Image Feature-based SLAM for Flat Surface Modeling in Indoor Environment

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ABSTRACT: In this study, we focused on image features in point cloud data to improve robustness of simultaneous localization and mapping (SLAM) for indoor mapping. We also focused on 3D area scanner to acquire point cloud data with reflection intensity images for image feature-based SLAM. Our methodology consists of five steps. First, point cloud data are acquired using a time-of-flight (TOF) camera from continuous viewpoints. Second, intensity images are generated from point cloud data. Third, the feature points are estimated from reflection intensity images with feature descriptors. Fourth, camera rotation matrices are estimated using corresponded feature points in intensity images. Finally, acquired point cloud data are registered using the estimated rotation matrices. We clarified that our methodology can integrate point cloud data successfully through our experiments in indoor environments.

1. INTRODUCTION

Recently, various indoor positioning systems, such as Wi-Fi, Radio-Frequency Identification (RFID), Bluetooth, ultra-wideband, and Indoor Messaging Systems (IMES), have been proposed (Adriano et al., 2011), because Global Navigation Satellite Systems (GNSS) are not available in indoor environments. Smart phones can receive signals from transmitters (Wi-Fi, Bluetooth, and IMES) located in buildings to estimate own location data. In mapping techniques, simultaneous localization and mapping (SLAM) algorithm (Durrant-Whyte et al., 2006, and, Bailey et al., 2006) is applied for mapping in unknown indoor environment. Moreover, there are various studies for SLAM and Iterative Closest Point (ICP) algorithm (Holz et al., 2010) using geometrical features extracted from point cloud data. The SLAM simultaneously estimates an environment map, rotation data, and translation data using differences among point cloud data acquired from continuous viewpoints with a loop closure restriction. Moreover, the ICP is one of the most popular methodologies for a point cloud registration. However, the stability of SLAM and ICP depends on a geometrical feature extraction from point cloud data. Thus, when measured scenes include no geometrical features, such as walls and floor, in indoor environments, it is not easy to estimate an environment map, rotation data, and translation data. Therefore, in this study, we focused on image features in point cloud data to improve robustness of SLAM for indoor mapping.

2. METHODOLOGY

Our methodology consists of four steps, as shown in Figure 1. First, temporal point cloud data are acquired using a TOF camera from continuous viewpoints (Jan Wülfing et al., 2010). The TOF camera is a range imaging camera based on TOF to acquire point cloud data with intensity values. The TOF camera is more robust than optical stereo cameras against illumination changes in indoor environments. Second, feature points are extracted from TOF intensity images with feature descriptors. The feature descriptors can transform a local pixel neighborhood into a compact vector representation. This representation permits comparison between neighborhoods, even if there are differences in scale and orientation. The feature descriptors can be applied to image registration, object detection, classification, tracking, and motion estimation. Corresponded images can be found using local features extracted from images with the feature descriptors, even if there are occlusion, and changes in measured scenes. Therefore, we applied feature descriptors to point cloud registration using TOF intensity images. Moreover, we selected Speeded up Robust Features (SURF) to extract feature points from the intensity images. Third, we estimated camera rotation matrices. In this process, we used feature points estimated in the second process. We estimated rotation matrices using feature points detected from two data based on affine transformation. Fourth, the feature points are used in mapping with an ICP algorithm. In the ICP algorithm, reference points in a dataset are kept fixed, and the other data is transformed using the reference points. Finally, acquired point cloud data are registered using the estimated rotation matrices.

Point cloud acquisition
↓
Feature points estimation
↓
Camera rotation estimation
↓
Temporal point cloud data registration

Figure 1. Overall processing flow

3. EXPERIMENT

3.1 Study Area

We selected flat surfaces in our campus as measured objects, as shown in Figure 2. The flat surfaces consisted of a wall, door, ceiling, and floor. The size of measured wall surface was 2.6 m height × 0.8 m width. The all measured objects had a flat surface without geometrical features and image features. Therefore, we prepared papers printed check pattern. Moreover, we pasted the papers on the door, as shown in Figure 3. In this study, we acquired point cloud data with 95% overlaps, as shown in Figure 4. Figure 5 shows registered point cloud data with ICP using image features.

