EVALUATION OF PROJECTION MODEL FOR RANDOM POINT CLOUD

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ABSTRACT: Recently, point cloud data are acquired by some platforms, such as a terrestrial laser scanner, land-based mobile mapping system (MMS), and airborne LiDAR. These systems can achieve a rapid and massive point cloud data acquisition for road surveying, mapping, structure maintenance, and environment monitoring. However, massive point cloud data require huge processing time in data sharing, visualization and 3D modeling. Therefore, we have proposed a performance improvement of point cloud processing based on point-based rendering approach. Our point-based rendering can select several projection models, such as a spherical, cylindrical, and orthogonal model. Each model has different advantages and disadvantages. Therefore, we proposed a methodology to select a suitable projection model in some point cloud editing works in a road monitoring, structure monitoring, surveying, and indoor mapping. In this paper, we evaluated each projection models through some experiments using terrestrial LiDAR and MMS data.

1. INTRODUCTION

Point cloud data are acquired using 3D scanner, such as terrestrial LiDAR and MMS, in a surveying, mapping, structure maintenance, and environment monitoring. The latest 3D scanners perform a rapid and massive data acquisition. Thus, the massive data require huge processing time in data sharing, visualization and 3D modeling. In particular, manual editing works using 3D modelers require a plenty of time. Therefore, we have proposed a performance improvement of point cloud processing based on point-based rendering approach which can reduce a processing time (Kataoka, 2013). This approach can reduce a processing time with a point cloud data projection into multi-layered panoramic image. Additionally, our point-based rendering can select several projection models, such as a spherical, cylindrical, and orthogonal model. Each model has different advantages and disadvantages. In this paper, we aim to propose a suitable projection model for several applications. In our definition, the suitable projection model can improve workabillity of construction process in a building information modeling (BIM) and construction information modeling (CIM) (Atul, 2013). Therefore, we evaluate each projection model which are suitable projection model in a road monitoring, structure monitoring, and surveying using a terrestrial LiDAR and MMS data.

2. METHODOLOGY

Figure 1 shows our processing flow.

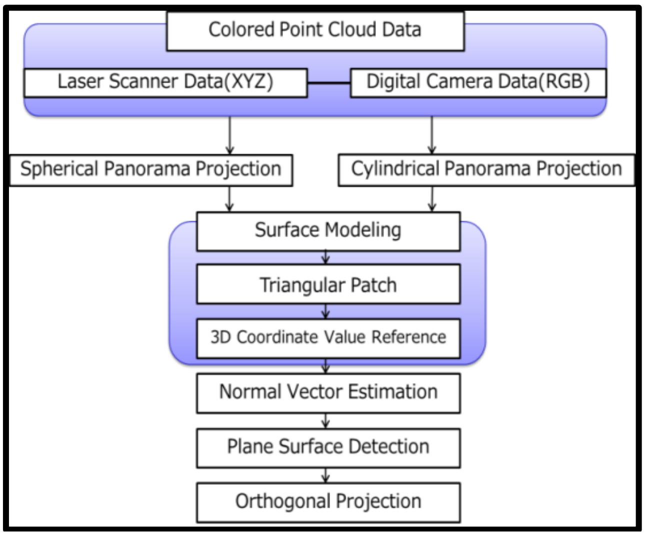

Figure 1 Processing flow

First, we acquire colored point cloud data with a digital camera and LiDAR. Second, point cloud data are projected into a multi-layered panoramic range image. This transformation simplifies viewpoint translation, filtering, and point-cloud browsing. The multi-layered panoramic range image can be a cylindrical, spherical, or orthogonal model. The LiDAR data comprise a panorama model and range data. The range data can preserve measured point data such as 3D coordinate values and color data in the multi-layered panoramic range image.
In the cylindrical and spherical model, azimuth and elevation angles from the viewpoint to the measured points can be calculated using 3-D vectors generated from the view position and the measured points. When azimuth and elevation angles are converted to column and row numbers in the range data with adequate spatial angle resolution, a spherical panoramic image can be generated from the point cloud (Nakagawa, 2011).
In this paper, firstly, point cloud data projected into a spherical and cylindrical model. Figure 2 shows spherical and cylindrical panorama projection flow. We also project into an orthogonal model. We describe this model's use case as follow. Figure 2 also shows the orthogonal model projection flow.

