REGISTRATION OF 3-D BUILDING MODELS AND LIDAR POINT CLOUDS USING LEAST SQUARE 3D SURFACE MATCHING

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ABSTRACT: A cyber city is an effective way to visualize the reality in a cyber space. 3-D building models are one of the core elements in a cyber-city. As Lidar point clouds are usually employed to reconstruct and evaluate the building models, the registration of 3-D building models and lidar point clouds is an essential work to ensure both data are in a unify system. In this study, we perform the data co-registration of 3-D building models and lidar point clouds using Least Squares 3-D (LS3D) Surface Matching algorithm. This method iteratively minimizes the 3-D Euclidean distance between these two surfaces using Least Squares Adjustment. First, we find the initial conjugate surface between these two data. Then, a seven parameters 3-D similarity transformation is established to compensate the registration error. All the calculated differences are applied to obtain the transformation parameters using Least Squares Adjustment. Finally, all the lidar points are transformed to the building models space. The test area is located in Taipei, Taiwan. The input data are 3-D building models generated from stereo aerial images and the airborne lidar acquired by Leica ALS 50 with 10 points per meter squares. As the accuracy of lidar data is higher than the building models, the shaping errors and the transformation parameters from Least Squares 3-D Surface Matching can be treated as a quality index of building models. Moreover, the area with large shaping error may represent the missing part of the building. The registration of 3-D building models and lidar point clouds is beneficial to accuracy analysis and model refinement of building models.

1. INTRODUCTION

Nowadays, cyber city has become a new technology to represent 3-D spatial data in a cyber space. One of the core elements in a cyber city is 3-D building models. Building model can be created by different sensors and technologies. Lidar point clouds are usually applied to evaluate the accuracy of building model and also to improve its detail. In order to ensure that both building model and lidar are in a unify system, data registration is an efficient way to transform the different coordinate systems to the unity coordinate system.

Data registration is a procedure to transform a dataset from its own coordinate system to another system. It can be classified into 2-D data registration and 3-D data registration. For example, image registration is the most common 2-D data registration and surface registration is one of the 3-D data registrations. The 3-D data registration includes three control features, i.e. control point, control line and control surface. Control point is the most popular feature in registration. Iterative Closet Point (ICP) (Besl and McKay, 1992) utilizes point feature to register two point sets. This algorithm selects the closest point as a conjugate pair and calculates the transformation parameters iteratively until the parameters meet the converge threshold. The ICP method can be improved by the invariant features in the lidar point cloud efficiently (Barnea and Filin, 2007). The second control feature is linear feature. Linear feature cannot be extracted directly from lidar point cloud. It is usually intersected by two planes. The reliable linear features can be used as control entities and calculate the transformation parameters. The usage of control lines includes the registration of two ground-based lidar data (Jaw and Chuang, 2008), registration of aerial stereo images and airborne lidar data (Habib et al., 2005), etc. The third control feature is control surface which employ in Least Square 3-D (LS3D) Surface Matching (Gruen and Akca, 2005). This algorithm establishes relationships between two overlapped data. This method may register two dataset not only by their geometry but also by their spectrum characteristic (Akca, 2006). This method has been applied to many applications, for example, surface registration for land deformation (Monserrat and Crosetto, 2007).

The objective of this study is to co-register the 3-D building model and lidar point clouds from different systems. In this study, the 3-D building model fulfills the CityGML LOD-2 standard and it is produced from aerial photogrammetry. The lidar data is acquired by an airborne lidar system with 10pts/m^2 and fulfills the USGS standard. However, these two data set cannot registered directly as they are produced from different systems. We assume that the accuracy of lidar data is higher than building model because the lidar acquired the 3-D surface directly. We perform the data co-registration of 3-D building models and lidar point clouds using Least Squares 3-D Surface Matching algorithm (Gruen and Akca, 2005). This algorithm minimizes the difference of building surface and lidar surface using seven parameters transformation iteratively. Finally, the calculated parameters can be treated as systematic errors and area contain large errors can be treated as the missing parts.