Figure 2. Study area

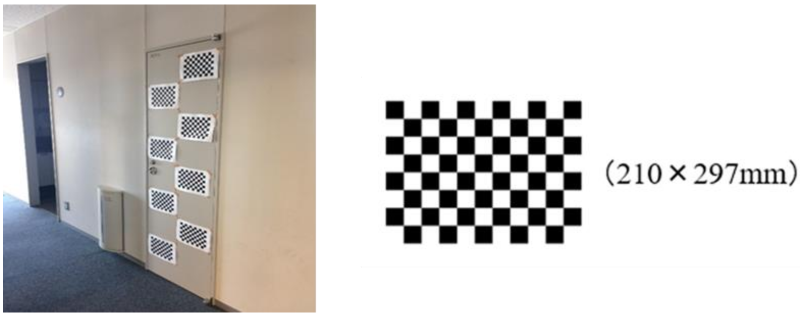

Figure 3. Study area

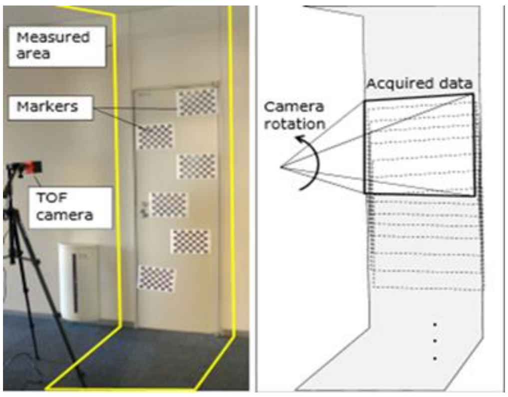

Figure 4. TOF data acquisition with 95% overlaps

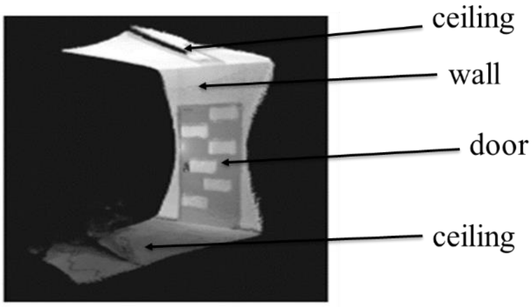

Figure 5. Registered point cloud data (door, wall, ceiling, floor)

We estimated feature points from reflection intensity images with SURF, as shown in Figure 6. Moreover, we rejected some intensity images which have less than three feature points, as shown in Figure 7.

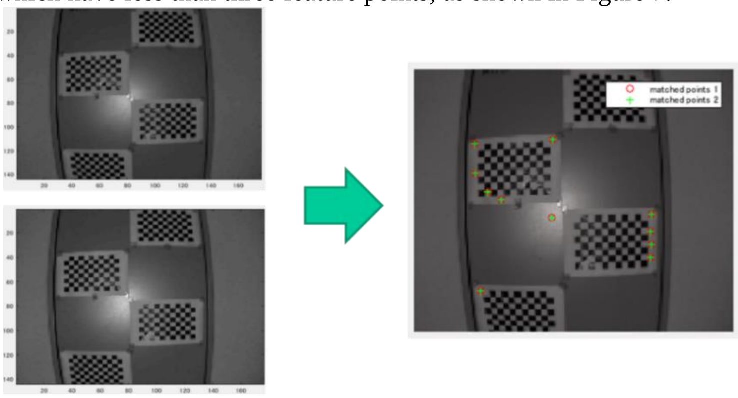
Figure 6. Feature point estimation with SURF

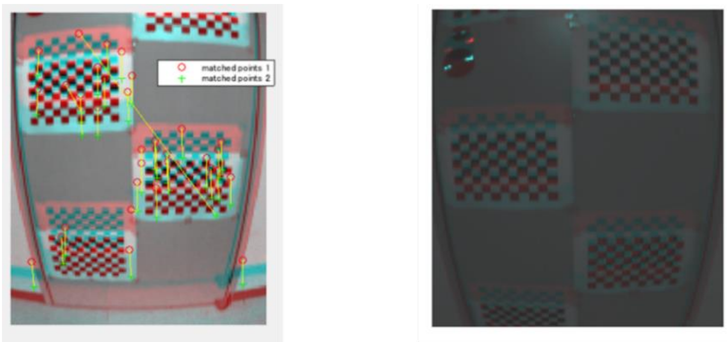
Figure 7. Result of SURF (left image: succeeded sample, right image: failed sample)

