DYNAMIC INDOOR SPACE RECONSTRUCTION USING TEMPORAL POINT CLOUDS

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ABSTRACT: Indoor positioning, route finding, and 3D modelling are essential techniques for indoor navigation. In indoor environments, users require the suitable route based on security, safety and efficiency, because an indoor navigation would be affected by various changing objects, such as pedestrian, escalators, and doors. Therefore, an indoor navigation requires a geometrical network model to represent changing space environments to be used for walkable path estimation. A geometrical network model is generally prepared using building blueprints or CAD data. However, there are technical issues such as high operation cost, because the geometrical network model is created manually. Moreover, a manual creation is hard to represent real-time environmental changes. Therefore, we aim to develop a methodology to provide the real-time geometrical space generation using temporal point clouds. The methodology consists of a point cloud interpolation, segmentation, clustering, and labeling to represent changing objects such as pedestrian and doors. We conduct experiments on dynamic indoor space reconstruction using multi-layered laser scanner to evaluate our methodology.

1. INTRODUCTION

Location based services (LBS) in indoor environments are required to integrate positioning, mapping, and navigation techniques. The current major indoor positioning methodologies are Wi-Fi, Bluetooth Low Energy (BLE), Indoor Messaging System (IMES), infrared (IR) sensors, and Pedestrian Dead Reckoning (PDR).

In 3D indoor modeling and mapping, two approaches mainly exist. The first approach is a CAD data creation from building blueprints. However, there are technical issues such as high operation cost, because the geometrical network model is created manually. Moreover, a manual creation is hard to represent real-time environmental changes. The second approach is 3D model generation from point clouds obtained with laser scanning or Photogrammetry (structure from motion and multi-view stereo). The second approach has an advantage to achieve automated processing and higher data processing speed. Zeng et al. presented an approach which recognizes indoor objects automatically from Kinect point clouds (2017). Tran et al. presented an approach to automatically reconstruct topological relations in geometrical model from grammar rules (2017). In terms of real-time environmental changes, Quintana et al. presented an approach which detects door opening and closing by 6D-space framework (2018).

In indoor navigation, a network model, such as walkable path, is prepared to represent relative linkages of spatial features. A network model consists of nodes, links, and topologies with attribute data. When a network model is created with geometrical data, such as point clouds generated with laser scanning or Photogrammetry, the crated model is called as a geometrical network model as shown in Figure 1.

Positioning data, such as Wi-Fi, BLE, IMES, IR, and PDR data, are used as seed points for navigation and path finding. Dijkstra's algorithm is the most popular shortest path finding approach for navigation. On the other hand, indoor users require a suitable route based on security, safety and efficiency. In indoor environments, a suitable path is usually better than the shortest path for various users and applications, such as evacuation route finding in disaster situations (Xiong et al. 2017), route finding for handicapped person (Díaz-Vilariño et al. 2019), and route findings by robots (Sun et al. 2016). Feature compositions of indoor environments have more complicated than those of outdoor environments, as shown in Figure 2. Moreover, many changing objects exist in indoor environments. When we apply realtime navigation, it is hard to prepare a realtime geometrical network model with changing objects in manual works. Thus, a geometrical network model is required to be generated and updated automatically to represent dynamic spaces.

In our related works, we have developed a methodology to generate a geometrical network model and navigation paths from point clouds (Nakagawa and Nozaki, 2018). We used ISPRS benchmark dataset, and we have confirmed that our methodology can reconstruct a geometrical network model and navigation paths from point clouds acquired with terrestrial laser scanner data and mobile laser scanner data, as shown in Figure 3. However, it is hard to extract changing and moving objects such as pedestrian and doors from point clouds. Therefore, in this study, we focus on changing object extraction from temporal point clouds.

We aim to develop a methodology to reconstruct a real-time geometrical space using temporal point clouds to represent changing objects in indoor environments. The methodology consists of a point cloud interpolation, segmentation, clustering, and labeling to represent changing objects such as doors and pedestrian with unique identifier (unique ID). We conduct experiments to extract changing objects using a multi-layered laser scanner in dynamic indoor spaces. Through our experiments, we verify that our methodology can represent changing objects and dynamic indoor spaces using temporal point clouds.