2. METHODOLOGY

2.1 Mathematic Model of Least Squares 3-D Surface Matching

Least Squares 3-D Surface Matching was proposed by (Gruen and Akca, 2005). This method assumes that two surfaces are created from the same object by different ways. In this study, one surface was sampled by airborne lidar and we call it template surface $f(x,y,z)$, and another surface from 3-D building models sampled by surveying is called search surface $g(x,y,z)$. If there's no error in an ideal case, the two surfaces should be the same, and all the patch surface in the template surface can correspond to the patch surface in the search surface like equation (1). In reality, the two surfaces are not totally equal. We represent the distance between the two conjugate patch surfaces as the error function $e(x,y,z)$, hence, equation (1) can be rewritten as equation (2). Then, we establish a 7-parameter 3-D similarity transformation as equation (3) from search surface to target surface. These parameters are used to minimize the error between the two conjugate surfaces. In equation (3), ***t*** is the translation vector formed by three translated parameters t_x,t_y,t_z along three axes, **R** is the rotation matrix formed by three rotation angles ω,ϕ,κ around three axes, and *m* is the scale factor we assume that is very close to 1.

$$\mathrm{f(x,y,z)} = \mathrm{g(x,y,z)} \tag{1}$$

$$\mathrm{f(x,y,z)} - \mathrm{e(x,y,z)} = \mathrm{g(x,y,z)} \tag{2}$$

$$[\mathrm{x\ y\ z}]^{\mathrm{T}} = t + mRx_0 \tag{3}$$

The parameters are estimated using Least Square Adjustment. The first step of non-linear function is Taylor expansion until the first order terms as shown as equation (4).

$$\mathrm{f(x,y,z)} - \mathrm{e(x,y,z)} = \mathrm{g}^0(x,y,z) + \frac{\partial g^0(x,y,z)}{\partial x}dx + \frac{\partial g^0(x,y,z)}{\partial y}dy + \frac{\partial g^0(x,y,z)}{\partial z}dz \tag{4}$$

We substitute $\mathrm{dx, dy, dz}$ in equation (4) by the differentiation of equation (3):

$$\begin{aligned} \mathrm{dx} &= \mathrm{dt_x} + a_{10}dm + a_{11}d\omega + a_{12}d\phi + a_{13}d\kappa \\ \mathrm{dy} &= \mathrm{dt_y} + a_{20}dm + a_{21}d\omega + a_{22}d\phi + a_{23}d\kappa \\ \mathrm{dz} &= \mathrm{dt_z} + a_{30}dm + a_{31}d\omega + a_{32}d\phi + a_{33}d\kappa \end{aligned} \tag{5}$$

In equation (5), the $\mathrm{a}_{10,..}\mathrm{a}_{33.}$ are the coefficient terms. We also replace the coefficient by the first derivatives of the surface function $\mathrm{g}^0(x,y,z)$ as equation (6). Finally we get the observation equation as equation (7).

$$\begin{aligned} g_x &= \frac{\partial g^0(x,y,z)}{\partial x} \\ g_y &= \frac{\partial g^0(x,y,z)}{\partial y} \\ g_z &= \frac{\partial g^0(x,y,z)}{\partial z} \end{aligned} \tag{6}$$

$$\begin{aligned} -\mathrm{e(x,y,z)} = {} & \mathrm{g_x}dt_x + \mathrm{g_y}dt_y + \mathrm{g_z}dt_z + (g_xa_{10} + g_ya_{20} + g_za_{30})dm + (g_xa_{11} + g_ya_{21} + g_za_{31})d\omega + \\ & (g_xa_{12} + g_ya_{22} + g_za_{32})d\phi + (g_xa_{13} + g_ya_{23} + g_za_{33})d\kappa - (f(x,y,z) - g_0(x,y,z)) \end{aligned} \tag{7}$$

A more in depth description of the least square adjustment details, in regards to the parameters determination can be found in Acka (2007).

