Uniform Sampling in Geodesic Metric for LOD Generation

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Abstract--**This paper describes a level-of-detail generation approach for large scale models. To make LODs preserve the overall appearance of original data, the presented approach is to perform uniform sampling in geodesic metric, resulting in adaptive meshes or points in Euclidean metric. Geometric attribute such as curvature help to establish geodesic metric and therefore control the sampling ratios in different regions. This method is rather simple and LODs are very fit for display. Some cases are provided to illustrate the capability and feasibility of the method for both meshes and unorganized points.**

Index Terms--**LOD, Geodesic Metric, Poisson Disk, FPS, Adaptive Sampling**

Ⅰ. INTRODUCTION

The fast growing popularity of laser scanners makes capturing 3D information of object simple and efficient. Visualizing and processing large amount of data have been a challenge due to the limitation of computer's capacity. Therefore, building LODs retaining fine details for the unorganized points and meshes can make rendering suffer little loss in details and be processed faster (Luebke, 2003).

Many approaches about LOD generation have been proposed in computer graphics society during past decade (Garland, 1997; Hoppe 1996; 1997; Hu, 2009; 2010). Their main purpose is to improve rendering speed, to compress models, to transfer data efficiently and to reduce the cost of geometric calculation. To date, most of those approaches are devised for generating LODs of meshes. For unorganized points, less related reports can be found. The main reason, we think, is that the original mesh can provide some basis for mesh models' LOD generation which isn't existed in unorganized points. Thus, generating LODs of unorganized points is the main motivation of this paper.

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The rest of this paper is organized as follows. Section 2 simply reviews LOD generation methods. Section 3 presents two famous uniform sampling algorithms which can be used in our method. In section 4, we apply uniform sampling to generate adaptive results by introducing weighted geodesic metric. Some experiments are conducted and results are discussed in section 5. At last, conclusion and possible future research are listed in section 6.

Ⅱ. RELATED WORK

This review tries to include important LOD generation methods. View-dependent approaches allow localized changes in resolution according to the viewing position in rendering. Their objectives are different from this paper, so we will not include them. Iteratively remove part of vertexes is a natural approach for LOD generation which is firstly introduced in (Schroeder, 1992). The decision whether to remove a vertex or not is based on the distance from the vertex to the plane determined by its neighbors. Vertices in smooth regions are preferred for removal. Simplification envelope is another similar approach (Low, 1997). Vertex clustering is to build a uniform grid of rectilinear cells, merge all vertices within a cell, and then compute a representative vertex to merge all triangles and edges. Each time a vertex and its incident triangles are removed, a hole is created, which should then be remeshed (Tan, 2004).

Edge collapse may be the most popular mesh's coarsening operation (Hoppe, 1996; 1997). The edge's vertices are contracted to a single one, thereby deleting this edge and its incident triangles. The merits are that the position of new vertex can be freely chosen and no further triangulation is needed. In general, it involves two decisions: where to place the new vertex; determining the sequence of collapses. This is usually performed implicitly by specifying an error metric (Tan, 2004). Hierarchical clustering is used to partition mesh into locally connected blocks. Hoppe creates a block hierarchy and simplifies the mesh portions in the leaf blocks. After the simplification, the leaf blocks are hierarchically merged and then simplified again. The process is repeated till the whole mesh is stored in the

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root cluster (Hoppe, 1998). The drawback is that all determinations are strictly based on local decisions and thus an assignment made early in the process mayn't be correct.

The idea behind those coarsening methods is to merge nearly coplanar faces into a large face or cluster vertexes into a new vertex. When multi-factors are involved in optimizing substitute vertex or modifying mesh, the computation is usually complex. Then, various techniques about management of memory and data structure have been researched. Even so, those algorithms are still not flexible and effective. To overcome them, this paper will investigate a sampling strategy which is uniform sampling under geodesic metric. It is not the different of sampling method in different metric, but we place the points or meshes into a new metric in which the distribution of points is related to the surface's variations of object. Compared with other methods, it is rather simple and robust results can be easily obtained.