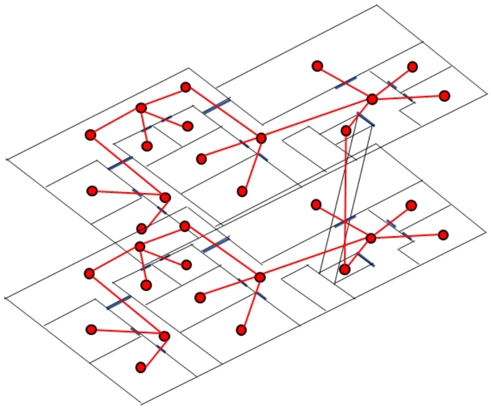

Figure 1. Geometrical network model

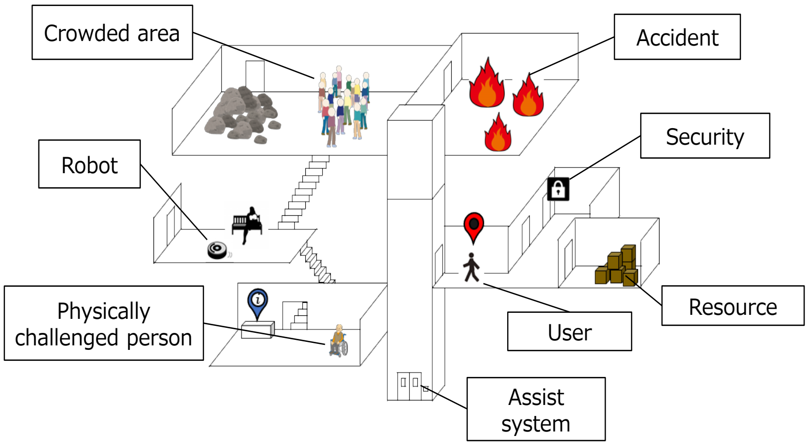

Figure 2. Dynamic indoor spaces

Figure 3. Reconstructed navigation path from point clouds

2. METHODOLOGY

Our methodology consists of five steps, as shown in Figure 4. First, temporal point clouds are acquired with a laser scanner from a static point. In our study, we select a multi-layered laser scanner to obtain changing objects in real time.

Second, acquired point clouds are interpolated to simplify the following processing, such as point cloud segmentation, object detection, and labeling. When we use a multi-layered laser scanner, the horizontal spatial resolution of point clouds is enough to detect objects. However, the vertical spatial resolution of point clouds is insufficient to detect objects. Therefore, point clouds are interpolated. In our study, we apply a linear interpolation methodology for point cloud interpolation, as shown in Figure 5.

Third, changing object detection is applied to extract pedestrian and doors from point clouds. Before the changing object detection, background point clouds are extracted from temporal point clouds. Background point clouds can be assumed as the furthest point clouds from a sensor position in temporal point clouds. Based on these assumptions, changing objects are extracted from temporal point clouds.

Fourth, point cloud segmentation is applied to classify changing object point clouds. In this study, we applied a voxel-based segmentation to generate point cloud clusters in temporal point clouds.

Finally, point cloud labeling is applied to distinguish pedestrian point clouds from door point clouds. Moreover, changing object behaviors are estimated in point cloud labeling using tracking results from temporal point clouds.

