A Scan Matching Method for Quadruped Robots in Outdoor Environment

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***Abstract*—In the outdoor unstructured environment, the relative displacement and rotation angle of the continuous laser scans are large due to the dynamic motion of the quadruped robots. Without good initial value, widely-used scan matching method ICP is prone to converge to a local optimum. In this paper, an improved Super 4PCS method based on fast and robust point cloud segmentation is proposed. Through point cloud segmentation preprocessing, unstable obstacles such as vegetation and leaves are removed and only large object point clouds with obvious features are extracted. More efficient point clouds to be registered are provided to Super 4PCS registration algorithm. Experiments prove that the improved method can be applied to quadruped robots in outdoor unstructured environment, speed up the matching and improve the accuracy of point cloud registration.**

Keywords-quadruped robots; scan matching; point cloud segmentation; Super 4PCS

I. INTRODUCTION

The quadruped robot [1] can walk slowly on the complex terrain in the static gait and achieve high-speed walking in a dynamic gait. They can cross the complex and rugged terrain, have strong field work ability, and have excellent sports flexibility and environmental adaptability, therefore the quadruped robot has been widely concerned by many domestic and foreign researchers.

Improving the environmental perception ability of quadruped robots is currently a mainstream research direction of quadruped robots [2]. Scan matching is one of the most important technologies of SLAM (Simultaneous Localization and Mapping), a method commonly used to realize the localization and environment perception of outdoor mobile robots, and it is the key to solve the problems of sensor localization, pose estimation and SLAM closed-loop detection. Therefore, the speed and accuracy of the scan matching is critical to the overall perception system.

This paper is based on the self-developed Hydraulic-driving quadruped robot of Shandong University, which can adapt to the undulating terrain and has the ability to cross obstacles and climb the steps. The perception sensors equipped with the robot include a ZED binocular camera and two Velodyne VLP16 laser scanners. The two laser scanners are mounted horizontally and tilted. The horizontal laser scanner is used for scan matching because that quadruped robots are often used in outdoor environments, and laser scanners are not affected by light and have high detection accuracy, while visual cameras are easily susceptible to light. Scan matching between 3D laser scans is also known as point cloud registration.

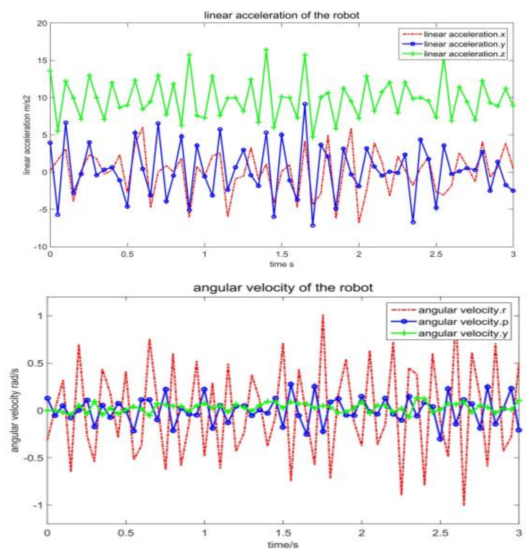

Figure 1. The motion analysis of the quadruped robot: (a) this is the acceleration curve of the three axes of the xyz measured by the IMU (the right-hand coordinate system, where the x-axis is the forward direction, the unit is m/s2). (b) this is the angular rate of the three corners of rpy, which are rotated around xyz (in rad/s).

At present, the most widely used scan matching method is the Iterative Closest Point (ICP) [3] proposed by Best and McKay. ICP uses an iterative approach to obtain the relative transformation between two scans by minimizing the Euclidean distance of the nearest neighbors. In a structured environment, ICP can achieve accurate registration when provided high quality initial value. But ICP is sensitive to the initial value, so it is easy to converge to a local optimum while the relative transformation between two scans is large and the initial value is poor.

