AUTOMATIC REGISTRATION OF LASER SCANNED COLOR POINT CLOUDS BASED ON COMMON FEATURE EXTRACTION

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ABSTRACT: *Point cloud data acquisition with laser scanners provides an effective way for 3D as-built modeling of a construction site. Due to the limited view of a scan, multiple scans are required to cover the whole scene, and a registration process is needed to merge them together. The aim of this paper is to introduce a novel method that automatically registers colored 3D point cloud sets without using targets or any other manual alignment processes. For fully automated point cloud registration without artificial targets or landmarks, this study uses 1) the Speeded-Up Robust Features (SURF) algorithm to identify geometric features among the series of scans and 2) plane-to-plane matching algorithm to achieve precise registration. For an initial alignment during the registration process, common feature extraction is utilized to perform a 3D rigid-body transformation followed by aligning the view into the reference system. Further alignment is obtained using plane segmentation and matching from the 3D point clouds. The test outcomes show that the method is able to achieve registration accuracy of less than 1° in deviation angle.*

KEYWORDS: *3D LIDAR; Point cloud; Registration; Feature Extraction; RGB image; Plane Segmentation.*

1. INTRODUCTION

A virtual 3D model of a construction site through point cloud construction and registration can foster the understanding of the scene of interest, monitoring construction progress, and recognizing potential safety hazards. The construction site should be scanned from various points of view to get a full reconstruction of the site. This is because some point clouds could be disturbed by obstacles and each scanned point cloud is described by its own local coordinate system. Therefore, the point cloud registration process is necessary to merge several collected point cloud data from many scan positions. Point cloud registration is the process of transforming of each point cloud set from its local coordinate frame to a global coordinate frame.

However, the current methodologies present some limitations. For instance, a manual alignment method, which is known as the simplest method, requires at least three common points between two overlapped point clouds in order to set a 3D rigid-body transformation matrix; due to the simplicity, many pieces of commercial software such as CloudCompare, employ this manual alignment method. It is straightforward, but it is time consuming because it requires to find matching points between point clouds manually. In addition, this manual process can be inaccurate especially when handling huge and complicated data sets, where it is difficult to identify point correspondences with the naked eye. There exists other commercial software for point cloud registration such as Faro Scene and Recap 360 Ultimate. Although these software tools provide functions for automatic point registration, they need a large amount of overlapping area and not robust yet for many cases. Becerik-Gerber et al. (2011) proposed 3D target-based point cloud registration. They experimented with three different types of targets such as fixed paper, paddle, and sphere, and with phased-based, time of flight laser scanners. According to their experiments, the sphere target with time of flight scanner provided the best results with respect to accuracy. However, the target-based point cloud registration requires an extra time for setting up and adjusting the targets at every scan. Also, the use of targets necessitates extra costs and is not desired on a busy construction site.

2. LITERATURE REVIEW

Over the last decade, laser scanning systems have been identified as an effective tool for measuring equipment in various application fields, especially in 3D reconstruction and mapping of the environment for construction fields, due to the fast and non-intrusive scanning process. However, a technique is needed to register and visualize the resulting 3D scans in a common coordinate system. The registration in high accuracy should be done to minimize the errors between the merged point cloud sets to acquire the best 3D reconstruction in visualization.

The most well-known method for point cloud registration is the iterative closest point (ICP) algorithm proposed by Besl et al. (1992) and Chen et al. (1992). ICP is an algorithm that finds common matching points of two point clouds that minimize the difference between them. In the ICP algorithm, one point cloud is used as a reference and the other point cloud is merged to the reference based on the criterion of minimum distance. The algorithm iteratively corrects the transformation parameters required to minimize the distance from the source to the reference point cloud. As an advanced method, the iterative closest compatible point (ICCP) algorithm was proposed by Akca (2003) to diminish the search area of the ICP algorithm. In the ICCP algorithm, the distance minimization is achieved between the pairs of points considered compatible on their viewpoint invariant properties. Men et al. (2011) developed a registration procedure using integrated Hue values to carry out a 4D ICP algorithm. The ICP algorithm with the Hue values can attain advanced accuracy and convergence. However, ICP-based registration methods still arouse issues with computing time because of the heavy calculation load related to the ICP algorithm. Also, the performance is not stable due to its dependence of overlapping area and the initial starting points (Wang et al. 2014).

