On Texture and Geometric Feature Based RGB-D Registration

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Abstract— **This work addresses the problem of point cloud registration in the context of RGB-Depth data. The Color and Geometric Feature (CGF) registration presented here utilizes both intensity and depth data, in order to achieve an optimal use of all available resources. Registration is achieved by performing optimization over a joint cost function, exploiting texture features and correspondences between planes. For this, a group of planar patches is extracted and matched, with covariances estimated based on the sensor's error model. Comparisons to other approaches highlight the advantages of CGF registration.**

I. INTRODUCTION

Intensity image and range image (point cloud) registration has been developing mostly independently, with a certain level of interleaving in the medical imaging field. The arrival of new compact integrated sensors, RGB-Depth cameras (e.g. Microsoft Kinect®), that capture a simultaneous stream of color and range images (RGB-D), has provided a strong impetus for realizing techniques that would successfully combine these. The goal of this work is devising a robust registration technique to be utilized for the RGB-D data alignment, that combines visual keypoints and features with salient geometric properties, in our case planar patches.

3D registration can be performed by finding point correspondences and optionally, also surface normal vector correspondences. The goal of the CGF algorithm is to determine a set of accurate normal and point correspondences across the scans, and perform a registration in a joint optimization framework. To overcome the difficulties posed by low quality depth information and to increase robustness, CGF registration utilizes planar patches for estimating reliable normal correspondences. Since RGB-D cameras are designed for interior environments, it is assumed that a number of reliable planes would be present in scans, e.g. walls, ceilings, floors, tables, cabinet doors, monitors, etc, whose orientations across the scans could be used for registration purposes.

A significant accent is given to the accurate plane extraction from the scans, given discretization artifacts in the RGB-D data. In order to achieve accurate statistical plane fitting with a covariance matrix estimation, an error model for the depth data stream is devised and experimentally estimated. A novel cost function is proposed for performing CGF registration, either independently, or as part of the Iterative Closest Point framework.

Color (texture) feature extraction is performed using the SURF detector-descriptor pair [1], which was applied here on the gray-scale image, but could be extracted for the three color channels separately as well. In [15] color information is used to check the plane correspondences, an idea that we employ in this work as well, but use the RGB information also as a source of sparse texture feature correspondences.

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II. RELATED WORK

Point cloud registration is a mature and well studied problem in computer vision. The most widely used and studied approach is the Iterative Closest Point registration (ICP) proposed by Besl and McKay [2]. The standard ICP minimizes "point-to-point" distance in the iterative scheme, while the related approach proposed by Chen and Medioni [6] performs "point-to-plane" minimization. A number of improvements of the ICP are proposed and evaluated in the work by Rusinkiewicz and Levoy [18]. Recent advancement of the ICP registration are related to the introduction of probabilistic techniques. Segal et al. proposed the Generalized ICP [20], that presents a direct probabilistic extension of the standard ICP. The algorithm achieves "plane-to-plane" minimization. Censi [5] proposed the deployment of the Generalized Hough Transform to use point pairs with known normals for "voting" in the 6D space of transformations. Registration and covariance estimation is found in the least squares manner using a linearized model.

An alternative to ICP is the more recent Normal Distribution Transform (NDT) proposed by Biber and Strasser for 2D registration [3], and extended to 3D registration approach by Magnusson [10]. The main idea behind NDT is the utilization of a point density matching. Initially, a point cloud is subdivided in voxel cubes, and for each cube the mean and the covariance matrix are estimated. Registration is performed by iteratively maximizing a sum of "point-to-voxel" belongingness probabilities, which is established using the assumed normal distribution in the voxel.

Additionally, a number of metaheuristic approaches were also proposed, e.g. Particle Swarm Optimization proposed in the context of medical image registration proposed by Wachowiak et al. [21]. However, inclusion of the metaheuristics imminently involves high computational costs.