However, the quadruped robot often works in unstructured and complex environments, the ground is unstable and there are many obstacles, slopes and rough terrains, the robot body cannot keep a stable state when running. Therefore, several problems will appear when scan matching methods are applied to legged robots. Firstly, some of the simplified hypotheses used in wheeled robots are not applicable, such as the quasi-planar assumption that limit the motion on the z-axis and the plane of the roll/pitch motions. What's more, the intense dynamic movement of the legs will

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affect lidar sensing. It is shown in Fig. 1 that the motion state measured by the IMU mounted on the robot. The xyz axis acceleration information is shown in (a) and rpy angular velocity information about the xyz rotation is shown in (b). The data indicates that the linear acceleration and angular velocity fluctuate greatly during the process of robot moving.

The instantaneous linear acceleration can reach $9m / s^2$ excluding gravity acceleration. The Violent motion of robot results in a large relative displacement and rotation and a low overlap rate between successive laser scans.

In addition, in outdoor environment, the GPS signal is unstable due to the obstruction of buildings and trees. In the absence of high-precision IMU, it is easy to cause a large positioning error so that the registration is not provided with the desired initial position. The application environment of the quadruped robot and the particularity of its own structure make it difficult to scan matching work. Thus, a robust scan matching method that can be applied to quadruped robots working in outdoor environment is of great significance.

Therefore, this paper proposes a robust scan matching method that can be applied to quadruped robots. A fast and robust point cloud segmentation algorithm is used to improve the registration method of Super 4PCS. At first, the environmental ground is extracted from the 3D point cloud, and then the point cloud is projected onto a range image and segment the obstacles outside the ground by using a fast point cloud segmentation algorithm. At the same time, noisy points are removed and only large obstacles with obvious features are extracted. This process reduces the impact of unstable obstacles, such as outdoor vegetation and leaves. After the point cloud pre-processing, Super 4PCS with certain robustness for low overlap is used to iteratively register the processed point cloud to obtain the optimal relative transformation T between the two laser scans. More efficient samples are provided to Super 4PCS by performing fast segmentation preprocessing on the point cloud to be registered. which makes the scan matching method more robust, speeds up the scan matching process and improves registration accuracy. Experiments verify that the improved algorithm is more robust to the large relative displacement and rotation angle between scans without initial values, speeds up the process of scan matching and improves the registration accuracy.

II. Related Work

Based on ICP algorithm, various ICP variants are proposed [4], in which Censi et al. [5] proposed PLICP (Point-to-Line ICP) to improve the accuracy of ICP by minimizing the distance from the point to the plane normal instead of the point-to-point distance. PLICP speeds up the match, however, is sensitive to initial values. Point to plane ICP algorithm that uses the point-to-plane error metric has been shown to converge much faster point-to-point error metric, but the optimization of Point-to-Plane ICP is a non-linear problem with relatively slow speed [6]. Minguez J et al. [7] proposed MbICP (metric-based ICP) for registering two scans when the robot rotation is large. The robustness against large rotational displacement is improved by taking into account the geometric distance of both translation and rotation. However, this method may oscillate around the local optimum when the angular displacement is small [8].

Constructing the feature description of the 3D point cloud provides a solution for the case where the initial value is poor. R.B. Rusu et al. [9] proposed FPFH (Fast Point Feature Histogram) by constructs a feature histogram with information such as the angles of normal vectors between points and their neighborhood points. RBRusu et al. [10] proposed VFH (Viewpoint Feature Histogram) by using the connection between the unitized viewpoint and the point cloud centroid as the normal vector of the entire 3D point cloud at the centroid. Darboux coordinate system is constructed for each center of mass in point cloud in turn, and the geometric characteristics of the center of mass and any point are calculated, and the histogram is formed. Feature-based methods don't need to know the initial transformation of the registration, and a better registration result can be obtained when the displacement is large. They have superiority in the accuracy of registration, but it takes more time to detect, describe and extract feature points, and it is easy to be affected by clutter and occlusion in outdoor feature detection.