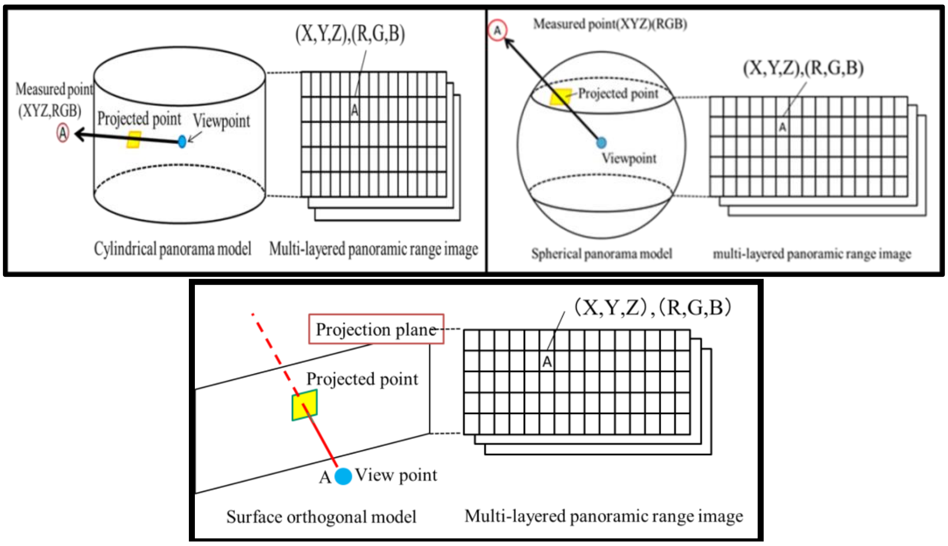

Figure 2 Point cloud projection flow (left image: cylindrical panorama model, right image: spherical panorama model, bottom image: orthogonal model)

Third, triangular patches are generated from projected point cloud data by Delaunay triangulation on panoramic range image, as shown in Figure 3. Clockwise topology is given to the triangular patches to determine the inside and outside on faces.

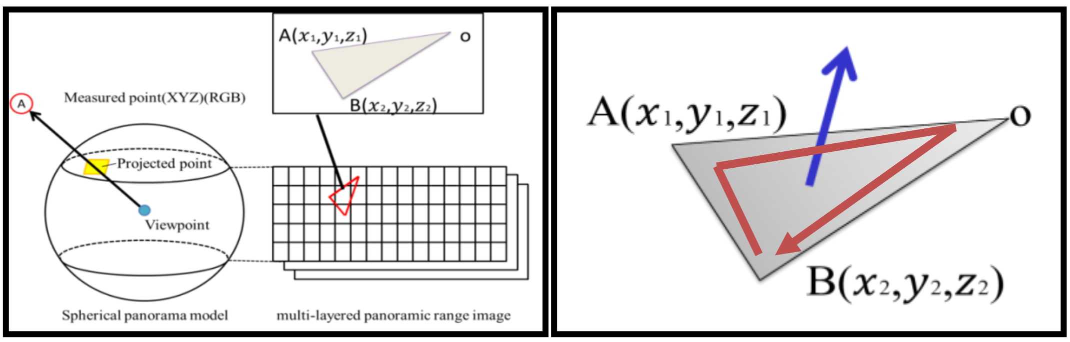

Figure 3 Delaunay triangulation on panoramic range image (left image: triangular patch generation on multi-layered panoramic range image, right image: definition of a normal vector and topology)

Fourth, we estimate normal vectors with the formula of cross product (Murai, 2007) on a visible faces of triangular patches from an arbitrary viewpoint. Additionally, the triangular patches are classified using the normal vectors to reconstruct polygonal surfaces, such as roads and walls. For example, when a horizontal direction parameter of normal vector on a face is approximately 0, the face is classified as a ground or horizontal roof. Then, segments are extracted from point cloud data. For example, measured line can be classified as straight features, such as buildings and roads (Ikeda, 2011). We detect flat surfaces from each normal vector of the triangular patch.
Finally, the flat surfaces are projected into the orthogonal model. In this paper, we describe about a vertical surface

orthogonal projection, as shown in Figure 4. First, a projection plane is set along an arbitrary view point perpendicularly. Next, the nearest points are projected on a vertical straight line from the projection plane. However, noises, such as vehicles and pedestrians, are projected on the plane. Thus, the projection plane is set along a center line of road, and we set a depth buffer to exclude these noises. When we estimate a distance from the center line of road to building façades approximately, we can efficiently edit or browse buildings in random point cloud data acquired along a street.