2.2 Search Correspondence

In the LS3D algorithm, the search correspondence is the most important step that resulting the registration success or fail. In this study, we use two conditions to find the right correspondence pairs. The first condition is distance between the conjugate surface pair. We accept the distance below 0.5m as correct correspondence. The second condition is the angle between the two surface normal vectors. These conditions ensure the correspondences are all correct. Figure 1 shows an example of surface correspondence.

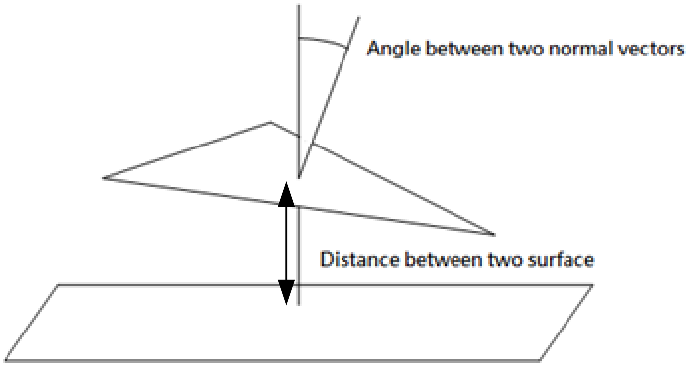

Figure 1. Two conditions of searching correspondence.

3. EXPERIMENTAL DATA

The test area is located in Taipei, Taiwan. The input data are 3-D building models generated from stereo aerial images and the airborne lidar acquired by Leica ALS 50 with 10 points per meter squares. The experiments are performed on both gable and flat roof buildings. Case 1 is a gable roof building while case 2 is a flat roof building. The detail of each data set is described as below. Case 1 has 3723 lidar points and 16 building 16 polygons. Figure 2 shows these data. Case 2 is a flat roof, which leads to the difficulty of registration. This data include 3865 points in point cloud form and 7715 triangles in TIN form. Figure 3 shows these data in point cloud form and building model.

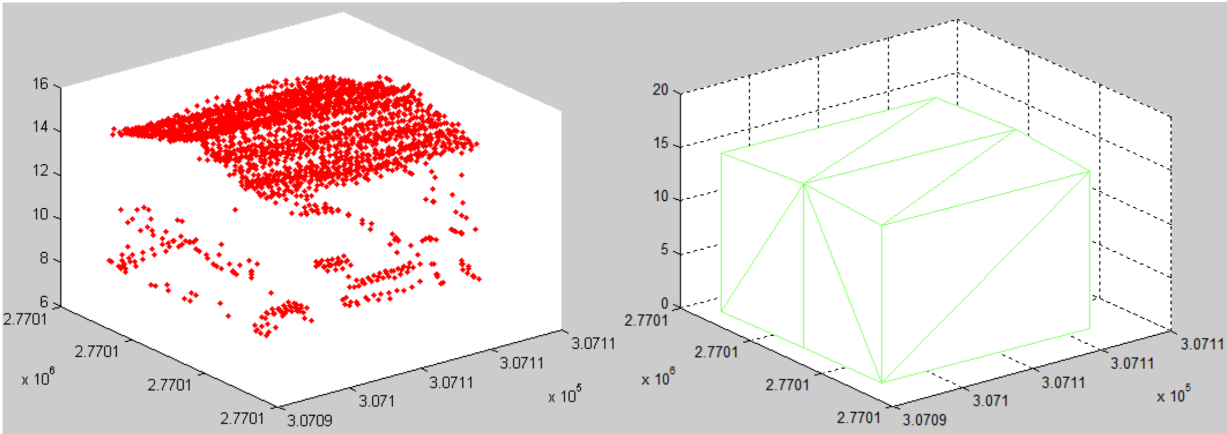

Figure 2. Lidar point cloud (left) and building model (right).

