Line-based Camera Pose Estimation in Point Cloud of Structured Environments

Huai Yu$^{1,2}$, Weikun Zhen$^2$, Wen Yang$^1$ and Sebastian Scherer$^2$

Abstract—Accurate registration of 2D imagery with point clouds is a key technology for image-LiDAR point cloud fusion, camera to laser scanner calibration and camera localization. Despite continuous improvements, automatic registration of 2D and 3D data without using additional textured information still faces great challenges. In this paper, we propose a new 2D-3D registration method to estimate 2D-3D line feature correspondences and the camera pose in untextured point clouds of structured environments. Specifically, we first use geometric constraints between vanishing points and 3D parallel lines to compute all feasible camera rotations. Then, we utilize a hypothesis testing strategy to estimate the 2D-3D line correspondences and the translation vector. By checking the consistency with computed correspondences, the best rotation matrix can be found. Finally, the camera pose is further refined using non-linear optimization with all the 2D-3D line correspondences. The experimental results demonstrate the effectiveness of the proposed method on the synthetic and real dataset (outdoors and indoors) with repeated structures and rapid depth changes.

I. INTRODUCTION

The 2D to 3D registration problem is to match a query image with a 3D model to establish the geometric correspondence between the two modalities and estimate camera pose [1]. It is essential for many applications, e.g. point cloud colorization [2], [3] and camera localization [4]. Based on the estimated transformation parameters, image textures can be used to colorize untextured point clouds, which is beneficial for further interpretation. With the developments of low-cost LiDAR sensors and the advancements in LiDAR-based SLAM algorithms [5], [6], point cloud 3D models can be easily obtained. Thus 2D-3D registration can be used to localize a small lightweight camera inside pre-built 3D maps, which is attractive and complementary to existing visual SLAM technology.

However, the 2D to 3D registration is very challenging because of the appearance differences and modality gaps. Generally, the current 2D to 3D matching methods are often established on the same kind of descriptors (e.g. SIFT) across different modalities [7]. Nevertheless, appearance and visual feature changes may occur between viewpoints, light conditions, weather and seasons, which make visual features not suitable for the registration of optical imagery with point clouds. Additionally, the same kinds of appearances and visual features are not always available for point cloud data.

On the other hand, LiDAR point clouds are 3D data with geometric position, while images are projected 2D data with textured information. The modality differences and description gaps make the common image registration methods fail to get correspondences. Fortunately, 2D images share some geometric consistent features with point clouds, such as line segments and planes [8]. Thus we can use geometric co-occurrence to find these feature correspondences. We focus on the scenarios with rich geometric information, such as urban scene with buildings. This kind of Manhattan world commonly consists of a triplet of 3D parallel lines, which are shown as 2D lines intersecting at vanishing points in image planes [9]. These geometric constraints are beneficial for establishing the correspondences between the two modalities.

The global 2D-3D registration is known as a difficult problem for the non-convexity and feature description gap, it is very vital to robotics because of drift-free localization. However, there is a lack of research on globally registering a single image to a point cloud map. In this paper, we propose a global 2D-3D registration pipeline to estimate line correspondences and the camera pose for structured environments. By discovering the geometric relationship of 2D-3D lines, we propose to match primary vanishing directions with 3D parallel orientations to decouple the camera rotation and position estimations. Then we further use a simple hypothesis testing strategy to eliminate the rotation ambiguities and simultaneously estimate the translation vector and the 2D-3D line correspondences. Compared with existing methods, our proposed method globally estimates the camera pose without any pose initialization or texture information. The pipeline of using vanishing direction matching and hypothesis testing gives more reliable 2D-3D correspondences, additionally can well avoid the camera pose estimation being stuck into a local optimum. It is also robust to feature outliers and can deal with challenging scenes with repeated structures and rapid depth changes.

The structure of this paper is organized as follows: Section II reviews previous work related to 2D-3D registration. Section III details the methodology. Experimental results and discussions are presented in Section IV. Finally, Section V gives the conclusion of this paper.

