POSTER: Information Transformation for Point Cloud

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ABSTRACT

We propose a method of Information transformation for point cloud, which reduces information amount of three dimensional point data. Our method generates clusters and spiral chain lists. These chain lists are consists of three dimensional points. After that, we adopt a predictive encoding to compress these chain lists. In addition, we will show effectiveness of our method with same experimental results. In these experiments, our method reduces the information amount of point cloud coordinate to 31.7% of original model.

Keywords

Computer graphics, CAD, data compression, information transformation, and point cloud.

1. INTRODUCTION

Many types of 3d scanner have been developed in recent years, and we can use point cloud representation for three dimensional shape design, sampled by those scanners from real shape. This is an easy way to modeling 3d shapes from real object. So it is thought that in the near future, point cloud data will be distributed in CAD and computer graphics areas. Fig.1 shows an example of point cloud data. Each point has three-dimensional coordinate and its normal vector.

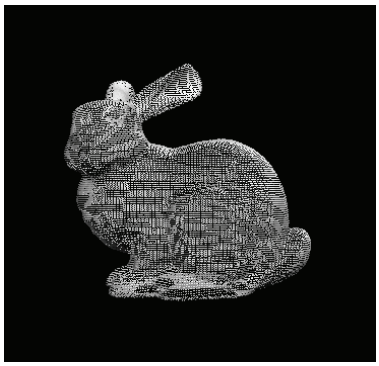

Figure 1. An example of point cloud

However, point cloud data is constructed by enormous numbers of points. As a result, it causes enlarging data size and increase of network traffic, in case of transfer via networks. So it is required to compress those data by transforming them into smaller representations. [Was04a] proposed a method which compresses coordinates and normals progressively by using binary tree. However it is for

both coordinates and normals, so the process needs both of them and does not work separately.

In this paper, we propose an information transformation method for point cloud captured by range scanner such as 3d laser scanner, reducing its information amount. With this method, we can convert it into smaller file using conventional compression techniques such as zip and so on.

Fig.2 shows outline of data compression process. The process consists of two procedures, information transformation and entropy encoding. First, information transformation technique is applied to point cloud data in order to reduce information amount with redundancy elimination. After that, entropy coding is applied to compress transformed data, for example, Huffman coding, arithmetic coding and so on.

2. Information transformation

First, our method generates clusters to manage points structuring

In this section, we propose a method which is one of information transformation techniques using chain list and differential encoding.

2.1 Point clustering

Our process generates clusters of point cloud to get more efficient result. Each cluster consists of points within a defined distance R_{th} form center of cluster, as shown fig.2. s_i is center of cluster and cluster C_i holds points and each distance from s_i is smaller than defined radius R_{th}. If we use larger R_{th}, the number of clusters becomes smaller. On the other hand, if we use smaller R_{th}, the number of clusters becomes larger. It is prefer to get more effective result, properties of points which belong to same cluster are similar, Where, properties are three-dimensional coordinate, normal vector, color and so on. So we should have to appropriate radius R_{th}. In general, smaller radius is preferable for the point cloud which has many flat or low curvature features, and lager radius is preferable for complex one.

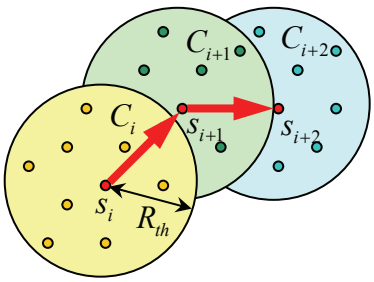

Figure 2. Clustering of point cloud and its overlapping.

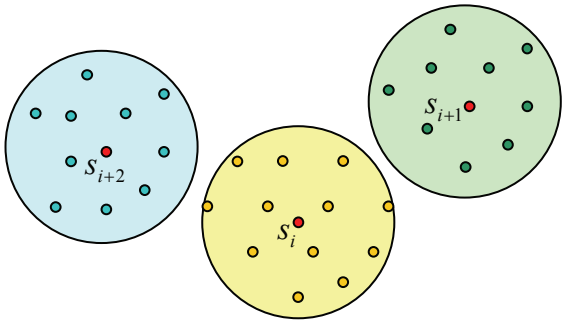

Figure 3. Reduction of overlapping.

