POSTER: Point Cloud Lossless Compression

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ABSTRACT

We propose a method of downsizing technique for point sampled data which reduces information amount of three dimensional point cloud data. Our method generates clusters and spiral chain lists. Each chain is consists of three dimensional points. After that, we adopt a predictive encoding to compress these chain lists. In addition, we show the effectiveness of our method with same experimental results by comparison with one of conventional methods. From these experiments, our method can reduce the information amount coordinate data 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 to design three dimensional shape by capturing form real shapes,. 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 generally distributed in CAD and computer graphics areas. Fig.1 shows an example of point cloud data. Each point has three-dimensional coordinate and normal vector.

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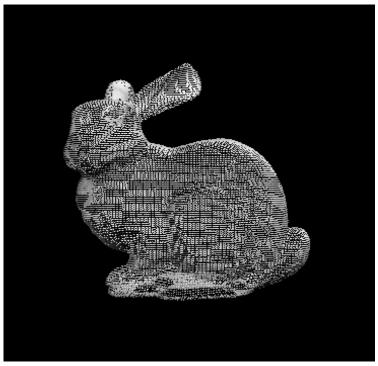


Figure 1. An example of point cloud

However, point cloud data consists of enormous number 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. Waschbüsch, et al [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 addition, it is not a lossless method but a lossy one. This is the point different from our method.

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 a general 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.

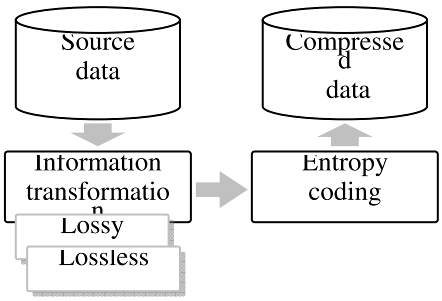


Figure 2. Outline of data compression.

2. Information transformation

First, our method generates clusters to manage data points.

In this section, we propose a new data structure. We call it Spiral Chain List(SCL). SCL consists of chain code representations listing each data point.

2.1 Point clustering

Our process generates clusters of point cloud to get more efficient result. Each cluster consists of points within a radius R_{th} defined by a user, as shown in fig.3. s_i is the center of cluster C_i. Each distance between cluster centers is longer than R_{th}. If we use bigger R_{th}, the number of clusters becomes smaller. On the other hand, if we use smaller R_{th}, the number of clusters becomes larger. The radius of clusters is the key to get better result. To get more effective result, we thought that properties of points which belong to same cluster should be similar. Those properties consist of three-dimensional coordinate, normal vector, color and so on. So we should have to

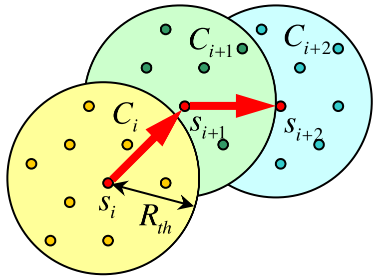


Figure 3. Clustering of point cloud and its overlapping.

choose 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.

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 as long as possible. With this strategy, the process can generate large clusters efficiently and get effective result.

In the latter of the process, remaining points which do not belong to any cluster yet, 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, SCL like a scroll print as shown in fig.4.

SCL connects points sequentially which begins at center of cluster s_i and glow out toward the boundary of cluster C_i. Differential values, such as differential coordinates and differential normals are calculated along SCL. 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 SCL and this process

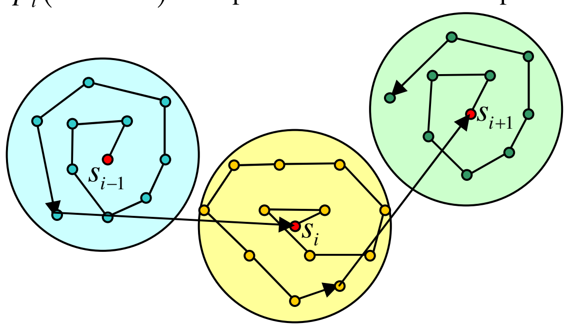


Figure 4. Spiral chain list.

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 a differential encoding result and in most cases, v_{diff} is smaller than v_{i+1} . With this prediction, the information amount of point cloud becomes smaller than original data.

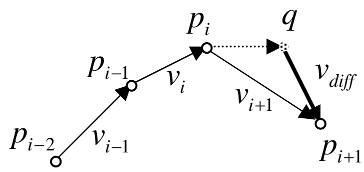


Figure 5. Prediction vector.

