A Test Environment for Feature-Based Range Data Registration

HENDRIK THAMER, DANIEL WEIMER
BIBA - Intelligent Production and Logistics Systems
Hochschulring 20
28359 Bremen
Germany
tha@biba.uni-bremen.de

BERND SCHOLZ-REITER
University of Bremen
Bibliothekstrasse 1
28359 Bremen
Germany
bsr@biba.uni-bremen.de

Abstract: The analysis of range data is an important step in many automation applications such as robotic manipulation, autonomous navigation or human machine interaction systems. Therefore, range sensors are usually used for acquiring geometric information about the relevant environment of interest. In order to cover the entire environment of interest, using one single sensor is often not sufficient. Hence, sensor systems consisting of multiple sensors are used or the object of interest is rotated relative to the sensor system. For integrating the single sensor data into a common reference system, a registration process must be performed in order to determine the rigid transformations between the single point clouds. This paper presents a test environment for registering multiple point cloud data into a common reference frame. The environment focuses on the case when no initial information regarding the transformation is available and allows efficient testing and evaluation of different parameter setups in particular steps within a common registration pipeline.

Key–Words: Registration, Range Data, Sensor Data Fusion, Computer Vision, Automation

1 Introduction

The analysis of range data in order to recognize and reconstruct real world objects is an important task in computer vision. Due to (self-) occlusions and limited field of views, using single range sensor devices such as Time-of-Flight (TOF) cameras, Laser scanner or stereo vision systems results in sensor data covering only a partial view of the scanned objects. However, in most applications a complete 3D representation of single objects or the entire environment is required. The process of aligning several point clouds in a common global reference frame is called registration. For registration of point clouds, various approaches have been proposed for determining the transformation between the single clouds. Registration algorithms can be categorized in coarse and fine registration [1]. Coarse registration algorithms estimate a initial transformation without prior knowledge. On the contrary, fine registration algorithms optimize a given initial transformation. Without an initial estimate, algorithms from both categories are usually performed sequentially. The transformation are realized by searching and identifying correspondences between two single point clouds. These correspondences can be established between points, surfaces or curves. Thereby, a line of research of this area is focusing on establishing point-to-point correspondences between point clouds.

This paper presents a test environment for the registration of 3D point cloud data. Finding the best parameter configurations and single methods within the registration process can be a time-consuming step . Therefore, the environment gives the opportunity to evaluate different configurations of the registration pipeline presented in the Point Cloud Library (PCL) [2] and in Rusu et al.[3]. The pipeline consists of different processing steps. The process starts with applying preprocessing algorithms such as downsampling or noise removal. Then, keypoints are identified using keypoint detectors. Afterwards, the identified keypoints are described by using local feature description techniques. By comparing the features in both clouds, corresponding points that have a similar feature descriptor are determined. Due to the fact that not all of the determined correspondences might be correct, wrong correspondences are removed by applying correspondence rejection algorithms. Then, the remaining correspondences are used for estimating the coarse transformation between the point clouds. Finally, a fine registration algorithm such as the Iterative-Closest-Point (ICP) algorithm [4] can be used for optimizing the transformation. Due to the modular software structure of the presented test environment, different methods or techniques in each processing step of the registration pipeline can be configured and evaluated. For instance, the environment gives the opportunity of selecting different keypoint detectors or local feature description techniques. Therefore, optimal configura-

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tions for specific applications can be easily defined. The remainder of the paper is structured as follows. In the next section, techniques and algorithms are presented concerning the registration of range data. Afterwards, the test environment is presented in detail following the aforementioned registration pipeline. Here, the configuration possibilities for each processing step are described. In the next section, we demonstrate the environment with an application scenario from the field of logistics. Finally, we close the paper with a short conclusion and an outlook for further research activities.

2 Registration of Range Data

The objective of registration is the determination of the euclidean transformation between a set of range images of an object of interest taken from different viewpoints, in order to transform them into a common reference frame. Salvi et al. [1] made a comprehensive survey of the most common techniques and have classified various approaches and techniques for registration based on strategy, robustness, motion estimation and kind of correspondence [1]. The following explanations are based on this survey. In general, registration methods can be divided into coarse and fine registration. Coarse registration methods compute an initial estimate of the transformation between two point clouds. They usually try to find correspondences between the range data sets. These correspondences can be established between points, surfaces and curves. Generally, the most commonly used correspondence method is point-to-point [1]. Therefore, feature description techniques such as Point Signatures [5] or Spin Images [6] are used for describing points in both range data sets and compared with each other. Then, the coarse registration estimation is defined using the best point-to-point correspondences. Examples for registration techniques using surface-correspondences are Principal Component Analysis [7] and algebraic surface models [8].