Common feature-based registration could be achieved without initial alignment because 2D images are employed to aid the recognition of feature points. This method uses 2D intensity images with Scale-invariant feature transform (SIFT) algorithm (Eo et al. 2012). However, it is sensitive to the overlapping size of point cloud data. In addition, a large number of scans are needed to get a good performance result, and the feature extraction is heavily influenced by the environment on behalf of brightness changes. Also, a heavy amount of computation is another disadvantage for common feature-based registration (Gai et al. 2013). To reduce the time during the computation process, Cho et al. (2014) used data fusion to track a certain target of interest. Although their method can rapidly perform the scanning and modeling of the scene, it was limited to track the dynamic target of interest, and thus, its application is suitable for tracking a dynamic object such as equipment and materials.

Geo-referencing based registration is using sensors such as GPS and RFID. Olsen et al. (2011) presented a registration method using GPS information. This method could be used in the outdoor domain, but suffers from a lack of accuracy. Valero et al. (2012) used RFIDs for indoor point cloud registration. This method is only suitable for indoor spaces, and the laser scanner is required to be mounted in close proximity to objects in order to recognize the RFID tags. Thus, geo-referencing based registration is not suitable for large-scale sites due to sensor performance dependence (Mastin et al. 2009).

For the registration of 3D point clouds and 2D image, fusing edge extracted in 2D images and 3D point cloud data using range images is proposed by a simple pixel corresponding mechanism (Wang et al. 2013). Their approach implies edge extraction from 2D images, but there are some flaws in border feature detection. Moreover, Moussa et al. (2012) proposed a procedure for automatic combination and co-registration of digital images and terrestrial laser data. The method used images associated with intensity and RGB values. For the common feature extraction, Bay et al. (2006) proposed Speeded Up Robust Features (SURF) algorithm, which is a local feature detector and descriptor. It can be used for object recognition, image registration, classification or 3D reconstruction. It is developed from the scale-invariant feature transform (SIFT) descriptor, and several times faster than SIFT. For automatic point cloud registration, Kim et al. (2016) presented a framework using feature extraction of RGB panorama images. The experiment result was good but it was performed only in an indoor location.

3. OBJECTIVE

The main objective of this study was to develop a target-free automatic point cloud registration method, based on common features extraction between multiple images. In this paper, the SURF feature extraction algorithm was used, which matches 3D point cloud data automatically by using 2D common features to increase registration speed and accuracy. Following sections will discuss the proposed framework, experimental results, and finally conclusion and future work.

4. METHODOLOGY

To achieve the requirements defined by the objective, a framework for automatic registration method was designed and it consists of four steps as shown in Figure 1. The first step is data acquisition using 2D line scanner and digital camera. The second step is RGB texture mapping, which is merging 3D point clouds with 2D RGB images by kinematics calculation. The third step is transformation based on common features detected and extracted from RGB images which correspond to a 3D point cloud data set for an initial alignment. Lastly, a final adjustment is performed by plane segmentation and fitting and matching point cloud data sets.

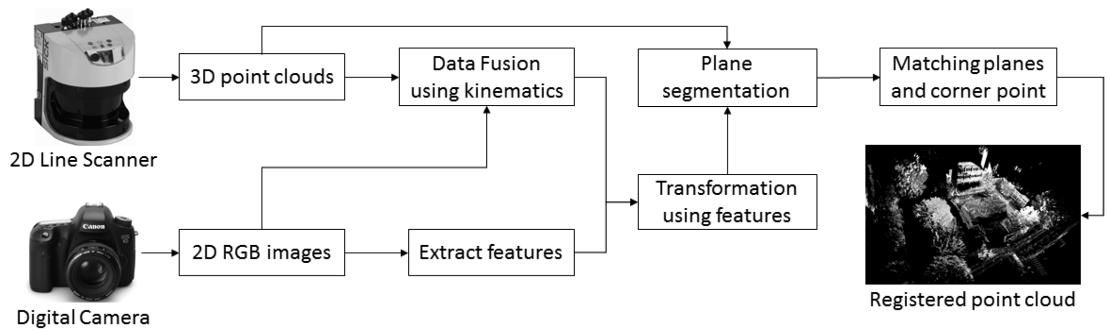


Fig. 1: Framework of the automatic point cloud registration

4.1 Data acquisition

To obtain point clouds and RGB images, a robotic hybrid Light Detection And Ranging (LiDAR) system was used, consisting of four SICK LMS511 2D line laser scanners, and a regular digital camera, as shown in Figure 2. Multiple degree-of-freedom (DOF) kinematics problems were solved based on the built-in mechanical information between laser scanners and a digital camera. The schematic diagram of the kinematics solution of the equipment used in this paper is shown in Figure 2.

