaces. Let m be the number of dimensions. The coordinates of study object obj_i are $obj_i^{coord}(z_{i0}, z_{i1}, ..., z_{im})$. The object obj_i has feature vectors $obj_i^{vect}(x_{i0}, x_{i1}, ..., x_{ik})$. To find mapping functions, we can use multiple regression analysis (stepwise). The predictor variables are obj_i^{coord} and the response variables are obj_i^{vect}. We need n samples to analyze by multiple regression.

$$z_{ij} = b_{i0} + \sum_{a=1}^{k+1} b_{ia} x_{i(a-1)} \qquad (1)$$

We can find the coordinate in dimension j of a point in an m-dimensional space from equation 1. Once mapping functions are found, coordinates of points for the entire tree database can be computed. In the preference space, similar objects are close together, while dissimilar objects are far apart. Therefore similarity retrieval can be done by a Euclidean distance computation.

3. SYSTEM IMPLEMENTATION

A similarity retrieval system was implemented in C++, Motif, and Inventor on an SGI Indigo2. Tree objects are displayed in individual windows, as shown in Figure 2. Since each window has an independent coordinate system, we can rotate, scale, and translate the object in each window. The system allows users to see tree objects in stereo viewing mode using stereo glasses.

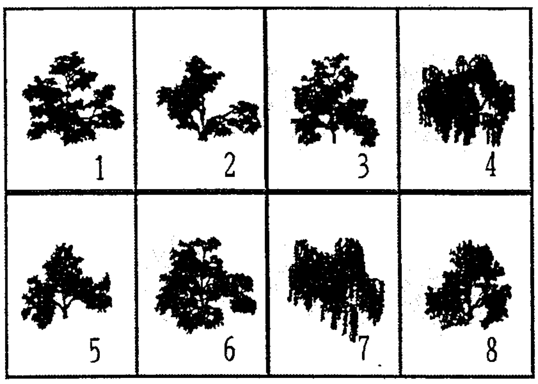

Figure 3. Retrieval 1 (OFS)

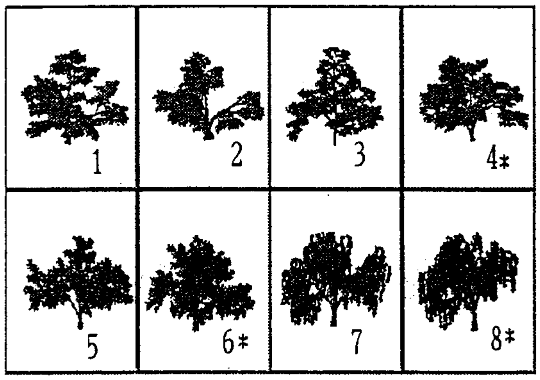

Figure 4. Our statistical retrieval 1 (UPS)

We tested our statistical method on the similarity retrieval system. Our tree database contains 300 VRML objects, and we have choose 50 tree objects as a study data set. The object feature space contains 35 vectors. User preference spaces are created by applying multidimensional scaling and multiple regression analysis. In this statistical process, stress [15] [16] [17] [18] is computed. Five dimensions are used to compose a user preference space, since stress converges at dimension five. Table 2 shows R2 (squared multiple correlation) and adjusted R2 for each axis. These values are computed during multiple regression analysis. Adjusted R2 values show the validity of the mapping of object feature space into user preference space. These values indicate that the mapping is

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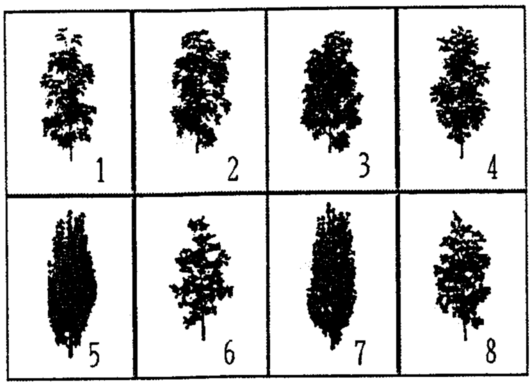

Figure 5. Retrieval 2 (OFS)

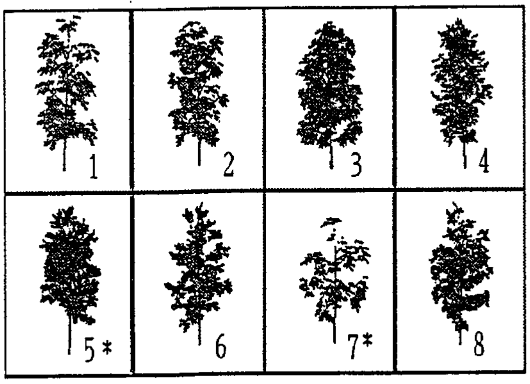

Figure 6. Our statistical retrieval 2 (UPS)

valid for use of regression functions.