Ⅲ. UNIFORM SAMPLING METHODS

Two popular sampling algorithms in image processing should be Poisson disk sampling and farthest point strategy (FPS). FPS iteratively places a new point at a time in the center of the emptiest region, which should be with largest amount of information (Elder, 1993). As shown in Fig.1, Voronoi diagram is devised to find this center in 2D Euclidean space. In non-Euclidean metric, Moenning proposed fast marching to find the farthest points on meshes. Its basic sampling process is as follows. Each sample can be taken as a source and its fronts approach outwards. When several fronts meet, meeting points can be saved in a max-heap according to the time they meet. The root of the max-heap is the farthest point and taken as the new sample (Moenning, 2003).

Poisson disk sampling intends to obtain samples that the distance between two arbitrary samples is more than a given value. It means that samples' distribution is random and uniform. Dart-throwing keeps throwing point onto the space to be sampled randomly one by one, rejects if it doesn't satisfy the specified separation from generated points. This process continues till no more points can be inserted. As shown in Fig.2, each black disk is a sample's disk, which is also the forbidden area for the new samples. When the plane is wholly filled with black, the sampling process is over. This method is straightforward, yet it may be too slow when lots of samples are required. Then, some alterations have been proposed which include tile-based methods, relaxation schemes and etc (Lagae, 2007). In our application, the situation has some difference from the common circumstances in that the pooled samples are finite. That is to say, the thrown sample must be one of original points. Thus, we can determine if the thrown point can be accepted or not according to the point's mark which represents if the point is located in forbidden regions. Accordingly, we can see those two sampling methods are substantially identical that is the new sample should be far from existed points. In practical applications, they can obtain similar results. Yet, the computation complexity of FPS is much more than that of Poisson disk which will be discussed in section 5.

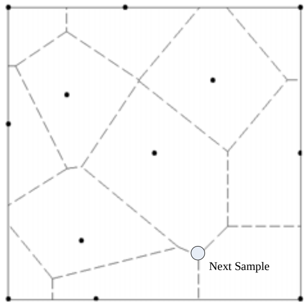


Figure 1. FPS sampling.

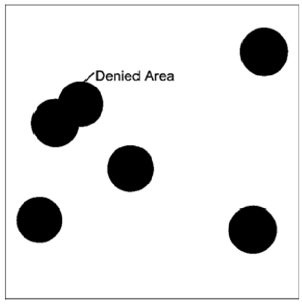


Figure 2. Poisson disk sampling.

Ⅳ. UNIFORM SAMPLING IN GEODESIC METRIC

When uniform sampling methods are used to perform coarsening for meshes or unorganized points in sense of Euclidean metric, LODs with uniformly distributed samples can be obtained. Yet, this isn't an efficient way since LOD means the degree of closeness between original and simplified model. In another word, the desired LODs should have more samples in regions with details, and vice verse. So, the nature idea for LOD generation is to establish a non-Euclidean metric in which the distribution of points can represent surface's variations of object. When uniform sampling is performed in new metric, adaptive samples can then be obtained in Euclidean metric. Geodesic distance builds a surface metric for unorganized points and meshes. In geodesic metric, if two points with certain Euclidean distance are located in smooth regions, the geodesic distance is close to their Euclidean distance; if they are located in rugged regions, it should be more than their Euclidean distance. Considering that, our method comes into nature by combining uniform sampling method and geodesic metric.