3.2 Equipment

We used a TOF camera (SwissRanger SR4000, MESA) in our experiments. Figure 8 shows the specification of TOF camera. The imaging range of TOF camera covers from 0.3 m to 5.0 m, and the frame rate was up to 50 fps. In this experiment, we installed the TOF camera on a tripod with 1.2 m distant from the door. We acquired 126 temporal TOF data.

Pixel array	176 (h)×144 (v)
Wavelength	850 nm
Angle of visibility	43.6° (h)×34.6° (v)
Measuring range	5.0 m
Frame rate	Maximum 50 fps
Frequency	30 MHz


Figure 8. Equipment (left: TOF camera, right: TOF camera installed on a tripod)

4. RESULTS

4.1 Point cloud registration

Figure 9, 10, 11, 12, and 13 show results of point cloud registration. In figure 13, the red indicates accumulated error (0.25 m approximately).

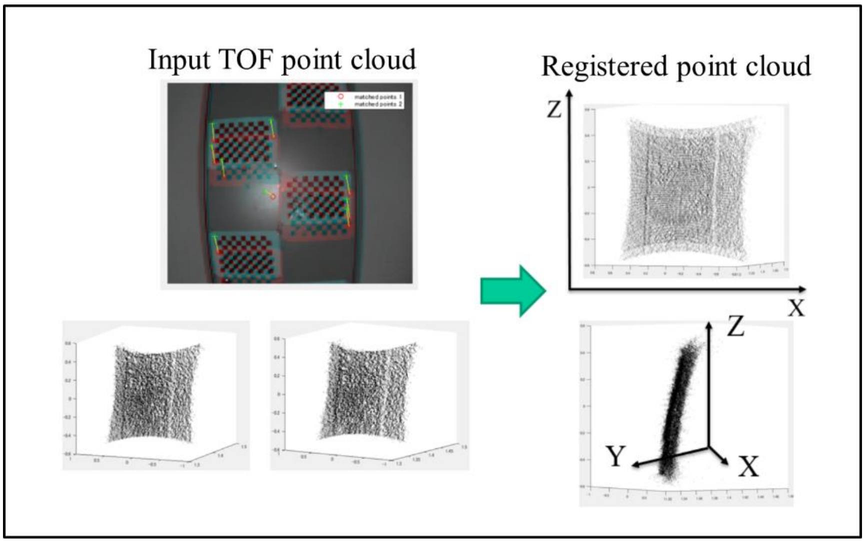

Figure 9. Point cloud registration result (door, 2 images)

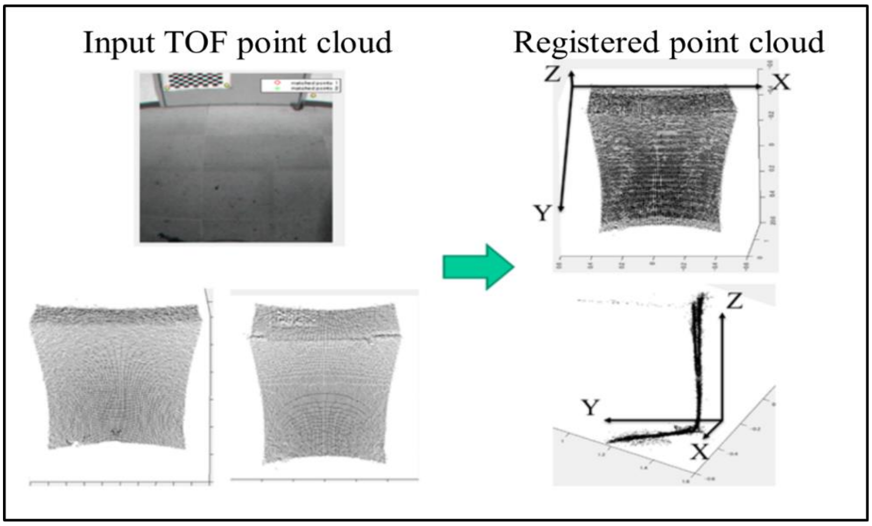

Figure 10. .Point cloud registration result (floor, 2 images)