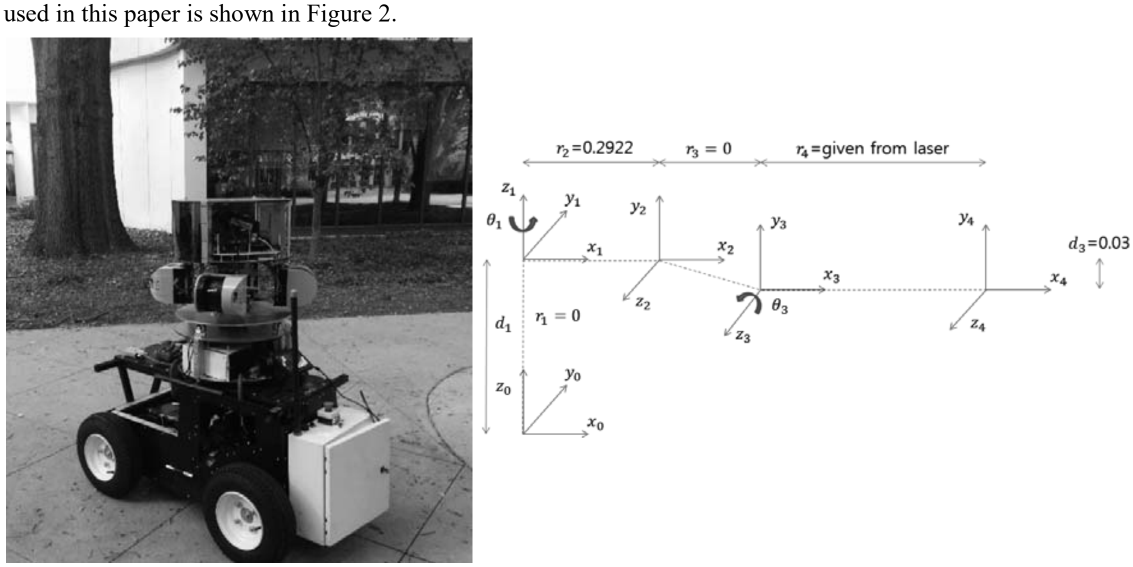


Fig. 2: Robotic hybrid 3D LiDAR System and its kinematics solution

The local Coordinate (x_0, y_0, z_0) means the mobile robot body coordinate located on the ground level, and the coordinate (x_1, y_1, z_1) is the laser scanner coordinate system located at the center of body frame. The local coordinates 2 and 3 are fixed at each laser scanner center. Finally, the local coordinate 4 indicates a measured point (x_4, y_4, z_4) on an object surface. In addition, θ_1 is a body rotate angle and θ_3 is an angle from laser scanner. From the relationship among these information, the kinematics problem is solved as shown in Equation (1).

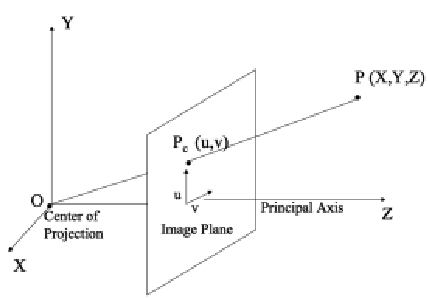
$$\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \begin{bmatrix} \cos(\theta_1)\cos(\theta_3) & -\cos(\theta_1)\sin(\theta_3) & \sin(\theta_1) & r_2\cos(\theta_1) + d_3\sin(\theta_1) \\ \sin(\theta_1)\cos(\theta_3) & -\sin(\theta_1)\sin(\theta_3) & -\cos(\theta_1) & r_2\sin(\theta_1) - d_3\cos(\theta_1) \\ \sin(\theta_3) & \cos(\theta_3) & 0 & d_1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_4 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} r_2\cos(\theta_1) + d_3\sin(\theta_1) + r_4\cos(\theta_1)\cos(\theta_3) \\ r_2\sin(\theta_1) - d_3\cos(\theta_1) + r_4\sin(\theta_1)\cos(\theta_3) \\ d_1 + r_4\sin(\theta_3) \\ 1 \end{bmatrix} \quad (1)$$

In Equation (1), $d_1, d_3, and\ r_2$ are fixed distance between a laser scanner and digital camera because of the mounted location on the robot, whereas r_4 is the sensed distance data from each laser scanner. The kinematics solution will be applied to the extrinsic parameters of digital camera while the intrinsic parameters including focal length, image sensor format, and principal point are estimated by the pinhole camera model as shown in Figure 3.

