Chapter 1 3D Point Cloud Based Hybrid Maps Reconstruction for Indoor Environments

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Abstract In this article we investigate the problem of constructing a useful 3D hybrid map for both human being and service robots in the indoor environments. The objects in our laboratory include different tables, shelves, and pillar, which are of great importance for indoor service robot. We detail the components of our map building system and explain the essential techniques. The environment is detected in 3D point clouds, after sophisticated methods operating on point cloud data removing noise points and down sampling the data, we segment the data into different clusters, estimate the posture for clusters that can be recognized from library and replace it with VRML model we built in advance, then reconstruct surface for which cannot be recognized. Finally the preliminary hybrid maps are represented with the form of point cloud, VRML model and triangular meshes in 3DMapEidtor.

Keywords 3D Point cloud · Hybrid map · Indoor environment

1.1 Introduction

Autonomous service robot are playing an increasingly important role such as moving objects and cleaning up in our everyday life, as a result they must have a detailed perception of the indoor environments: the position of different objects, the length and width of the wall and other important information.

Map is essential for these service robots designed to navigate around a space with some persistent memory of the features of that space. However, high-quality maps for robots may not be very useful to human being, people want good visual

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effects but robot need more location information. Our goal is to construct a hybrid map useful for both robot and people, this way it can simplify man-robot communication and save a lot of time. For example, [1] represents a navigation system based on hybrid map for intelligent wheelchair.

We approach the map reconstruction problem by designing a structured system, then we attach the system with a large database (knowledge library) prepared in advance, in the database there are both VRML models and point cloud model feature of objects in our building, VRML models and point cloud model are linked correspondingly. In actual experiments we first collect point cloud data, after some processing work we compare the segmented point clusters with objects in library, then we estimate the posture for those objects we can recognize, for those clusters cannot be recognized we reconstruct their surface, the final map can be imported into 3DMapEditor for better visualization effect without losing important information for robot navigation.

The reminder of the paper is structured as follows. The next section briefly describes an overview of related work, followed by an architecture of our system in Sect. 1.3. In Sect. 1.4, we present the preparation of point cloud data. Section 1.5 presents the results of our experiment. Finally, we conclude and plan for future work.

1.2 Related Works

For many years the field of map building with mobile robot platform have attracted lots of researchers, many efforts have been made. But most of them focus on localization and navigation using 2D map [2, 3], a few researchers develop algorithm for 3D point cloud processing [4, 5]. Our system is the result of combination of different algorithms and publications.

In [4], Rusu et al. investigates the problem of acquiring 3D object maps of indoor household environments, in particular kitchens. The objects modeled in these maps include cupboards, tables, drawers and shelves. Rusu et al. also investigated semantic labeling of planar surfaces in indoor environments in [5]. Their proposed approach includes a processing pipeline, including geometric mapping and learning, for processing large input datasets and for extracting relevant objects useful for a personal robotic assistant. In our approach, we improve this type of approach using larger scale scanned scenes that include multiple point clouds taken from different positions.

In [6], Alexander et al. presents an extension to their feature based mapping technique that includes information about the locations of horizontal surfaces such as tables, shelves, or counters in the map. Their preliminary results are presented in the form of a feature based map augmented with a set of 3D point clouds. We improved the hybrid map into a map containing three kinds of data structure, including point cloud, triangular mesh and VRML models.

In Dr. Martin Magnusson's doctoral thesis [7], The Normal Distribution Transform (NDT) algorithm is explained in detail, it can serve as a registration algorithm that uses standard optimization techniques applied to statistical models of 3D points to determine the most probable registration between two point clouds. We employ this algorithm to determine a rigid transformation between point cloud data sets gathered from different positions in our lab. [7] classifies 3D data from a laser sensor into walls, floor, ceiling, and doors, but their segmentation scheme are very limited, we also improve it in the segmentation section.

1.3 System Overview

An overview of our reconstruction system is given in this section, mainly including on-line process and off-line process, as well as outlier removal, point cloud registration and segmentation, feature extraction and other components.

