FEATURE-BASED REGISTRATION OF TERRESTRIAL LIDAR POINT CLOUDS

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ABSTRACT:

Complete scene description by using terrestrial LIDAR systems usually requires multiple scans from different stations. Point cloud of each scan is associated to its own coordinate system on a station basis. Therefore, before all the scans can be registered onto a common coordinate system, the parameters of transformation between different coordinate systems have to be first established. In this study, the authors investigate the functional and stochastic models of employing point, line, and plane features as a means for estimating the 3D spatial similarity transformation parameters. In addition, a feature extractor that collects three types of features, if existing, has been developed and used providing observations for feature matching and transformation parameter estimation among all scans. Depending on the scene geometry, each one of the features can be exclusively used or combined features are involved in estimating transformation parameters. The experiments show that the feature-based approach actually offers high degree of flexibility and renders high accuracy for the task of registering terrestrial LIDAR point clouds.

1. INTRODUCTION

For recent years, terrestrial LIDAR systems have emerged predominantly for scene reconstruction in engineering and research aspects. The point clouds of targets, however, can be collected only on the visible sides so that the registration of all point clouds from consecutive scans is an indispensable requirement for the complete scene reconstruction. For establishing the transformation among all scans, point-based, line-based and plane-based approaches have been extensively considered. Among various alternatives, Iterative Closest Point (ICP) algorithm developed by Besl and McKay (1992), Chen and Medioni (1992), and Zhang (1994), and later improvements reported by Masuda and Yokoya (1995) and Bergevin et al. (1996) have been commonly recognized and long employed as a registration tool. In addition, the developments for more stable algorithm towards faster convergence rate (Mitra et al., 2004) and robustness against weak overlap (Makadia et al., 2006) have further promoted ICP. As for line-based and plane-based registration literature, Stamos and Allen (2002) illustrated partial task for range-to-range registration where conjugate 3D line features for solving the transformation parameters between scans were manually corresponded. Stamos and Leordeanu (2003) developed an automated registration algorithm where pair-wise registration strategy with the additional information of the supporting planes on which the 3D lines lie facilitated the match. Habib et al. (2005) utilized straight-line segments for registering LIDAR data sets and photogrammetric data sets though. Gruen and Akca (2005) developed the least squares approach tackling surface and curve matching. Furthermore, designed target or landmarks that can be easily identified from point clouds are well served for point cloud registration (Akca, 2003). Rabbani *et al*. (2007) proposed a framework for pair-wise registration of shapes represented by point cloud data. They assumed that the points are sampled from a surface and formulate the problem of aligning two point clouds as a minimization of the squared distance between the underlying surfaces. Hansen (2007) presented a plane-based approach that the point clouds are first split into a regular raster and made a gradual progress for automatic registration.

In general, solving transformation parameters is usually established based on a single feature type out of all alternatives, therefore, when faced with the problems, such as obstruction of corresponding pairs, weak geometry of feature distribution, lack of measurements and so forth, the negative effects upon the registration quality are apparent. In this study, the authors focus on performing the LIDAR point clouds registration task by employing point, line and plane features. These three kinds of geometric features are the essential elements and appear as major primitives in urban scenes, especially for man-made structures. By means of utilizing combined feature types for the task of registering terrestrial LIDAR point clouds, the high degree of working flexibility and highly accurate result are more likely to be met. At the methodological level, registering successive scans of LIDAR point clouds on feature basis, the spatial transformation of point clouds can be established by the point-to-point correspondence or via the conjugate 3D line features which show high similarities in line trajectory with adequate spatial closeness upon transformed onto the same coordinate system or using the normal vectors of corresponding conjugate 3D plane features. Strategically, this study also demonstrates the simultaneous registration scheme for all scans, which avoids error accumulations and would reach better solutions. The tools developed in this study for LIDAR point clouds registration on features basis are introduced in more detail in the following section.