A. Weighted Geodesic Distance

In general, geodesic distance between two neighbor points i and j is approximated with their Euclidean distance. Geodesic distance between two arbitrary points can be estimated by adding up all geodesic distances along the shortest path connecting them. To further control the sampling ratios in different regions, we prefer to weighted geodesic distance. The weight is related to geometric attributes and can be easily adjusted. As an example, we take point's curvature to compute weight. For each point, its curvature is

$$v_i = \sum_{j=0}^{k} (1 - |n_i \cdot n_j|) / k . \quad (1)$$

In formula (1), k is the number of neighbors, n_i and n_j is the normal of point i and j, j represents neighbor of i. Then, weighted geodesic distance between i and j is defined as

$$g_{ij} = f(v_i - v_j) \cdot S_{ij} . \quad (2)$$

In equation (2), v_i and v_j are the curvature of i and j, g_{ij}, S_{ij} represents the weighted geodesic distance, Euclidean distance between them. Consequently, weighted geodesic distance between two arbitrary points can be approximated by adding up all weighted geodesic distances along the shortest path connecting them. In the experiments, formula (3) is used to compute weight in this paper, in which c adjusts the sampling ratios in different regions.

$$f(v_i - v_j) = \exp(pow(|v_i - v_j|, \quad c)) . \quad (3)$$

B. Weighted Geodesic Distance Computation

Geodesic distance computation is a well-researched problem. Among all situations, we only concern the case of "one source, all destinations". That is to say, we want to find the farthest point for FPS and find points within certain weighted geodesic distance from a point for Poisson disk sampling. This has been transformed into the problem of solving Eikonal equation (Falcidieno, 1993). Fast marching considers upwind, entropy-satisfying finite difference approximations to the equation. Then, it provides an efficient algorithm for geodesic distance computation on meshes. So, fast marching is used in mesh cased LOD generation in this paper.

Dijkstra is a graph search algorithm that solves the single-source shortest path problem for a graph with nonnegative edge path costs (Cormen, 2001). It is therefore an efficient algorithm for computing geodesic distance in case of unorganized points. When the data is in great amount, Dijkstra can't be used due to great memory and computation time is demanded. So, it is mainly applied when Poisson disk sampling in unorganized points since the computation complex and memory consumption is relative less. In this case, Dijkstra is to find the shortest paths from a source node to other nodes by stopping propagation when the geodesic distances of the current nodes exceed the radius of disk. Note that propagation should approach on point set using k-NN strategy.

Fast marching and Dijkstra share same idea that is information just propagates from smaller one to large one. For unorganized points, neighbors refer to points in notion of Euclidean vicinity. Yet, in case of mesh, neighbors represent points which are directly connected with current point. This is the main difference between them.

C. Outline of Algorithm

The implementation of FPS sampling in geodesic metric can be devised according to (Moenning, 2003; Peyre, 2006), we will not discuss it. The main steps of Poisson disk sampling for LOD generation are as follows:

- Establish k-d tree for point set and set disk's radius.
- Mark all nodes as unvisited. Randomly sample a point from points. Set this point as current and accepted.
- Take current as source, finding points whose geodesic distance to the source is less than radius using Dijkstra for unorganized points and fast marching for meshes. Set those points as visited.
- Randomly sample a point from unvisited points, set it as current and accepted, return back to step 3. If there are no unvisited points, break loop.
- Accepted points are the sampling results.

Finding the points within geodesic distance from a point using fast marching or Dijkstra can be described as follows.

- Assign to each node a geodesic distance. Set it to zero for source node and to infinity for all other nodes.
- Mark all nodes as unvisited. Set source node as current.
- For current node, calculate its neighbors' tentative weighted geodesic distances. If each of geodesic distances is less than the previously recorded value, overwrite it.
- If the geodesic distances of current node's neighbors are all not infinity, mark current node as visited. Visited node will not be checked again, its geodesic distance recorded now is the final.
- If all nodes have been visited, or the geodesic distance of current point is more than radius of disk, finish. Otherwise, set unvisited node with the smallest geodesic distance as the next current node and return to step 3.

In step 5, if point which has smallest geodesic distance is taken as current node only, it will result in more computation time. We usually take some nodes with less geodesic distances from unvisited nodes as current nodes in the algorithm's implementation. This may be the compromise between computation efficiency and accuracy of geodesic distance.