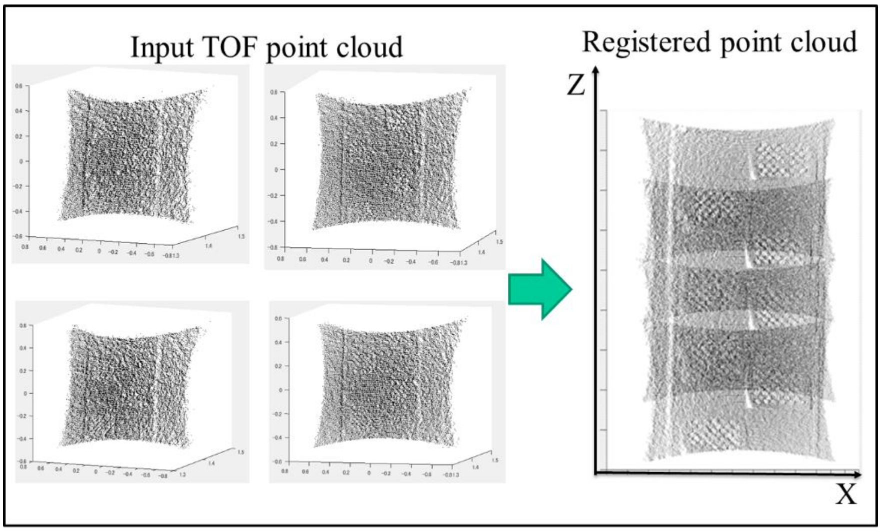

Figure 11. Point cloud registration result (door, 4 images)

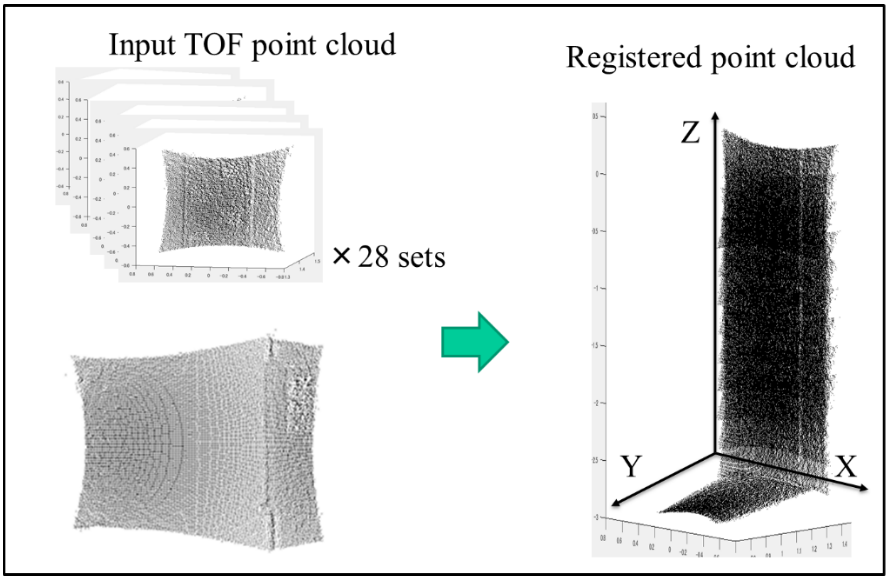

Figure 12. Point cloud registration result (door, 28 images)

