

## Perceptual LOD under Low Resolution Conditions\*

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In this paper, we propose a *Perceptual LOD (Level of Detail)* system based on a skeleton structure by integrating the concepts of the *human perceptual system* and *3D skeletons* into the weighting mechanism of error metrics for mesh simplification. The human reception system refers to the way a human being identifies a graphic object. It consists of “*template-matching theories*”, “*prototype-matching theories*” and “*feature-discrimination theories*”. From the psychological point of view, the 3D skeleton of an object can be considered as an extremely simplified description of its original shape. It provides important visual clues to keep a model recognizable even if it is extremely simplified. The 3D skeleton is extracted from the model by a *DCG (Domain Connected Graph)* algorithm first. In accordance with their alignment to the skeleton structure, the vertices of a given model are hierarchically clustered. *Fuzzy sets* are then adopted to identify the possible prototype from a prototype database. During the model-simplification stage, the weighting value of each vertex is adjusted not only depending on the geometric and topological information, but also on those perception-oriented considerations. A preliminary experiment result shows that our method is effective for shape-preserving with low resolution LOD.

**Keywords:** computer graphics, level of detail, 3D skeleton, human perceptual system, QEM

### 1. INTRODUCTION

In the field of computer graphics, the models of 3D objects are often represented in the form of polygons. For representing more realistic visual effects, numerous polygons are often used in CG scenes and VR environments. Obviously, the more polygons adopted, the higher rendering cost is required. Yet, it is not always possible to keep up with the demands for high-resolution models even with rapidly developing hardware. In such a circumstance, there have been many studies suggesting that LOD can improve graphic generation rates by reducing system loads effectively [1-5].

The main purpose of LOD is to reduce these computational costs at the rendering stage by switching among the multi-resolutions of 3D models according to the current needs of the system and environment. The fundamental concept is to compress the complexity of scene by reducing the number of polygons, according to the projected size of an object on the screen, and the requirements of the system and environment. However, the appearance of an object will certainly become coarser while the resolution of model is reduced. Therefore, simultaneously simplifying the complexity of models and preserving the shape of objects is a very important research issue for LOD.

In this paper, we propose a Perceptual LOD (P-LOD) system based on a skeleton structure. The key point of our approach is to integrate the concepts of the human percep-

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tual system and 3D skeletons into the weighting mechanism of the error metrics for mesh simplification. The rest of this paper is organized as follows. In section 2, related works are briefly explained. In section 3, our system configuration and algorithms are described. In section 4, experiment results are shown. Finally, we conclude in section 5.

## 2. RELATED WORKS

In this section, first, we briefly discuss the previous works on LOD algorithms. Then, the pattern recognition theories of human beings and the concepts of fuzzy set are introduced.

### 2.1 Level of Detail Algorithms

There is a great amount of research regarding LOD. One of the most representative continuous LOD methods is the Progressive Mesh [5, 6]. In PM, the sequence of collapsing is pre-calculated and recorded so that the computing time is greatly reduced during run time.

Later, D. Luebke *et al.* integrate lots of interesting concepts such as local illumination, screen-space projection, visibility culling, and silhouette boundaries into a system to solve the model simplification problem [7]. These advanced approaches take current viewing parameters into account to select the best representation for the current view. Therefore, view-dependent LOD methods have better granularity than continuous LOD because they allocate polygons where they are most needed.

Among the various related works, the Quadric Error Metric (QEM) algorithm is one of the most representative view-independent LOD methods [1]. The QEM algorithm was published by M. Garland and P. Heckbert of Carnegie Mellon University. The quadric error calculation is represented by the sum of squared distances to its planes. In order to reduce computation costs, these fundamental quadrics are summed together, and an entire plane is represented by a single matrix,  $Q$ . The algorithm is briefly summarized as below:

1. Compute the error matrices,  $Q$ , for all the initial vertices.
2. Select all valid pairs.
3. Compute the optimal contraction target  $v$  for each valid pair  $(v_1, v_2)$ . The error  $v^T (Q_1 + Q_2) v$  of this target vertex becomes the cost of contracting that pair.
4. Place all the pairs in a heap keyed on cost with the minimum cost pair at the top.
5. Iteratively remove the pairs  $(v_1, v_2)$  of least cost from the heap, contract this pair, and update the costs of all valid pairs involving  $v_1$ .