3. Experiments

We 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 amount of original Bunny is 72.8KB for coordinate and 88.6KB for normal. The results of our method are 23.1KB and 86.1KB respectively. Total compression ratio is 67.7% and this is not so good. 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 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, the 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 also.

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%

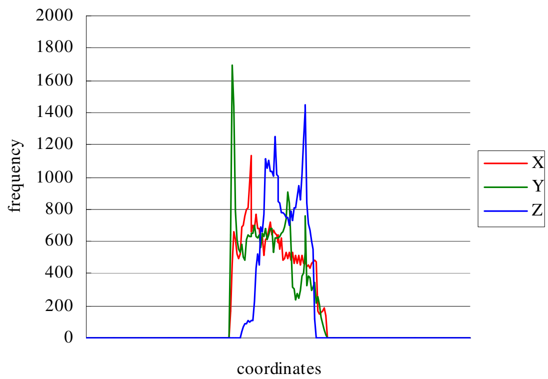
Table 2. Information amounts for Buddha.

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

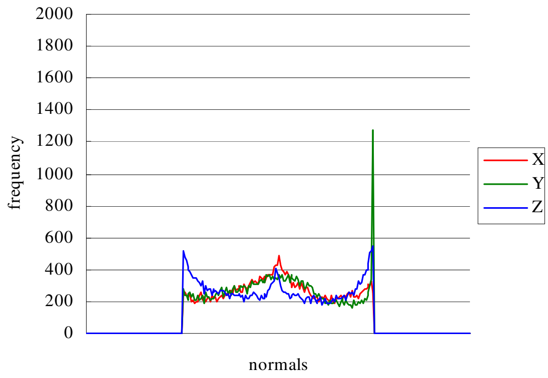
4. Conclusions

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 data size and reduction of network traffic when point cloud data is transferred via network.

Now we're trying to implement one of compression techniques to reduce information amount of point cloud. We will show the results of comparison our method and conventional one.

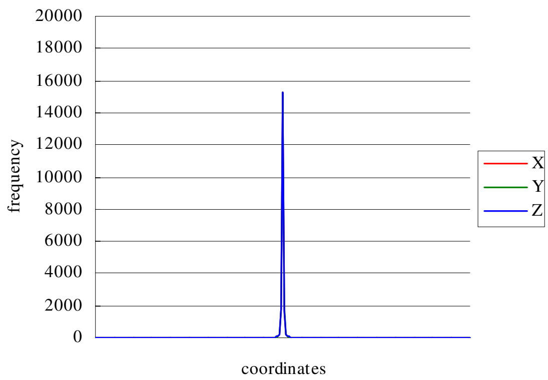


(a) Coordinates

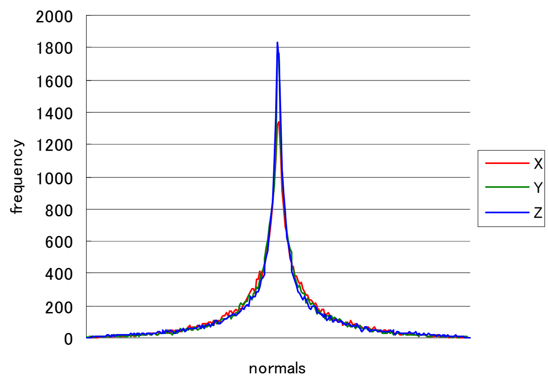


(b) Normals

Figure 6. Histograms of original Bunny.



(a) Coordinates



(b) Normals

Figure 7. Histograms of transformed Bunny.

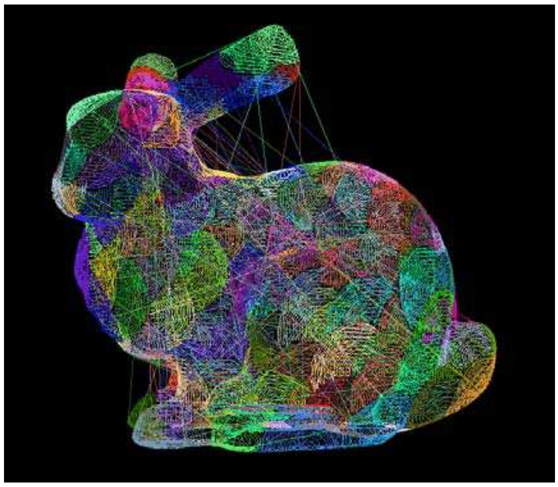


Figure 8. Path of spiral chain list for Bunny.

