

## ALIGNMENT OF POINT CLOUD DATA ACQUIRED FROM CONTINUOUS VIEW POINTS ON FLAT SURFACE

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**KEY WORDS:** Simultaneous Localization and Mapping (SLAM), Iterative Closest Point (ICP), Handheld 3D scanner, Flat surface

**Abstract:** A three-dimensional point cloud data measured with terrestrial 3D scanner is suitable for a spatial representation in a plant management, disaster monitoring and verification in traffic accident. Moreover, the latest 3D scanners can acquire massive point cloud data in wide range for a short time. However, 3D data measured in outdoor environment contains optical errors caused by a mirror reflection and point noises caused by movers. Therefore, generally, an additional 3D measurement is conducted and the additional data are integrated to an initial measured point cloud data with a procedure of 3D data alignment. Moreover, conventional 3D alignment methodology requires geometrical features. In other words, these approaches are limited to uneven surface. Therefore, a flat surface is a difficult object for the conventional data alignment methodology. In our experiment, Time-of-Flight camera was used as a handheld 3D scanner. Moreover, we used infrared images taken from the camera as feature values. Then, we conducted an alignment of point cloud data acquired from continuous view points on flat surfaces. Additionally, we have confirmed that our approach can integrate point cloud data even if measured object is a flat surface.

### INTRODUCTION

Generally, geometry of objects in urban area and natures is too complicated to represent as polygon data. Therefore, 3D point cloud data measured with terrestrial 3D scanner is suitable for a plant management, disaster monitoring and verification in traffic accident. Moreover, the latest 3D scanners can acquire massive point cloud data in wide range for a short time.

However, three dimensional data measured in outdoor environment contains optical errors caused by a mirror reflection and sunlight and point noises caused by movers such as pedestrians and vehicles. Therefore, generally, an additional 3D measurement is conducted and the additional data are integrated to an initial measured point cloud data with 3D data alignment procedure.

The Iterative Closest Point (ICP) algorithm and Simultaneous Localization and Mapping (SLAM) algorithm are applied to 3D data integration and alignment among 3D data taken from two or more viewpoints. These algorithms can achieve a precise data alignment using characteristic features such as vertex points and curved surfaces easily. However, general ICP and SLAM approaches use only geometrical features. In other words, these approaches are limited to uneven surface. Therefore, a flat surface such as floor surfaces and building walls is a difficult example for a point cloud data alignment.

On the other hand, a color or intensity information has a possibility to be used as feature points for the data alignment. Therefore, we focus on color or intensity information with 3D data to use as additional feature values. Moreover we proposed a point cloud data alignment methodology based on ICP and SLAM approaches for flat surfaces.

### METHODOLOGY

Firstly, we prepare base point cloud and reference point cloud acquired from sequential viewpoints.

Next, feature points are extracted from the base range image. A group of extracted feature points is defined as  $P_{base}$ . Then corresponded points are detected from the reference range image. A group of corresponded feature point is defined as  $P_{ref}$

When, the base point cloud is defined as  $X$  and the reference point cloud is defined as  $X_{rr}$ , the  $X$  and  $X_{rr}$  are described to explain a model alignment using a rotation matrix  $R$  and translation matrix  $t$ , as follows.

$$X_{rr} = R X + t \quad (1)$$

The rotation matrix  $R$  and translation matrix  $t$  consist of unknown parameters such as translation parameters ( $X$ ,  $Y$ ,  $Z$ ) and rotation parameters ( $\omega$ ,  $\phi$ ,  $\kappa$ ). Therefore these parameters are estimated approximately with the Singular Value Decomposition (SVD) approach. Then ICP algorithm is applied to approximate alignment result using feature points  $P_{base}$  and  $P_{ref}$ .

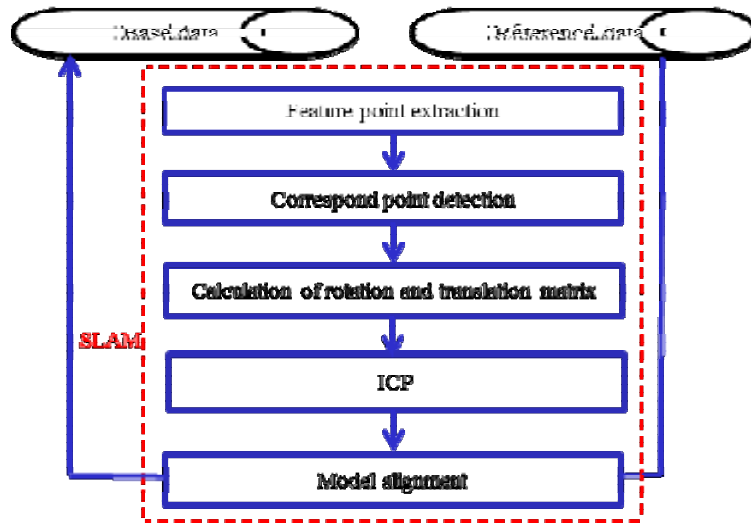


Figure 1: Processing flow

### Feature extraction

Feature points and correspond points are used to align base data with a reference data. Generally, geometric features such as vertex points and boundaries are extracted from data or images. However, when we focus on a flat surface, no geometric vertex points exist in measured data. Thus, color information is used as feature points in our experiment.