II. RELATED WORK

For image to point cloud registration, the general approach is transferring one modality to the other, i.e. project the point cloud to image space [10], [7] and reconstruct the point cloud using multi-view geometry [2], and then registering at the same dimension. However, the reconstruction approaches do

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$^1$Huai Yu and Wen Yang are with the Electronic Information School, Wuhan University, Wuhan 430072, China \{yuhuai, yangwen\}@whu.edu.cn
$^2$ Weikun Zhen and Sebastian Scherer are with the Robotics Institute, Carnegie Mellon University, Pittsburgh, PA 15213, USA \{weikunz, basti\}@andrew.cmu.edu
not work well for the registration of a single image to point clouds. For the projection approaches, because there is no texture information in the point cloud, geometric features are often used, which are more robust than appearance features. Therefore, the main issue is how to estimate 2D-3D feature correspondences and the camera pose.

With 2D-3D feature correspondences, the pose estimation problem can be well solved by PnP or PnL algorithms [11], [12]. However, in our cases, it is very challenging because both the pose and correspondence are unknown, which is considered a chicken-and-egg conundrum. A conventional approach is using the RANSAC-based strategy [13], which can simultaneously consider feature correspondence and geometric information. However, without any constraint, RANSAC suffers from a large search space and high time complexity to avoid the local optimum. To guarantee global optimum and improve the efficiency, the existing approaches mainly rely on point and line feature correspondence [4], [14], [15], [16], [17]. Several approaches simultaneously determine the correspondence and pose between 2D and 3D points, such as SoftPosit [14] and BlindPnP [18]. However, they are local optimization methods requiring good pose initializations. And camera to LiDAR sensor calibration methods [19], [6] also optimize the extrinsic transformation based on a very reliable pose initialization. Besides, recent 2D-3D tracking methods [20], [21] use the pose of previous frame to predict the current frame pose to implement 2D-3D matching, which also belong to the local optimization methods. More recent works use branch-and-bound strategies to guarantee the global optimum without a pose prior [22], [4]. However, these approaches start from the existing point features and are conducted on synthetic data which guarantees the proportion of inlier correspondences, which are very difficult to follow for real data.

For real 2D-3D data, it is troublesome to extract the highly repeatable features across modalities. Point features are often used (e.g. Harris, SIFT, junctions [23]), but they need careful design to encode geometric information and maintain the co-occurrence ability across modalities. Compared with these point features, line features are more suitable for 2D-3D registration, which share the characteristics of stability and representiveness. However, it is difficult to describe the local information of line feature for both 2D and 3D data. An early approach modifies SoftPosit algorithm for line feature [24]. However, it needs a good initialization and may get stuck in a local optimum. Recently, Brown et al. [22] utilize both point features and line features to minimize the projection error, then use branch-and-bound formulation to guarantee the global optimization.

Structured environments like buildings are different to natural scenes because of the repeated structure and weak texture. The aforementioned methods may fail to find a good pose. Fortunately, many 3D parallel lines in structured environments generate vanishing points in 2D images. In previous work [25], [26], vanishing points have been used for rotation estimation between images, but rarely used in registration between 2D and 3D data. A systematic 2D-3D registration method is proposed for 2D-image and 3D-range in an interactive manner [16]. The camera orientation is recovered by matching vanishing points with 3D directions and translation is estimated by RANSAC among all the linear features. Because it is hard to determine the correspondence between vanishing points with 3D directions, the authors interactively rotate the 3D model to align 3D directions with 2D vanishing directions. Therefore, there is a great demand for exploring the automatic 2D-3D registration problem of data in structured environments.

III. OVERVIEW OF THE PROPOSED METHOD

To address the automatic registration of a single image with point clouds in structured environments, we propose to separately estimate the rotation matrix and translation vector by using geometric correspondences. It starts from a single image and untextured point clouds, and outputs the 2D-3D line correspondences and camera poses related to the point cloud frame. We first extract line segments from both 2D and 3D data and cluster them into two sets (vanishing point lines for 2D and parallel lines for 3D). Based on the relationship of vanishing points and the parallel directions of 3D lines [25], we then coarsely match primary
2D vanishing directions and 3D parallel orientations to compute feasible rotation matrices. With each rotation matrix candidate, we use a hypothesis testing strategy to estimate the translation vector. The estimation with the most line correspondence inliers is a reliable initialization of camera position. Additionally, by comparing the number of inliers for different rotation candidates, we can estimate the final line correspondences and translation vector, simultaneously removing the wrong rotation estimations. After obtaining the 2D-3D line correspondences we further optimize the camera pose by minimizing the line projection error. The main steps include line segment extraction, rotation matrix candidate estimation, line correspondence estimation, and final pose refinement using line correspondence (Fig.1).