The registration technique proposed in the "Kinect-Fusion" series of articles by Newcombe, Izadi et al. [12][8] was one of the first attempts to develop a registration technique specifically tailored for RGB-D sensors. The main idea is to perform simultaneous camera tracking, i.e. 3D registration, and mapping. The approach involves a volumetric representation of the scanned environment. Registration is performed by aligning the current point cloud against the existing volumetric map using the standard "point-to-plane" cost function. As with the other ICP based registration techniques, it is very sensitive to a local minima entrapment.

The approach that could be considered as a direct predecessor to the CGF registration presented here, is the RGBD-ICP approach proposed by Henry et al. [7]. RGBD-ICP involves utilization of both color feature and "common" point correspondences, within the ICP framework. This is achieved by incorporating matched distinctive feature points into a standard "point-to-plane" ICP cost function. Additional weighting allows tuning the level of influence of the distinctive feature points vs. "common" points.

III. MATCHING CORRESPONDING PLANES

A. Plane extraction and statistical estimation

The plane extraction algorithm used in the CGF registration is an adapted version of the Randomized Hough Transform (RHT) technique proposed by Xu et al. [23]. A plane is represented by three parameters: the angles ϕ and θ encoding the normal orientation, and distance d of the plane from the origin. Here, we employ a ball accumulator with a nearly equal cell sizes on the surface, as proposed by Bormann et al. [4]. Voting is done by randomized triplet selection, plane parameter calculation and a corresponding cell update in the accumulator. Further improvements to the point selection are accomplished by restricting the selected triplet inter-point distance, under the assumption that points that are close to each other lie on the same plane with a much higher probability [4]. Taking into account that discretization artifacts of the RGB-D sensors grow with an increasing distance of a point from the sensor, the triplet selection process is performed in a depth adaptive probabilistic manner.

Plane extraction is performed whenever a peak threshold is reached in the accumulator. The algorithm is repeated until a certain percentage of points in the original point cloud have either voted or been extracted (e.g. 99%). This method proved to be advantageous over RANSAC-based solutions for extracting small planar patches as well.

Next, we use statistical plane fitting to provide a highly accurate plane parameters estimation and the plane covariance matrix estimation. There are several established approaches for the plane covariance matrix estimation: an application of the eigen-value perturbation proposed by Weng et al. [22], renormalization approach proposed by Kanazawa and Kantani [9], and the recently proposed maximum likelihood based approaches [14] [17]. In the CGF registration, a closed form solution for the optimal plane parameters fitting and covariance matrix estimation is used, based on the approach proposed by Pathak et al. [14] [17], with an experimentally devised range data error model.

B. Plane correspondences

Finally, it is necessary to establish plane correspondences between point clouds in order to utilize them in registration. There are a couple of algorithms published for tackling this issue, with the most recent being the ones proposed by Pathak et al. [16] [13]. The plane correspondences algorithm in the CGF registration follows a similar philosophy.

Given a rigid body transformation, a mutual orientation between corresponding planes remains constant irrespective of the field of view. Taking each of the planes in the first point cloud as a "landmark" plane, the orientation of all the other planes is computed with regard to the clockwise offsets of ϕ and θ, thus obtaining a set of angular differences between planes. Plane correspondences between the point clouds are established by finding the maximal sets of planes with the same relative orientations. To increase robustness, additional color and size similarity constraints are enforced.

IV. CGF REGISTRATION

In the CGF algorithm, texture based interest points are extracted and matched between images, corresponding to point clouds which are to be registered. In the implementation presented here, a widely used SURF detector-descriptor pair is used [1], while the Fast Approximate Nearest Neighbors (FLANN) [11] is employed for feature matching. Having obtained color and plane correspondences, the key equations describing the CGF registration are developed as follows.