### Simultaneous Localization and Mapping (SLAM)

Simultaneous Localization and Mapping (SLAM) is a methodology that robot measures surrounding environment information to estimate a self-position, and to generate environmental map. The SLAM has two approaches. One is an approach based on Bayes' theorem. Another is a scan matching. We apply the scan matching in our experiment. The scan matching is an approach to estimate a self-position using a movement of 3D data obtained with 3D scanner. Usually, the SLAM is effective in unevenness points included vertex points of objects. In the other words, a flat surface is a difficult object for a conventional SLAM. Therefore, we focus on color or intensity information as features on point cloud to improve the SLAM in a flat surface measurement

### Iterative Closest Point (ICP) algorithm

Iterative Closest Point (ICP) is an algorithm to align models without determining the pair of congruent point. Figure 2 shows the flow of ICP algorithm.

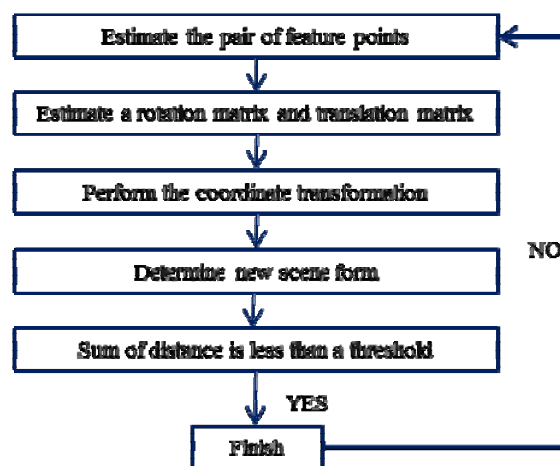


Figure 2: ICP algorithm

As a precondition of ICP algorithm, base data and reference data should include enough common regions and to

be corresponded with initial values such as rough sensor orientations. Based on this precondition, firstly, we estimate some pairs of feature points in base data and reference data. Next, we estimate approximate coordinate transformation parameters using estimated feature point pairs. The approximate parameters are calculated with the singular value decomposition. The ICP algorithm is applied to approximate transformation parameters to acquire fine transformation parameters. After that, these procedures are iterated to merge sequential point cloud data

### Singular Value Decomposition

Singular Value Decomposition (SVD) is a factorization of a real or complex. The singular value decomposition of an  $m \times n$  real matrix  $A$  is given the following formula (2).

$$A = U \Sigma V^T \quad (2)$$

Matrices  $U$  and  $V$  are unitary. Moreover,  $\Sigma$  is zero outside of the diagonal element is zero. Thus,  $U$  and  $V^T$  can be regarded as rotation matrices and  $\Sigma$  can be regarded as a scaling matrix. Since the matrix  $A$  can be estimated using the matrices  $U$  and  $V$  directly, an error and noise are not expanded. Moreover, a safe coordinate translation can be conducted numerically.

## EXPERIMENTS

A stereo camera or a combination of laser scanner and digital camera can acquire color point cloud data. Generally, these kinds of sensors require some complex procedures such as a camera calibration. In this experiment, we focus on a development of point cloud alignment procedure and easy 3D data acquisition. Therefore, we selected an infrared Time of Flight camera (SR4000, MESA, Figure 3) to omit an accuracy verification of camera calibration. A detail of the Time of Flight camera shows in Table 1.



Figure 3:SR4000 (MESA)

Table 1: Specification of TOF camera (MESA SR4000)

TOF camera	MESA SR4000
Viewing angle	43.6°(H)×34.6°(V)
Measuring range	0.3~5.0m
distance accuracy	±1cm
repeat accuracy	Under 5mm
Scene/sec	50scene/sec

Although the Time of Flight camera can acquire precise data, measurement error exists in case of a measurement on a black region due to an infrared reflection problem. Figure 4 shows a flat surface taken with digital camera and point cloud data taken with Time of Flight camera. Figure 4 also shows that measurement errors exist on a black region.