4.2 RGB texture mapping

A digital camera takes pictures for RGB data from the surroundings of scan area, which can be mapped on the 3D point cloud data. To get this fusion data, the pinhole camera model concept should be used. Using these intrinsic and extrinsic parameters, the laser scanned 3D point cloud can be transformed to 3D camera coordinates according to Equation (2) and (3). Thus, the coordinate systems of 3D point cloud data and RGB image data are aligned



$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = K_{int}K_{ext} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} R_{11}R_{12}R_{13}T_x \\ R_{21}R_{22}R_{23}T_y \\ R_{31}R_{23}R_{33}T_z \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \frac{x}{z} \\ \frac{y}{z} \end{bmatrix} \quad (3)$$

using the concept of perspective projection. This
enables a correct texture mapping between a point cloud and digital camera images.

Fig. 3: Pinhole camera model

4.3 RGB feature extraction and transformation

In this study, SURF feature points are used to obtain the initial transformation between point clouds. Once the feature points of each image are extracted, corresponding points in the 3D point cloud can be tracked by matching feature points in the image plane to the RGB-fused point cloud data set. The Kabsch algorithm (root mean square distance concept) is used to estimate the transformation matrix between point clouds.

To match each point cloud set, the initial rigid transformation matrix is defined. In this case, the transformation is a perspective projection for six degrees of freedom, composed of a rotation matrix and a translation vector in 3 dimensions. This transformation can be written as 3x4 matrix. Then, a point P can be projected, where $P = [x\ y\ z\ 1]^T$, simply by applying this transformation to the point:

$$P' = TP = \begin{bmatrix} U_{11} U_{12} U_{13} D_x \\ U_{21} U_{22} U_{23} D_y \\ U_{31} U_{23} U_{33} D_z \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} \tag{4}$$

4.4 Plane matching

The two point clouds can be further registered using the method of plane-to-plane matching. This method relies on finding three plane correspondences between the point cloud to be registered and the reference point cloud. The selected planes have to be linearly independent and intersect at a unique point in order to fully recover the transformation parameters. For example, one of the planes can be the ground plane whereas the second plane is a vertical wall in the x-axis whereas the third plane is a vertical wall in the y-axis.

First, the Random Sample Consensus (RANSAC) algorithm is used to perform plane segmentation for each point cloud. Second, the rotation component R of the transformation matrix is calculated using the plane normal vectors found in the previous step. Third, the translation component T of the transformation matrix is calculated by comparing corner points between the two point clouds. This process is illustrated in Figure 4 where the rotation R is derived from aligning the blue planes while the translation T is derived from matching the red corner points.

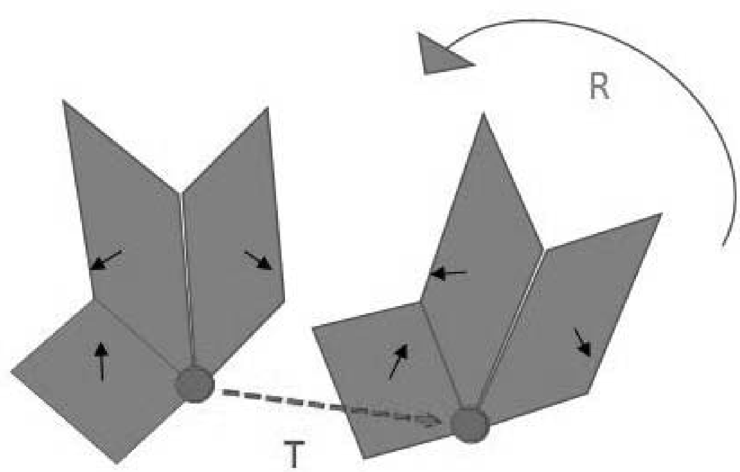


Fig. 4: Plane and corner point matching

5. EXPERIMENT

The data acquisition process for validating the proposed framework was performed near the Mason building in Georgia Tech campus. To register two point cloud sets, it was needed to find the point of the extracted features. Figure 5 shows two RGB images of interesting building captured at different position. At each position, a point cloud also was collected. Figure 6 shows RGB colored point cloud of the scene that is shown in Figure 2 with the proposed texture mapping algorithm. It is possible to find (x, y, z) information of point cloud data from 2D feature information because they are already connected.