Ⅴ. EXPERIMENTS AND ANALYSIS

Experiments on different 3D point sets and meshes are provided to illustrate the effectiveness of our idea. Formula (3) is used to compute weighted geodesic distance and c is set to 1.0. In computing the normal and curvature of point, we treat all data as unorganized points and set the number of neighbors is 20. When Dijkstra is used to compute geodesic distance in unorganized points, the number of neighbors is set to be 10. Experiments on different parameters will not be discussed since we mainly intend to introduce our idea.

A. Uniform Sampling in Geodesic Metric

Fig.3 shows our idea taking Poisson disk sampling as an example. Randomly distributed red points on the model represent the samples and regions with different color are their corresponding disks. Different regions are usually overlapped and each sample is inside its disk only. So, the geodesic distance between neighbor samples must be more than disk's radius. In geodesic metric, the shapes of disks are all circle with same radius. As we can see in Euclidean metric, the disk in smooth region covers larger range which makes the sampling chance be less than that in rugged regions. This is what we propose that uniformly sampling in geodesic metric, resulting with adaptive samples in Euclidean space.

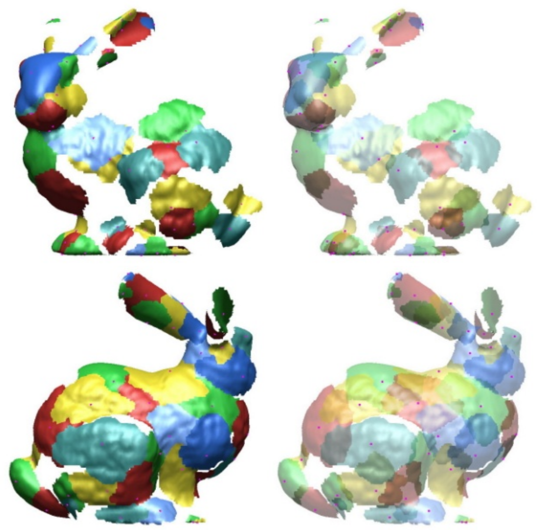


Figure 3. Dragon Point Sets. (a): original 40k points; (b),(c),(d): samples of 20k 10k 5k.

B. Poisson Disk Sampling in Unorganized Points

In this section, we treat all data as **unorganized points**. Dijkstra is used to compute geodesic distances between points. Fig.4 shows the samples of Dragon using Poisson disk sampling under geodesic metric. 4(a) is the original points which are uniformly distributed. Samples in 4(b)-(d) mostly preserve the original details with reduction of sampling rate. Many redundant points in smooth parts are removed.

Fig.5 shows the simplified 3D models of Statuette. The original point's number is about 5M. For the points of LODs, we recovered their 3D models using Geomagic which should be one of best software in computer graphics. There exist relatively less differences among the surface models of 5(a)-5(d), yet the numbers of points have distinctive differences. As shown in 5(e)-5(l), the distributions of samples are wholly adaptive to the surface's variations, which make the LODs preserve the original details better.