QEM is a very successful view-independent LOD method because it integrates LOD with the factors of Human Visual System. However, for the perception model of humans, there are various kinds of information being interpreted by human brain to “measure” and “recognize” the shape of objects. In another words, in addition to the geometric errors, other information extracted from the shape should also be taken into consideration for LOD algorithm.

To improve the performance of the conventional QEM method, Kho and Garland proposed a user-defined simplification method [8]. By strengthening the user-assigned weight-

ing value and adopting a constraint quadric, their method can preserve the designated region during the simplification process. This approach relies on the appropriateness of user's decision.

Lee *et al.* proposed adopting the mesh saliency to further improve the simplified result of QEM [9]. By taking the surface curvature into consideration, the locally protrusive vertex can be preserved effectively.

LOD with perception consideration has been emphasized in recent years [10, 11]. For example, N. Williams pointed out the effect of illumination to LOD. The areas which displayed high contrast retained greater priority. This is due to humans' sense of sight being sensitive to high contrast objects and areas. These approaches improve the effect of simplification by taking the concepts of human visual system into consideration. However, the psychological theories of pattern recognition are still not well-integrated with the LOD systems.

## 2.2 The Pattern Recognition Theories and Fuzzy Set

Pattern recognition is the capability and fundamental operations in a human mind when he/she is identifying an object. Nearly all pattern recognition types can be categorized into the following three types [12]:

- (1) Template-matching Theories: This is the simplest idea. We keep all the outside graphs we encounter in our brains and create an imprint or template of these objects. When the next time these outside graphs appear in front of us, our brains will compare these graphs with the templates stored. When one of the templates matches the graph, identification is achieved.
- (2) Prototype-matching Theories: When we sketch a flower, the flower is not really one that we see in the real world. It is an "average" or "typical" flower that we think of subjectively. However, the difficulty of using this theory is that we are unable to clearly define a typical case of each object. Some psychologists believe that the typical case should be most commonly seen as an object by a particular group of people. For example, the most commonly seen bird in country may be the sparrow or finch, whereas in a city, it may be the pigeon or crow.
- (3) Feature-discrimination Theories: This theory depicts that every object or graph as having its own characteristics or features. Thus, it is necessary to analyze these characteristics or features in order to discriminate the object or graph, and then the value of its features can be identified.

## 3. SYSTEM ARCHITECTURE AND ALGORITHMS

In this paper, we propose the P-LOD based on the 3D skeleton structures. Fig. 1 illustrates our system architecture. Each component will be explained in more detail later in this section.

### 3.1 Extracting 3D Skeleton Structure

From the psychological point of view, the 3D skeleton of an object can be considered

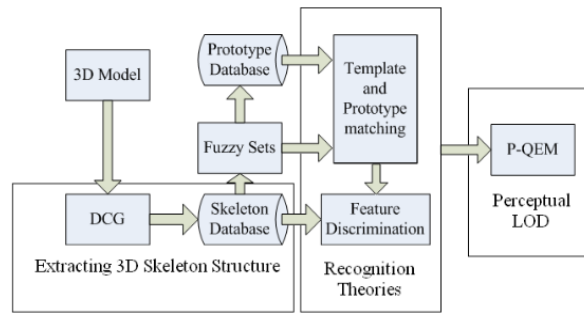


Fig. 1. The system architecture of P-LOD.

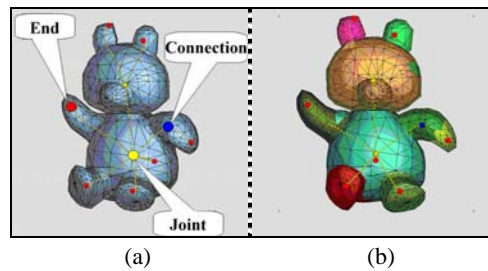


Fig. 2. (a) Teddy with DCG skeleton; (b) Model segmentation.

as an extremely simplified description of its original shape. It provides important visual clues to keep a model recognizable even while it is extremely simplified.

Therefore, a good skeleton result is necessary to improve the result of model-simplification with very low LOD to the original 3D object. To extract a 3D skeleton structure from the original input model, there are several algorithms reported [13-15]. For our research convenience, we adopt the DCG algorithm to implement our prototype system.

There are two advantages for us to adopt DCG algorithm. First, by using DCG, it is quite intuitive to hierarchically segment the model into featuring regions as a combination of main body and branches, since DCG classifies the skeleton nodes as joint points, end points, and connection points (Fig. 2 (a)).