2. METHODOLOGY

The feature-based transformation models in this study consist of point-based, line-based and plane-based 3D similarity transformations. The working scheme proposed in this study for registering LIDAR point clouds is illustrated in Figure 1. The 3D similarity transformation is mathematically described by a 7-parameter spatial similarity transformation, including a scale parameter (S), a translation vector (T_X, T_Y, T_Z), and three rotation angles $(\omega, \varphi, \kappa)$. Note that, for the reason of simplicity for data processes, 3D line segment expressed by two 3D end-points is employed to present 3D line features, and 3D plane patch expressed by normal vector is employed to present 3D plane features throughout this study.

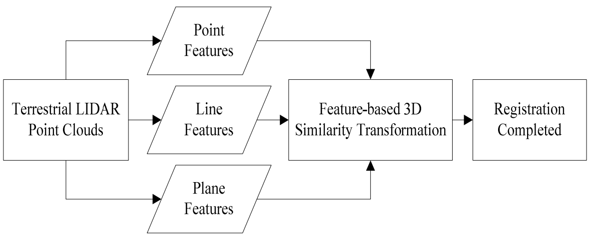


Figure 1. Proposed working scheme

As shown in Figure 1, conditions that lead to solutions can be met either by using single type or combined features, offering a highly flexible working environment for registration tasks.

2.1 Point-based Transformation Model

The spatial transformation of point clouds on point features basis can be established by a point-to-point correspondence and solved by least-squares adjustment. The functional model can be formulated as Equation (1)

$$\begin{bmatrix} X_i^{1'} \\ Y_i^{1'} \\ Z_i^{1'} \end{bmatrix} = \begin{bmatrix} T_X \\ T_Y \\ T_Z \end{bmatrix} + S \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} X_i^1 \\ Y_i^1 \\ Z_i^1 \end{bmatrix}, \qquad (1)$$

where $[T_X \quad T_Y \quad T_Z]^T$: the translation vector from system 1 to system 2;
S: the scale parameter;
$m_{11} \sim m_{33}$: elements of the rotation matrix.

Equation (1) can be expressed as the model of observation equations (indirect observation equations), seen as Equation (2)

$$y_{3n\times1} = A_{3n\times7}\xi_{7\times1} + e_{3n\times1}, \; e \sim (0, \sigma_0^2 P^{-1}) \;, \qquad (2)$$

where n : number of conjugate points;
y: coordinate vector of points;
A: partial derivative coefficient matrix of form of equation (1) with respect to parameters;
e: error vector of points;
P: weight matrix;
ξ: incremental parameter vector.

To balance the transformation equation for solving seven parameters while providing a sufficient datum, three independent points are at least needed. Note that the coplanar 3D point features should be excluded for a non-singular solution under minimum number required for the solution.

2.2 Line-based Transformation Model

The condition for line-based transformation model I is realized by constraining that a 3D line feature transformed to another coordinate system be collinear with its conjugate counterpart, implying that point to point correspondence is not needed. The aforementioned collinearity property for one end point can be established by Equation (3)

$$\frac{X_i^2 - X_i^{1'}}{l_i^2} = \frac{Y_i^2 - Y_i^{1'}}{m_i^2} = \frac{Z_i^2 - Z_i^{1'}}{n_i^2}, \qquad (3)$$

where i: the i^{th} line feature, $i = 1, 2, 3 \cdots n$;
n: the number of conjugate line features;
$[l_i^2, m_i^2, n_i^2]^T$: the directional vector of i^{th} line feature in coordinate system 2;
$(X_i^{1'}, Y_i^{1'}, Z_i^{1'})$: the end point (X_i^1, Y_i^1, Z_i^1) transformed from system 1 to system 2;
(X_i^2, Y_i^2, Z_i^2): the end point of conjugate line in coordinate system 2.

The mathematical model upon linearization can be regarded as the model of “condition equation with unknown parameters” and expressed as equation (4)

$$w_{4n\times1} = A_{4n\times7}\xi_{7\times1} + B_{4n\times12n}(y_{12n\times1} + e)$$
$$e \sim (0, \Sigma = \sigma_0^2 P^{-1}), \qquad (4)$$

where n: the number of conjugate line pairs;
y: coordinate vector of end points of 3D lines;
A: partial derivative coefficient matrix of form of Equation (3) with respect to parameters;
B: partial derivative coefficient matrix of form of Equation (3) with respect to point coordinates.