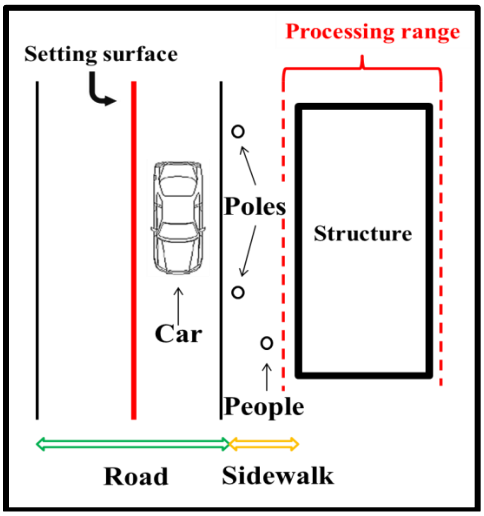

Figure 4 Object extraction using depth data

3. EXPERIMENTS

Data acquisition

We conducted two experiments to confirm a performance of our approach using random point cloud data acquired in streets. In the first experiment, we prepared colored point cloud data taken from terrestrial LiDAR. Our study area was Onomichi city in Japan. This area consisted of a long slope and steps with 2m width under forests as shown in Figure 5. We acquired 600 million colored point cloud data were acquired with RIEGL VZ-400 from 30 installation points at intervals from 5 m to 10 m. Measured objects were mainly roads, buildings, fences, stairs, and billboards.

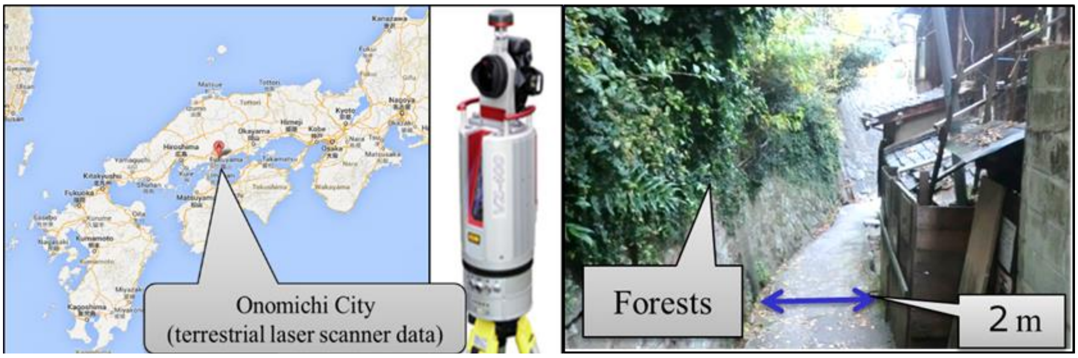

Figure 5 Onomichi dataset (left image: study area, center image: laser scanner (RIEGL VZ400), right image: experimental environment)

In the second experiment, we prepared colored point cloud data taken from MMS, as shown in Figure 6. Our study area was Kesennuma city in Japan. This area included intersections, buildings, poles and pedestrians. We used 20 million points colored points measured by GeoMaster NEO (Asia Air Survey Co., Ltd.) Measured objects were mainly road and buildings.

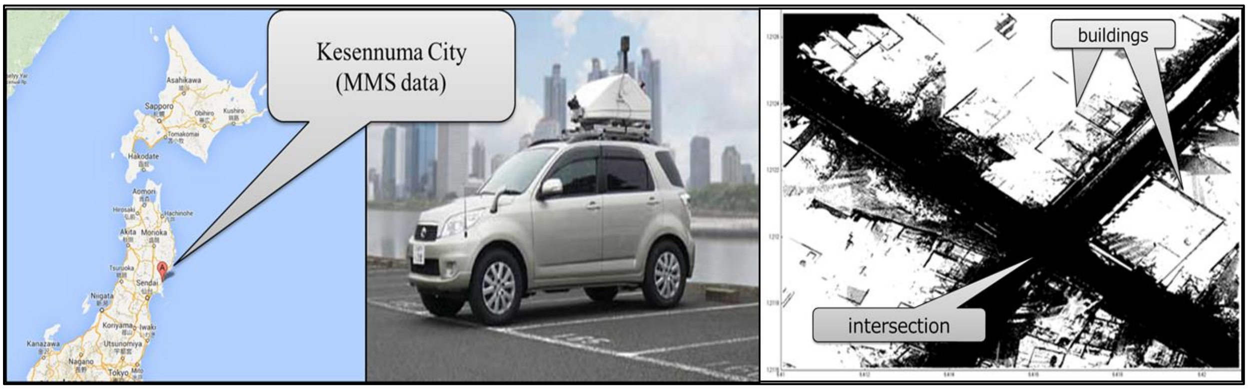

Figure 6 Kesennuma dataset (left image: study area, center image: MMS (GeoMaster NEO), right image: acquired point cloud)

3D modeling

First, we selected several point cloud applications, such as a road monitoring and building façade mapping. Second, we projected point cloud data with some projection models. In this paper, a spherical, cylindrical, and orthogonal model were evaluated as projection models.