A. Line segment extraction for image and point cloud

For line segment extraction of images, many state-of-the-art methods exist in literature [27], [28]. Considering the computation efficiency and quality of extracted lines, we choose the LSD method [27]. However, the line segment extraction methods for unorganized point clouds are specified by the geometric structures. Here, we utilize a simple and efficient 3D line detection algorithm [29], which is very suitable for the structured environments with the existence of many plane features. Fig. 2 shows an example of the line segment extraction results for both 2D and 3D data. Their structures are very similar and share many co-occurring line segments, which is very important for later correspondence estimation.

![2D line detection](image1.png) ![3D line detection](image2.png)

Fig. 2: A demonstration of the 2D and 3D line segment extraction method.

B. Rotation matrix candidate estimation

The projections of 3D parallel line segments are 2D line segments sharing with the same vanishing point. As shown in Fig.3, there is a set of 3D parallel lines with normalized homogeneous orientation $\tilde{v}_{3d} = [V_x \ V_y \ V_z \ 0]^T$ in the point cloud frame. Their projections on the unit sphere in camera frame are great circles intersecting at one point on the sphere. The direction from camera center to the point $v_{2d} = [v_x \ v_y \ v_z \ 0]^T$ forms a vanishing direction which is corresponding to the parallel 3D lines in camera frame. Thus, the transformation from $\tilde{v}_{3d}$ to $v_{2d}$ is a typical Euclidean 3D transform

$$\tilde{v}_{2d} = [R \ t] \cdot \tilde{v}_{3d}$$
$$v_{2d} = R \cdot v_{3d}$$ (1)

where $R$ and $t$ are the rotation and translation parameters from point cloud coordinate system to camera coordinate system, $v_{2d}$ and $v_{3d}$ denote the inhomogeneous unit vanishing directions and 3D orientations. We can observe that the rotation is totally determined by the direction correspondences. The rotation matrix can be estimated with at least 2 correspondences.

$$[v_1^{2d} \ v_2^{2d} \ v_3^{2d}] = R \cdot [v_1^{3d} \ v_2^{3d} \ v_3^{3d}]$$ (2)

where $v_1^{2d}$ is corresponding to $v_1^{3d}$, $v_2^{2d}$ is corresponding to $v_2^{3d}$, respectively. $v_3^{2d}$ and $v_3^{3d}$ can be the cross products of the former two orientations or another correspondence. It should be noticed that the vanishing directions are rays while 3D line orientations are direction ambiguous. Thus with two correspondences we can get four rotation matrices. We first obtain several matrices using $M = v_{2d} \times v_{3d}^{-1}$. For each estimation $M$, we need further find the orthonormal matrix $R$ to represent the rotation matrix.

From the extracted 3D and 2D line segments, we need to cluster at least two primary 2D vanishing directions and two corresponding 3D directions. For 2D lines, we use a multiple RANSAC-based vanishing direction detector [30] to cluster the lines into several sets. After clustering, vanishing direction is computed using PCA. SVD decomposition is utilized on the normals of the great circles of these lines (Fig.3), the eigenvector with the smallest eigenvalue is the vanishing direction. Likewise, we cluster 3D parallel lines in the point cloud frame using RANSAC-based detector. We randomly select one 3D line segment, clustering the other 3D lines with similar normalized 3D directions ($< 1^\circ$) to get the largest number of inliers. To maintain the robustness of the vanishing direction and 3D orientation estimation, the number of 2D and 3D clusters (denoted as $c$) needs to be set more than 3, e.g. $c=5$. After getting $c$ directions, we further merge the line sets with collinear and adjacent directions as [16] and select the former two vectors with largest number of lines as the final 2D and 3D directions. Although there may exist more than two primary sets of line segments in 2D and 3D data, we only use the former two or three ones because it is already very stable for structured data.

However, the geometric distribution of line segment sets is not robust enough to distinguish the orientation correspondences between 2D-3D line segment sets. Giving two pairs...
of vanishing directions and 3D orientations, 2 possible correspondences can be obtained. Additionally, the ambiguity of 3D orientations (two opposite directions) gives 4 possibilities of rotation estimation. Thus there will be 8 rotation candidates. For three sets of 2D-3D line correspondences, the additional correspondence can be used for validation of the estimation. Thus there will be less than eight candidates. The rotation candidate estimation algorithm is outlined in Algorithm 1.