Another strategy to solve the problem of scan matching without initial values is RANSAC-based approach. Chen C S et al. [11] proposed RANSAC-based DARCES (Data Aligned Rigidity Constrained Exhaustive Search) to solve partially overlapping 3D point cloud registration problems without any initial position. The transformation relationship is guaranteed to be a true solution in the absence of noise. Arger et al. [12] proposed a global registration algorithm 4PCS, which uses the affine invariance principle of coplanar 4-points for registration and can process noisy data. This algorithm has a quadratic time complexity. Mellado et al. [13] proposed Super 4PCS, which uses effective algorithms and intelligent indexes to improve 4PCS. Super 4PCS not only allows arbitrary initial pose, but also makes registration more robust. In addition, it speeds up search and only has a linear time complexity. Theiler et al. [14] used Gaussian key point detectors to extract key points and then applied the improved 4PCS algorithm for registration, this method overcomes the problem that 4PCS algorithm does not work well when the point density changes strongly as a result of the fixed angle scan of the laser scanner. RANSAC-based method can achieve global registration and is robust to noise, but is random and requires multiple iterations to achieve optimal registration quality.

III. A Scan Matching Method based on Fast Point Cloud Segmentation

An improved Super 4-PCS point cloud registration method based on fast point cloud segmentation is proposed in this paper. For the source point cloud A and the target point cloud B, the 3D point cloud projected onto a range image is preprocessed separately by the point cloud segmentation algorithm first of all, and then the noise points and the points of unstable obstacles with insignificant features in the outdoor environment are eliminated in cluster segmentation. Finally, Super 4PCS is used to register the set of points with obvious features in point cloud A and B, and the rigid transformation between A and B is obtained, and then the rigid transformation is applied to the feature set for verification to obtain the optimal transformation matrix T. The scan matching method is mainly divided into two parts: point cloud segmentation and point cloud registration.

A. Point Cloud Segmentation

Let $P_t = \{p_1, p_2, \ldots, p_n\}$ be the point cloud acquired by the lidar at time t, where p_i is a point in P_t. Environmental data scanned from multi-channel lidar typically includes ground information and obstacle information. In the point cloud segmentation process, the ground point cloud P_g is extracted firstly, and then the non-ground point cloud P_{ng} is clustered.

The quadruped robot is usually used in outdoor or wide environments, so that the ground is a plane is not assumed in this paper. To extract the ground surface with slope changes, GPF [15] (Ground Plane Fitting) is applied. The space is divided into several sub-planes along the x-axis direction (the forward direction). For each sub-plane, a ground plane fitting algorithm is used and the ground surface is extracted by using deterministically assigned seed points in an iterative fashion. After this step, the entire ground point cloud P_g is obtained.

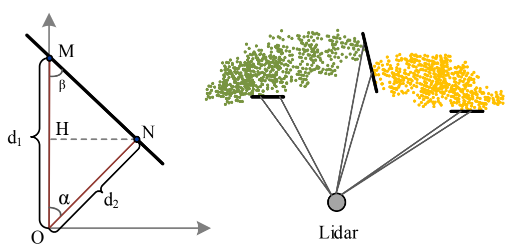


Figure 2. Point cloud segmentation diagram

The next step is to cluster P_{ng}. Since VLP-16 fixed on the quadruped robot only has 16 laser channels in the vertical direction, the point cloud is sparse. Therefore, we introduce a sparse point cloud segmentation method [16] based on range image to cluster P_{ng} points. This method is fast and robust, and only has one parameter β, which makes it easy to adjust parameter. The point cloud Pt is firstly projected onto the 2.5D range image with a resolution of 1800×16, where each pixel point p_i is associated with the angle and the range of the point relative to the sensor. In the set of the non-ground points P_{ng} on the range image, points M and N are adjacent in the row or column direction as shown in Fig.2, point O is the center of the laser scanner. And point M is the point far from point O, Point N is the point closer to O. The segmentation parameter β is the degree of ∠OMN in the triangle composed of three points OMN. This parameter actually represents the depth distance between M and N. The smaller the β value, the larger the depth distance between the two points. According to Eq. (1), the value of segmentation parameter β between M and N can be calculated from α and d_1 and d_2, where α is the degree of the angle ∠ MON and d_1 and d_2 are respectively distance values of the points M and N to point O. Set a segmentation threshold γ. If β is greater than γ, it is considered that the two points M and N belong to the same object and are divided into the same cluster; otherwise, they are classified into different clusters. In the search process, the BFS (Breadth First Search) algorithm is used to speed up search, and similar points are marked together to form a cluster, giving a unique label. After the above work, the ground point cloud and many clusters with different labels are obtained.