A. Initial transformation

Plane based registration of point clouds, with a known set of plane correspondences, can be performed by simply minimizing the difference between the Hessian plane parameters. Let us denote corresponding planes with ${}^{l}\xi_i$ and ${}^{r}\xi_i$, in l and r point clouds respectively. If a 3D point transformation ${}^{l}_{r}T$ is to be determined, describing the motion from the coordinate system r to the coordinate system l, the corresponding plane parameters transformation ${}^{l}_{r}T_\xi$ can be derived by combining plane and point transformation relations. Given the Hessian plane equation in the form: $\vec{n}\cdot\vec{p} = d$, the plane transformation matrix ${}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_\xi$ is given in Eq. 1.

$$ {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T} = \begin{bmatrix} {}^{l}_{r}R_{3x3} & {}^{l}_{r}t_{3x1} \\ 0_{1x3} & 1 \end{bmatrix} \Longrightarrow {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_\xi = \begin{bmatrix} {}^{l}_{r}R_{3x3} & 0_{3x1} \\ {}^{l}_{r}t^T \cdot {}^{l}_{r}R_{1x3} & 1 \end{bmatrix} \quad (1) $$

Given the plane parameters and covariance matrices, a maximum-likelihood approach for obtaining the optimal transformation can be expressed in the form of Eq. 2 [13].

$$ {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_\xi \longleftarrow \underset{T}{\operatorname{argmin}} \quad \begin{array}{l} \frac{1}{2}\sum_i^N ({}^{l}\xi_i - {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_\xi\, {}^{r}\xi_i)^T\, \mathbf{C}_i^{+}\, ({}^{l}\xi_i - {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_\xi\, {}^{r}\xi_i) \\ \quad + \frac{1}{2}\sum_i^N log|\mathbf{C}_i|_{+} \end{array} \quad (2) $$

Here, $\mathbf{C}_i$ denotes the corresponding plane's joint covariance matrix. By denoting the covariance matrices of the planes from l and r with ${}^{l}\mathbf{C}_i$ and ${}^{r}\mathbf{C}_i$ respectively, $\mathbf{C}_i$ can be found as follows [17] [13]:

$$ \mathbf{C}_i = {}^{l}\mathbf{C}_i + {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_\xi\, {}^{r}\mathbf{C}_i\, {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_\xi^{\,T} \quad (3) $$

Since the obtained covariance matrices are rank deficient, the inverse of a joint covariance matrix is found using the Moore-Penrose pseudo-inverse, denoted by superscript $^{+}$. The subscript $_{+}$ in the Eq. 2 refers to the pseudo-determinant.

In the CGF registration presented here, the initial transformation estimation is achieved by minimizing Eq. 2 using the Levenberg-Marquardt algorithm (representing rotations as quaternions), obtaining the "plane-based maximum likelihood" transformation estimation: ${}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_{\mathbf{PML}}$.

The initial ${}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_{\mathbf{PML}}$ transformation estimation, is further corrected using the extracted color feature correspondences ${}^{l}f_j$ and ${}^{r}f_j$, from point clouds l and r respectively. Firstly, both sets of feature points are evaluated for possible plane belongingness. In case a point belongs to a plane, new point coordinates are set as being the projection onto the plane along the focal ray. After applying ${}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_{\mathbf{PML}}$ to a vector of features ${}^{r}f_j$, the translation of the ${}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_{\mathbf{PML}}$ is updated by adding a mean difference along each axis, between the feature points ${}^{l}f_j$ and the corresponding transformed feature points ${}^{r}f_j$. The newly obtained transformation is denoted by ${}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_{\mathbf{I}}$, and is used as an initial transformation estimate in the CGF registration. In case there is only one or no plane matched between point clouds l and r, the initial transformation is established by using only color feature matches by applying the RANSAC alignment implementation from PCL [19].

B. Joint optimization of the cost function

The CGF algorithm could be considered as a direct successor of the RGBD-ICP approach [7], that utilizes joint point and feature correspondences in the ICP framework, but CGF registration is plane correspondences (and color features). In case of extension of the cost function to include "common" points correspondences in the ICP framework, the registration is named the CGF-ICP. The CGF-ICP algorithm follows the established iterative ICP two-step framework:

1) find point correspondences between two point clouds given current transformation estimation, and
2) update transformation estimation by minimizing a cost function; if not converged repeat from 1).