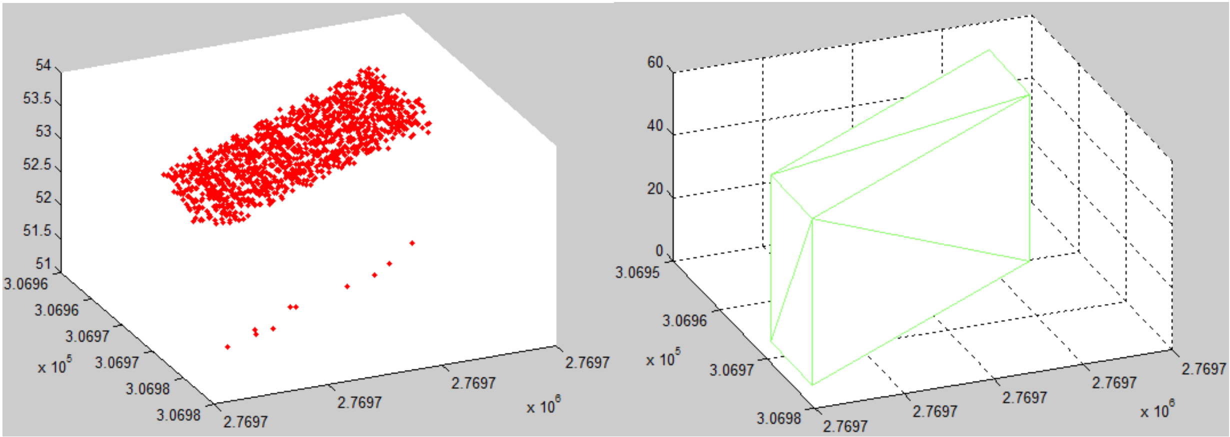

Figure 3. Lidar point cloud (left) and building model (right).

4. EXPERIMENTAL RESULTS

4.1 Gable Roof Building

In this experiment, the selected convergence thresholds are 10^{-3} meters for length parameters (translation and scale factor), and 10^{-3} grads for rotation parameters (omega, phi and kappa). The search correspondence conditions are the distance less than 0.5m and the angle less than 10°. After 30 iterations, the parameters converge met the predefine thresholds. Figure 4 shows the profile of roof top and lidar points. Figure 5 is the residual of lidar points before and after registration. The brightness point is the point with higher residual. Tables 1 and 2 are the residual of points and the accuracy of transformation parameters, respectively. As we only apply 3-D similarity transformation function in the registration process, it is not able to modify the slope of these slanted roofs. Nevertheless, the registration accuracies are improved while the systematic errors are removed.

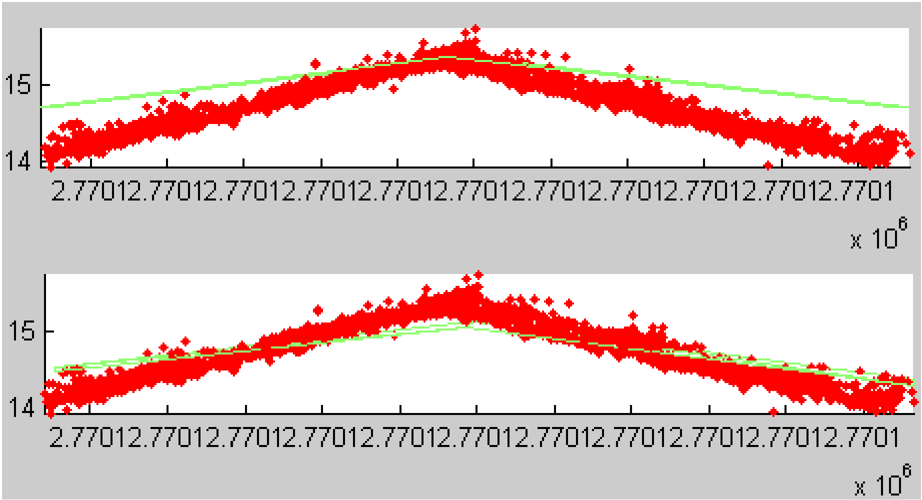

Figure 4. The two datasets before registration (up) and after registration (down).