Second, the domain ball approach helps us to cluster vertices. All of the vertices inside or on the boundary surface of a domain ball belong to the same skeleton node, which is the center of the domain ball. In this way, the vertices of model are hierarchically clustered in accordance with their alignment to the skeleton structure. Boundary points between domain balls are used to divide the model (Fig. 2 (b)).

### 3.2 Template, Prototype, and Fuzzy Sets

By adopting DCG, we extract the skeleton from a 3D model. A DCG skeleton consists of three types of nodes; joint points, connection points, and end points. The joint point represents the main body. This is especially true in the case of animals. Generally speaking, there are one to three joint points depending on the appearance of a model. The end point represents the branch. According to the psychological point of view, the number

of branches is also an important visual clue for recognition. The connection point is used to indicate the curvy nature of the 3D shape.

### 3.2.1 Template

We simulate the template of a model by constructing an abstraction which uses basic geometric primitives to replace the line segments between adjacent skeleton nodes. This abstraction suggests the possible lowest resolution of LOD, that is, the estimated smallest number of vertices which are necessary to be preserved for the “most simplified model”. In other words, if the model is further simplified so that its resolution becomes under the lower bound, it may become difficult for users to make a feasible identification.

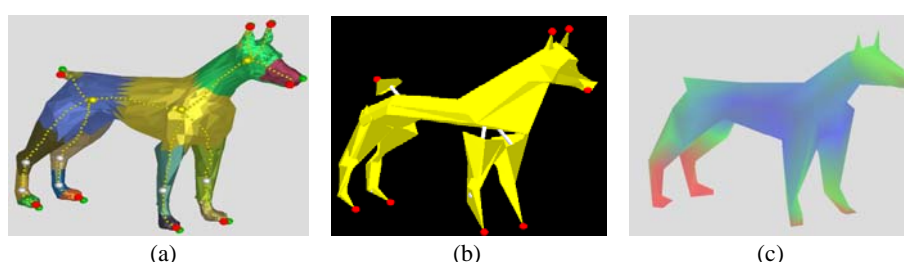


Fig. 3. (a) Dog model with DCG skeleton; (b) Abstraction; (c) P-LOD with 102 vertices.

Fig. 3 illustrates an example of the above concept. Based on the DCG skeleton (Fig. 3 (a)), we use hexagonal prisms and hexagonal pyramids as the geometric primitives to construct the abstraction model (Fig. 3 (b)). The minimal number of vertices is determined to estimate the lower bound of simplification. As shown in Fig. 3 (c), the dog model is simplified to contain only 102 vertices while remaining recognizable.

The usage of hexagonal prisms and hexagonal pyramids in the above example is not deterministic. In fact, different geometric primitives may better suit different shapes. Also, the lower bound of retained surfaces should change according to the type of geometric primitives used to abstract the object or model. More research efforts are necessary to determine the appropriate type of geometric primitive. One possible solution is to use the volume information of each subpart, as was used to determine bounding volume [17].

### 3.2.2 Prototype and fuzzy set

A prototype sometimes is referred to as a typical case. The prototype of a group of models comes from the average of this group. However, it is very difficult to perform this average operation to multiple 3D surface models directly. Therefore, instead of generating the prototype directly, we construct the prototype skeleton by calculating and averaging the following values first:

1. The distance,  $EJ$ , is measured between the end point and closest joint point along the skeleton.
2. The domain ball radius of each joint point is determined. Domain balls are produced based on Voronoi diagram, and refined by MAT [13].

Using the average domain ball radius of each joint point and the lengths, EJs, we calculate the fuzzy attribute values of proportional similarity by the following algorithm.

- (a) Find out the number of end points as  $x_1$ , and the number of joint points as  $x_2$ .
- (b) The average domain ball radius of each joint point is  $d_1$ , and the summation of lengths EJs is  $d_2$ . Let  $x_3 = d_2/d_1$ .
- (c) Giving the feature values of another model as  $x'_1$ ,  $x'_2$ , and  $x'_3$ , respectively. The function of each feature will be:

$x_i \in X, i = 1, \dots, 3, X$  is the world set.