Let us denote feature correspondences with ${}^{l}f_j$ and ${}^{r}f_j$, plane term correspondences with ${}^{l}\xi_j$ and ${}^{r}\xi_j$, and the common point correspondences with ${}^{l}p_k$ and ${}^{r}p_k$. The joint cost function of CGF-ICP can be written as:

$$
\begin{aligned}
&{}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T} \longleftarrow \underset{T}{\operatorname{argmin}} \Bigg\{ \\
&\alpha \cdot \rho \left(\tfrac{1}{N_f} \textstyle\sum_{j=1}^{N_f} |{}^{l}f_j - {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}\, {}^{r}f_j|^2 + \omega \cdot |\{{}^{l}f_j\}^U - \{{}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}\, {}^{r}f_j\}^U|^2 \right) \\
&+\beta \left(\tfrac{1}{N_\xi} \textstyle\sum_{i}^{N_\xi} ({}^{l}\xi_i - {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_\xi\, {}^{r}\xi_i)^T\, \mathbf{C}_i^{+}\, ({}^{l}\xi_i - {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_\xi\, {}^{r}\xi_i) \right) \\
&+\gamma \cdot \rho \left(\tfrac{1}{N_p} \textstyle\sum_{k=1}^{N_p} |{}^{l}p_k - {}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}\, {}^{r}p_k|^2 \right) \Bigg\}
\end{aligned}
\tag{4}
$$

The cost function (Eq. 4) is built to include three terms: the feature point term (first line), plane term (second line) and the common point term correspondences provided by the ICP framework (third line). If the registration is performed utilizing only feature points and planes, i.e. using only the first two terms from the Eq. 4, the algorithm reduces to the CGF registration. The feature point term consists of the corresponding points squared distances, and additionally the corresponding points distances on the image plane; where a feature point projection on the image plane is denoted with $\{f_j\}^U$. Given that the image plane distances are several orders of magnitude lower than the actual 3D point distances, an additional normalizing term ω is included.

The plane term is equivalent to the first part of the maximum likelihood plane-based registration equation (Eq. 2), i.e. the covariance matrix weighted least squares equation. A reason for avoiding inclusion of the full maximum-likelihood equation lies in problems induced by the "co-existence" of planar and point based terms in the same cost function. When the maximum likelihood equation is used, a value of the cost function fluctuates rapidly as the optimization is performed. On the other hand, in order to allow for the controlled weighting of the plane and point terms in the joint cost function, predictability of the values of each term is of high importance. Therefore, for all plane correspondences a joint covariance matrix inverse is found prior to the actual optimization process, using the the provided initial transformation estimate (${}^{\mathbf{l}}_{\mathbf{r}}\mathbf{T}_I$).

An important part of the cost function is the weight ρ that adapts the magnitude of the squared point distances to the magnitude of the plane term. Each of the cost function terms is further weighted, in order to establish control over the specific term influence on the registration: feature point term coefficient α, plane term coefficient β, and the common point term coefficient γ. The cost function minimization is performed again using the Levenberg-Marquardt algorithm.

V. Evaluation

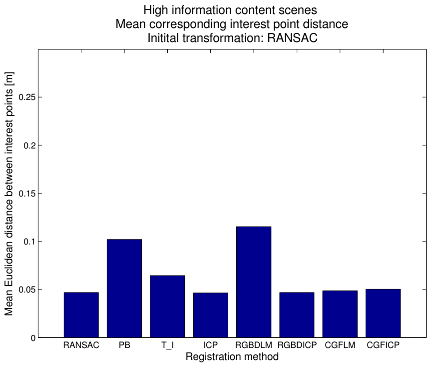
For the evaluation of the proposed CGF-ICP algorithm two sets of point cloud pairs were considered, denoted HIC/LIC:

- High Information Content scenes: point cloud pairs containing many well distributed distinctive features;
- Low Information Content scenes: point cloud pairs containing low number of color based features, as well as low geometric structural information content.