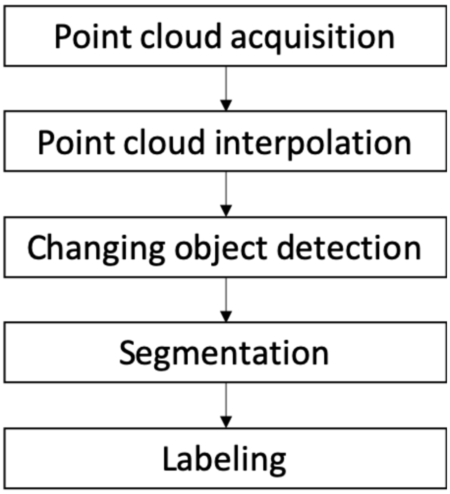

Figure 4. Overall processing flow

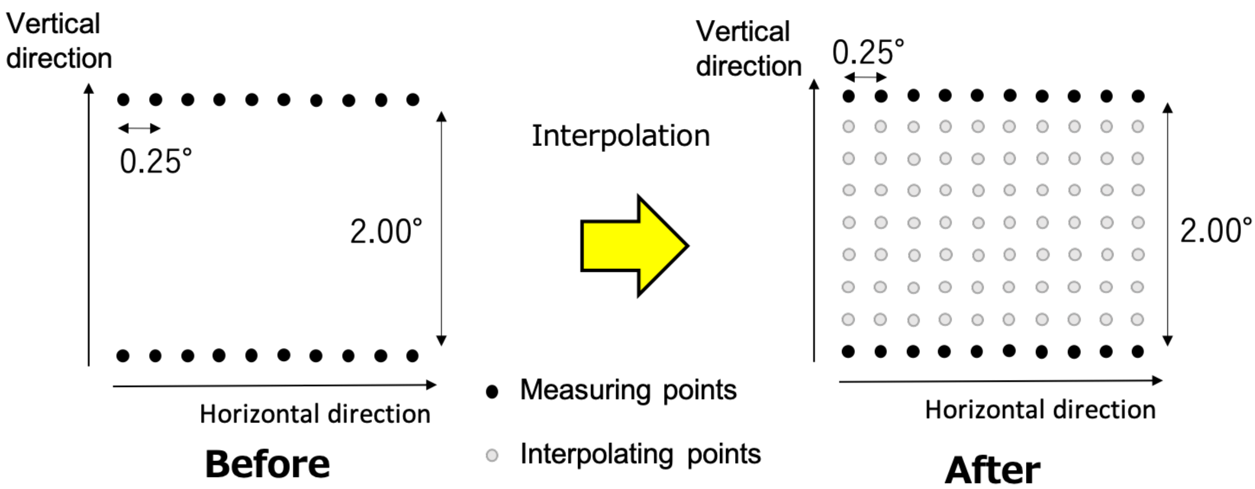

Figure 5. Point cloud interpolation

3. EXPERIMENTS

3.1 Study area

We selected a roof garden and elevator hall in our campus as our experiment areas (Figure 6). These experiment areas included doors and walking and sitting people.

Figure 6. Study areas

3.2 Equipment

We used a multi-layered laser scanner (VLP-16, Velodyne) in our experiments. Figure 7 shows the specification of used multi-layered laser scanner. The horizontal spatial resolution of point clouds was 0.028m and the vertical spatial resolution of point clouds was 0.165m at 5m distance from the scanner.

Product Name	VLP-16 (Velodyne)
Field of View	Horizontal : 360° Vertical : 30° (+15° ～-15°)
Accuracy	±3cm
Number of Points	300,000 points/sec
Size	Height : 71.7mm × Diameter : 103.8mm
Resolution (per 5m)	Horizontal : 0.028m Vertical : 0.165m

Figure 7. Multi-layered laser scanner (VLP-16, Velodyne)

4. RESULTS

Figure 8 shows acquired point clouds in the first experiment (roof garden). Figure 9 shows point clouds after interpolation processing.

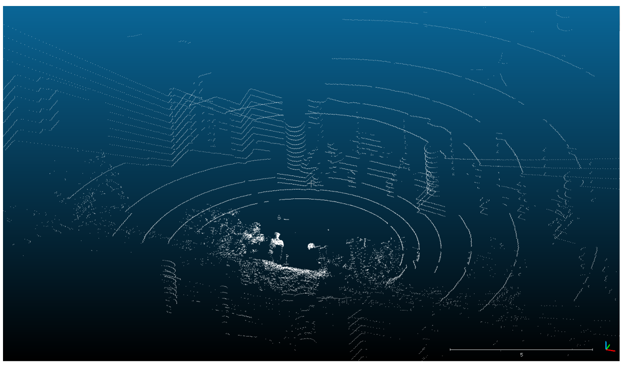

Figure 8. Acquired point clouds

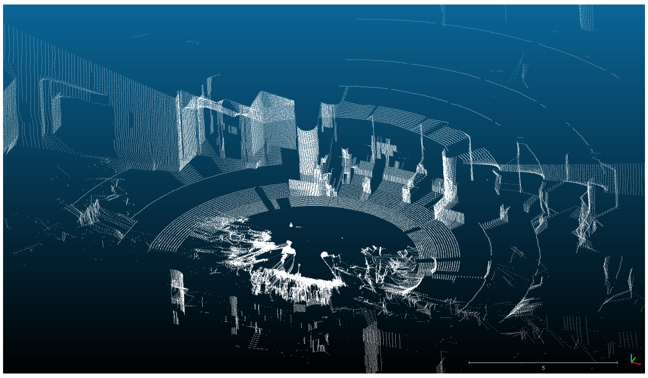

Figure 9. Interpolated point clouds

Figure 10 shows acquired point clouds in the second experiment (elevator hall). Figure 11 shows extracted changing objects from point clouds. We have confirmed that our methodology can extract and trace pedestrian and doors. We have also confirmed that our methodology can recognize each objects' behaviors.