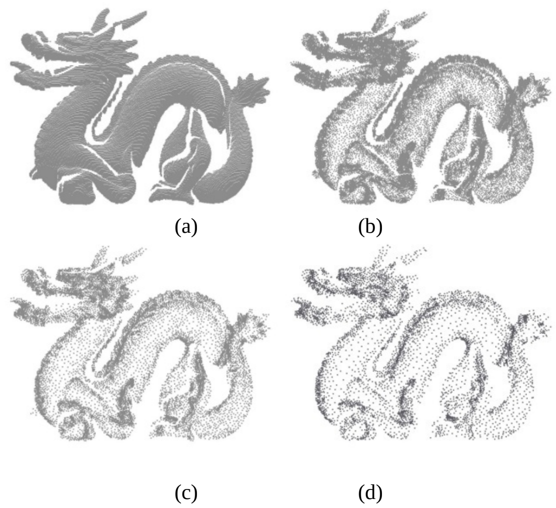
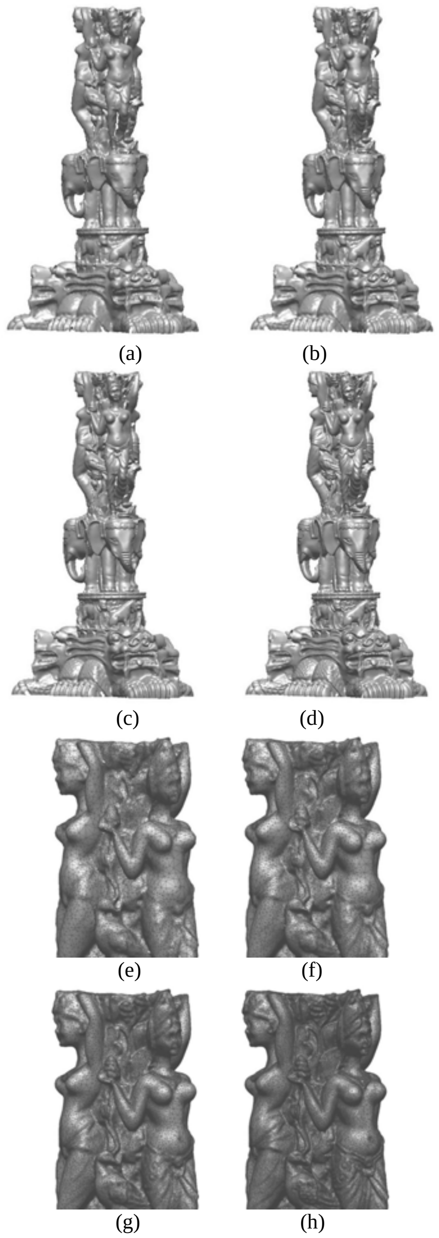


Figure 4. Recovered Model of Statuette. (a),(b),(c),(d): samples of 100k, 150k, 300k and 600k. (e)-(l): parts of mesh models..



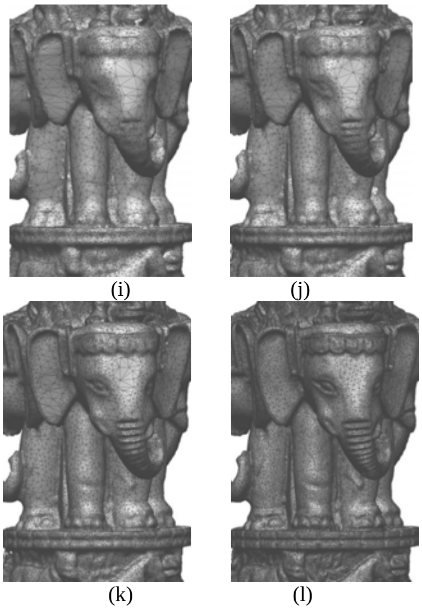


Figure 5. Recovered Model of Statuette. (a),(b),(c),(d): samples of 100k, 150k, 300k and 600k. (e)-(l): parts of mesh models.

Besides the adaptability, other merits of Poisson disk sampling in geodesic metric are that low memory is needed and high efficiency can be obtained. The original point's number of Lucy is about 14M. Then, error metric based LOP generation methods almost can't deal with this data. FPS still can't handle it due to the great requirement for memory and computation. Compared with them, the demanded computation is greatly decreased in Poisson disk sampling. 6(a)-(d) show the LOD mesh models of Lucy. Similar to the results of Statuette, there exist slight differences among mesh models. However, the samples' numbers have distinct differences. Parts of mesh models of Lucy are shown in 6(e)-(l). From them, we can see that our method is actually to find the compromise between adaptive sampling and uniform sampling. Note that original meshes of the tested data aren't used in this experiment.