$$A_1: X \rightarrow [0, 1], A_1(x_1) = \exp\left(-\left|\frac{x_1 - x'_1}{5}\right|\right) \quad (1)$$

$$A_2: X \rightarrow [0, 1], A_2(x_2) = \exp\left(-\left|\frac{x_2 - x'_2}{10}\right|\right) \quad (2)$$

$$A_3: X \rightarrow [0, 1], A_3(x_3) = \exp\left(-\left|\frac{x_3 - x'_3}{100}\right|\right) \quad (3)$$

Outputs (proportional similarity of model to prototype)

- (a) Similarity is  $s \in S_1 = [0, 1]$ , where:  
0: the lowest similarity;  
1: the highest similarity.
- (b) Fuzzy rules:  $A_1 \times A_2 \times A_3 \rightarrow S_1$ . (4)
- (c) Set the membership function for proportional similarity:

$$S_1(s) = \frac{A_1(x_1) + A_2(x_2) + A_3(x_3)}{r}, \quad (5)$$

where  $r$  is the number of featuring functions.

### 3.3 Feature Discrimination

We analyze the model based on its skeleton from the view point of the perception model. Weighting value of each vertex is adjusted not only according to the geometric and topological information, but also the above-mentioned perception-oriented considerations.

We modify the QEM algorithm to compute the quadric error and implement our LOD methods. The importance of a vertex is decided by the  $Q$  matrix. If we adjust the contents of a  $Q$  matrix, it will then affect the sequence of edge contraction. In the previous section, we found out the significant featuring regions and points via the 3D skeleton. Therefore, we should retain these points during simplifying the model by assigning certain vertices with higher weighting value and adjusting the  $Q$  matrix.

The QEM algorithm selects all valid vertices pairs of model and places all of the pairs in a heap to choose the minimum cost pair. By iteratively removing the pair with the minimum cost, the model is simplified in a greedy method manner. However, this way of collapsing vertex-pairs with the minimum cost is not guaranteed to be appropriate for feature-

preservation.

In our algorithm, we re-evaluate the weighting values of  $Q$  metrics by re-considering the meaning of each vertex from the points of a human perception model. As mentioned above, according to the information that is provided by the skeleton structure, we can segment the model into several featuring regions which are also coincident with the topology of the model. Every region has different properties, and the relationships between regions represent the topology of a model. Therefore, during the operation of edge contraction, our system will try to delay the selection of the edge as a valid candidate, if collapsing this edge will cause the model to lose its topological relationships.

### 3.3.1 Terminal vertices

By analyzing the relationship between the skeleton structure and the prototype, the branches with important features are determined. From a psychological point of view, the number of branches is also an important visual clue for recognition. Thus, it is very important to retain as many of these branches as possible during model simplification. The vertex which is nearest to the intersection point of the model and the ray shot from the end point is used as the terminal vertex. The terminal vertex is adjusted to have the highest weighting value in our system. (Fig. 4 (a))

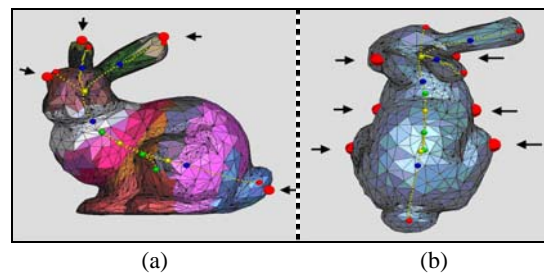


Fig. 4. (a) Terminal vertices; (b) Volumetric vertices.

In addition to the terminal vertices, we preserve the basic shape of each branch by using the information of the abstraction. The priority of each branch is adjusted according to its volume proportion.

### 3.3.2 Volumetric vertices

We also assign volumetric points, which are related to the skeleton, with higher weighting values during simplification. To implement this idea, we shoot several rays from the viewer to the joint points of skeleton. The vertex which is nearest to the intersection point of the model and this ray is used as the volumetric vertex. We can retain the thickness of model by adding the weighting values of these points. (Fig. 4 (b))

Due to the view independence of this operation, changes in camera angle require recalculation. By preserving the volumetric information of the model, overall shape curvature can be approximated. This approach prevents the appearance of flattening of the simplified model, allowing shading effects to be taken into account for recognition.

## 4. EXPERIMENT RESULT

### 4.1 Comparison Between the P-LOD and Traditional LOD with QEM

We will show our simplified result and comparison with the traditional QEM algorithm. Additionally, we will also offer the statistic outcome from our surveys. We designed a questionnaire with sets of questions to verify our experiment results. This test was completed by 80 visitors. Based on the results of this survey, the following graphs show comparison between perception-oriented LOD and conventional LOD using QEM.