Algorithm 1 Rotation matrix candidate estimation

Input: 2D line segments \( \{l_{2d}\} \), 3D line segments \( \{l_{3d}\} \);
Output: 8 rotation candidates \( R = \{R_1, R_2, ..., R_8\} \);
1: Clustering 2D lines into \( M_{2d}(M_{2d} > 3) \) sets and calculating the \( M_{2d} \) vanishing directions;
2: Merging the 2D lines into \( M_{3d}(M_{3d} > 3) \) parallel line sets calculating the \( M_{3d} \) 3D orientations;
3: Merging the \( M_{3d} \) 3D directions and picking the former 2 with most number of line segments \( v_{2d} = (v^1_{2d}, v^2_{2d}) \);
4: Calculating the rotation matrices using Eq.2 \( \{R\} = \{R_1, R_2, ..., R_8\} \);
5: return \( \{R\} \);

C. Translation vector and line correspondence estimation

Although there exists ambiguities of the rotation estimation, the searching space is greatly decreased. For each rotation estimation candidate, the correspondence of 2D line sets with 3D line sets is determined. By analyzing the projection model from point cloud frame to camera frame, it is still a non-linear and non-convex problem. Bad initialization of the position will result in local optima. Thus a hypothesis testing method on individual line correspondence can be used to decrease the possibility of getting stuck in a local optimum since there are only three translation parameters left. Before picking 2D-3D line correspondences, some isolated short segments are removed for better efficiency. For each 2D-3D line segment correspondence, the transformed 3D line segment in camera frame is co-planar with the 2D line segments (Fig.4), thus the transformation of the 3D line center point \( P \) is perpendicular to the normal of the corresponding 2D line segment \( n \),

\[
(RP + t) \cdot n = 0. \quad (3)
\]

By randomly selecting 3 pairs of 2D-3D line correspondences, a translation vector can be calculated. Then the estimated \( R \) and \( t \) are used to estimate the total inlier correspondences. Each 3D line is first transformed to the camera coordinate system. For each 2D segment, several co-planar 3D segments are selected using Eq.3 and are projected to the image plane as finite 2D lines. We calculate the overlap length and select the inliers with more than 50% of 2D segment length. This constraint using overlap avoids the degenerate case where all 3D line segments become inliers when the camera is sufficiently distant. For each RANSAC iteration, we can get a translation estimation and a certain number of 2D-3D line correspondences. When the number of inliers exceeds 70% of the total number of 2D (3D) line segments, or the iteration time reaches the setting maximum, it returns the estimation with the largest number of inliers as the estimated translation. Thus, we can get 8 translation estimations for 8 rotation candidates, respectively. Then the one with the most inliers is selected as the final translation vector. At the same time, we obtain pairwise 2D-3D line correspondences and eliminate the rotation ambiguities. The hypothesis testing strategy takes the geometric distribution and individual line segment correspondence into consideration, which greatly decreases the possibility of being stuck into local optimum. The pseudocode of translation estimation part is shown in Algorithm 2.

Algorithm 2 Translation and line correspondence estimation

Input: 2D line segments \( \{l_{2d}\} \), 3D line segments \( \{l_{3d}\} \) and 8 rotation candidates \( R \);
Output: Optimal rotation \( R^* \), translation \( t^* \) and 2D-3D line correspondences \( V_{2d-3d} \);
1: Merging 2D and 3D line segments and removing short isolated segments;
2: for all \( R_i \in R \) do
3: Initializing number of correspondences \( N_i = 0 \);
4: loop
5: if \( N_i > 0.7 \times N(l_{2d}) \) or max iterations then terminate;
6: end if
7: Randomly matching 3 pairs of 2D-3D segments, using Eq.3 to compute \( t \);
8: Calculating line overlap length and counting the number \( N \) of matching line sets \( V \) with line overlap length \( (>0.5 \times \text{length}(l_{2d})) \);
9: if \( N > N_i \) then \( N_i = N, V_{2d-3d} = V, t_i = t \);
10: end if
11: end loop
12: end for
13: Picking \( N^* = \max\{N_1, N_2, ..., N_8\} \) and the corresponding \( R^*, t^*, V_{2d-3d} \);
14: return \( R^*, t^* \) and \( V_{2d-3d} \);