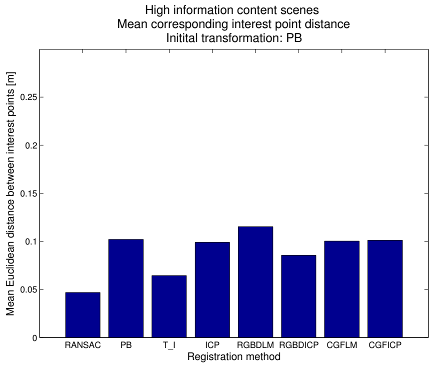
Both types of scenes contain 24 point cloud pairs. On these, the following registration techniques were tested:

1) RANSAC registration of color feature points [19];
2) Plane-based maximum likelihood registration; denoted PB registration further on (Eq. 2);
3) Initial plane based registration corrected by the mean color features offsets; denoted T_I (Sec. IV-A);
4) Point-to-point ICP [2];
5) RGBD-LM registration; represents a transformation obtained by optimizing the RGBD-ICP cost function once, i.e. a single run of the Levenberg-Marquardt [7];
6) RGBD-ICP registration [7];
7) CGF registration; represents a transformation obtained by optimizing the CGF-ICP cost function once, with planes and color based features terms included (Eq. 4);
8) CGF-ICP registration (Eq. 4).

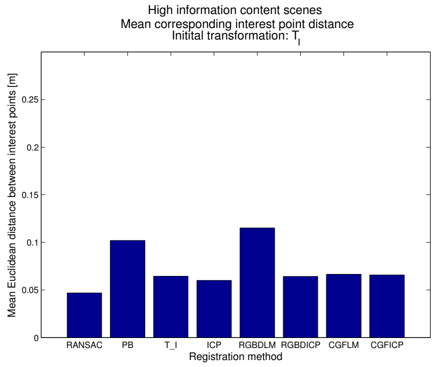
In total, three experiments were performed using both the HIC and the LIC point cloud sets, with the difference in initial transformation estimation of the registration algorithms 4 to 8 from the previous list. Registration approaches



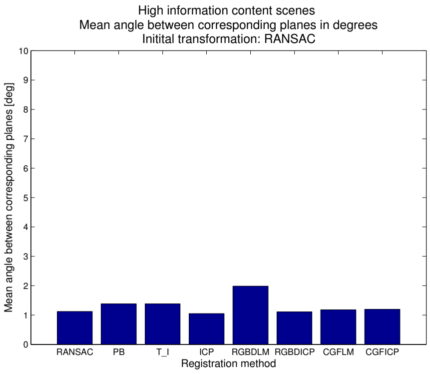
(a) Initial transform RANSAC: μ_f mean Euclidean distance between corresp. feature points



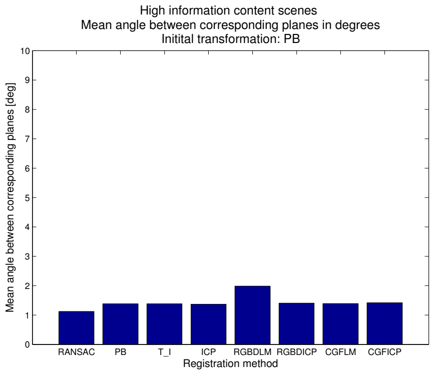
(b) Initial transform PB: μ_f mean Euclidean distance between corresponding feature points