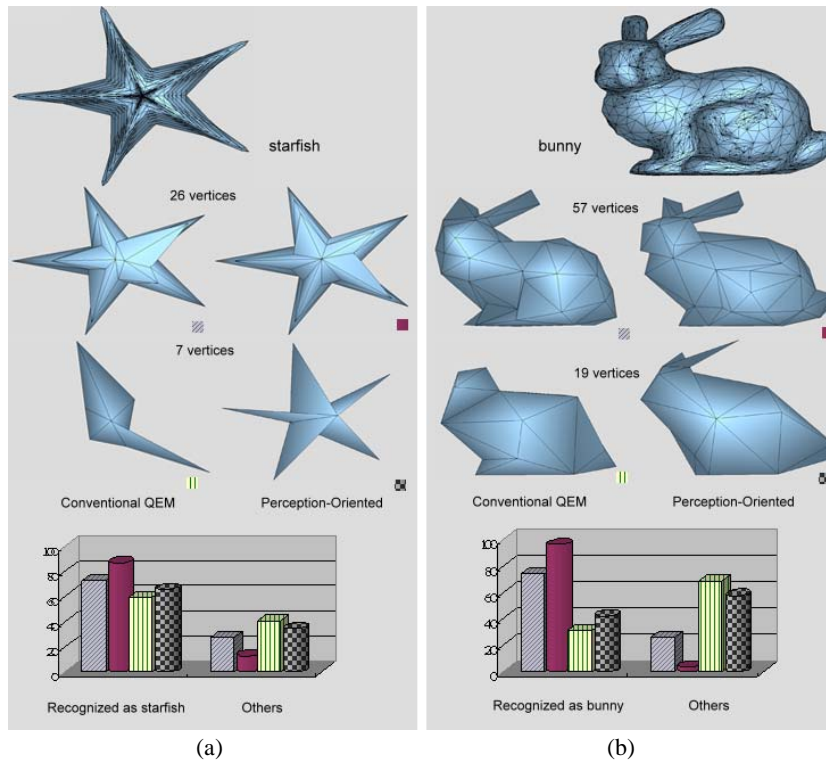


Fig. 5. (a) Comparison of starfish; (b) Comparison of bunny.

For the model of the bunny as shown in the experimental results, when the total number of vertices is reduced to 57, the conventional QEM begins to eliminate the vertices of the ears (which are considered very important features of a rabbit). On the contrary, PQEM can still preserve the basic appearance of the whole head. The conventional QEM will lose both ears completely when only 19 vertices are retained. However, PQEM can still keep the ear features until 15 vertices are retained.

In another example of the starfish, the conventional QEM begins to lose parts of the arms while the model is simplified to have 7 vertices. Under the same condition, PQEM can still guarantee all five arms being presented.



#### 4.2 Building the Prototype of a Group of Models

The skeleton and the related abstraction of the prototype for large cat species is obtained by averaging from four models; a lion, a tiger, a leopard, and a saber-toothed tiger. Fig. 6 illustrates these models and the abstraction of the prototype.

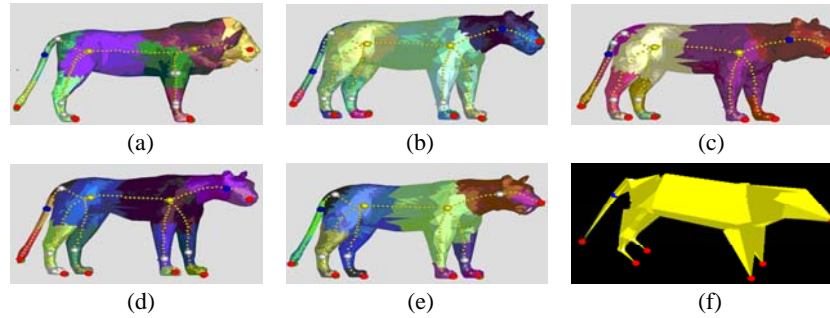


Fig. 6. The models of large cat species.

