3-D mesh-classification method based on angular histograms

Tomasz Zawadzki

Florida Institute of Technology
150 W. University Blvd

USA, 32901, Melbourne, Florida
E-mail: tzawadzki@my.fit.edu

Slawomir Nikiel

University of Zielona Gora
Licealna 9

Poland, 65-417, Zielona Gora
E-mail:s.nikiel@issi.uz.zgora.pl

Eraldo Ribeiro

Florida Institute of Technology
150 W. University Blvd

USA, 32901, Melbourne, Florida
E-mail: eribeiro@cs.fit.edu

ABSTRACT

Methods for analyzing of 3-D mesh topology play an important role in computer graphics problems such as segmentation, correspondence, shape recognition, editing, and animation. We present a new approach for recognition, analysis, and classification of 3-D mesh-based objects. Here, we show how histogram descriptors based on the angles between vertices can be used for grouping similar shapes and for shape classification. Our method can be customized to classify objects of varying mesh complexity (i.e., level of detail) by changing the descriptor's resolution parameter. We demonstrate the effectiveness of our method on a 3-D object database generated using shape grammars and a hybrid morphing algorithm.

Keywords

Verification method, 3D mesh, recognition, histogram.

1. INTRODUCTION

Feature-based classification of three-dimensional-meshed objects allows for efficient and robust editing of complex CAD models by effectively representing shapes using shape descriptors [Hof98, She04]. A current trend is to try to make 3-D shape descriptors available not only for applications such as shape retrieval [Fun03, Liu10] but also for shape matching [Bus05]. Unlike its 2-D domain counterparts, 3-D shape description of mesh-based solids remains an open problem both in terms of feasibility and accuracy. Since databases containing 3-D objects have become more accessible to users with no previous CAD/CAM software experience, the need to develop new methods for 3-D search becomes highly relevant [Fun03, Bus05].

Usually, designers and manufacturing companies use semantic keywords, or meta-description to search for graphical 3-D objects in databases. Given a small set of initial objects that resemble the intended target, these objects are iteratively shaped (morphed) to render the final shape that the artist had in mind. In

this paper, we introduce an alternative approach to meshed-object description and recognition. Our 3-D mesh classification method works in two phases. In the first phase, we set up a database of objects with different topologies and create average angular histograms for each class of meshed objects (i.e., caves, clouds and architecture). In the second phase, we generate random objects for which baseline histograms are created. After that, we recognition is achieved by comparing the generated baseline histograms with those that were created in the first stage and then we can check if objects are recognized correctly. Actually few independent research teams working on software development in project AIM@SHAPE [www]: MeshLab – editing of unstructured 3D triangular meshes, TriMesh2MT – convert mesh to multi-triangulation, AXEL – algebraic software-components for geometric modeling, COMREN – multi-resolution coding of mesh files.

2. OTHER WORKS

Methods for the analysis and classification of 3-D objects use a metric, which prescribes a distance function over the object's surface. Tasks for which shape metrics play a key role include shape decomposition, shape signatures representation, and surface parameterization. Well-known surface metrics include the geodesic [Car76] and the isophotic [Pot04] distances, where the latter measures angles between surface normals; a combination of the

two is also common [Lai07]. Anisotropic geodesic metric based on the curvature tensor has also been considered for parametric surfaces [Seo08]. Another metric receiving recent attention is the diffusion distance [deGoe08], which accounts for the degree of connectedness between two surface points.

Alternatively, one can derive a discrete distance function for mesh primitives by assigning attributes to primitives, defining edge weights between adjacent attributes, and finally computing distances over the shortest paths in the primal or dual graph of the mesh [Kat03].