$$\beta = \arctan \frac{\|NH\|}{\|MH\|} = \arctan \frac{d_2 \sin \alpha}{d_1 - d_2 \cos \alpha} \tag{1}$$

In outdoor or the wild environments, the environments are often noisy, and there are some unstable targets, such as leaves of trees and other suspended objects, which may lead to mismatch. In order to obtain a more efficient registration sample, clusters with fewer than 40 points are excluded. Only the large target point cloud P_c is retained after the segmentation.

B. Point Cloud Registration

The point cloud registration method adopts Super 4PCS, which is a global registration algorithm of 3D point cloud based on RANSAC framework. In the case of low point cloud overlap rate, there is still better point cloud registration effect. Its time complexity is low and the matching speed is faster. Different from the traditional Super 4PCS method, we use the large target point cloud extracted by point cloud segmentation to random points selection and registration, instead of the original point cloud.

Super 4PCS is mainly based on the theoretical basis of affine invariance of coplanar four-point pairs. As shown in Fig. 3, for a given non-all collinear coplanar four points $\{p_1, p_2, p_3, p_4\}$, the line segments p_1p_2 and p_3p_4 intersect at the point e, and three invariants in affine transformation can be determined, which contain two ratios r_1 and r_2 and one angle θ. For a given set of coplanar points Q, a set of 4 points that are invariant to $\{p_1, p_2, p_3, p_4\}$ can be determined according to these three invariants, such as $\{q_4, q_2, q_3, q_1\}$, shown in the Fig. 3.

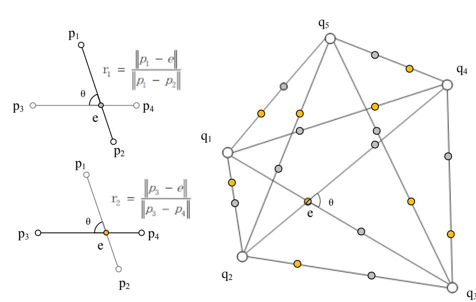


Figure 3. Affine invariance congruent 4-points extraction

Let point cloud P and point cloud Q be the set of large target point cloud of source point cloud A and target point cloud B after point cloud segmentation, respectively. ε is the uncertainty of distance, and f is the estimate of overlap rate between P and Q. The registration steps are as follows:

(a) Select the coplanar four points $\{p_1, p_2, p_3, p_4\}$ in the point cloud P to form a base M randomly, and the corresponding ratio invariants r_1 and r_2 can be calculated by Eq. (2) and Eq. (3).

$$r_1 = \frac{\|p_1 - e\|}{\|p_1 - p_2\|} \tag{2}$$

$$r_2 = \frac{\|p_3 - e\|}{\|p_3 - p_4\|} \tag{3}$$

(b) Constructing sets S_1 and S_2 in point cloud Q according to Eq. (4) and (5).

$$S_1 = \{(q_i, q_j) \mid q_i, q_j \in Q, \|p_i - p_j\| \in [d_2 - \varepsilon, d_2 + \varepsilon]\} \tag{4}$$

$$S_2 = \{(q_i, q_j) \mid q_i, q_j \in Q, \|p_i - p_j\| \in [d_2 - \varepsilon, d_2 + \varepsilon]\} \tag{5}$$

For each point q_i in Q, draw two spheres of radius $R=d_1$ and $R=d_2$ centered at the point q_i. Near the spherical surface, the points in the range of $[d_1 - \varepsilon, d_1 + \varepsilon]$ forms a set S_1 with q_i, and the points in the range of $[d_2-\varepsilon, d_2 + \varepsilon]$ forms a set S2 with q_i.

(c) Extract the four-point set corresponding to the base M in the point cloud Q while rejecting the wrong 4-points set. A unique corresponding 4-points set can be determined in Q from $<d_1, d_2, r_1, r_2, \theta>$ of a given base M.