If cluster circles overlap each other, the number of points in each cluster gets to be smaller and the information amount of each cluster gets to be smaller too. So our method chooses centers of cluster in order to place apart from each other. With this strategy, the process can generate large clusters efficiently and get effective result.

In the latter of the process, remaining point which does not already belong to any cluster are scattered and the size of cluster becomes small as process advances. However, sizes of clusters become larger as a whole result.

2.2 Spiral chain list

This process applies differential encoding to points in each cluster. Differential encoding converts properties of points into difference value. So the process generates point lists like a scroll print as shown fig.4. In this paper, we call it spiral chain list.

Spiral chain list connects points sequentially which begins at center of cluster s_i and glow out to the boundary of cluster C_i. Differential values, such as differential coordinate and differential normal are calculated along this spiral chain list. In addition our method has adopted a predictive encoding. In this process, points are connected sequentially as shown in fig.5. $p_i(i=1\ldots n)$ is a point on spiral chain and this process calculates predictive point q. Then there is difference between next point p_{i+1} and q. So the differential Vector v_{diff} is stored as differential encoding result and in most cases, v_{diff}

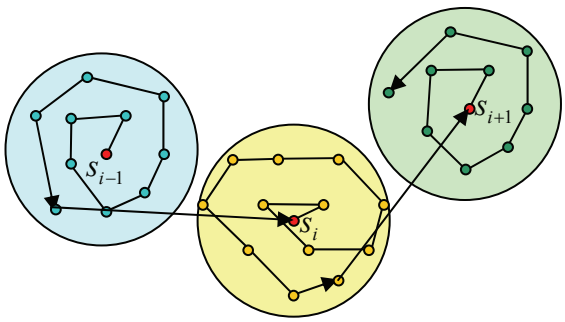

Figure 4. Spiral chain list.

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is smaller than v_{i+1} . With this prediction, the information amount of point cloud becomes smaller than original data.

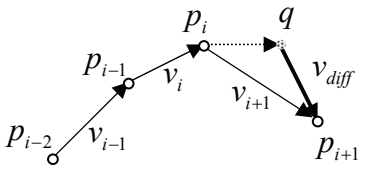


Figure 5. Prediction vector.

3. Experiments

We have evaluated effectiveness of our method and measured the difference between original point cloud data and transformed data about information amounts. In this experiment, we used 2 models, Bunny and Buddha. Each model consists of 34,834 and 543,652 points with three dimensional coordinate and normal.

Experimental results are shown in table 1 and table 2. The information amounts of original Bunny are 72.8KB for coordinate and 88.6KB for normal. The results of our method are 23.1KB and 86.1KB.Total compression ratios are 67.7%. However, the compression ratio for coordinate is 31.7%. The results for Buddha are 195.4KB, 852.7KB and 1046.1KB respectively. Total compression ratio is 44.1%, and Coordinate compression ratio is 19.7%.

Fig.6 and 7 show frequencies of original and transformed Bunny respectively using 8-bit quantization,. Fig 8 shows the path of spiral chain list generated by proposed method and its close up image is shown in fig.9.

The results of Buddha are shown in fig 10,11 and 12.

From this experiment, our method is effective just for coordinate to reduce information amount of point cloud. It is thought that in our method predictive encoding is applied only to coordinate, so compression ratio for normal is not effective. We think this may be improved by adopting prediction to normal.

Table 1. Information amounts for Bunny.