In contrast to coarse registration techniques, fine registration methods optimize an initial transformation in order to find a more accurate solution. The registration strategy can be distinguished between registering the range data pair-wise or registering the single data at the same time which is called multi-view registration. Fine registration methods are often computational expensive. In order to optimize the computation time some methods use techniques such as k-d trees for fast nearest-neighbor search. Thereby, the distance to be minimized can be between point-correspondences or between points and a corresponding tangent-plane. The most famous fine registration method is the ICP presented by Besl and McKay [4]. Here, the distance between point-correspondences is minimized known as closest points. The algorithm requires a good initial transformation in order to prevent converging in a local optimum. After the application of the initial transformation estimation, a search for closest points between each point in the first point cloud and in the second cloud is performed in order to minimize the distance between these correspondences. A main requirement for the application of the ICP is a significant overlap of the clouds.

This paper focuses on coarse registration with identifying point-to-point correspondences in two point clouds for gaining a complete representation of an object. Therefore, the feature-based registration pipeline within PCL is followed. Usually, the configuration and the method selection of the single steps depends on the properties of the sensor data. Hence, the determination of the optimal configuration is a time-consuming step. In order to tackle this issue, we introduce a test environment for experimental determination of methods and parameter configurations for feature-based registration.

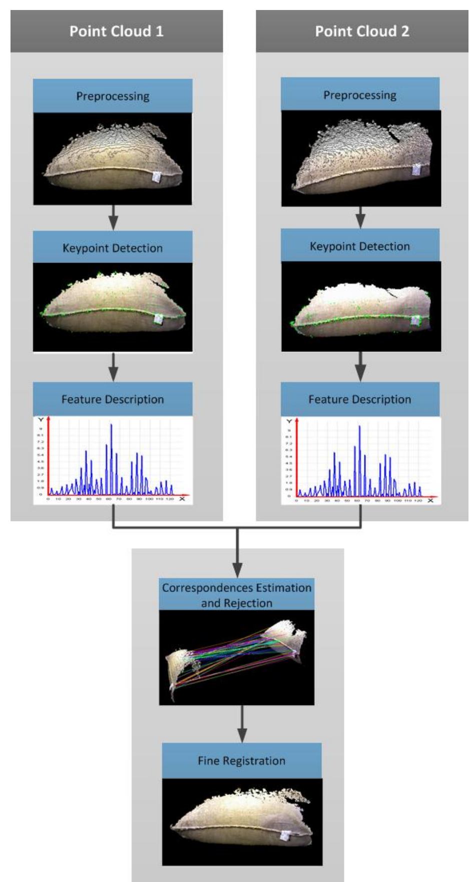

Figure 1: Registration pipeline based on [2][3]

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3 Test Environment

The system consists of five processing steps representing the whole registration pipeline from coarse to fine registration. The system has a modular architecture and each module is arbitrarily configurable. The selected combination and configuration of modules can be stored in order to reproduce experimental results. Additionally, new keypoint detectors or feature description techniques can be easily included. Figure 1 shows the presented system structure using two point clouds of a surface containing of a sack from a logistic scenario. The clouds represent a partial view of the sack object. A screen shot of the main graphical user interface is visualized in figure 2. The system is implemented in the programming language C++ and Qt for the graphical user interface. It uses PCL [2] and OpenCV [9] as main libraries for point cloud processing and computer vision algorithms. In the following section the single steps are described in more detail and methods that are integrated in the test environment are presented.

3.1 Preprocessing

The preprocessing module contains algorithms for enhancing the quality or the size of the data. Improving the quality of the range data has a particular importance regarding noisy sensor data. Due to the working principle of local feature description techniques, measurement noise has a strong influence on the resulting feature descriptor. Therefore, different filters are implemented or integrated in the test environment which can be applied for reducing the influence of measurement noise such as median filtering or outlier removal. For some applications, the descriptiveness of a surface description is also sufficient with a reduced number of points. Downsampling of point clouds can significantly improves the computation time and is also integrated as module in the preprocessing step.