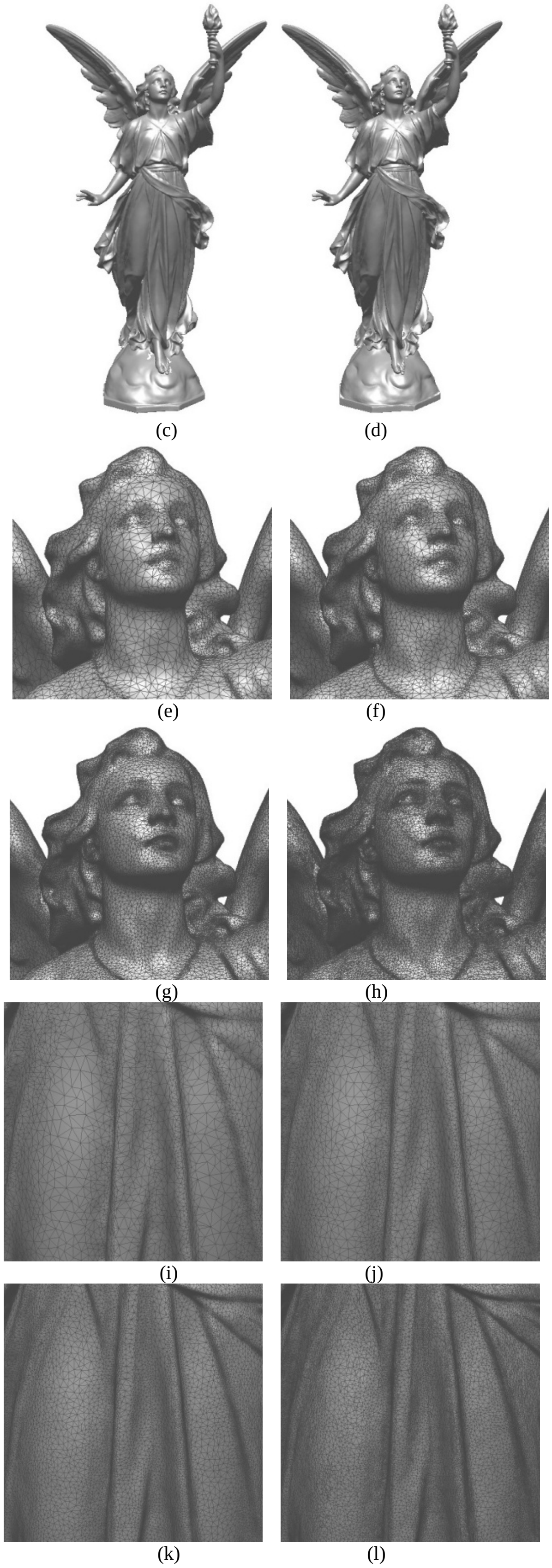


Figure 6. Recovered Model of Lucy. (a),(b),(c),(d): surface model with points of 100k, 200k, 400k and 900k. (e)-(l): local mesh models.

C. Poisson Disk Sampling in Meshes

Digital elevation model (DEM) is widely used in geography information system (GIS) to describe terrain's information. In most situations, DEM is expressed with grid or TIN mesh. Then, fast marching can be used to compute weighted geodesic distance and 4 nearest neighbors strategy is adopted. In order to do comparison, we still perform sampling by taking the vertexes of DEM as unorganized points. The original grid mesh is with 1500×1500 nodes. Fig.7(a)-(d) show the depth maps of terrain when considering the original mesh. 7(e)-(h) are the corresponding depth maps taking DEM as unorganized points. There exist slight differences among those simplified models, which demonstrates the geodesic distances obtained using Dijkstra and fast marching are almost same. In Fig.7, the color becomes duller with height decreasing and the meshes of samples are constructed according to 2D Delaunay rule. Samples can describe terrain with relatively less data. We believe it is a very useful method for terrain's LOP generation.