A more detailed diagram of the system description can be seen in Fig. 1.1. The whole system is built on PCL (Point Cloud Library, an open project for 2D/3D image and point cloud processing), 3DMapEditor (Developed by SJTU in China, developed for 3D display and simulation) and other open source tools.

The first step of processing point cloud data and constructing 3D map is registration and segmentation, after that we can match different parts of point cloud with models in our libraries built previously, the second step is to calculate the position and rotation of all the objects, with all the information we got from steps above it would be simple to replace the whole point cloud with 3D hybrid map (Fig. 1.2).

The hybrid map refers to the combination of different data structure in the map, which indicates points, triangle meshes, 3D models, geometry shapes, and so on. Different tasks can require proper data structure from this map. For example, 3D collision detection may need triangular meshes, and object recognition requires geometry feature of point cloud. In our implementation the hybrid model map is formed by 3 different types of maps:

- (1) VRML model. We build 3D VRML model for featured furniture in our lab, including different tables, pillars, and some other robots. The scale and structure is totally the same with real objects, once a point cluster is recognized as a specific object, we can replace the point cluster with our VRML model.
- (2) Triangular meshes, used for 3D collision detection, also it shows a better visual effect than point cloud, as shown in Fig. 1.3.
- (3) Point cloud, used for those environment parts like ceiling, wall, and floor. These parts are thought of as being static or unmovable, which indicates that they are rarely manipulated or changed. However, they provide us a lots of useful information for indoor robots completing tasks.

In the following sections we will explain the key technique used when building hybrid map in detail.



Fig. 1.1 The main frame of our map reconstruction system



Fig. 1.2 The relationship between point cloud model and VRML model, *left* point cloud; *right* VRML model

1.4 Point Cloud Registration and Segmentation

In this section, we describe our approach for 3D point clouds registration, as well as for segmenting 3D point cloud into independent clusters.



Fig. 1.3 From *left* to *right* the real scene, point loud cluster, and corresponding triangular meshes

1.4.1 Registration

Registration is the technique of combining several datasets into a global consistent mode, its goal is to find the relative positions and orientations of the separately acquired views in a global coordinate framework. The main idea is to identify corresponding points between the data sets and find a transformation that minimizes the distance between corresponding points.

The specific description of our robot platform can be checked in Sect. 1.5, when we manually drive the robot through our lab environment, we periodically stop the robot to take 3D scans using our tilting laser scanner LMS200, also odometry information is also logged. So from hardware system we can get a series of data set of point cloud gathered from different positions, as well as odometry information used as initial values in iteration of registration algorithm.

For every set of point cloud data acquired from different positions, we use NDT algorithm [8–10] to align them together into a single point cloud model, so that subsequent processing steps such as segmentation and object reconstruction can be applied.

1.4.2 Segmentation

Point cloud registration will yield a complete 3D point cloud map of indoor environment with all things together. But real environment may be filled with all kinds of objects, such as tables, desks, robots, and so on, segmentation is to tackle with the problem of separating different objects from each other, making it possible to recognize and replace objects in the following procedure, at the same time reducing processing time.



Fig. 1.4 The two largest plane components extracted from point cloud data set, the ceiling plane is on the *left* and floor on the *right*, the positions where we gather data are marked with *red* number from 1 to 10

There are mainly two steps in this process, the first step is to separate ceiling, floor, and walls from the rest part of the map, to do this we use the well-known RANdom SAmple Consensus (RANSAC) method [1]. Specifically in our case the ceiling contains the most points, so we first extract the largest horizontal plane which contains most inliers, then we extract the second largest plane at approximately the position of the floor. In this process, only horizontal planes (which can be distinguished inside RANSAC algorithm) are considered. If one estimated plane is not horizontal, it would be trimmed from original point cloud, then we seek for the next largest plane, this way we can save a lot of computation time. Once we found the horizontal plane, we check its average coordinate of z-axis to decide if the result is right, the extracted ceiling and floor can be seen in Fig. 1.4. Then we estimate all the vertical planes which represent walls from the rest points, before moving to step two, all the inliers of the ceiling, floor, and walls are all trimmed.