4. EXPERIMENT AND RESULTS

We evaluated the statistical method and the non-statistical method in an experiment with four users. The preference model was created based on averaged similarity preferences from four users. In our statistical method, weight-of-shape descriptors are properly assigned based on users' subjective measures. In the non-statistical method, weight-of-shape descriptors are the same. User preference space (UPS) is used as the retrieval domain for the statistical method. For the non-statistical method, only object feature space (OFS) is used. Figures 3 and 5 show query results for the OFS method based on graphical features.

Table 3. Results (Average)

	5%	10%
OFS	89.7%	83.6%
UPS	93.8%	91.2%

Figures 4 and 6 show query results for the UPS method based on subjective measures. In Figures 3 and 5, some trees are not similar in terms of shape in users' similarity point of views. However the statistical approach allows some trees to appear for the query by considering users' similarity preference as shown in Figures 4 and 6. The statistical method can capture human perceptual similarity of trees by considering subjective measures.

Tables 3 and 4 compare the results of the OFS method and the UPS method. To evaluate the effectiveness of the statistical approach, we first chose 10 query keys at random and sorted the query results based on similarity distances. The distance that is most far apart is set as maximum region 100%. Secondly, we asked users if similar objects are contained in the 5% region. Numbers of similar objects are counted in the 5% region, then the numbers are divided by the total number of objects in each 5% region. The 10% region is computed in a similar manner. Figures 11 and 12 show query results for different users. Although the same search key is used, the system shows different query results, reflecting different user models. Figures 7, 8, 9 and 10 show query results of the UPS method.

The statistical method UPS requires at most 20 vectors (variables) to retrieve tree objects, as shown in Table 2. Once the user preference space is created, similarity retrieval can be done in time O (n log n).

5. SUBJECTIVE SEARCH AND ITS APPLICATIONS

5.1. Tree Object Database

Many applications in computer graphics and virtual reality systems require complex objects. However, complex objects contain huge amounts

Table 4. Results

User A	5%	10%
OFS	83.2%	80.0%
UPS	93.4%	91.9%
User B	5%	10%
OFS	90.1%	93.3%
UPS	95.7%	95.6%
User C	5%	10%
OFS	85.0%	84.9%
UPS	90.2%	90.1%

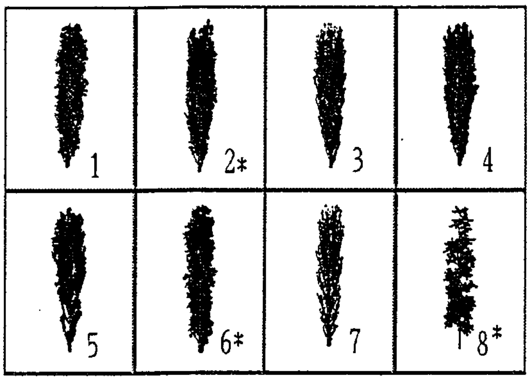

Figure 7. Our statistical retrieval 1 (UPS)

of polygonal patches, and the rendering cost is expensive. Generally, trees are highly complex objects compared to other simple objects, because of their structures. One solution to speed up rendering is to replace complex trees by simpler trees, but this solution may lead to loss of image quality that is noticeable. Since our similarity retrieval system shows a set of similar trees, we can substitute trees that have fewer polygonal patches from this set without losing image quality.

5.2. Users' Subjective Measures

From the coefficients of mapping functions, we found that some feature descriptors, such as trunk height, leaf density, branch angle, and bough length have a strong influence on users' similarity measures compared to the 30 other feature descriptors.

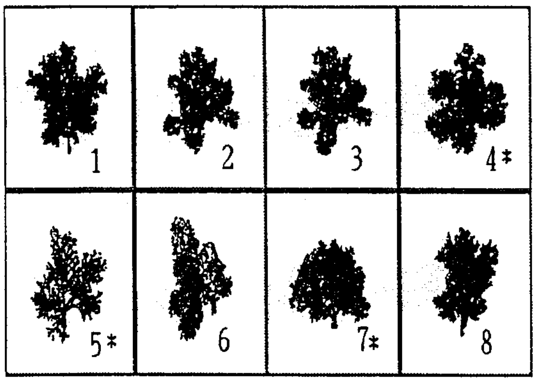

Figure 8. Our statistical retrieval 2 (UPS)