Now let $\bar{y} = w - By$ and $\bar{e} = Be$, Equation (4) can be further derived and expressed as the model of observation equations, seen as equation (5)

$$\bar{y}_{4n\times1} = A_{4n\times7}\xi_{7\times1} + \bar{e}_{4n\times1}$$

$$\bar{e} \sim \left(0, \Sigma_{\bar{e}} = B \Sigma_{e} B^{T} = \sigma_0^2 \bar{P}^{-1}\right). \quad (5)$$

As revealed in Equation (3), one 3D line correspondence contributes four equations (two for each end point). There must be at least two matched pairs of 3D line features in order for solving seven parameters. Similar to the case of point-based transformation model, the coplanar 3D line features should not be included for a non-singular solution under minimum number required for the solution either. More detail about the line-based 3D similarity transformation can be referred to (Jaw and Chuang, 2007).

2.3 Plane-based Transformation Model

The spatial transformation of point clouds on plane features basis is based on the correspondence of normal vector $(a, b, c, 1)$, as expressed in Equation (6)

$$\begin{bmatrix} a_i^{1\prime} \\ b_i^{1\prime} \\ c_i^{1\prime} \\ d_i^{1\prime} \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} & 0 \\ m_{21} & m_{22} & m_{23} & 0 \\ m_{31} & m_{32} & m_{33} & 0 \\ -m_{41} & -m_{42} & -m_{43} & S \end{bmatrix} \begin{bmatrix} a_i^1 \\ b_i^1 \\ c_i^1 \\ d_i^1 \end{bmatrix}, \quad (6)$$

where $m_{41} = m_{11}Tx + m_{21}Ty + m_{31}Tz$;
$m_{42} = m_{12}Tx + m_{22}Ty + m_{32}Tz$;
$m_{43} = m_{13}Tx + m_{23}Ty + m_{33}Tz$;
$a_i^{1\prime}, b_i^{1\prime}, c_i^{1\prime}, d_i^{1\prime}$: the normal vector of $(a_i^1, b_i^1, c_i^1, d_i^1)$ transformed from system 1 to system 2.

Due to the four elements of normal vector are not independent, equation (6) can be simplified as equation (7)

$$\begin{cases} \dfrac{a'}{c'} = \dfrac{am_{11}+bm_{12}+cm_{13}}{am_{31}+bm_{32}+cm_{33}} \\[2ex] \dfrac{b'}{c'} = \dfrac{am_{21}+bm_{22}+cm_{23}}{am_{31}+bm_{32}+cm_{33}} \\[2ex] d' = -(am_{11}Tx + bm_{21}Ty + cm_{31}Tz) \\ \quad -(am_{12}Tx + bm_{22}Ty + cm_{32}Tz) \\ \quad -(am_{13}Tx + bm_{23}Ty + cm_{33}Tz) + dS. \end{cases} \quad (7)$$

Through least-squares adjustment, equation (7) can be expressed as the model of observation equations, shown as Equation (8)

$$y_{3n\times1} = A_{3n\times7}\xi_{7\times1} + e_{3n\times1}, \; e \sim (0, \sigma_0^2 P^{-1}), \quad (8)$$

where n: number of conjugate planes;
y: normal vector of planes;
A: partial derivative coefficient matrix of form of Equation (7) with respect to parameters.

In accordance with Equation (8), one 3D plane correspondence brings three equations. Therefore, the transformation needs three planes to balance the solution system. Three normal vectors, however, can span only for translation and rotation parameter space, thus requiring a forth plane in order to solve the scale parameter if considered.