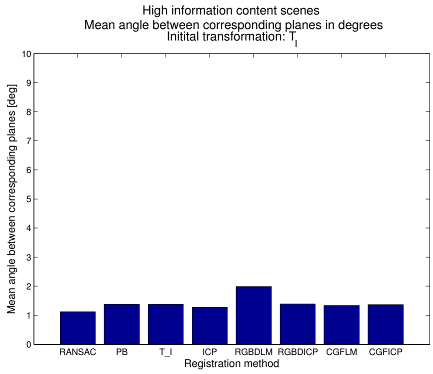
(c) Initial transform T_I: μ_f mean Euclidean distance between corresponding feature points



(d) Initial transform RANSAC: μ_ξ mean angle between the corresponding planes



(e) Initial transform PB: μ_ξ mean angle between the corresponding planes



(f) Initial transform T_I: μ_ξ mean angle between the corresponding planes

Fig. 1: High information content point cloud pairs: evaluation of Euclidean and rotational errors

1-3 are used as initial transformation estimators. All experiments were performed using unsmoothed point clouds. Further, RGBD-ICP was used with the coefficient $\alpha = 0.3$, as proposed in the original paper [7].

With regard to the proposed CGF-ICP cost function weighting, as given in Eq. 4, an optimal set of coefficients is as follows: $\alpha = 0.4$, $\beta = 0.3$ and $\gamma = 0.3$. In the CGF registration, the following coefficients proved to provide an optimal results: $\alpha = 0.7$, $\beta = 0.3$ and $\gamma = 0$.

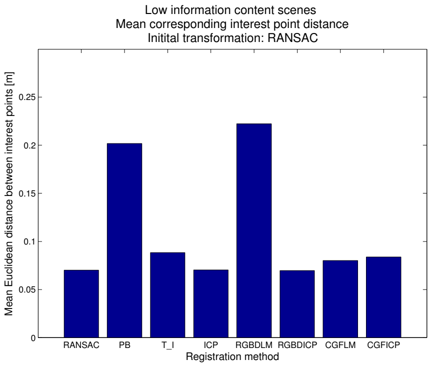
Given the knowledge of plane correspondences and color feature correspondences between the point clouds, the following two qualitatively different measures are used to determine an accuracy of the registration (instead of using the typical a mean closest point distance):

- μ_f : mean Euclidean distance between the corresponding feature points, given the transformation, and
- μ_ξ : mean angle between the corresponding planes, given the transformation.

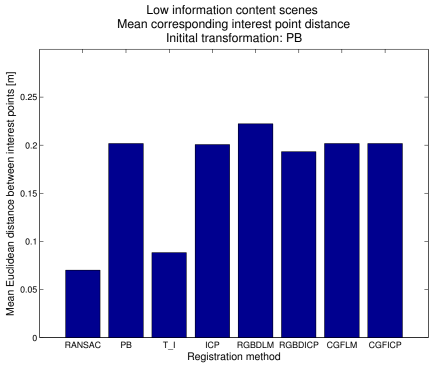
In Fig. 1, the evaluation of the registration methods in the context of the HIC point cloud pairs is given. On average between 40 and 150 well dispersed features were matched in those scans and an average of 3.3 plane correspondences. Comparing the results of the different approaches, given different initial transformations, it is evident that the simple RANSAC based transformation provides superior results. A significant mean offset of the PB initial transformation (cca. $5cm$), with respect to the distances of feature points μ_f, is due to the fact that many of the evaluated registration pairs did not contain three non-parallel plane correspondences, for achieving correct registration. Analyzing the results of RGBD-LM and CGF-LM, it is evident that the CGF-LM performs considerably better given RANSAC initial transformation, and slightly better given PB and T_I initial transformations. Overall, the CGF-LM performs at par with the ICP techniques. This result is expected given high information content of the point clouds, allowing for convergence in a single run of the Levenberg-Marquardt optimizer. Another important lesson is the performance of the registration approaches given T_I initial transformation. It is evident that results are only slightly less accurate, when compared to the RANSAC initialization.