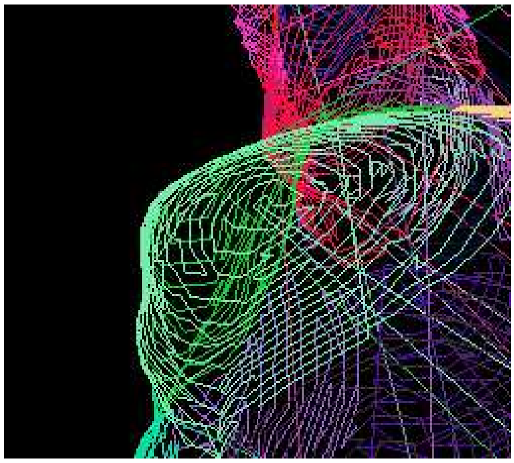
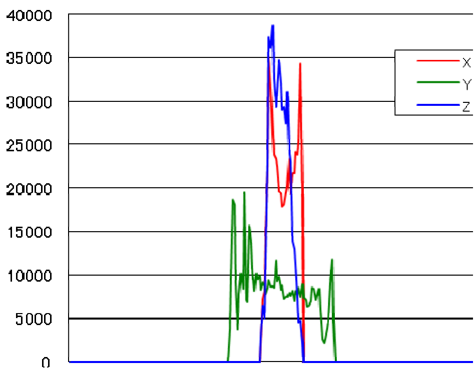
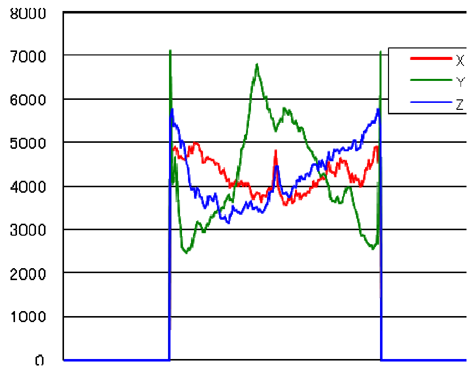


Figure 9. Detail of spiral chain list.

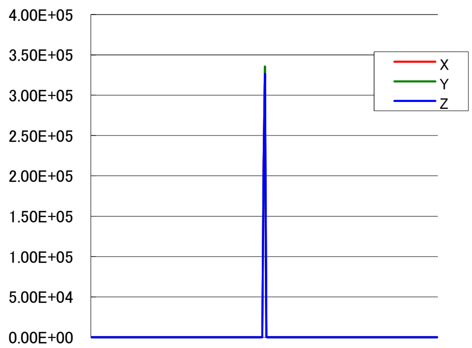


(a) Coordinates

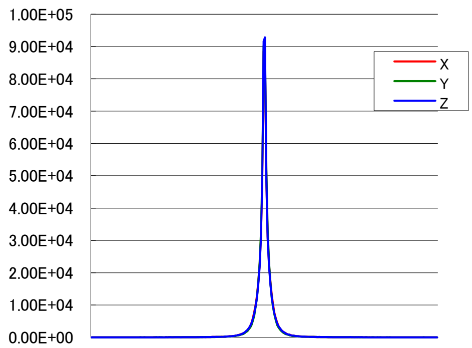


(b) Normals

Figure 10. Histograms of original Buddha.



(a) Coordinates



(b) Normals

Figure 11. Histograms of transformed Buddha.

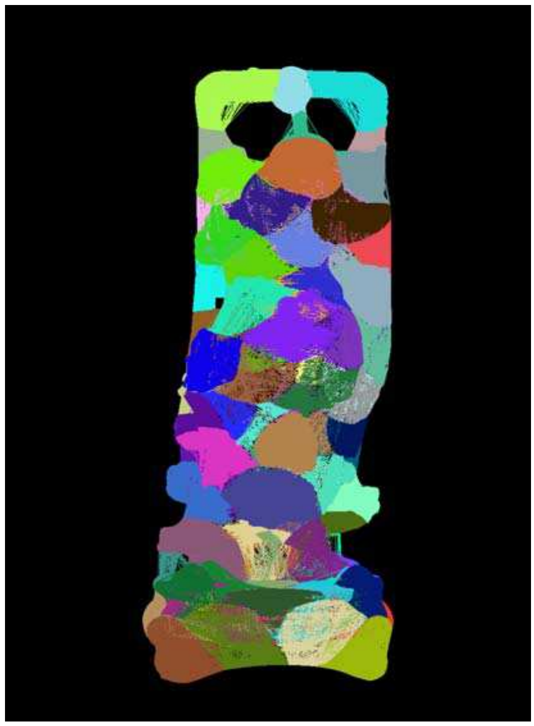


Figure 12. Path of chain list for Buddha.

5. REFERENCES

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