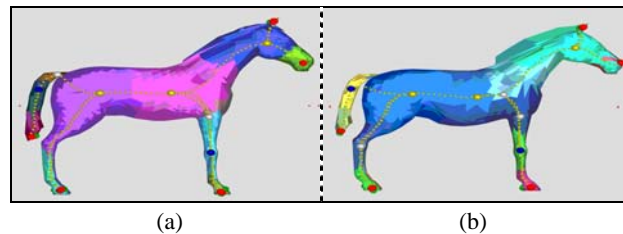


Fig. 7. (a) Horse\_A model; (b) Horse\_B model.

#### 4.3 Finding the Possible Prototype by Using the Membership Function for Proportional Similarity

Take the Horse\_A model shown in Fig. 7 (a) as the prototype. The DCG skeleton is extracted to determine the length of each section and the domain ball radius of each joint point.

The result of  $x_1 = 8$ ,  $x_2 = 3$  and  $x_3 = 83.17$  is obtained based on the fuzzy rule. Then, the Horse\_B model shown in Fig. 7 (b) is used as the target to determine the similarity.

Then the result of  $x_1 = 8$ ,  $x_2 = 3$  and  $x_3 = 92.49$  is calculated. Substitute this set of data from Horse\_B and prototype model data from Horse\_A for comparison in the algorithm, to obtain a similarity of = 0.97.

Perform the similarity comparison to the dog model used in Fig. 3 and those models of the large cat species shown in Fig. 6 with the Horse\_A model to obtain the following similarity comparison chart. As shown in Table 1, the Horse\_B model has a better similarity value to the prototype of Horse\_A in comparison with other models.

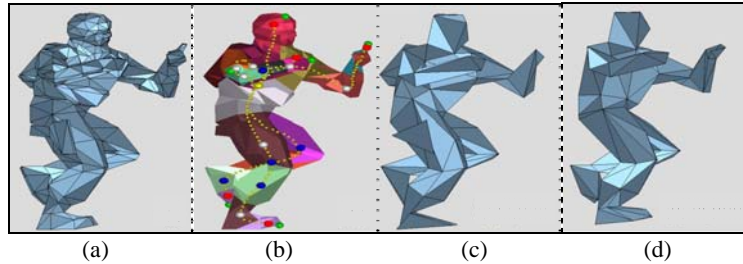
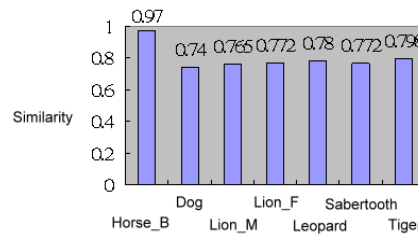
**Table 1. Similarity comparison chart to prototype Horse\_A.**

Fig. 8. (a, b) The human model and its DCG skeleton with a backpack and pistol; (c, d) Images with resolution reduced to 181 faces.

#### 4.4 The Limitation of the Described Method

The skeleton extraction algorithm sometimes ignores the additional subparts, or accessories of models, if these subparts are not obviously protruding. For example, the backpack and pistol (carried on the belt) of the human character shown in Fig. 8 may be discarded while constructing the DCG skeleton. This fact can cause the vertices on these subparts be simplified and removed at an earlier stage when our Perceptual QEM is adopted, as compared with the simplification sequence of conventional QEM. In instances where subparts are not crucial to recognize the model, early elimination will not cause serious problems. However, sometimes the existence of a pistol may be important information for users (for example, to determine whether the character is a civilian or armed). Providing this information presents an obvious challenge in these circumstances, and currently requires manual assignment of weighting values to resolve.

In addition, the texture of a model is another key feature of the human recognition mechanism [16], and is another important issue to be considered for LOD.

Furthermore, there are obvious differences existing between the skeleton extracted from 3D models and the anatomical structure of real animals. The extracted skeleton is always aligned with the center axis of the volume. However, the anatomical skeleton tends to be located near the back side of the torso. Therefore, it is an interesting research issue to further explore and implement an anatomical skeleton to specialize an LOD algorithm for life forms.

## 5. CONCLUSION

In the field of computer graphics, the relative algorithms of model simplification usu-

ally take the property of topology to be the essential consideration. However, a result of simplification that has the lowest quadric error may not be in agreement with the result of the visual perception, since the cognitive activities are much more complicated than just taking the property of topology into consideration.

In this paper, we not only propose an effective approach to improve the QEM under lower resolution, but also show the importance of reconsidering the basic issue of LOD by introducing features of human recognition. One of the key features is the 3D skeleton structures of models. Therefore, we provide a method to integrate the weighting mechanism of LOD with the concepts of DCG skeletons. The experiment results show that our research direction is correct.