Interesting recent approaches include: a part-aware surface metrics [Mar11] (Fig. 1) and cubeness measure [Liu09] (Fig. 2).
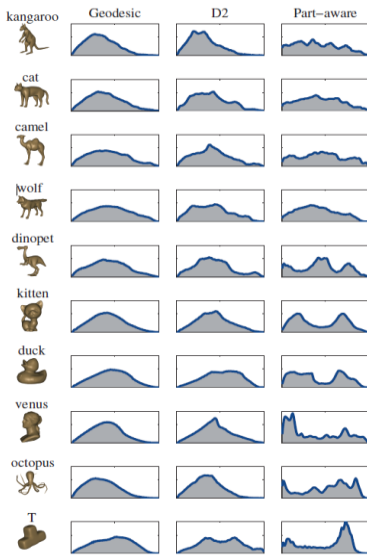

Figure1. The last three columns show the distance histograms of each model, obtained using geodesic, D2 and part-aware distances.
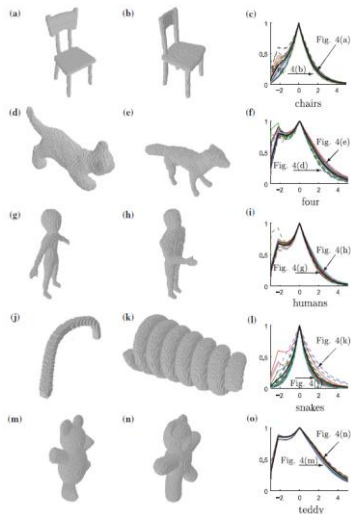

Figure 2. Each row presents the graphs GS(β) of all shapes from certain class (on the right), and two shapes whose GS(β) graphs differs

Another interesting approach is a Surflet-Pair-Relation Histograms [Wah03] based on a novel four-dimensional feature that describes the intrinsic geometrical relation between a pair of surflets, i.e., oriented surface points in 3D space. The statistical distribution of this feature as sampled from an object's surface captures both local and global aspects of shape. Empirically learned histograms of the feature distribution are demonstrated as a compact and efficient representation of arbitrary 3D shapes. This representation allows for rapid classification of shapes based on a single histogram per object model, independent of translation and rotation.

3. HISTOGRAMS

Our method represents shapes using a histogram of inter-vertex angles. We assume that models consist of edges, each of them determined by two points (i.e., vertices). In addition, the vertices are assigned normal vectors. We begin to build the representation by creating a set of edges of all triangles of the model. Here, edges belonging to two triangles are added twice, but perhaps with different normal vectors. Then, a value in the interval [0, 1] is calculated for each edge. This value is the difference of the two angles between normal vectors and the line containing the vertices (Fig. 3).
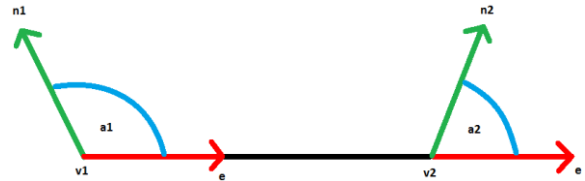

Figure 3. Calculation of the angles between the vertices.

$$e = \frac{(V_2 - V_1)}{|V_2 - V_1|} \tag{1}$$

$$a_1 = \arccos(e \bullet n_1) \tag{2}$$

$$a_2 = \arccos(e \bullet n_2) \tag{3}$$

$$d = a_2 - a_1 \tag{4}$$

$$V = \frac{d}{2(\rho+1)} \tag{5}$$

where: n_1 and n_2 are the normal vectors. For concave surfaces, this value belong to the interval [0,0.5]. For convex surfaces, it lies the interval (0.5, 1].

In the next step, a discrete histogram is created indicating the frequency of numbers lying in the given interval. This is done as follows – for each value from the set interval histogram is calculated according to the formula:

$$i = floor(v * R) + 1 \qquad (6)$$

where: R is the number of histogram intervals.

Then the multiplicity of the i-th interval is incremented by one. After consider all values in the set, the histogram is normalized by dividing its compartments by the total number of edges. The normalization ensures that the sum of the ranges of the histogram equals to 1. For classification, it is necessary to prepare the histograms corresponding to a master object classes (Fig. 4.).

Verification of the correctness of the model depends on the density of the grid. We obtained the best results for $L_D=10$ (Fig. 5.).
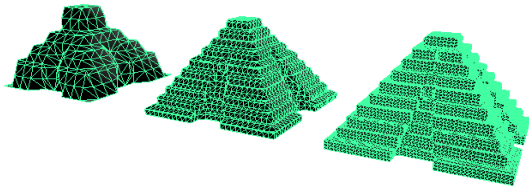

Figure 4. Level of detail (L_D), from left L_D=2, L_D=5, L_D=10.