D. Pose refinement using line correspondence

At the former stage, we obtain pairwise line correspondences and 6DOF pose parameters. Similar to point-based
registration methods [31], we further optimize the camera pose by minimizing the projection error of all correspondences. However, it is not easy to use Euclidean distance to measure the projection error for line correspondences. For a pair of matching 2D-3D line segments, the registration error contains overlap distance and angle difference. Because the overlap length has been constrained at the inlier estimation step, we further optimize it with the collinear constraint. If the projections of two 3D-line end points are collinear to the corresponding 2D lines, there will be no angle difference between the correspondence. For two 3D end points $P_i = (P_i^x, P_i^y)$, the variables are camera pose $R, t$, its Lie algebra is $\xi$. The projected end points are $u_i = (u_i^x, u_i^y)$.

$$u_i \sim K\exp(\xi)P_i. \quad (4)$$

We want to minimize the distance of both end points to the corresponding infinite 2D line $Ax + By + C = 0$, whose coefficient vector is denoted as $H = [A \ B \ C]$. Considering all the matching 2D-3D line segments, the minimization function can be formulated as

$$\xi^* = \arg\min_\xi \sum_{i=1}^{N} e_i$$

$$= \arg\min_\xi \frac{1}{2} \sum_{i=1}^{N} \frac{||H \cdot \exp(\xi)P_i||^2}{A^2 + B^2}, \quad (5)$$

where $P_i$ contains two end points, the $L_2$ distance is the sum of the end points to the corresponding infinite line. It is finally formulated as a non-linear least squares problem. With Lie algebra, we can transform it to the unconstrained optimization problem and use the L-M algorithm to solve it. For a 3D end point $P$, the 3D transformed point $P' = [X' \ Y' \ Z']^T = RP + t$, the projected 2D point is $u = [u_x, u_y]^T$. The Jacobian matrix of the cost function is

$$\frac{\partial e}{\partial \xi} = \frac{\partial e}{\partial u} \frac{\partial P'}{\partial u} \frac{\partial u}{\partial \xi}, \quad (6)$$

where $\frac{\partial e}{\partial u}$ is the partial derivative of a 2D point to a 2D line,

$$\frac{\partial e}{\partial u} = \begin{bmatrix} \frac{\partial e}{\partial u_x} \\ \frac{\partial e}{\partial u_y} \end{bmatrix} = \begin{bmatrix} A \\ B \end{bmatrix} \begin{bmatrix} 1 \\ \frac{\sqrt{A^2 + B^2}}{A^2 + B^2} \end{bmatrix}, \quad (7)$$

and $\frac{\partial u}{\partial \xi}$ is the standard 3D to 2D projection model [32],

$$\frac{\partial u}{\partial \xi} = \begin{bmatrix} \frac{\partial u_x}{\partial \xi} \\ \frac{\partial u_y}{\partial \xi} \end{bmatrix} = \begin{bmatrix} 0 & -\frac{L_x}{2} & -\frac{L_y}{2} \\ \frac{L_x}{2} & 0 & -\frac{L_y}{2} \end{bmatrix} \begin{bmatrix} X' \\ Y' \\ Z' \end{bmatrix}. \quad (8)$$

We can use g2o library [33] to implement the optimization (Eq.5). To remove outliers, we iteratively optimize the cost function and reject the outliers using the refined pose. The iteration terminates when there is no outliers or maximum iterations reached.

**IV. EXPERIMENTS**

To demonstrate the effectiveness of the proposed method, we test it on both synthetic (IV-A) and real data (IV-B). Both data are structured environments including 3D parallel lines, which is the prerequisite for the vanishing direction matching. It should be noticed that the proposed method works with the assumption of a large overlap between point clouds and images, which is consistent with the condition of previous methods [4], [8], [16].

