REAL TIME GRASPING OF FREELY PLACED CYLINDRICAL OBJECTS

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Abstract: In the near future, service robots will support people with different handicaps to improve the quality of their life. One of the required key technologies is to setup the grasping ability of the robot. This includes an autonomous object detection and grasp motion planning to fulfil the task of providing objects from any position on a table to the user. This paper presents a complete system, which consists of a fixed working station equipped with a laser-range scanner, a seven degrees of freedom arm manipulator and an arm prothesis as gripper. The contribution of this work is to use only one sensor system based on a laser-range scanning head to solve this challenge. The goal is that the user can select any defined object on the table and the robot arm delivers it to a target position or to the disabled person.

1 INTRODUCTION

At the beginning of the 1970's the development of service and rehabilitation robots started to support disabled people in their daily life. The goal is to make them more independent. Today we differ between fixed systems, in which an industrial robot is mounted on a working station and mobile systems, e.g. wheelchair mounted manipulators, like MANUS (Mokhtari, 2001) or FRIEND-I (Martens, 2001) and FRIEND-II (Ivlev, 2005). Popular fixed systems are e.g. DeVar (Van der Loos, 1995), ProVar (Van der Loos, 1999), RAID (Eftring, 1994), MASTER-RAID (Dallaway, 1995) or CAPDI (Casals, 1999).

Our vision is a fully autonomous mobile robot, which is able to detect, grasp and manipulate any kind of object. One of the key challenges of this work is the robust perception of objects. This challenge is analyzed by a fixed setup consisting of a laser-range scanner and a robot arm. We use an AMTEC[1] robot arm with seven degrees of freedom, which is used for object grasping and manipulation. The joint setup is assembled similar to a human arm. The robot arm is equipped with a hand prothesis from the company Otto Bock[2], which we are using as gripper. It is thought that elderly persons will accept this type of gripper more easily than an industrial gripper, due to the form and the optical characteristics.

The outline of the paper is as follows: In the next section the state of the art of grasp robot systems, grasping technology and object perception based on structure in 2-d and 3-d is presented. Section 3 introduces our robotic system and its components. Section 4 describes the object identification to calculate the object position and Section 5 details the grasping and manipulation. Section 6 gives some experimental results during a live demo presentation and Section 7 finally concludes the paper.

2 STATE OF THE ART

In the early 1970's one of the first wheelchair mounted manipulator was developed at the V.A. Rehabilitation Engineering (formerly Prosthetics) center (Prior, 1993). From 1983 to 1988 the mobile manipulator MoVAR (Van der Loos, 1995) was developed. This PUMA-250 robot was instrumented with a camera for remote sensing, a six-axis force sensor and a gripper with finger pad-mounted proximity sensors. A nice overview of different systems, such as the Wolfson-Robot and the Wessex-Robot is given by Hagen and Hillmann (Hagan, 1997). Up

[1] http://www.amtec-robotics.com
[2] http://www.ottobock.de/

to now a number of scientists have been working on the same idea to develop a wheelchair mounted robot or a mobile robot system with arms to handle objects and assist elderly and handicapped persons, e.g. (Martens, 2001), (Volosyak, 2005). In the FRIEND systems (Martens, 2001), (Ivlev, 2005) the robot arm is controlled by a PC, which is fixed on the backside of the wheelchair. Both systems use a stereo camera system for object detection. The user interaction is based on a LC-display. The object must be placed on a predefined position on a tray, mounted at the front side of the wheelchair. A successful execution of the grasping task in this system is only possible for similar types of objects. Additionally they developed a ”smart tray” that is used in combination with the vision sensors. This ”smart tray” measures the weight and the position of objects with a matrix foil position sensor.

In comparison to the FRIEND systems, Saxena et al. (Saxena, 2006) developed a learning algorithm that predicts the grasp position of novel objects as a function of 2-d images, without building an explicit 3-d model of the object. This algorithm is trained via supervised learning using synthetic images for the training set. The work focuses on the task of identifying grasping positions without taking any complex manipulation tasks into account. A similar system describes Miller et al. (Miller, 2003). Their work specifies an automatic grasp planning system for hand configurations using shape primitives. By modeling an object as a sphere, cylinder, cone or box. They also use a set of rules to generate grasp positions.

In our case the vision task is to detect edges of objects that indicate grasp points. Accurate 3-d data is achieved by direct depth measurements, like laser-range scanning. In the range images, grasp points are indicated by object edges and grasp surface patches. Wang et al. (Wang, 2005) developed a general framework of automatic grasping of unknown objects by incorporating a laser scanner and a simulation environment. Their algorithms need a lot of time to detect grasp points. To aid industrial bin picking tasks Boughorbel et al. (Boughorbel, 2007) developed a system that provides accurate 3-d models of parts and objects in the bin to realize precise grasping operations. Due to their superquadrics based object modelling approach only rotation-symmetric objects can be used. To that effect Biegelbauer et al. describes a new approach of a hierarchical RANSAC search to obtain fast detection results of objects, which are modeled using approximated Superquadrics (Biegelbauer, 2007).