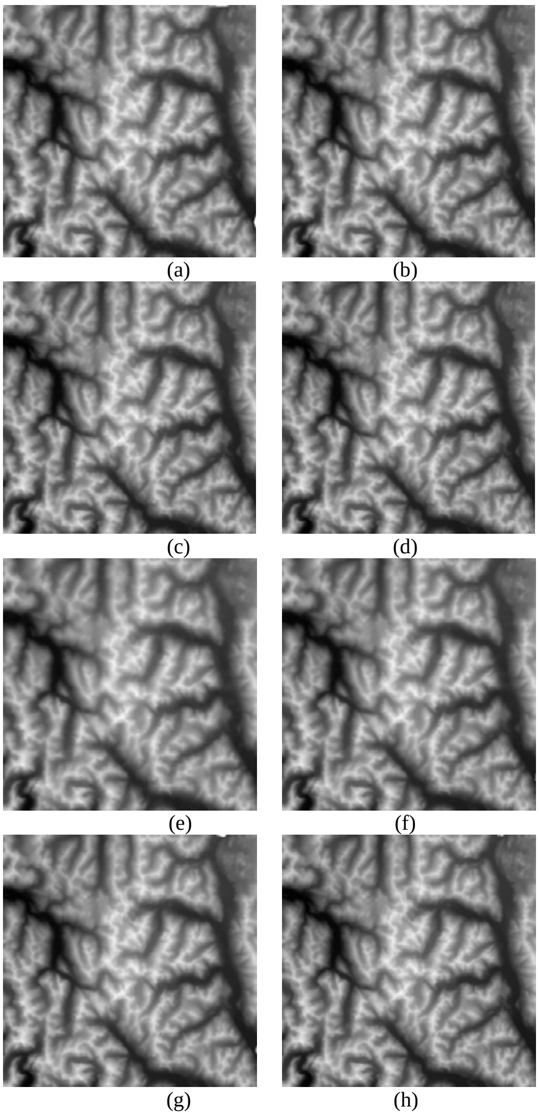


Figure 7. Depth Map of Terrain. (a)-(d): mesh cased simplified models with samples of 1%, 2%, 5% and 25%; (e)-(h): unorganized points cased simplified results corresponding to (a)-(d).

D. FPS Sampling in Meshes

As stated above, FPS sampling will cost more computation and memory. So, we make FPS sampling for mesh models of Golf and Foot which have relatively less data. Fast marching is used to compute the geodesic distances from source(s) to other points. In each step, the point with longest distances from the sampled points will be next sample. Compared with Poisson disk sampling, FPS can accurately control the number of samples. Fig.8 shows the simplified mesh models.

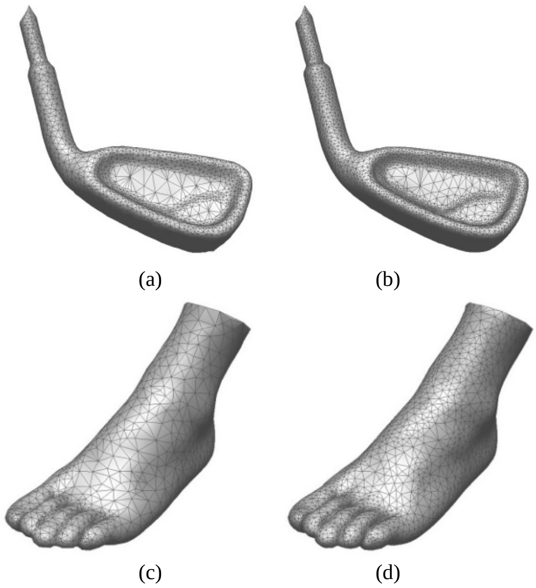


Figure 8. Recovered Mesh Model of Samples. (a), (b) the golf models with samples of 3k and 5k; (c), (d) the foot models with samples of 2k and 5k.