Based on the principle of affine invariance, calculate the intersections e_{1ij} and e_{2ij} that determined by the ratios r_1 and r_2 for each pair of points (p_i, p_j) in S_1 respectively. Searching in the set S1 and S2 for the point pairs that satisfy the approximate equality of e_{1ij} and e_{2ij} and the angle between the line of two pairs of points is approximately equal to θ. A four-point set $\{q_1, q_2, q_3, q_4\}$ corresponding to the base M can be extracted in Q.

(d) Calculate the rigid body transformation matrix T between the corresponding point set $\{p_1, p_2, p_3, p_4\}$ and $\{q_1, q_2, q_3, q_4\}$, transform the point cloud P using T, and count the number of inner points k_i: The number of points where the distance between the transformed point cloud and the point cloud Q is less than the threshold δ.

(e) Comparing the number of inner points, if it is greater than the current maximum number of inner points N_i (the initial N_i is 0), the current transformation matrix T is recorded as the current best matrix estimation, and the maximum inner point number N_i is updated.

(f) When several iterations are performed on the above five steps (reaching the maximum number of iterations or the number of inner points remains basically unchanged), the transformation matrix T corresponding to the maximum number of interior points N_i is the relationship between the point cloud A and the point cloud B.

After the above six steps, the registration between the source point cloud A and the target point cloud B can be realized, and the optimal relative transformation matrix between the point cloud A and the point cloud B is obtained.

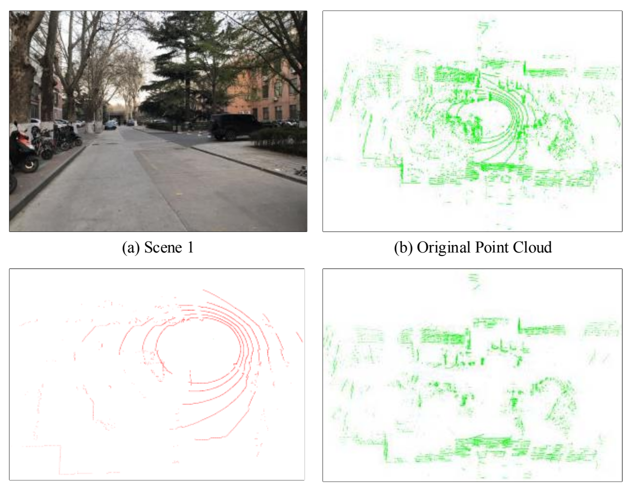
IV. EXPERIMENT

Using the Velodyne VLP16 lidar installed horizontally on the quadruped robot for point cloud data acquisition, an experiment was carried out. With the maximum measurement range of 100 meters, the VLP16 supports 16 channels and can acquire approximately 300,000 points per second. It has 360° horizontal field of view, 30° vertical field of view (+15° to -15°), horizontal angular resolution of 0.1°-0.4°, vertical angular resolution of 2.0° and 5Hz to 20Hz rotation frequency. This paper sets the rotation frequency to 10Hz, and the CPU of the computing platform is an i5-8400.

The experiment has two scenes: urban road environment (scene 1) and wild forest environment (scene 2). The two frames of point cloud used in the experiment were from the same one acquisition process of the experimental platform. The experiment is divided into three parts, including point cloud segmentation, point cloud registration and comparison of registration time and precision before and after algorithm improvement.

A. Point Cloud Segmentation

Scene 1 is an urban road environment with multiple vehicles and multiple dynamic objects, which is an outdoor large-scale scene. The original point cloud and point cloud segmentation result are shown in Fig. 4. In the urban road environment, the ground is relatively flat, there is no large terrain fluctuation, so the GPF ground extraction algorithm performance well (Fig. 4(c)). After the rapid clustering and segmentation algorithm, the cluttered point cloud is removed, leaving only large objects such as vehicles, trees and buildings (Fig. 4(d)), and the segmentation results good.