Fig. 5: RGB feature extraction

Fig. 6: RGB texture mapped point cloud

Figure 7 shows another test result for RGB feature extraction, and Figure 7 shows RGB colored point cloud of the scene that is shown in Figure 7.

Fig. 7: RGB feature extraction

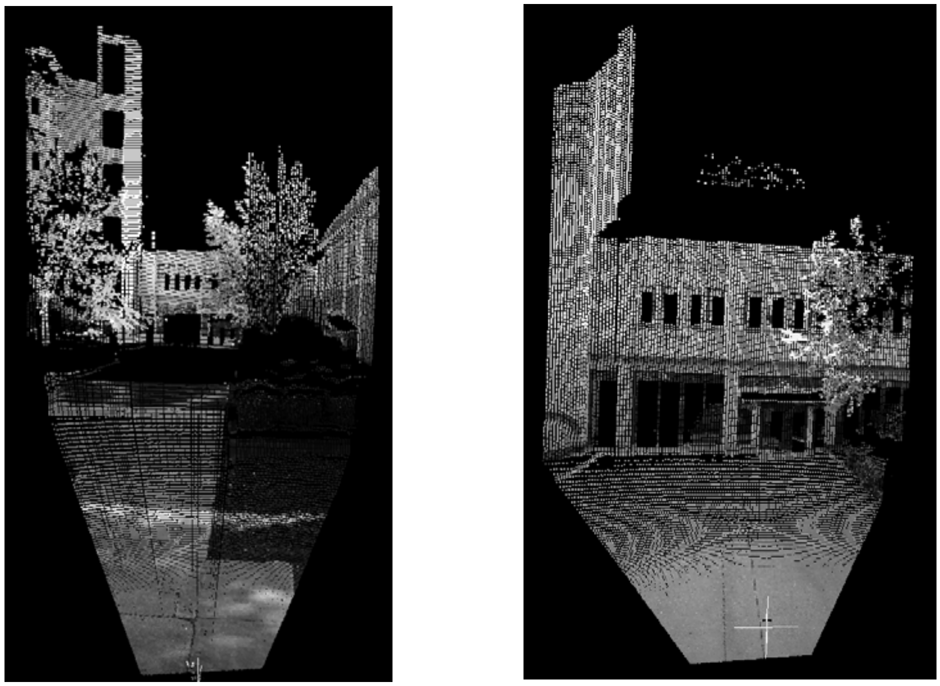


Fig. 8: RGB texture mapped point cloud

Fig. 9: Registered point cloud

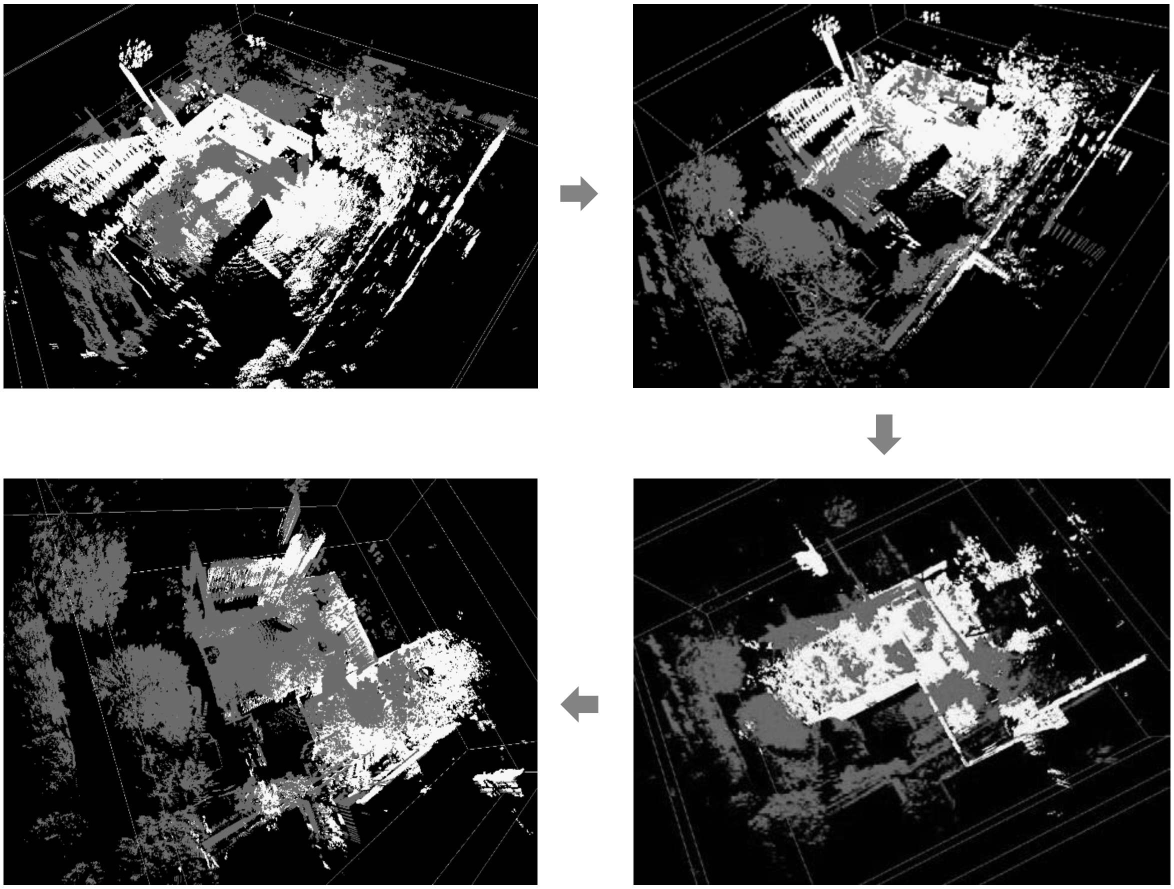


Fig. 10: Sequence for point cloud registration for three different scan position

Figure 9 shows the final registered point clouds with three different scan positions marked with red circles. Figure 10 reveals the difference between point clouds during the registration process. The red points in Figure 10 are from the aligned point cloud and the yellow points are from the reference point cloud. To verify the result for this experiment, the second scan position was assumed as a ground truth for the first registration process and measured the deviation angle from each reference axis at each step of the proposed framework. Then, the third scan position was assumed as a ground truth for second registration process. It can be verified from the reduced deviation angles in Table1.

From the experimental results (Table 1), it can be observed that the initial transformation using RGB feature points is effective in obtaining a coarse estimate for registration. The measured deviation angle after the initial transformation is between 1^{o} and 13^{o}. On the other hand, the final transformation obtained using plane and corner point matching is necessary for a more precise estimate of the transformation parameters. For both registration sequences, the final transformation is able to reduce the deviation angle to less than 1^{o}.