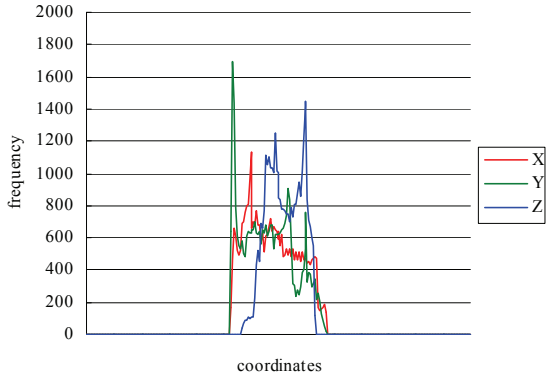
	Original	Transformed	Ratio
Coordinate	72.8KB	23.1KB	31.7%
Normal	88.6KB	86.1KB	97.2%
Total	161.4KB	109.2KB	67.7%

Table 2. Information amounts for Buddha.

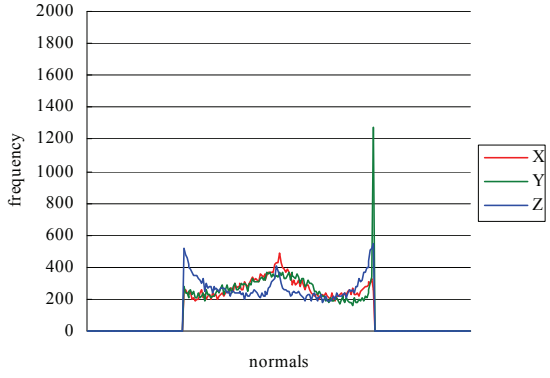
	Original	Transformed	Ratio
Coordinate	989.7KB	195.4KB	19.7%
Normal	1388.2KB	852.7KB	61.4%
Total	2377.8KB	1048.1KB	44.1%

4. Conclusions

From this experiment, our method is effective to reduce information amount of point cloud and provide more compact representation for point cloud. It is thought that our method is effective for coordinate to reduce file size and reduction of network traffic when point cloud data is transferred over network.



(a) Coordinates



(b) Normals

Figure 6. Histograms of original Bunny.

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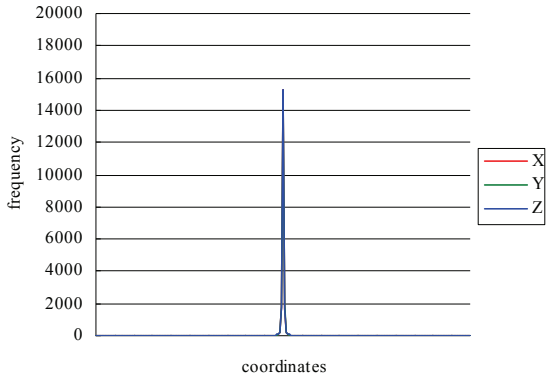
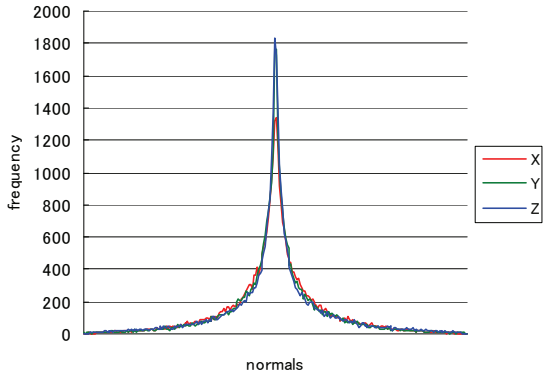


(a) Coordinates



(b) Normals

Figure 7. Histograms of transformed Bunny.

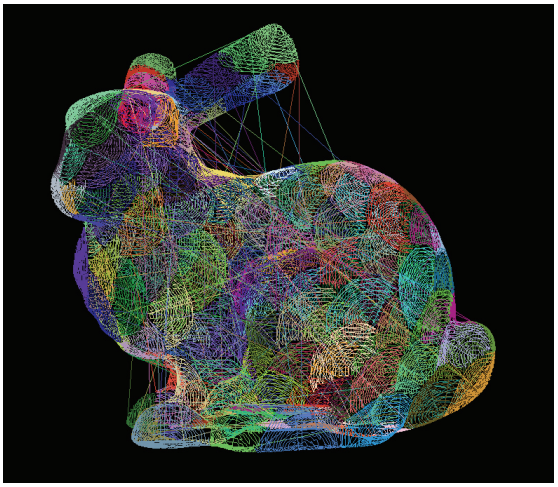


Figure 8. Path of spiral chain list for Bunny.