2.3 Feature-based Transformation Model

Feature-based transformation model integrates point, line and plane transformation models to solve transformation parameters. No any kind of features is indispensable as long as the condition of solving parameters is satisfied. Due to combined measurements, feature-based transformation model can afford higher degree of flexibility and offer higher accuracy of point clouds registration tasks. The mathematical model can be regarded as a condition equation with unknown parameters, as seen in Equation (9), and the unknown parameters can be estimated through least- squares adjustment

$$\begin{aligned} & w_{j\times1} = A_{j\times7}\xi_{7\times1} + B_{j\times k}(y_{k\times1} + e) \\ & e \sim (0, \Sigma = \sigma_0^2 P^{-1}) \;, \end{aligned} \quad (9)$$

where $j = (3n_{Point} + 4n_{Line} + 3n_{Plane})$
$k = (6n_{Point} + 12n_{Line} + 6n_{Plane})$
n_{Point}: the number of conjugate points;
n_{Line}: the number of conjugate lines;
n_{Plane}: the number of conjugate planes;
A: partial derivative coefficient matrix of form of Equations (1), (3) and (7) with respect to parameters;
B: partial derivative coefficient matrix of form of Equations (1), (3) and (7) with respect to point coordinates;

2.4 Simultaneous Adjustment of Feature-based Transformation Model

The registration of point clouds involves multiple successive scans for a complete reconstruction. The registration process can follow the pair-wise approach and eventually combine matching results for the whole scene, but the errors between neighbouring point cloud sets would be propagated from the first through the last scan. Or, alternative way is to drive the system to perform multiple-set registration. The proposed model for simultaneous adjustment of all scans is expressed in Equation (10) where one of the data sets is chosen as the datum onto which all others are registered by using all features

$$\begin{aligned} & w_{j\times1} = A_{j\times[7(m-1)]}\xi_{[7(m-1)]\times1} + B_{j\times k}(y_{k\times1} + e) \\ & e \sim (0, \Sigma = \sigma_0^2 P^{-1}), \end{aligned} \quad (10)$$

where $j = \sum_{i=1}^{Npoint}\left(3(nPoint_i - 1)\right) + \sum_{i=1}^{Nline}\left(4(nLine_i - 1)\right)$
$+\sum_{i=1}^{Nplane}\left(3(nPlane_i - 1)\right)$

$k = 6\sum_{i=1}^{Npoint} nPoint_i + 12\sum_{i=1}^{Nline} nLine_i + 6\sum_{i=1}^{Nplane} nPlane_i$

m: number of overlapping data sets;
Npint: number of point feature total matching mates;
Nline: number of line feature total matching mates;
Nplane: number of plane feature total matching mates;
$nPoint_i, nLine_i, nPlane_i$: numbers of conjugate features of i^{th} matching mate.

The minimum numbers of needed features for point-based, line-based, and plane-based transformation models are listed as in Table 1.

	Number of parameters	Min. numbers of features	Redundancy
Point-based	7	3	2
Line-based	7	2	1
Plane-based	7	4	5

Table 1. The configuration of minimum features and redundancy

3. EXPERIMENTS AND ANALYSES

The following tests, including simulated and real data sets, were aimed to demonstrate the flexibility, reliability and accuracy that the feature-based transformation model would supply.

3.1 Simulated Data Set

For its simplicity, two overlapping scans with well distributed features under minimum requirements for each transformation model were configured, as shown in Figure 2. Ten check points were set to compare registration accuracy of all transformation models with various random errors. The tested standard deviations are 0.005, 0.01, 0.03, 0.05, 0.09 meters for each coordinate component. Figure 3 together with Table 2 shows total root mean square error (RMSE) for point-based, line-based, plane-based and feature-based transformation models. As revealed in Figure 3 as well as in Table 2, feature-based transformation model renders better registration accuracy than other transformation models for all levels of measurement error.