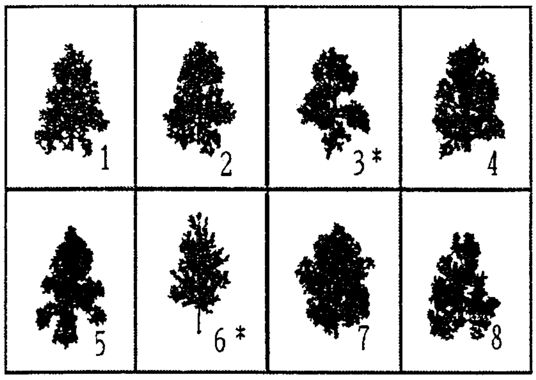

Figure 9. Our statistical retrieval 3 (UPS)

5.3. Browsing Trees In User Preference Space

When user preference spaces are created, we can walk through the space by using three axes. In this space, similar trees are close together, while dissimilar trees are far apart. We can thus visualize users' similarity preferences. Figures 13 and 14 show snap shots of the preference space based on averaged three users' similarity measures.

6. CONCLUSIONS

In this paper, we presented a statistical method for retrieving 3D polygonal trees by shape descriptors considering user preferences. Multidimensional scaling and multiple regression analy-

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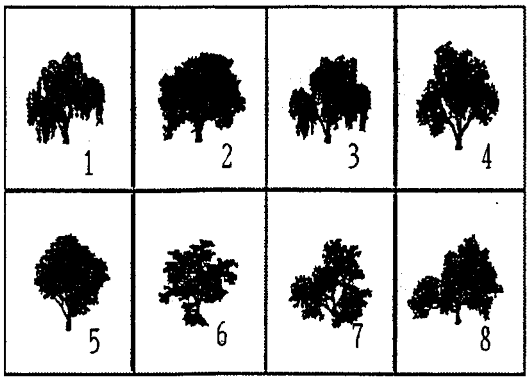

Figure 10. Our statistical retrieval 4 (UPS)

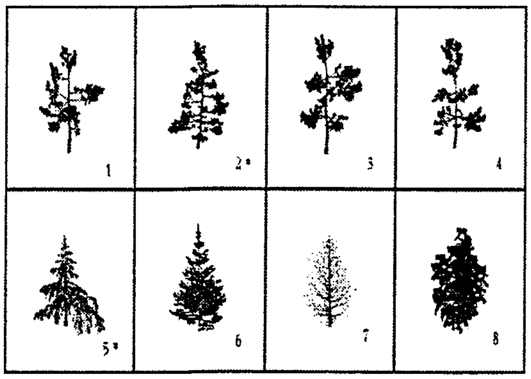

Figure 11. User A (UPS)

sis were used to create user preference models. The retrieval system was implemented on an S-GI Indigo2. Experimental results indicated that a statistics-based technique is an effective approach to retrieve 3D objects.

7. FUTURE WORK

We did not include color and texture for the similarity retrieval models, because the evaluation of similarity can not be done linearly if we include color and texture. In future work, we intend to extend our models to be able to handle colors and textures.

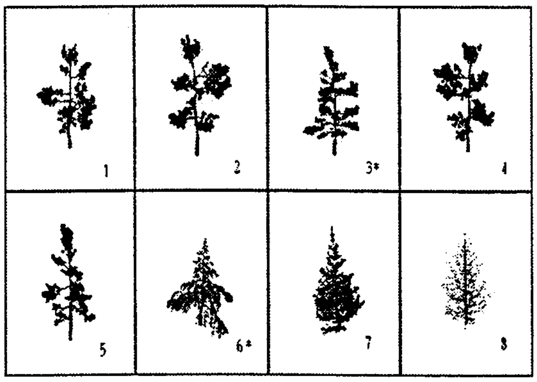

Figure 12. User B (UPS)

References

[1] P. Prusinkiewicz and A. Lindenmayer: The algorithmic beauty of plants, Springer-Verlag, New York, 1990.

[2] H. Meinhardt: The algorithmic beauty of sea shells, Springer-Verlag, New York, 1995.

[3] R. Mech and P. Prusinkiewicz: Visual Models of Plants Interacting with Their Environment, Proc. of SGGRAPH 96, pp.397-410, Aug. 1996.

[4] P. Prusinkiewicz, M. Hammel, J. Hanan and R. Mech: Visual models of plant development, Handbook of formal languages, Springer-Verlag, 1996.

[5] Solina F. and Bajcsy R.: Recovery of parametric models from range images: The case for Superquadrics with global deformations, IEEE PAMI-12, pp.131-147, Dec. 1990.

[6] Gupta A. and Bajcsy R.: Surface and volumetric segmentation of range images using biquadrics and Superquadrics, Proc. of 11th ICPR, pp.158-162 1992.

[7] T. Kato, H. Shimogaki, T. Mizutori. and K. Fujimura: TRADEMARK: Multimedia Database with abstracted representation on knowledge Base, Proc. of 2nd International Symposium on Interoperable Information Systems, pp.245-252, 1988.