3.2 Keypoint Detection

In order to prevent computing feature descriptions for each point in both clouds, keypoints are identified by applying keypoint detectors. A key point is a point within a point cloud that has a specific property like corner or other geometric significant properties of an object in the scene. A famous keypoint from 2D computer vision is the SIFT-keypoint (Scale Invariant Feature Transform) proposed by David G. Lowe [10]. The detected features are highly distinctive and are invariant to image scale and rotation. There exists many research work transferring the concept to the three-dimensional domain such as [11][12]. Within the test environment the version from PCL is used as module for key point detection.

Another famous keypoint detector from 2D domain is the Harris corner detector [13]. The adaption to point clouds uses surface normals instead of image gradients for detecting corners [14]. The last keypoint detector integrated in the test environment is called NARF (Normal Aligned Radial Feature) [15]. The method analyzes object borders and extract features in regions where the investigated surface is stable but has large changes in the neighborhood. The final keypoints are chosen by using non-maximum suppression. Within the framework, keypoints based on local principal curvature values and the Intrinsic Shape Signatures (ISS)[16] keypoint detector are also integrated.

3.3 Feature Description

Local feature description techniques describe points according to a specific neighborhood. Surface normals or curvatures are not distinctive enough to be used as a robust local feature descriptor. Therefore, multi-dimensional feature spaces are commonly used in order to classify points lying on the same surface to the same shape class. Feature description can be distinguished by using signatures or histogram-based feature descriptors. The presented test environment focuses on generating and comparing histogram-based feature description techniques. The integrated feature descriptors are Point-Feature Histograms (PFH)[17], Fast Point Feature Histograms (FPFH)[3], and Spin Images [6]. The main working principle of these techniques are to determine a local reference frame and describing geometric properties between source and neighboring points. Finally, the description is stored in an histogram.

3.4 Correspondence Estimation and Rejection

After finding keypoints and computing the corresponding feature descriptor, point correspondences in both point clouds have to be computed. Thereby, the best correspondences should be used for estimating the coarse registration between the clouds. Therefore, wrong correspondences must be automatically rejected since they can negatively effect the estimation. Within the test environment, this is realized by applying median rejection and the RANSAC algorithm [18]. The median rejection step rejects all correspondences with correspondence values k-times higher than the median of the complete data.

After applying median rejection the RANSAC algorithm is applied in order to find the best sub-