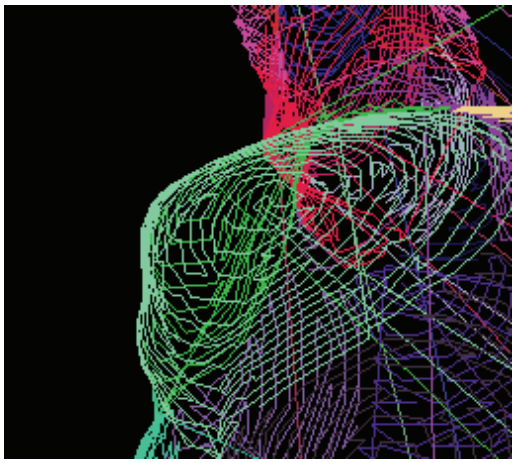
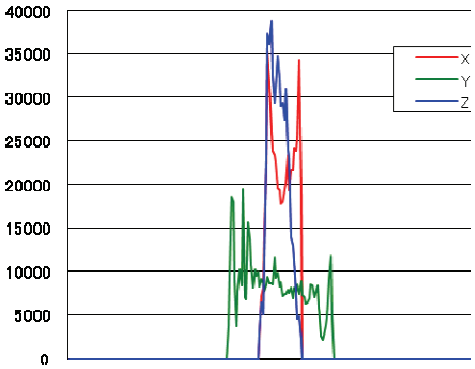
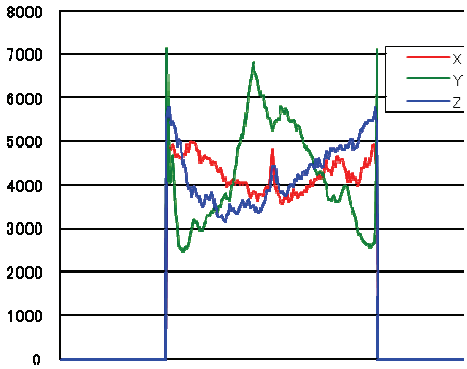


Figure 9. Detail of spiral chain list.

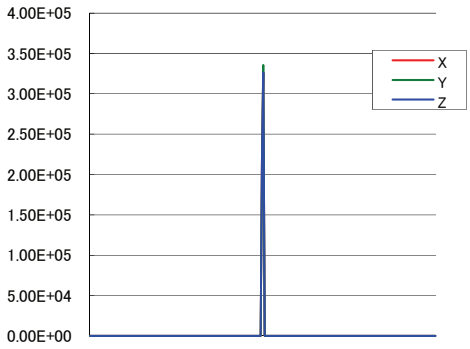


(a) Coordinates

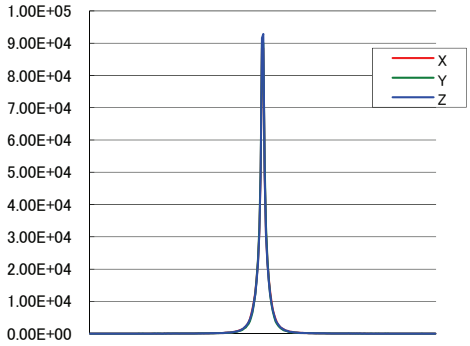


(b) Normals

Figure 10. Histograms of original Buddha.



(a) Coordinates



(b) Normals

Figure 11. Histograms of transformed Buddha.

Figure 12. Path of chain list for Buddha.

5. REFERENCES

[Was04a] Waschbüsch, M.. Progressive Compression of Point-Sampled Models. Proceedings of the Eurographics Symposium on Point-Based Graphics 2004, pp. 95-102.