**A. Synthetic data experiments**

To evaluate the proposed method with a setting where the true camera pose was known, 50 independent Monte Carlo simulations are conducted. Two sets of random 3D parallel lines are generated from $[-1, +1]^3 \in \mathbb{R}^3$, a fraction of 3D lines with random orientations are added to form the original 3D line segments; a fraction of the 3D lines are randomly selected as outliers to model occlusion; the inliers are projected to a 640 x 480 pixels virtual image with a synthetic camera $f_x = f_y = 800$; Gaussian noise is added to the 2D line endpoints with a standard deviation $\sigma$ of 2 pixels; and some 2D lines with random orientation are added to the image as the 2D line outliers. Based on these setups, we do not need to conduct line segment extraction for images and point clouds. Visualization of synthetic setups and registration results are shown in Fig.5.

![Fig. 5: Synthetic 3D and 2D experimental results using random 3D lines. (a) 3D models(red lines), generated pose priors(green points) and estimated camera pose (o-xyz). (b)2D projection alignment results. 3D line projections shown as green lines, red as 2D image lines.](image)

The quantitative results are shown in Fig.6 and Fig.7. The success rates measure the fraction of trials where the correct pose is found, where the rotation error $R_c = acos(\frac{\text{trace}(R_c^T R_0) - 1}{2})$ is less than 0.1 radians and position error related to the ground truth $||t_c||/||t_{GT}||$ is less than 0.1, as used in [4]. Compared with RANSAC (RS), the proposed method (VP) has a higher success rate with the growth of line feature numbers. When there are more lines, there will be more number of outliers. In this case, it will be easier to fall into a local optimum, thus the successful pose estimation rate will drop. The running time becomes a little longer but the growth rate is much smaller than RANSAC. The time costs are less than 5 seconds for each trail. Fig.6(c) shows the RMSE and the standard deviations of the pose estimation errors. The rotation error is less than 1.5 degrees, while the position error is less than 0.4 meters. Additionally, we can observe from Fig.7 that the proposed method is very robust to 2D and 3D outliers.

**B. Real data experiments.**

The dataset consists of four outdoor and indoor scenes of structured environment, CMU NSH wall, Hamburg Hall windows, Hamerschlag Hall and NSH lounge. For each...
scene, there are a point cloud and 10 images taken with different poses. A FARO laser scanner focus3D S and FLIR BFLY-U3-13S2C-CS camera are used to capture 3D point clouds and 2D images. To get the ground truth of each camera pose, we manually and uniformly pick 20 pairs of 2D-3D correspondences for each image, then use the PnP solver to find camera pose with minimal projection error. It is time-consuming but we trust the manually labeled 2D-3D correspondences.

To validate the effectiveness of the rotation estimation framework, we show an example of the estimated vanishing directions and the corresponding 2D line segment sets in Fig.8(a), while the primary 3D orientations and the corresponding 3D parallel line segments in Fig.8(b). The two primary vanishing directions for 2D image are corresponding to the two primary 3D line orientations. However, without visualization of 2D lines in images and 3D lines in point clouds, it is difficult to compute 2D-3D direction correspondence. Thus, we keep the possibilities of orientation matching and get 8 rotation matrix candidates.

Some qualitative results of line correspondences are shown in Fig.9 for four scenes. All the matching 3D line segments are projected to the image plane (in green) using the estimated pose for visualization, while the red are the corresponding 2D lines. We can observe that the global geometric structure aligns well. Some 2D lines have more than one corresponding 3D lines and vice versa. This is reasonable because we can not guarantee that the fragments in 2D and 3D line segments are totally removed. There exists some (both 2D and 3D) lines having no correspondence because they contribute to the vanishing direction matching but not for translation estimation. Based on these 2D-3D line correspondences and the coarse estimated pose, we further use the local optimization method in Sec. III-D to refine the pose. The iterations of pose refinement often less than 5 times when there is no outlier.

The final camera poses are shown in Fig.10. For each scene, we give an example of the true pose and our estimated pose on the point cloud map. The true poses are marked as $txyz$ in dash lines, while the estimations are $xyz$ in continuous lines. There is a small drift of camera positions, but the orientations of axes are parallel to each other. To better visualize the registration results, we project the original point cloud to the image plane with the same camera model and the estimated camera pose, which are shown on the top-right of each figure. The projected image is fused with the original camera image to visualize the misalignment. The overlapped area (brighter area) with small motion blur means that the registration result is better. From the global perspective, it overlaps well and the motion blur is minimal.
When the depth changes dramatically, there exists some drift caused by misalignment.