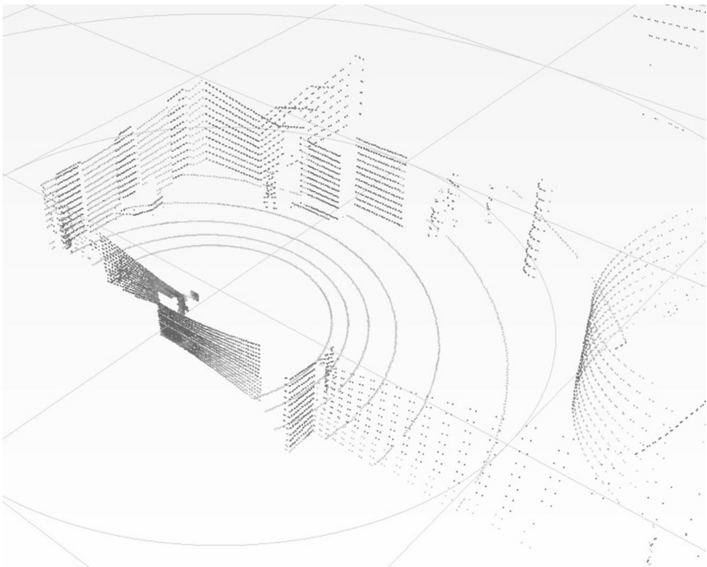

Figure 10. Acquired point clouds (elevator hall)

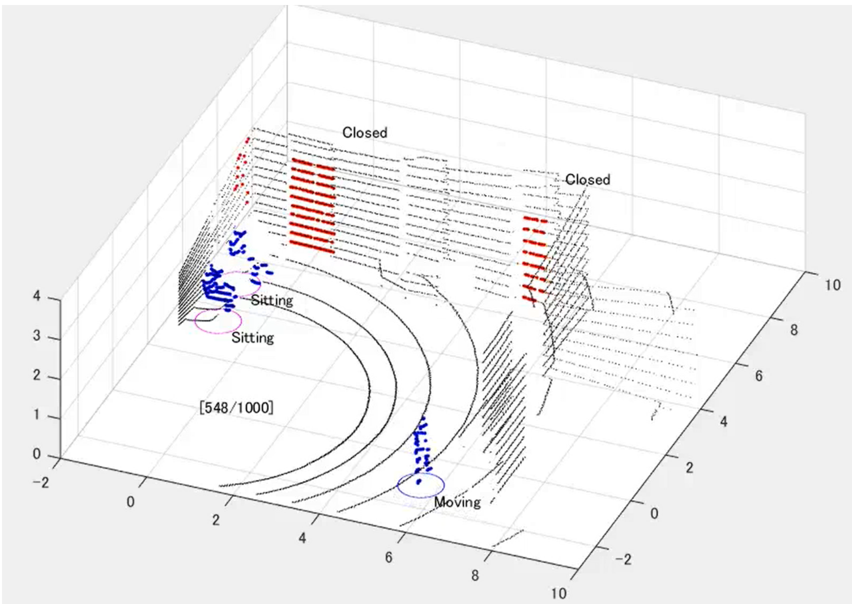

Figure 11. Extracted changing objects

5. CONCLUSION

We have developed a methodology to reconstruct a real-time geometrical space using temporal point clouds. The methodology consists of a point cloud interpolation, segmentation, clustering, and labeling to represent changing objects such as doors and pedestrian. We also conducted experiments to reconstruct changing spaces from temporal point clouds. Through our experiments, we confirmed that our methodology can reconstruct changing objects with behaviors and provide the unique IDs for changing objects such as pedestrian and doors.

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