[8] T. Kato and T Kurita: Visual Interaction with Electronic Art Gallery, Proc. of the International Conf. on Database and Expert Systems Applications DEXA90, pp.234-240, Aug. 1990.

[9] T. Kato: Cognitive view mechanism for context-based multimedia information retrieval, Proc.

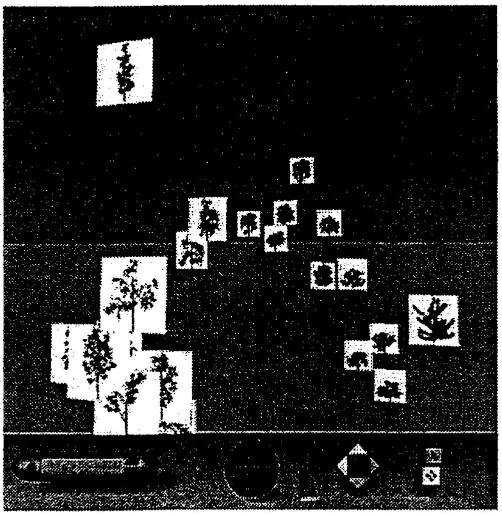

Figure 13. Walk-through

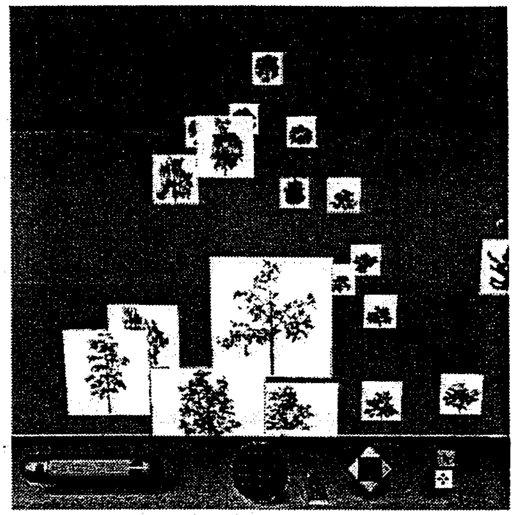

Figure 14. Walk-through

of the International Workshop on Interfaces to Database systems, IDS1992, pp.244-262, July 1992.

[10] K. Hirata and T. Kato : Query by visual Example: Context based Image Retrieval, Proc. of the International Conf. on Extending Database Technology, EDBT92, pp.56-71, Mar. 1992.

[11] Toshikazu Kato : Intelligent visual interaction with image database systems, Journal of Information Processing, Vol.14, No.2, Apr. 1991.

[12] C.Dorai, A.K.Jain : Shape Spectrum Based View Grouping and Matching of 3D Free-Form Objects, IEEE Trans. on PAMI, Vol.19, No.10, Oct. 1997.

[13] M Nabil, A. H. Ngu, and J. Shepherd : Picture Similarity Retrieval Using the 2D Projection Interval Representaion, IEEE Trans. on Knowledge and Data Engineering, Vol.8, No.4, pp.533-539, Aug. 1996.

[14] C. H. Wesley, W. Chu, and R. K. Taira : A Knowledge-Based App.roach for Retrieving Images by Content, IEEE Trans. on Knowledge and Data Engineering, Vol.8, no4, pp.522-532, Aug. 1996.

[15] J. B. Kruskal, and M. Wish : Multidimensional scaling, Newbury Park, Sage, 1978.

[16] F. W. Young : Multidimensional scaling (history,theory,and applications), L.Erlbaum Associates, Hillsdale, 1987.

[17] T. F. Cox, M. A. Cox, "Multidimensional scaling," Chapman Hall, London, 1994.

[18] I. Borg, P.J.F. Groenen : Modern multidimensional scaling theory and app.lications, Springer, New York, 1997.

[19] D.S.Moore, G.P.McCabe : Intro. to the practice of statistics, W.H.Freeman and company, New York, 1993.

[20] J.H. Friedman, J.L. Bentley and R.A. Finkel : An algorithm for finding best matches in logarithmic expected time, ACM Trans. on Math. Soft., Vol.3 No.3, pp.209-226, Sep. 1977.

[21] J. Hartman, J Wernecke : VRML 2.0 Handbook, Addison-Wesley, Aug. 1996.

[22] J. Wernecke : The Inventor Mentor, Addison-Wesley, Aug. 1994.

[23] M. T. Suzuki, T. Kato, and H. Tsukune, 3D Object Retrieval based on Subjective Measures, Proc. of Database and Expert Systems Applications, DEXA98, pp.850-856, Vienna, Aug. 1998.