First, we created 2D triangular patches using projected point cloud in a range image. Second, we created 3D surface model after a triangular patch clustering with 3D data references in the range image. In this case, we set a projection plane (10 m length). Additionally, a distance of depth buffer was set as 3 m from the projection plane.

Projection model evaluation

Three criteria are prepared for our projection model evaluation. The first criterion is an environment recognition performance. The second criterion is a geometry detection performance. The third criterion is availability in a structure monitoring and mapping.

4. RESULTS

3D modeling

Figure 7 shows results in the spherical and cylindrical panoramic projection using Onomichi dataset. Figure 8 shows that a comparison of spherical panoramic projection to vertical surface orthogonal projection.

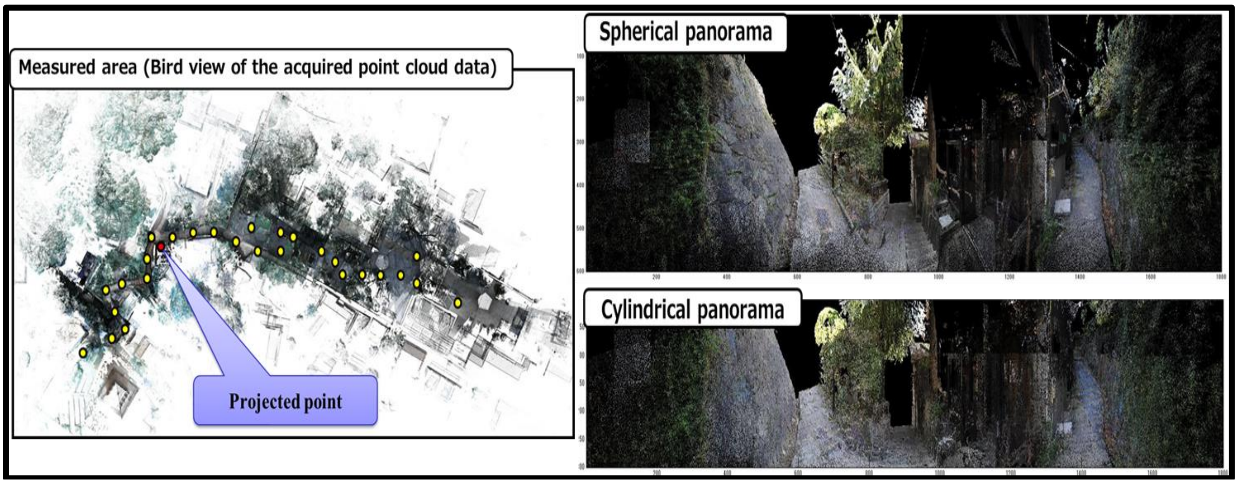

Figure7 Results of point cloud projection using Onomichi dataset (left image: measured area (ortho image from point cloud), right image: comparison of a spherical panoramic projection to cylindrical panoramic projection)

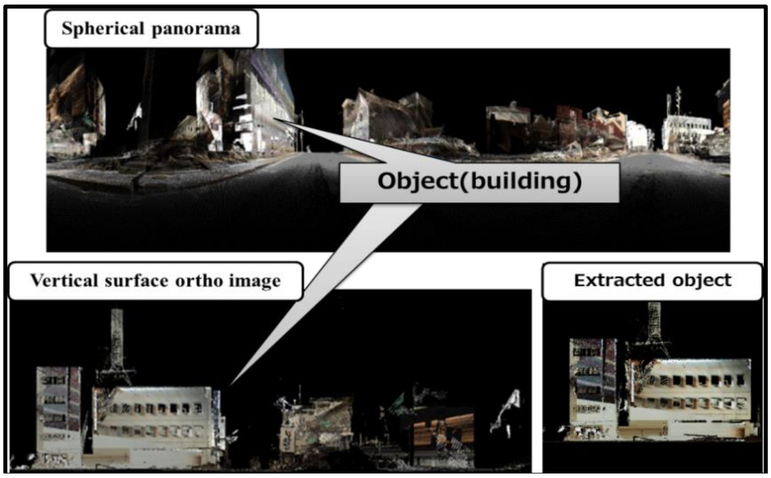

Figure 8 Comparison of a spherical panoramic projection to vertical surface orthogonal projection

We confirmed that the depth filtering separated into main structures or the others, such as roads and poles, as shown in Figure 9.