The importance of the initial transformation estimation can be readily seen: in the case of the RANSAC initial transformation, all ICP based techniques remain in the correct convergence basin, A more interesting class of scenes with regard to the CGF registration is the set of low information content scenes (Fig. 2). The number of feature points in these scenes vary between 20 and 50, with the number of matched planes being around 2.7. The major problem in these scans are matched features grouped in only one part of the scan, often inducing gross misalignments.

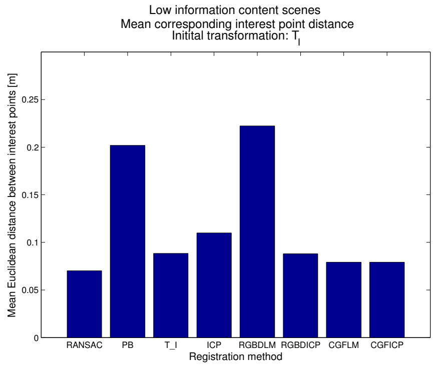
In the LIC set of point cloud pairs, feature point distances often provide “false” accuracy results, i.e. a low number of



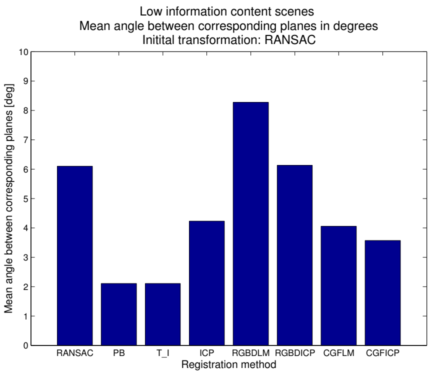
(a) Initial transform RANSAC: μ_f mean Euclidean distance between corresp. feature points



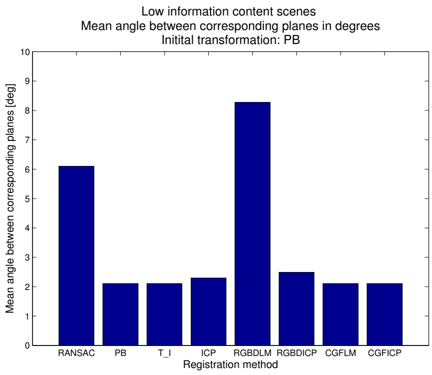
(b) Initial transform PB: μ_f mean Euclidean distance between corresponding feature points



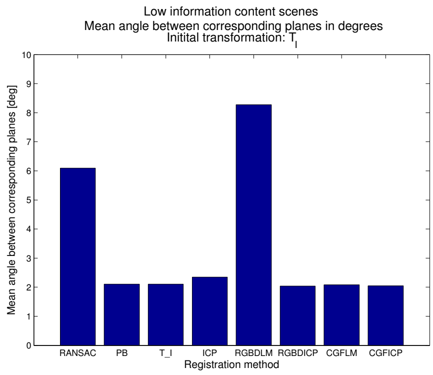
(c) Initial transform T_I: μ_f mean Euclidean distance between corresponding feature points



(d) Initial transform RANSAC: μ_ξ mean angle between the corresponding planes



(e) Initial transform PB: μ_ξ mean angle between the corresponding planes



(f) Initial transform T_I: μ_ξ mean angle between the corresponding planes

Fig. 2: Low information content point cloud pairs: evaluation of Euclidean and rotational errors

feature points can provide significantly inaccurate transformation, while the inter-point distance would be very low.

It is evident that the RANSAC based initialization induces severe registration offset with regard to the corresponding angle differences. Even the CGF and the CGF-ICP provide, although better than other approaches, significant plane misalignments of cca. 4^o. Given PB initial transformation, results are better in terms of angle differences, but the offsets are still very high in terms of feature point distances. Finally, satisfying results are obtained when using T_I initial transform. However, corresponding plane average angle of almost 2^o indicates still fairly significant misalignment.