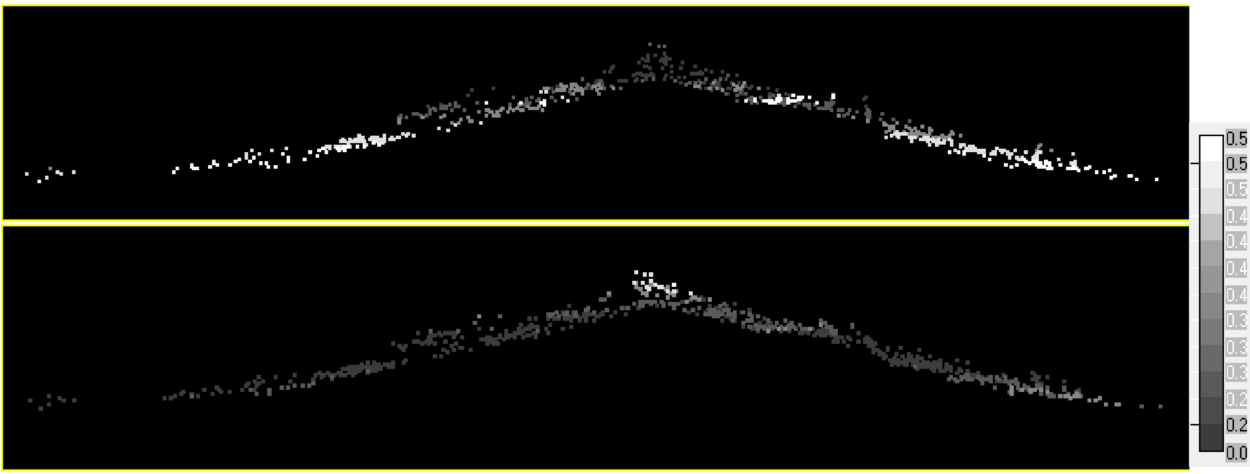

Figure 5. Correspondence residual plot before registration (up), after registration (down) and color bar (right).

Table 1. Residuals Statistic of mean and standard deviation

	Mean (m)	Standard deviation(m)
Before registration	0.274	0.128
After registration	0.127	0.075

Table 2. Accuracy of transformation parameters

	t_x(meter)	t_y(meter)	t_z(meter)	m	ω(degree)	ϕ(degree)	κ(degree)
Initial parameters	0.000	0.000	0.000	1.000	0.000	0.000	0.000
Estimated parameters	-0.001 ±0.053	-0.003 ±0.053	-0.295 ±0.002	1.000 ±0.000	-1.119 ±0.201	0.273 ±0.079	1.700 ±0.369

4.2 Flat Roof House

In this experiment, the convergence thresholds are 10^{-4} meters for length parameters and 10^{-3} grads for rotation angle parameters. Due to the characteristic of data, the search correspondence conditions are conjugate distance less than 0.1m, angle between the normal vectors is less than 15°. The number of iteration is 21. Figure 6 shows the overlapping of roof and lidar points before and after the registration. Figure 7 shows the registration residuals. This figure indicates a systematic error along the Z-axis. It can be removed through the registration process. Table 3 statics the mean and standard errors before and after the registration. The registration accuracy has improved from 0.26m to 0.07m. Table 4 shows the calculated parameters. The standard error of kappa angle is relatively higher than other parameters, because the kappa angle is not easy to determine while the roof is only a plane.