Step two aims at separating objects in the room from each other, we use Euclidean clustering method to realize it. The main thought is to use a Kd-tree structure for finding the nearest neighbors, the detailed algorithmic steps for that would be from [11]. The clustering step serves 3 purposes: (1) to remove small individual clusters with points less than threshold value (in our work the threshold is set to 800); (2) to separate multiple objects from different position which distance larger than threshold value; (3) to reduce processing time. The clusters with sufficient points are saved into separate files for further purpose. The number and position of clusters is also sent to mapping system.

We use Viewpoint Feature Histogram (VFH) feature [12] to compare objects with models in our knowledge library, in our preliminary experiment the knowledge library contains 15 different objects including desks, tables, cupboards, shelves, robots, and so on. Those clusters can be recognized will be registered to the reference model, and get the position and angle values. Replace objects from point cloud to VRML model is the final step before we get the hybrid map, the position, the position and rotation of VRML models has already been calculated. Finally we save these three kinds of map according to XML file format for 3DMapEditor to load in and check out.

1.5 Experimental Results

In this section, we provide an overview of our robot platform, describe our data collecting process, display the environment we mapped and our result hybrid map.

1.5.1 Robot Platform

The robot used in our experiment is mainly composed by a modified mobile base from our soccer robot, a SICK LMS-200 for data collection, a motor used for rotating LRF to get data of 360°, and a laptop computer for calculation, processing and display. The robot is also equipped with a panoramic digital camera, even though not used in this work, in our future work we may integrate these two sensors (LRF and camera) together.

1.5.2 Data Collection

The robot was manually driven through our building, it was stopped at some certain places to record the odometry and point cloud data, while moving to the next place it would process the data collected from last position, saving lots of time.

The scans were taken from 10 different positions (7 of them are shown in Fig. 1.5) through this journey, position 1, 2, 6 were located in the corridor while position 2-5 were chosen in the hall, position 8-10 were chosen in a room. We tried to make scan spots distribute evenly so that different objects would end with the same detail, but still some objects have denser coverage than other areas. The elementary point cloud map after registration is displayed in Fig. 1.6.



Fig. 1.5 The layout of our experiment environment, the positions where we gather data are marked with *red spots* and are numbered from 1 to 7



Fig. 1.6 The registration outcome of point data sets from 10 positions. The complete point cloud map is in the middle, with *red lines* lead from their registered locations to their original form in the surrounding area





1.5.3 Hybrid Map

The data recorded from our robot platform contains approximately 3 million points. We tests our mapping algorithm on that point cloud data set, the intermediate result can be seen in Fig. 1.7 while the final hybrid map shown in Fig. 1.8.

In Fig. 1.7, the ceiling section is removed to achieve better perspective view, different sections are colored distinctly. The walls, floor, tables can be seen clearly from each other, almost all objects are separate successfully.



Fig. 1.8 The final hybrid map loaded in 3DMapEditor, as is shown in the map, point cloud, triangular mesh and VRML model are all displayed together

We performed a qualitative analysis of the hybrid map. The whole point cloud map of the SiYuan building's 1st floor is more than 100 MB, after down sampling the map become a little more than 31 MB without apparent reduce in accuracy. After constructing hybrid map, the final result map is approximately 10 MB, which can be used in most mobile robots with moderate memory, and also achieves a better visual effect.

1.6 Conclusions

We have presented a comprehensive system for constructing 3D hybrid map based on 3D point clouds and explained the key methods used to achieve that. Our hybrid map contains 3 components: (1) a point cloud map which contains the fixed parts of indoor environment with pragmatic value (such as walls, ceilings and floor). (2) a VRML model map which is composed by the VRML model built in advance. (3) a triangular mesh map. The point cloud map is built through extracting planar regions in the original dataset, and provide pragmatic information for mobile robots. After that step, point cloud clusters will be compared with models in our knowledge base, if a point cloud cluster is recognized as an object, its pose will be estimated and it will be replaced with VRML model. Triangular mesh serves for 3D collision detection and path planning. **Acknowledgments** This work is supported by National Natural Science Foundation of China (Grant No. 61273331), National 863 Key Program on Advanced Manufacturing Technology Field of China (Grant No. 2012AA041403) and Yaskawa Electric Corporation.

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