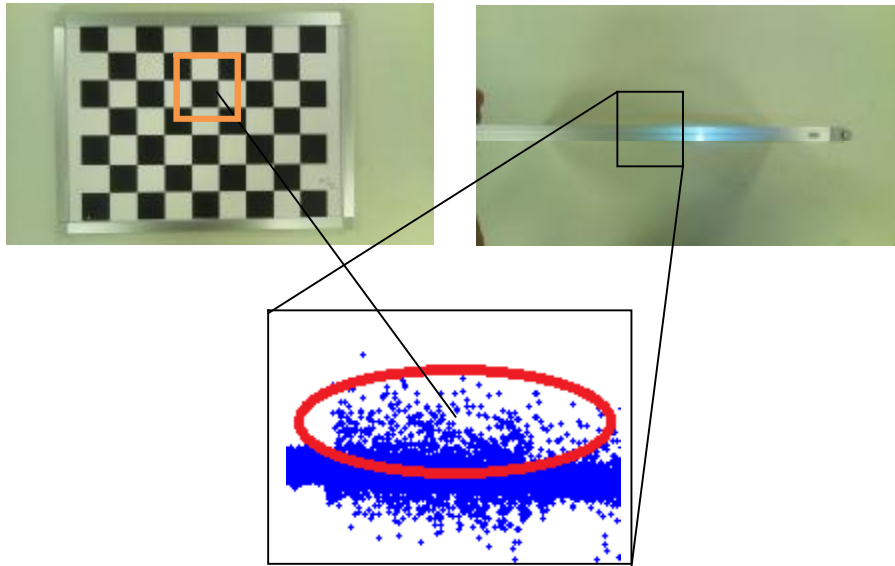


Figure 4: Flat surface

In our experiment, we focus on flat surfaces. Therefore, a floor in a room was selected as a sample. Moreover, some thin objects such as papers were prepared to extract reflective intensity features on the floor. The point cloud data of 100 scenes were taken with the Time of Flight camera. A data capture distance of sensor positions was approximately 50 cm from a start point to end point. Figure 5 shows the measured objects in our experiment.



Figure 5: Measured objects in our experiment

Figure 6 and Figure 7 show point cloud data taken with the Time of Flight camera.



Figure 6: Point cloud data taken with the Time of Flight camera (a bird view)



Figure 7: Point cloud data taken with the Time of Flight camera (a section view)

## RESULTS

Figure 8, Figure 9, and Figure 10 show results after point cloud alignments. Figure 8 shows a result in a bird view after the point cloud alignment using 50 scenes. Figure 9 shows a result after the point cloud alignment using 10 scenes. The result in Figure 8 is shown as a section view in Figure 10.

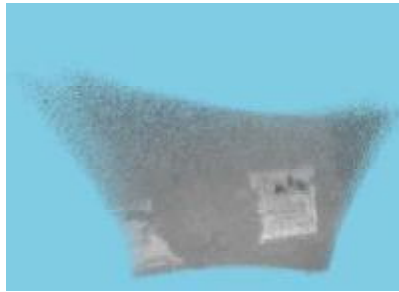


Figure 8: Aligned and overlaid point cloud data using 50 scenes (a bird view)



Figure 9: Aligned and overlaid point cloud data using 10 scenes (a section view)



Figure 10: Aligned and overlaid point cloud data using 50 scenes (a section view)

## DISCUSSION

We have confirmed that our methodology can conduct point cloud data alignment, even if objects are flat surfaces.

An infrared intensity values taken with a Time of Flight camera are available as feature values for a matching procedure. Therefore, we can mention that intensity information is effective as feature values in 3D data alignment

Moreover, a precondition of the ICP algorithm is that base data and reference data should include enough common regions to be corresponded with initial values such as rough sensor orientations. In our approach, measurements from continuous viewpoints provide common regions among sequential scenes with initial values of relative sensor orientations. Hence, we have confirmed that our approach satisfies the preconditions of the ICP.

However the result in Figure 7, Figure 9, and Figure 10 show that point cloud alignment error accumulates based on a general SLAM problem. Therefore, a cancellation of cumulative error in a point cloud alignment is required to improve a reliability of the point cloud alignment.

Additionally, when black regions exist in scenes, point cloud alignment could not perform well, as shown in Figure 11. Because feature extraction and corresponding point detection depend on intensity values extracted from infrared images taken from Time of Flight camera, infrared reflection problem causes feature matching errors. Therefore, a feature point filtering is required to improve our point cloud data alignment approach.

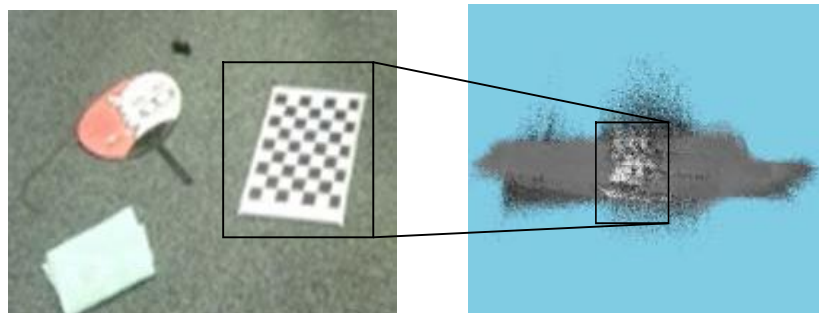


Figure 11: Failed example in 3D data alignment

## CONCLUSIONS

In this paper, we proposed a point cloud data alignment methodology based on ICP and SLAM approaches for flat surfaces. Moreover, we focused on intensity information taken from infrared data as feature points to be used in point cloud alignment. From the experimental result using a Time of Flight camera, even if measured objects are flat surfaces, our proposed methodology can align base data and reference data. A feature filtering and general SLAM problem remain in this research as our future works

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