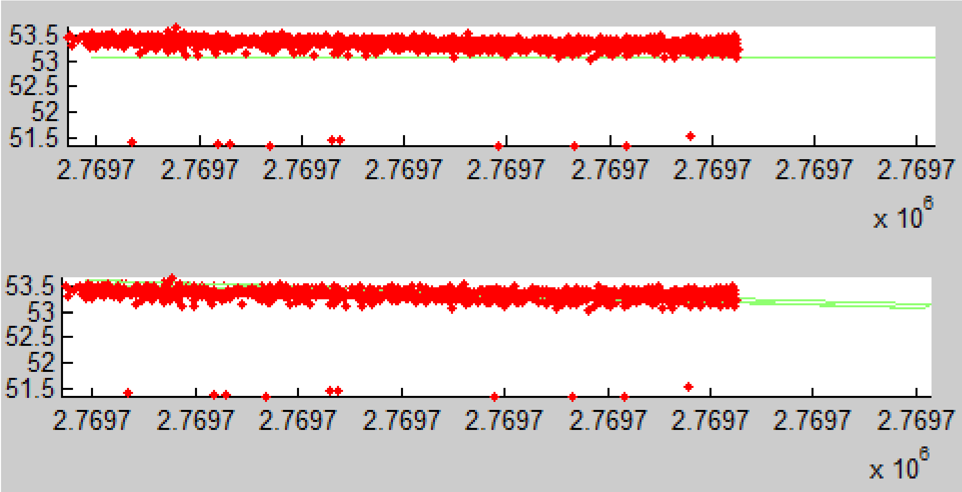

Figure 6. The two datasets before registration (up) and after registration (down).

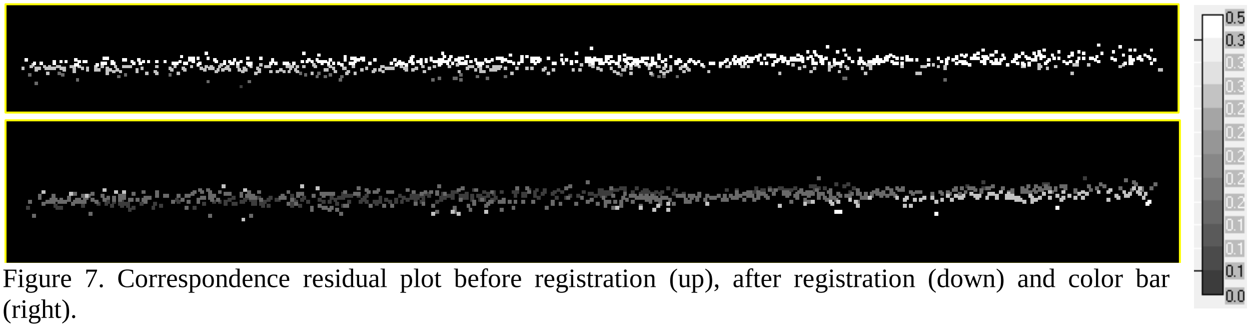

Figure 7. Correspondence residual plot before registration (up), after registration (down) and color bar (right).

Table 3. Residuals Statistic of mean and standard deviation

	Mean(m)	**Standard deviation(m)**
Before registration	0.268	0.055
After registration	0.072	0.052

Table 4. Accuracy of transformation parameters

	t_x(meter)	**t_y(meter)**	**t_z(meter)**	**m**	**ω(degree)**	**ϕ(degree)**	**κ(degree)**
Initial parameters	0.000	0.000	0.300	1.000	0.000	0.000	0.000
Estimated parameters	0.000 ±0.081	0.000 ±0.081	0.287 ±0.075	1.000 ±0.000	-2.015 ±1.465	0.376 ±0.967	0.000 ±4.663

5. CONCLUSION

In this study, we co-register the lidar point clouds and 3-D building model using LS3D algorithm. The LS3D minimizes the Euclidean distance between the conjugate surface in lidar data and building model. The estimated parameters can be used to transform the lidar points to the system of building model. Then, the inconsistent of lidar points and building model are the residuals or missing part. The quality of the building model can be observed from the residuals. The error may cause by the procedure of building generation or change of building. Moreover, the transformation parameters can be used to estimate the system error caused by coordinate system. Experimental results indicate that the overall point residuals before registration is around 0.3m, after registration, the mean residuals have improved to 0.1m.

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