(a) Scene 1 (b) Original Point Cloud

(c) Ground Point Cloud (d) Point Cloud after Segmentation

Figure 4. The point cloud segmentation result of scene 1

Scene 2 is an unstructured forest environment with multiple trees and vegetation. There are large terrain fluctuation and many messy objects. Fig. 5 shows the original point cloud and point cloud segmentation result of scene 2. As shown in Fig. 5(a), the forest environment has many undulations and the ground has a large inclination angle. By comparing the original point cloud and the clustered point cloud, the GPF algorithm extracts the ground relatively completed (Fig. 5(c)). However, some points of the high terrain still exist after the ground extraction, such as the horizontal point cloud in the upper right corner as shown in the Fig. 5(d). Through the fast point cloud segmentation algorithm, the cluttered point cloud is removed, leaving only the large objects such as trees and stone piles and some remaining ground, and the segmentation clustering results good.

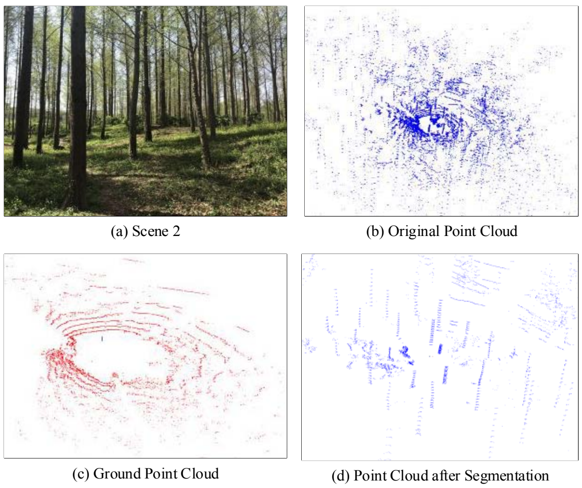


Figure 5. The point cloud segmentation result of scene 2

B. Point Cloud Registration

In the same two scenes, the laser scanning data during the movement of the quadruped robot is collected. In order to test the result of point cloud registration better, two laser scanning frames separated by a certain time are manually selected for registration, so that the relative distance and the rotation angle between the two frames are large. The original point clouds and the clustered point clouds are respectively registered by Super 4PCS algorithm, as shown in Fig. 6 and Fig. 7, where (a)(b) are the original point clouds and the original point clouds registration result, (c) is the point cloud after fast point cloud segmentation of (a), and (d) is the registration result of (c). In the image of point clouds, yellow indicates the target point cloud, red indicates the source point cloud, and green indicates the source point cloud after registration.

In Scene 1, there are many obstacles with little similarity, and the point cloud of the buildings by the road are relatively regular. The relative distance and rotation of the two original point clouds in Fig. 6(a) are both large. After directly registration, the two points of the cloud are roughly aligned, as shown in Fig. 6(b), but the details are not accurately registered such as the clear distance between the corners of the building and the distance between vehicle obstacles. Implementing the improved registration algorithm on the clustered and segmented point cloud (Fig. 6(c)), It can be found that the obstacles and buildings in the point clouds are basically aligned (Fig. 6(d)), the corners of the building and the point cloud of the vehicles are completely coincident. It shows that the improved algorithm has higher accuracy than directly registration.