In addition, we propose a reasonable lower bound estimation for the minimum numbers of retaining vertices, while still preserving the recognizability of extremely simplified models. This information may be used for estimating the lower bound of a scene's complexity to manage the rendering performance of the system.

The traditional QEM method is still a very good LOD algorithm under most of the resolutions, since the property of geometry is also an important factor to shape recognition. However, when the resolution becomes substantially low, there is no guarantee for QEM to preserve the features of the shapes for observers to recognize the original models. By contrast, the P-LOD generated by our algorithm preserves more characteristic features of the model to the observers. We will continue to improve the perception-oriented simplification algorithm by adopting more complicated psychological perception models.

The performance of our P-LOD algorithm greatly depends on the quality of 3D skeleton. A better set of skeletons will certainly provide a better result for model simplification. However, there are still some problems remaining unresolved for the 3D skeleton generation of arbitrary models. More research effort is necessary to introduce more skeleton-extraction algorithms into our system. Furthermore, developing a sketch-based GUI for users to assign the skeleton structure manually is also an interesting direction.

## REFERENCES

1. M. Garland and P. S. Heckbert, "Surface simplification using quadric error metrics," in *Proceedings of ACM SIGGRAPH*, 1997, pp. 209-216.
2. J. D. Cohen, "Concepts and algorithms for polygonal simplification," in *Proceedings of ACM SIGGRAPH Course Tutorial #20*, 1999, pp. C1-C34.
3. D. Luebke, "A developer's survey of polygonal simplification algorithms," *IEEE Computer Graphics and Applications*, Vol. 21, 2001, pp. 24-35.
4. T. K. Heok and D. Daman, "A review on level of detail," in *Proceedings of International Conference on Computer Graphics, Imaging and Visualization*, 2004, pp. 70-75.
5. H. Hoppe, "Progressive meshes," in *Proceedings of ACM SIGGRAPH*, 1996, pp. 99-108.
6. H. Hoppe, "View-dependent refinement of progressive meshes," in *Proceedings of ACM SIGGRAPH*, 1997, pp. 189-198.
7. D. Luebke, M. Reddy, J. D. Cohen, and A. Varshney, *Level of Detail for 3-D Graphics*, Morgan Kaufmann, San Francisco, 2002.

8. Y. Kho and M. Garland, "User-guided simplification," in *Proceedings of ACM Symposium on Interactive 3D Graphics*, 2003, pp. 123-126.
9. C. H. Lee, A. Varshney, and D. Jacobs, "Mesh saliency," in *Proceedings of ACM SIGGRAPH*, 2005, pp.659-666.
10. D. Luebke, B. Hallen, D. Newfield, and B. Watson, "Perceptually driven simplification using gaze-directed rendering," Technical Report No. CS-2000-04, Department of Computer Science, University of Virginia, 2000.
11. N. Williams, D. Luebke, J. D. Cohen, M. Kelley, and B. Schubert, "Perceptually driven simplification of lit, textured meshes," in *Proceedings of ACM Symposium on Interactive 3D Graphics*, 2003, pp. 113-121.
12. C. M. Cheng, "The human graphical recognition system," *Science Monthly*, Vol. 13, 1982, pp. 14-22.
13. F. C. Wu, W. C. Ma, R. H. Liang, B. Y. Chen, and M. Ouhyoung, "Domain connected graph: The essential skeleton of a 3D shape," *The Visual Computer*, Vol. 22, 2006, pp. 117-135.
14. N. D. Cornea and D. Silver, "Curve-skeleton properties, application, and algorithms," *IEEE Transactions on Visualization and Computer Graphics*, Vol. 13, 2007, pp. 530-548.
15. O. K. C. Au, C. L. Tai, H. K. Chu, D. Cohen-Or, and T. Y. Lee, "Skeleton extraction by mesh contraction," *ACM Transactions on Graphics*, Vol. 27, 2008, pp. 44.1-44.10.
16. H. Hoppe, "New quadric metric for simplifying meshes with appearance attributes," in *Proceeding of IEEE Visualization*, 1999, pp. 59-66.
17. J. S. Chang, A. C. C. Shih, H. R. Tyan, and W. H. Fang, "Principal component analysis-based mesh decomposition," in *Proceedings of the 9th IEEE Workshop on Multimedia Signal Processing*, 2007, pp. 292-295.



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