One of the most fundamental techniques for edge detection in range images is the scan line approximation (Jiang, 1999). It is well known and more efficient than the standard Canny (Canny, 1986) algorithm. The raw data points are approximated by a set of bivariate polynomial functions, in which the discontinuity of the fitted functions indicate the edge position. Katsoulas (Katsoulas, 2004) proposed an improved scan line approach by using an additional statistical merging step for a better handling of outliers. Based on these techniques we developed a 3-d edge detection method that enables a faster cylinder fit in 3-d range data.

3 SYSTEM APPROACH

The goal is, that the user can select any object on a table and the robot arm delivers it to a defined position or to the disabled person. The main challenges to solve are the robust detection of edges and their interpretation as grasping points. Our approach is based on scanning the objects by a rotating laser-range scanner and execution of subsequent path planning and grasping motion. Hence the system consists of a pan/tilt-mounted red-light laser and scanning camera and a seven degrees of freedom robot arm, which is equipped with a human like prosthesis hand (see Fig. 1).

Figure 1: Overview of the system components and their interrelations.

3.1 Laser-Range Scanner

The laser-range scanner records a snap-shot of the object scene with the help of a pan/tilt-unit. At present, it is mounted on a table. We are working to miniaturize the laser-range scanner to mount it on the shoulder of the robot later. A high resolution sensor is needed in order to detect a reasonable number of edge-points of the objects with the required accuracy. The laser-range scanner used for this work consists of a red-light LASIRIS laser from StockerYale[3] with 635nm and a MAPP2500 CCD-camera from SICK-IVP[4] mounted on a pan/tilt-unit (PowerCube Wrist from AMTEC robotics). With the help of a cylinder lens, the laser-light is expanded and moves horizontally over the scene of interest. The camera grabs the laser-light profiles and extracts the laser-lines with the integrated microprocessor. The 3-d data is transformed to the world coordinate system. Finally the result can be displayed as a point cloud (see Fig. 2).

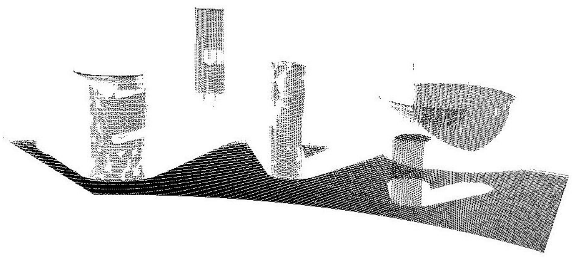

Figure 2: Exposure of the raw point cloud with 75.863 voxel. The two shadows from laser and camera are clearly visible.

3.2 Robot Arm and Gripper

For this work we use the "Light Weight Arm 7 DOF" from AMTEC robotics and a hand prothesis from Otto Bock as gripper. The robot arm exhibits seven degrees of freedom with a joint configuration similarly to the human arm (shoulder, elbow and wrist). The seventh degree of freedom is required to enable complex object grasping and manipulation and allow for some flexibility to avoid obstacles. The prosthesis as end effector is selected due to the integrated force sensors as well as its increased acceptance of elderly and handicapped persons. It has three active fingers, the thumb, the index finger and the middle finger. The last two fingers are just for cosmetic reasons. Since, they have no active function in the grasping process their uncontrollable behavior must be considered, which reduces the grasping radius (see Fig. 1). As a huge advantage the integrated tactile sensors are used to detect a potential sliding of objects, which initializes a readjustment of the fingers.

3.3 Operation Sequence

The first step is to scan the scene on the table by the laser-range scanner. The camera converts the laser-profiles to a 3-d point cloud, which can be visualized. Now the user can select the desired object. The developed algorithm analyzes the point cloud and calculates the position of the searched object. A commercial path planning tool from AMROSE[5] calculates the trajectory to grasp the object. Before the robot arm delivers the object, the user can check the calculated trajectory in a simulation sequence. Then the robot arm executes the off-line programmed trajectory. The algorithm is implemented in C++. For displaying the results the Visualization Tool Kit (VTK)[6] is used.

4 OBJECT IDENTIFICATION

The main goal of our work is to robustly detect cylindrical objects in the recorded point cloud in real time. Robustness includes the positive detection of defined objects despite any noise and outliers in a point cloud, which can be caused by specular surfaces (see Fig. 2, edges of the objects). To reduce complexity we only consider cylindrical objects for object detection for this work. An additional challenge is the complex interaction between the different operation parts. Finally to keep the standby time acceptable for the user the complete operating cycle should be finished within 20sec.. This time limit is challenging since usual object detection starts with an exhaustive segmentation step. As an example, object segmentation alone by recursive flood-filling with region-octree (Burger, 2007) of the desired table scene takes more than 30sec. (see Fig. 3). Thus a faster solution must be found. One alternative, which we exploited in our work is based on well investigated curvatures. Fig. 4 presents the steps of the fast object detection method. In the first step, the *"raw data preprocessing and vector estimation"* the raw data points are preprocessed with a low pass filter to reduce any noise.