When density is large, the histogram is reduced to a single bar representing the most common angle. The user can control the histogram resolution (R) to improve object classification. Figure 5 shows a set of histograms of an object for varying resolutions.
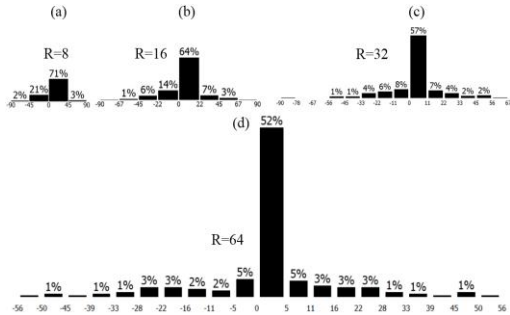

Figure 5. Varying resolutions for an object: (a) 8, (b) 16, (c) 32, (d) 64.

Creating a shape base

One stage of classification is to create a wide shape base that will be used for shape recognition.

From all objects selected to one class, we created average histograms for three main classes: architecture, clouds, and caves (Fig. 6).
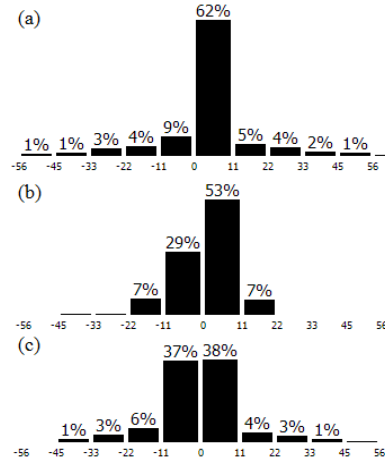

Figure 6. Main histogram classes: (a) architecture, (b) clouds, and (c) caves.

Our method produced different histograms for all of tested classes and in the next step it helps in recognition based on comparison of main classes with randomly generated objects using a calculation of Mean Squared Error (MSE).

4. RECOGNITION

We have tested our method using a database of 60 objects consisting of 20 caves, 20 clouds, and 20 architectural buildings. All objects were recognized correctly. Here, we are showing only a few selected objects from each class. Based on the average histograms, it was possible to recognize new objects (Figs. 7-9).

Figure 7. An example objects recognized as architecture.
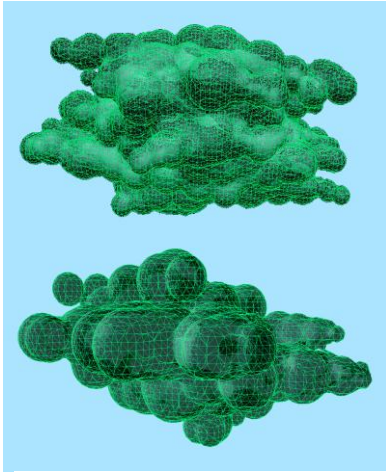
Figure 8. An example objects recognized as a clouds.
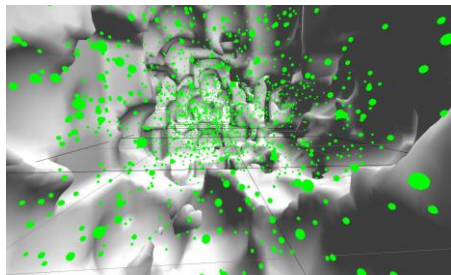
Figure 9. An example object recognized as a cave – view directly from editor.

5. SUMMARY

In this article new approach for analysis and classification of meshed models was presented. The method was evaluated on a database containing shapes generated by hybrid of shape grammar and morphing. 3D-meshes were created from functional description of implicit objects. That technique did not produce predictable results because generated set of points and triangles dependent only on mesh density – sampling.

The 3-D classification method based on histograms of the number of vertices and the angles between them. The method was able to group different models and then assign them to the pre-selected classes. The method achieved the best results for $L_D=10$ but it can be useful for every values of the L_D parameter. The metric can be used in identifying any three-dimensional shapes with hard-surfaces. In future work, we plan to extend the database and improve selection of angles for more detailed objects having most angles between (-10 and 10 degree) for a better classification.

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