3D line matching based on [34]. The performances on two large scale maps are shown in Fig. 11. Both the position errors are less than 0.5 meters and the rotation errors are less than 1 degree. To visualize the registration results, we further use the RGB image and camera pose to reproject the RGB information to the point clouds, so the visible point clouds are colorized. For Fig. 11(b), we reproject the color information of two non-overlapping images to point clouds using the estimated camera poses. We can observe that there is no artifact in these areas, which means the localization is accurate.

![Fig. 10: Camera pose estimation visualization. (First row: NSH wall, Hamburg Hall windows; Second: Hamerschlag Hall, NSH lounge)](image)

![Fig. 11: Colorization of large scale point clouds using estimated camera poses.](image)

To quantitatively analyze the results, we use the mean and standard deviation of 2D-3D matching pairs’ number $Num$, rotation error $R_e(\circ)$, position error $t_e(m)$, and position error related to the ground truth to measure the performance. Table I shows the registration results for each scene with 10 images respectively. For NSH wall data, the total number of matching 2D-3D line segments is relatively smaller compared with other two outdoor scenes, but the line distributions are reliable. For Hamburg Hall windows, there exists more repeated structures, but the results are still feasible. There are more than 180 matching segments for each image. For Hamerschlag Hall, there are both repeated structures and dramatic depth changes. The estimation errors are slightly bigger, 0.62 degrees for the mean rotation error and 0.54 meters for the mean position error. For NSH lounge, because it is an indoor environment, the total number of matching 2D-3D line segments is much smaller compared with outdoor scenes. Fortunately, the distance from camera to object is relatively small, so we can get very high precision of pose estimation once sufficient 2D-3D line correspondences are found. We can also observe that there exist some disturbances for both rotation and position errors within acceptable ranges due to some negative factors (e.g., motion blur).

![Table I: Matching quantities and registration errors for real data.](image)

For the testing on large scale environments, we extend our method to match a single image with a large scale point cloud map. When a pose estimation is obtained, we further check the visibility of 3D line features and discard the invisible

![Image 314x520 to 434x597](image)

![Image 437x520 to 557x599](image)

Regarding the processing time, the 3D line segment extraction costs the most time, which is related to the volume of point cloud. With the extracted 3D line segments, it takes about 8 seconds to estimate the camera pose of a single image on the Matlab implementation using an 8-core Intel i7 CPU. However, the time changes a little depending on the number of merged 2D and 3D line segments. We use parallel computing for different rotation candidates, thus it does not add much time for the estimation of translation vectors.

During the experiments, we recommend to set the clusters of the vanishing point and 3D parallel line as 5. In Manhattan world, the common vanishing point number is 3. But 3 clusters sometimes result in 2 or 1 vanishing points after merging. Therefore, 5 clusters can yield more stable and robust output. Another parameter is the overlap length threshold. It is a valid 2D-3D correspondence when the overlap length exceeds half of the 2D line length. This is an empirical setting based on the performance. A larger setting can reject more inliers while smaller yields more outliers. This setting suits well both in the synthetic and real data experiments. In general, the estimated poses are promising, especially for the rotation calculation being less than 1 degree error for different scenes. The translation error may change a lot with structure repetitions and depth changes. Meanwhile, if we use RANSAC from the beginning with 6 line correspondences to estimate both $R$ and $t$, it rarely succeeds. This is because the search can easily fall into a local optimum. In our proposed method, the strategy using vanishing direction matching and hypothesis testing greatly reduces the chance of getting stuck into a local optimum.

V. Conclusion

In this paper, we have presented an image to point cloud registration method to simultaneously estimate line
correspondence and camera pose in structured environments. Based on geometric information, the method decouples the rotation calculation and translation estimation in two steps. Eight rotation candidates are obtained using the correspondence of vanishing directions to 3D primary parallel directions. Then a hypothesis testing approach is used to estimate the line correspondence and translation vector. Specifically, the framework using the hypothesis testing approach successfully deals with the rotation ambiguity from matching vanishing directions with 3D orientations. Experiments were conducted on synthetic and real data (both outdoors and indoors) with challenging repeated structures and rapid depth changes. The results demonstrate that the proposed method can effectively estimate line correspondence and camera pose. In the future, we will exploit more efficient ways to find the global solutions of camera pose using line correspondence.

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