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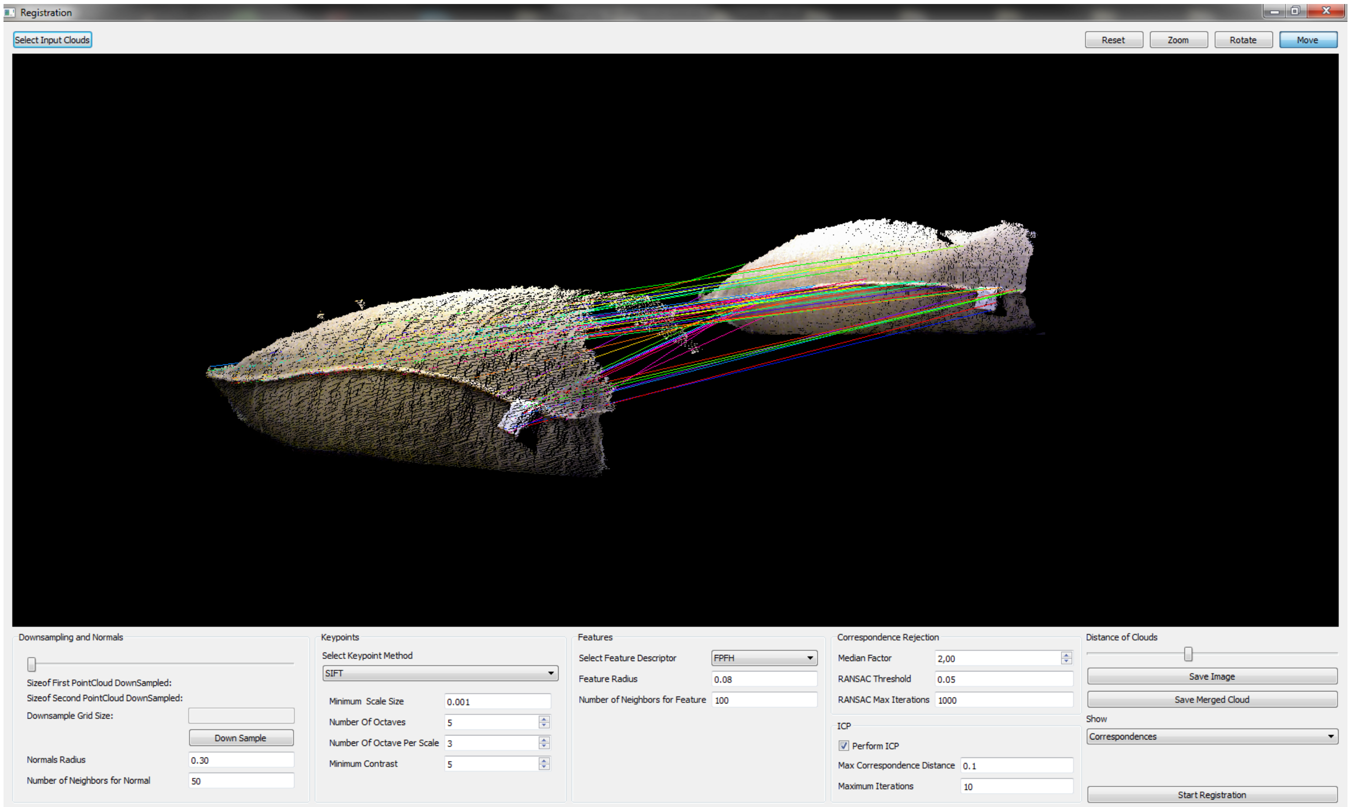

Figure 2: Screenshot of the main GUI

set of correspondences and rejecting wrong matches. RANSAC is an iterative method that produces results with a certain probability which is strongly affected by the number of iterations.

3.5 Fine Registration

The resulting coarse transformation can be refined by applying the ICP-algorithm. The convergence criteria of the algorithm are the maximum correspondence distance and the maximum number of iterations. Both parameters can be specified within the test environment. In addition to the fine registration matrix, the ICP delivers also a value indicating the accuracy of the estimation.

4 Example Application

The functionality and benefits of the test environment are demonstrated using two examples point clouds of a sack object. The two point clouds are rotated by 20 degrees towards each other. Therefore, a sufficient amount of overlap is guaranteed. The clouds are acquired by using the Microsoft Kinect Sensor. Naturally, the sensor data acquisition could be realized with all possible range sensors. Nevertheless, for application of the SIFT keypoint detection method color or intensity information must be also available.
Finding the optimal combination and configuration of the single modules of the registration pipeline leads to optimize several parameters depending on the selected configuration. Here, the selection strongly depends on the properties of the sensor data such as influence of measurement noise or point density and has to be specified according to the investigated application. In order to reduce the influence of measurement noise or reducing the amount of data, the environment offers a set of filters for improving data quality or downsampling the cloud to a specific size. The first critical choice in the registration pipeline is the selection of the keypoint detection method. Figure 3b-d shows the results of the SIFT, HARRIS, and keypoints based on principle curvatures6 for one of the sack objects. The results show that each detector delivers different keypoints. After localizing keypoints in both clouds, feature description for each detected keypoint are generated based on the local neighborhood. As mentioned in section 3, the test environment offers various local feature description techniques. Additionally, different distance metrics for histogram comparison can be selected. Keypoints with a similar feature description are classified as a possible correspondence. Thereby, wrong correspondences can negatively effect the reg-

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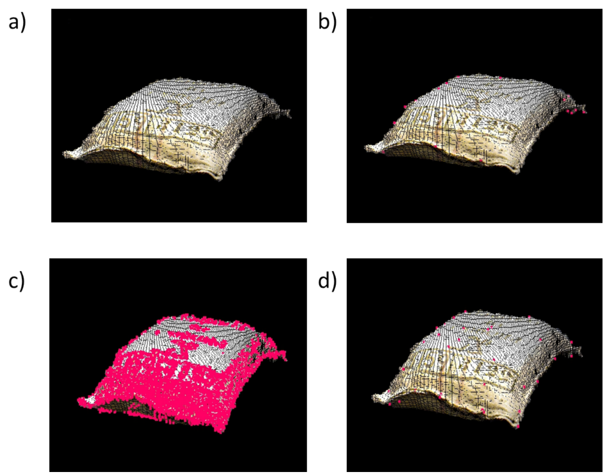