Table 1: Deviation angle in degrees

	First registration sequence			Second registration sequence		
	Original point clouds	After initial transformation	After final transformation	Original point clouds	After initial transformation	After final transformation
X axis	-19.326	-5.823	0.872	9.201	2.238	-0.621
Y axis	-5.962	-1.402	0.259	-14.692	-4.217	0.365
Z axis	174.652	10.276	-0.923	191.421	12.726	0.427

6. CONCLUSIONS

A unique method for automatic point cloud registration without using marked targets was demonstrated and validated for an outdoor environment. A laser scanning system with a digital camera was used to obtain point clouds with mapped RGB texture data. The proposed framework consists of four steps. The first step involves data acquisition. The next step fuses the point clouds from laser scanner and RGB information from digital images. The following involves attaining an initial transformation by common features extracted from digital images and finding their corresponding 3D positions in point clouds. Lastly, plane matching is performed for accurate registration using a plane segmentation algorithm. Although the presented framework must have three plane with one corner point on overlapped area, it accomplished automatic point cloud registration without any target references and manual adjustments. For future work, the research team will apply this approach to commercial laser scanner products. The advantage of this framework can be extended to any types of laser scanners which have a built-in digital camera as long as the kinematic relationship between collected 3D point cloud data and captured RGB images are known.

7. ACKNOWLEDGEMENT

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