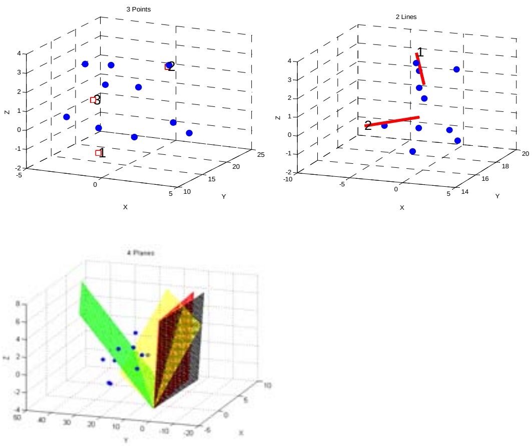


Figure 2. The distribution of features; Dots are the check points

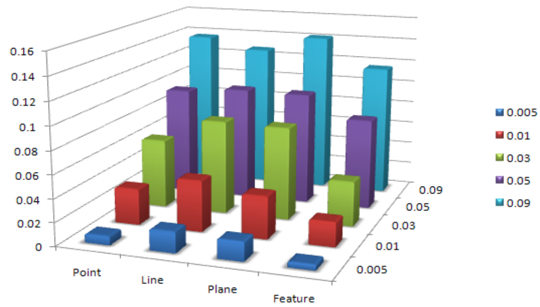


Figure 3. The total RMSE(unit: m) of different transformation models

Error-Std.	Point-based	Line-based	Plane-based	Feature-based
0.005	0.0076	0.0182	0.0166	0.0048
0.01	0.0316	0.0448	0.0372	0.0213
0.03	0.0609	0.0826	0.0817	0.0395
0.05	0.0951	0.0997	0.0992	0.0801
0.09	0.1372	0.1277	0.142	0.1164

$$*Total\ RMSE = \pm\sqrt{(RMSE\_X)^2 + (RMSE\_Y)^2 + (RMSE\_Z)^2}$$

Table 2. The total RMSE*(unit: ±m) of different transformation models

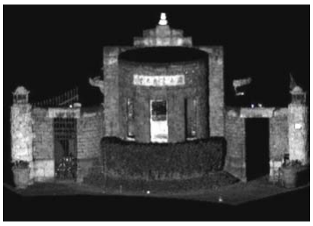
The feature combining scheme offers alternative ways to processing the point clouds registration. One can combine the measurements among three features to solve seven parameters. Table 3 depicts several effective feature combinations for solving transformation parameters under the minimum requirement.

Combined features	Number of obs.	Degree of freedom
1 Point – 1 Line	7	0
1 Point – 2 Planes	9	2
1 Line – 1 Plane	7	0
1 Plane – 2 Lines	11	4

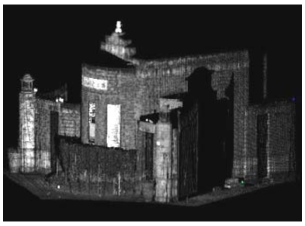
Table 3. The examples of effective feature combinations

3.2 Real Data Set

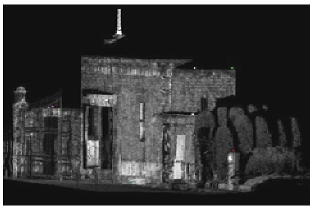
3.2.1 Description of Data Sets: Five successive scans of LIDAR point clouds, as shown in Figure 4, covering the facades of guardroom of National Taiwan University were collected by Trimble Mensi GS200 for verifying the registration achievements of simultaneous adjustment of feature-based transformation model. The evaluation of the registration accuracy was to compute the total RMSE of 15 external check points. The information of the five scans of point clouds is listed in Table 4.



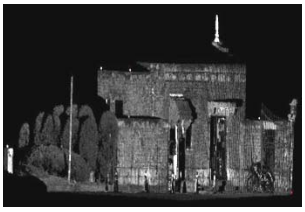
(1)Station 1



(2)Station 2



(3)Station 3



(4)Station 4

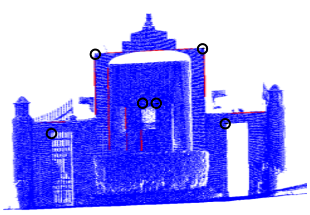
(5)Station 5

Figure 4. The LIDAR point clouds textured with intensities

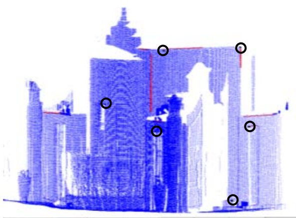
	Number of Pts.	Scanning Distance	Point interval
Station 1	209838	15 m	0.015 m
Station 2	157755	16 m	0.017 m
Station 3	275944	20 m	0.020 m
Station 4	277300	22 m	0.021 m
Station 5	423840	26 m	0.023 m

Table 4. The information of point clouds

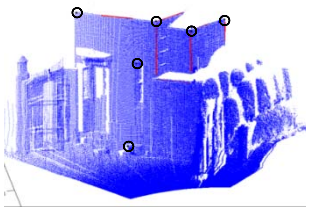
3.2.2 Feature Measurements: The point and plane features were collected by manual measurements while the line features were extracted via an automatic platform (Jaw and Chuang, 2007). The feature measurements included 15 points, 20 lines and 7 planes. The distribution of features is shown as Figure 5.