Figure 3: a) Point Cloud of a sack object b) HARRIS c) SIFT d) Principal Curvature

istration results. Therefore, a RANSAC module can be configured an used for wrong correspondences rejection. Figure 4 shows the resulting correspondences for the SIFT and HARRIS keypoints with FPFH feature descriptions after applying RANSAC for rejecting wrong correspondences.

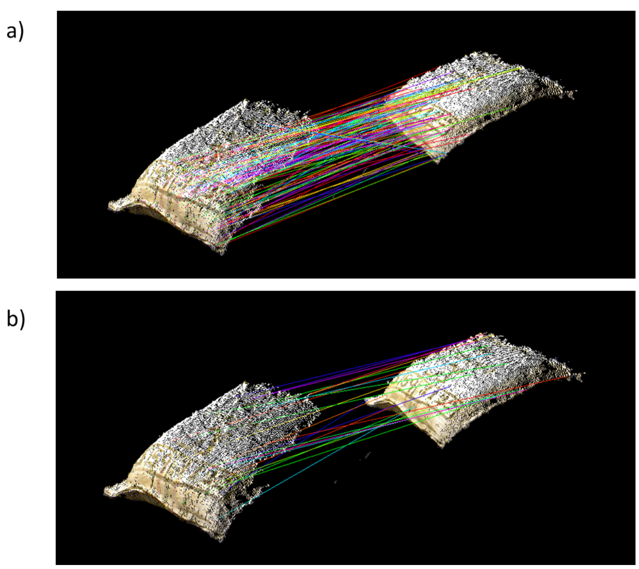

Figure 4: a) SIFT keypoints b) HARRIS keypoints

After rejecting wrong correspondences, the transformation matrix is based on the remaining correspondences. For fine registration, the ICP algorithm can be applied on the coarse registration transformation in order to optimize the registration result. Figure 5 shows the two clouds and the final merged cloud after application of the ICP algorithm.

For the presented application scenario, using SIFT keypoints with FPFH has shown the best results concerning registration accuracy. Nevertheless, the selection and configuration of the single modules strongly depends on the investigated application scenario.

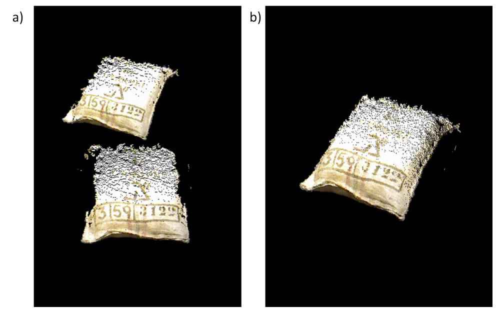

Figure 5: a) Two clouds of the sack object b) Merged cloud

5 Conclusion

Range data registration methods can be distinguished in coarse and fine registration methods. Coarse registration methods estimate a transformation without any knowledge or initial estimate about the transformation. Fine registration methods optimize an initial transformation in order to find the most accurate transformation between the clouds. The coarse registration of range data is often performed by identifying point-to-point correspondences in the point clouds. Therefore, local feature-based methods applied on keypoints in the point cloud data have a high potential for finding correct point-correspondences due to their high descriptiveness. Nevertheless, selecting the right methods and techniques and determining the best parameter can be a time-consuming step and often needs expert knowledge.

In this paper we presented a test environment for a feature-based range data registration pipeline. By using the test environment, the best configuration dependent on a specific application can be easily selected and evaluated. Additionally, single configurations can be stored and automatically applied to other experiment data. In further research, we will use our test environment for specific applications from the field of production and logistics. The production scenario is the combining partial views of micro parts to a complete 3D representation in order to perform quality inspection tasks. The partial range data is acquired by a confocal laser microscope. Within the logistic application scenario, the registration of partial views from logistic goods such as boxes, barrels or sacks will be performed. Here, the objective is also a full 3D representation in order to enable an automatic handling by robotic systems.

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