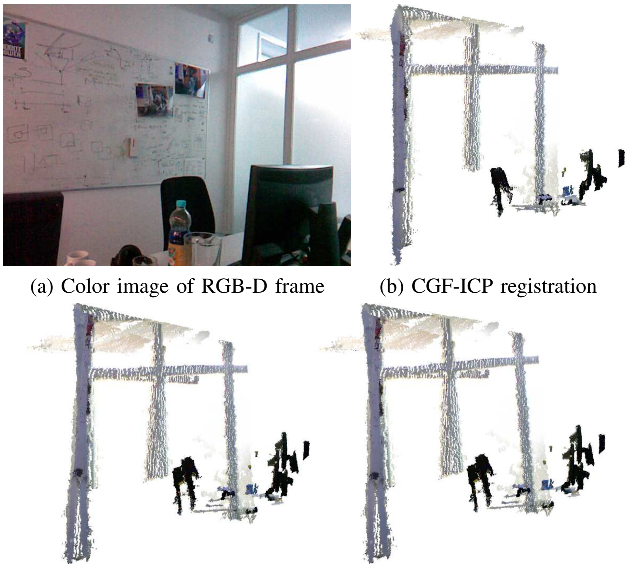
Evidently, CGF registration is highly sensitive to the initial transformation estimation, to a similar extent as other ICP based approaches. Further, the CGF registration provided almost the same results as the CGF-ICP. Regarding scenes with a high number of extracted features, RANSAC registration provides the overall best results. Again, it is important to notice that T_I initialization does not corrupt the resulting registrations significantly. In the case of low information level scans, initialization based on corresponding planes and feature points induces significantly better results.

An interesting observation can be made regarding the good overall performance of the standard ICP, when initialized with the plane and feature based transforms. This leads us to the main problem of the proposed CGF-ICP registration in form of a joint plane and feature optimization, within the ICP framework: the cost function inflexibility with regard to the weighting coefficients. It has been noticed during the experiments that the point-to-plane range adaptation coefficient ρ has the greatest impact on the behavior of the objective function. Further on, the flexibility of the cost function is very low, referring to the relative influence of term coefficients α, β and γ. The problem lies in the different rates of convergence between the point and planar terms, that should be tackled by introducing a specially developed function instead of ρ for the transformation of the point term range to the plane term range. As a starting point, the behavior of the point and the planar terms should be studied in the vicinity of optimal registrations. Additionally the orientation and the number of the matched planes should be taken into account, as well as the number and dispersion of the color based features.

However, it can be stated that the CGF registration combined with the proposed initial transformations, allows the successful registration of data that present great problems for other registration approaches. An example of the registration achieved by the CGF-ICP compared to the RANSAC and RGBD-ICP is given in Figure 3.

VI. CONCLUSIONS AND FUTURE WORK

In this work a novel registration approach combining color features and plane correspondences in a joint optimization has been proposed, where the error model of the depth data



(a) Color image of RGB-D frame (b) CGF-ICP registration

(c) RANSAC registration (d) RGBD-ICP registration

Fig. 3: Example of registration results on a LIC scene

is utilized in the statistical plane fitting and the covariance matrix estimation. An important part of the algorithm is the adapted plane extraction and matching technique between point clouds captured from different viewpoints, and the cost function that allows for utilization of both plane and color feature based correspondences for constraining transformation in the iterative closest point framework. Regarding the robustness of the CGF registration, the sensibility to the initial transformation estimation is somewhat reduced, while the performance of the proposed registration technique could be improved by an inclusion of a "light" metaheuristics, for avoiding local minima in the transformation estimation.

For a possible deployment in SLAM and accurate map building applications, it would be of vital importance to develop a registration covariance estimation. This would allow the inclusion of the CGF registration into the widely used EKF framework, or weighted bundle adjustment registration.

The combination of plane- and texture-based registration lays the foundation for a semantics-based registration framework, where the parts of the environment or objects are identified that are semantically relevant (e.g. tables, cupboard doors, object parts), and used to fuse the data coming from different viewpoints more accurately, by obtaining semantically meaningful correspondences.

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