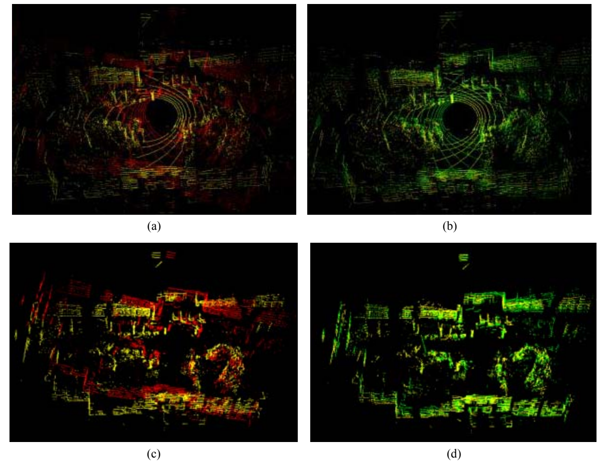


Figure 6. The point cloud registration result of scene 1

Compared with scene 1, the point cloud of scene 2 is sparser and the obstacles are also fewer, furthermore the features are very similar. And due to the special environment, when the tilt angle of the lidar is too large, the effective point cloud is less on the side of the larger tilt angle. Therefore, scene 2 presents a greater challenge to the registration algorithm. Directly registration of the original point clouds of Scene 2 (Fig. 7(a)) results basically failed (Fig. 7(b)), there is rarely overlap between the ground and the trees. With the preprocessing by the fast point cloud segmentation algorithm (Fig. 7(c)), and then the registration is performed by the Super 4PCS algorithm, the result is shown in Fig. 7(d). From the details, the overlap rate of the trees is higher, this result is better than the registration of the original point cloud.

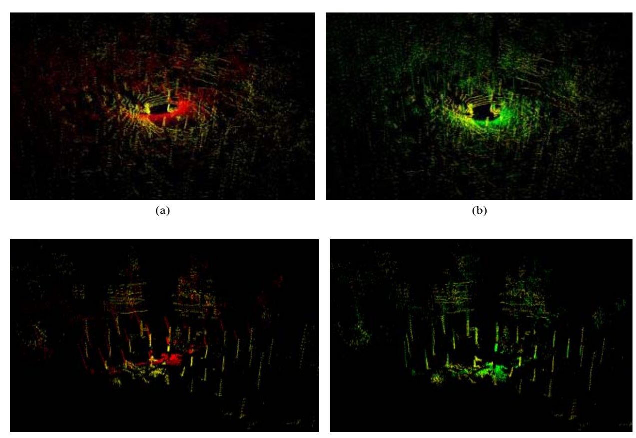


Figure 7. The point cloud registration result of scene 2

C. Registration Algorithm Comparison

In this paper, the Super 4PCS registration algorithm (method 1) and the Super 4PCS registration algorithm based on fast point cloud segmentation (method 2) are compared from the registration time and the registration accuracy. The main indicators are the number of points in the one-frame point cloud to be registered, the time-consuming of the one-frame point cloud segmentation, the point clouds registration time-consuming of two frames and the registration error. Multiple point clouds registration experiments were performed in the two scenes and the average values of the indicators were taken as shown in Table I.

TABLE I. THE RESULTS OF COMPARATIVE EXPERIMENTS

scene	Number of points in a scan		Runtime of segmentation (ms)	
	Method 1	Method 2	Method 1	Method 2
scene 1	26483	14451	N/A	10.18
scene 2	27538	8957	N/A	12.25
scene	Runtime of registration (ms)		Registration error	
	Method 1	Method 2	Method 1	Method 2
scene 1	28.32	15.06	2.563	0.492
scene 2	34.87	19.19	3.483	0.985

From Table I, it can be clearly seen that after the point cloud segmentation preprocessing, the number of points in the point cloud is greatly reduced, especially in the sparse environment in the wild forest. The preprocessor greatly reduced the difficulty of registration and improved the quality of the point clouds to be registered.

After the improvement, although an extra step is added, the total time consumption of the algorithm still has greatly reduced. The registration error also decreased greatly, and the accuracy of the registration is improved, which makes the algorithm more suitable for the field of the quadruped robot in the outdoor unstructured environment.

V. CONCLUSION

Aiming at the problem of point cloud registration in the complex environment of outdoor quadruped robot, an improved Super 4PCS method based on fast and robust point cloud segmentation is proposed. By adopting the fast point cloud segmentation algorithm to remove the interference of cluttered points in the environment, only the large object point cloud with obvious features and suitable for registration will be extracted. In the absence of initial values, the improved registration algorithm is better to adapt to point cloud registration with larger relative displacement and rotation angle, it can reduce the registration time and greatly improves the accuracy of registration.

However, there are still some problems in the algorithm. For example, the ground segmentation with large undulations is incomplete. In the field environment with similar obstacle characteristics, the registration result is not ideal. In the next step, we will further study these issues, for example, combining semantic information for segmentation, and using the segmented tags to provide more information for registration to achieve a better registration effect.

ACKNOWLEDGMENT

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