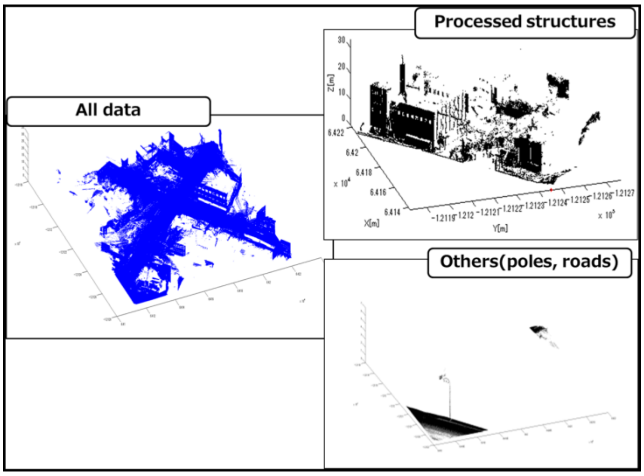

Figure 9 Results of depth filtering

The triangulation generated a surface model with 3D patches using projected point cloud in a range image, as shown in Figure 10. Several structure attributes, such as a road and wall, were also classified from the surface modeling results.

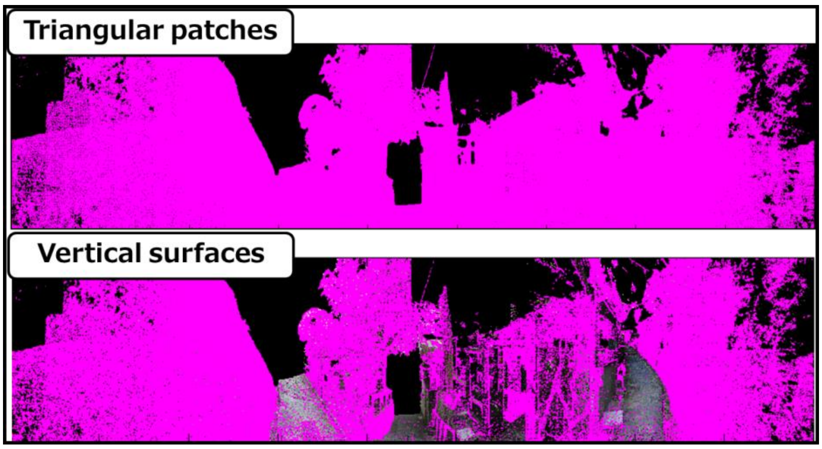

Figure 10 Results in surface modeling (top image: triangular patches using the projected point cloud in a range image, bottom image: estimated vertical surface)

In Onomichi dataset, 3D Delaunay triangulation approach was applied to we used to a surface modeling as a conventional technique. The processing time for the surface modeling via single-thread MATLAB programming was 8161.0 s using Intel Core i7 3.40 GHz processor. On the other hand, we also processed those point cloud data using our point-based rendering approach. The processing time for surface modeling via single-thread MATLAB programming was 684.0 s using the same environment.

5. DISCUSSION

We have confirmed that our approach can improve manual editing works for using random point cloud data. Through our experiments, we have summarized the most efficient projection models as follows.

First, we have evaluated our projection models using terrestrial laser scanner data. In our experiment, a spherical panoramic projection was the most suitable to recognize unknown environments, because the spherical panoramic projection can provide a wider angle space than the cylindrical panoramic projection. On the other hand, the cylindrical panoramic projection can provide a radial space in a horizontal direction with homogenous spatial resolution in a vertical direction. Thus, the cylindrical projection is the suitable for artificial object recognition. Moreover, the orthogonal projection was the most suitable for a road shape detection. When data acquisition area is large, far points are invisible from a viewpoint. Thus, orthogonal projection is the most suitable for large area representation.

Second, we also evaluated our projections using MMS data. In our experiment, a perpendicular orthogonal projection was the most suitable for a structure monitoring and mapping. On the other hand, we have confirmed that a spherical panoramic projection was inefficient in a manual mapping because of a distortion in projected range image. Therefore, a perpendicular orthogonal projection was also suitable for a building façade mapping.

Finally, we have confirmed that our approach can improve workability for point cloud manual editing works through our evaluations.

6. CONCLUSION

We have evaluated and defined that a suitable point cloud projection model for several applications. Those results could be used for a dynamic model selection of point cloud projection. Our future work is to create dynamic selection methods of suitable projection model for several applications to improve workabillity in construction fields.

ACKNOWLEDGMENT

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