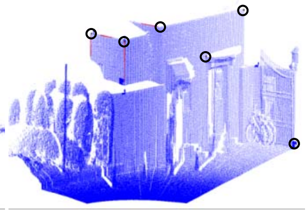
(1)Station 1



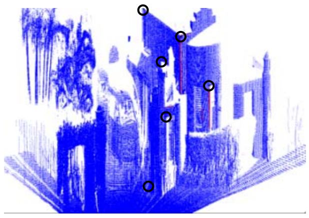
(2)Station 2



(3)Station 3



(4)Station 4



(5)Station 5

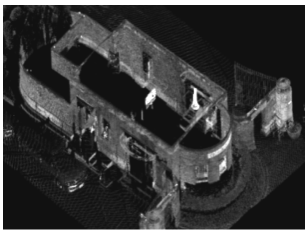
Figure 5. Extracted features superimposed on point clouds

3.2.3 Registration Achievements: The registration accuracies are listed in Table 5. The registration qualities are affected by the accuracy of measurements, distribution of features, and quantity of features. Note that the plane-based transformation model failed to accomplish the registration due to the lack of usable measurements. Overall, feature-based model behaves better than any other model that uses single feature by about 1.4 ~ 2.9 mm. Although the gain of accuracy is not obvious in this test, the feature-based transformation does provide a qualified path for point clouds registration.

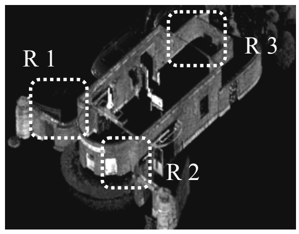
	Point-based	Line-based	Plane-based	Feature-based
Total RMSE	0.0427 m	0.0442 m	N/A	0.0413 m

Table 5. The registration accuracy

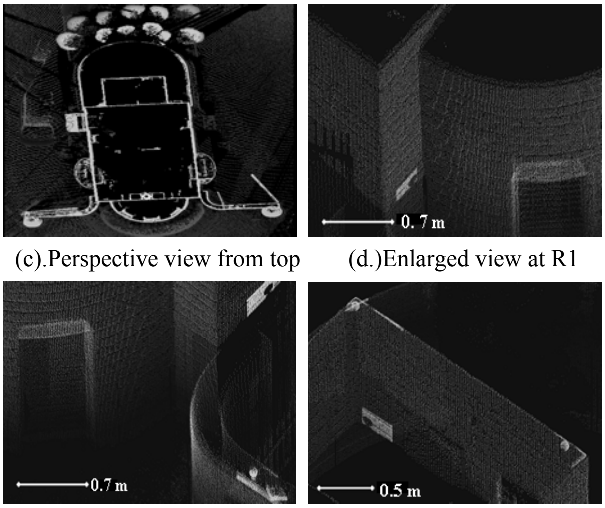
3.2.4 Visual Inspection on the Registration Results: The registration of point cloud can be checked through visual inspection as well, as depicted in Figure 6. When zooming into the detail, the discrepancies between overlapping features nearly confirm the registration quality assessed by external check points.



(a).Perspective view



(b).Perspective view



(c).Perspective view from top (d.)Enlarged view at R1

(e).Enlarged view at R2 (f).Enlarged view at R3

Figure 6. The visual inspection on the registered scenes based on feature-based transformation model

4. CONCLUSIONS

The proposed feature-based 3D similarity transformation model has been proven effective and satisfactory through this study. Scenes, especially man-made construction, are normally rich in various types of features, thus registrations for LIDAR point clouds from successive scans can be achieved without artificial marks. Finally, the proposed model is robust against scene geometry and actually offers a high degree of flexibility.

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