E. Quantitative Analysis

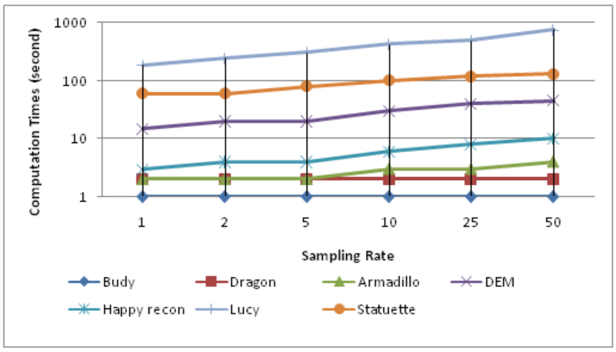
For quantitative analysis, we establish LODs of the points of Bunny, Dragon, Happy Recon, Armadillo, Lucy, Statuette (Stanford, 2011) and DEM (Geographx, 2011) with Poisson disk sampling method. Mesh models of all sampling sets are obtained using Geomagic. Then, we evaluate the performance of our method by comparing the differences between the original meshes and the simplified models. In this paper, we estimate two models' difference according to the following way. Let p_i, n_i be the coordinate and normal of a point i from original point set. The projection of p_i along n_i on a simplified model M_j can be obtained by computing the intersection between line $\langle p_i, n_i \rangle$ and M_j. Then, the difference of M_j from original model can be estimated by averaging the distances between p_i and its projection point. Further discussion about estimation of the difference is beyond this paper. Yet, we think this way is an unbiased and reliable strategy.

As shown in Tab.1, the value in each cell's top denotes the difference between the original data and our simplified model, the bottom value is the difference between original model and simplified model obtained using the function “curvature sampling” of Geomagic. For Dragon, the mesh models can’t be reasonably constructed when sampling rate is below 10%, so we don’t list the related data in Tab.1. The error should be overestimated since it includes the error of establishing mesh, but we think this quantitative evaluation is still informative. From this table, we can come to a conclusion that our method can preserve the details better. The accuracy’s differences between our method and Geomagic are obviously increased with the increasing of sampling rate, which illustrates our method can sample key points with more chance. Tab.2 lists the computation times to perform above operations. When the point’s number is less than 1M, the process is very quickly. For great amount of data such as Lucy, the computation is still not costly even when sampling rate is 50%. All experiments were conducted with program under VC 6.0 on an Intel 2 Core, 2.83GHZ, 4GB, windows XP machine. As the samples number is hard to be controlled precisely in Poisson disk method, approximated number of samples obtained by adjusting disk radius are shown instead in this experiments.

TABLE I.
QUANTITATIVE EVALUATIONS ON SIMPLIFIED POINTS

	Bunny	**Dragon**	**Happy recon**	**Armadillo**	**Lucy**	**Statuette**	**DEM**
	(30K)	(43K)	(540K)	(170K)	(14M)	(5M)	(2.25M)
50%	0.00003	0.000012	0.000006	0.022	0.002	0.005	0.4
	0.00004	0.000017	0.000007	0.023	0.005	0.008	0.6
25%	0.00006	0.00011	0.000015	0.035	0.006	0.012	1.2
	0.00008	0.00017	0.00002	0.05	0.011	0.018	1.7
10%	0.00025	0.00033	0.000039	0.09	0.015	0.03	2.7
	0.00022	0.0005	0.000055	0.11	0.023	0.05	3.5
5%	0.00031	-	0.000077	0.18	0.028	0.05	5.4
	0.00045		0.000091	0.3	0.037	0.08	6.2
2%	0.0022	-	0.00038	0.53	0.06	0.06	7.1
	0.0018		0.00051	0.49	0.06	0.09	8.6

TABLE II.
COMPUTATION TIMES



VI. CONCLUSION

This paper presents LOD generation method for unorganized points and meshes with uniform sampling method by taking geodesic distance as a basis. Poisson disk sampling, FPS and other uniform sampling algorithms can be applied in our method. Compared with FPS, Poisson disk sampling can get more efficiency with similar results. Experiments show that adaptive results can be obtained with desired effects. Comparison and evaluation for the reconstructed models demonstrate the effectiveness of our method.

The main contribution of this paper is that it introduces an idea of uniformly sampling in non-Euclidean metric for LOD generation. The distribution of samples is locally uniform and wholly adaptive in Euclidean metric, and therefore obtains better display effect. However, there is still other research work to do. Geodesic distance plays an important role in our method, so some new computation methods should be studied in future, which can further improve computation efficiency. The sampling number can’t be controlled in Poisson disk sampling, then how to estimate the relationship between sampling number and radius of disk should be attractive.

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