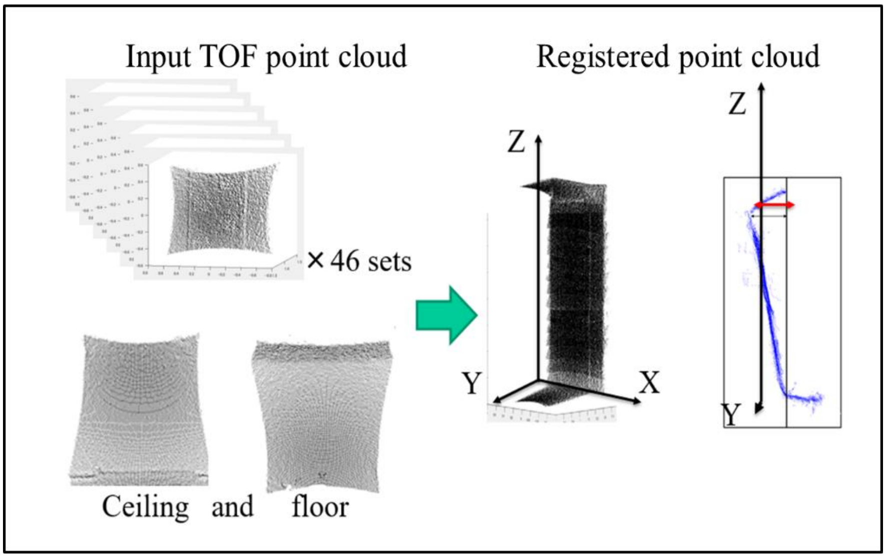

Figure 13. Point cloud registration result (wall, floor and ceiling, 46 images)

4.2 Comparison between proposed approach and conventional approach

Figure 14 shows point cloud data registered with a conventional approach. As shown in Figure 14, the conventional approach failed to integrate point cloud data, because the approach is based on feature matching using geometrical features. Furthermore, we confirmed that the processing time with proposed approach was shorter than that of conventional approach with numerical analysis software (proposed approach: 38 min, conventional approach 60 min).

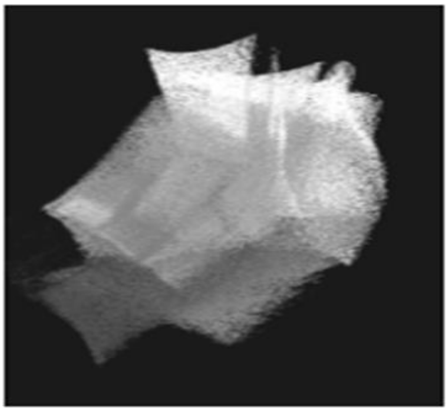

Figure 14 Registered point cloud data with conventional approach (door, wall, ceiling, floor, 112 images)

5. DISCUSSION

In this study, we confirmed that SURF can be suited to estimate image features in TOF point cloud as reference points for point cloud registration. In our experiment, we also confirmed that our methodology can improve robustness of SLAM in indoor environments including flat surfaces. Figure 9 and Figure 10 show point cloud registration results using two TOF images. This result indicates that our methodology could register point cloud data. The registration errors shown in the vertical and horizontal directions in Figure 9 and Figure 10 were almost approximately zero. Moreover, our methodology could register four TOF point cloud data, as shown in Figure 11. The error in vertical and horizontal direction was also zero approximately. However, there was an accumulated error in vertical was 0.18 m approximately. Moreover, 28 TOF point cloud data were registered, as shown in Figure 12. There was also an accumulated error in vertical was 0.21 m approximately. From above-mentioned, although an accumulated error problem and TOF noise problem were still remained as technical issues, we confirmed that our methodology could register temporal point cloud. Therefore, we would focus on noise filtering to reduce the accumulated error in point cloud registration for 3D mapping in larger indoor environments, as our future works. Moreover, we would reduce GCPs for point cloud registration to cover a larger area with our proposed methodology.

6. CONCLUSION

In this paper, we focused on image features in point cloud data to improve robustness of SLAM for indoor mapping. We used a TOF camera to acquire point cloud data with reflection intensity images for image feature-based SLAM. We proposed an approach to achieve a point cloud registration using image features in point cloud data. Our approach consists of five steps. Moreover, we clarified that our methodology can integrate point cloud data successfully through our experiments in indoor environments, even if the measured object was flat surfaces. In our future works, we will improve our approach for more accurate registration to achieve a robust indoor mapping.

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