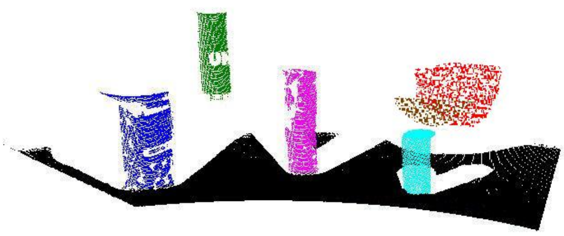

Figure 3: Segmentation of the different objects by recursive flood-filling. Images are best viewed in color.

[3]http://www.stockeryale.com/index.htm

[4]http://www.sickivp.se/sickivp/de.html

[5]http://www.amrose.dk/

[6]Freely available open source software, http://public.kitware.com/vtk.

One of the most time consuming calculations is the normal vector estimation based on the orientation of the local neighborhood of 20mm, for what a region-octree is used. These vectors are required to compute the axis of the cylinder objects. A lot of tests have shown that for a neighborhood of 20mm a reasonable accuracy can be achieved, while the calculation time stays acceptable. The *"range image segmentation"* starts by detecting the surface of the table with a RANSAC (Fischler, 1981) based plane fit. Then we analyze the curvature of the remaining points to filter neighbouring voxels with an angle difference between $\pm 78°$ and $\pm 90°$ (see Fig. 5) .

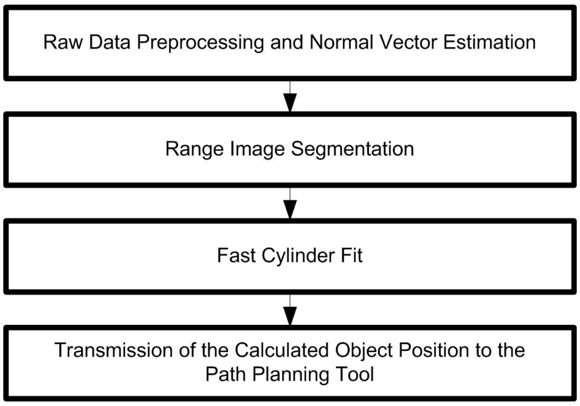

Figure 4: Flow chart of the object detection approach.

The *"fast cylinder fit"* starts with a RANSAC based circle fit. Randomly three high curvature points are picked. The resulting circle is extended to a potential cylinder along its circumscribed axis down to the table. For every vicinity point, within a defined distance of 2mm of the calculated cylinder barrel, the normal distance to the cylinder barrel is calculated. The trial with the lowest mean of these distances is selected as cylinder (see Fig. 6). For comparison Jiang et al. (Jiang, 2005) published a method for 3-d circle fitting. They reduce the number of local minima, but the error function is no more Euclidian. Here another simple proposal with an Euclidian function is used. For an explicit description, the raw data points of a profile scan are defined as (xi, yi, zi), n is the number of voxels and (xa, ya, za) is the circle's center. The resulting error function e is:

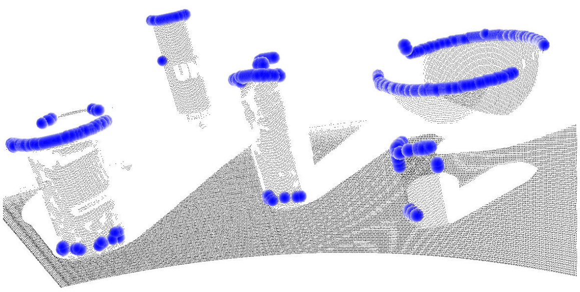

Figure 5: The acquired range image of the current table scene. The points with a high curvature are marked with blue dots. Images are best viewed in color.

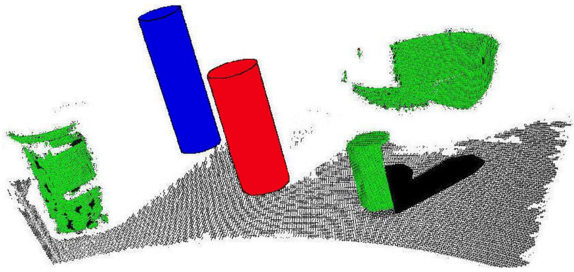

Figure 6: Detected objects in the table scene (blue cylinder - spray-on glue, red cylinder - beverage can, green points - rigid obstacles). Images are best viewed in color.

$$e = \sum_{i=1}^{n} \sqrt{(xi-xa)^2 + (yi-ya)^2 + (zi-za)^2)} - r \quad (1)$$

The error must be smaller or equal than a defined threshold. In our case we use a distance of $2mm$:

$$|e| \leq 2mm \quad (2)$$

In the last step of Fig. 4 *"Transmission of the Calculated Object Position to the Path Planning Tool"* the calculated object position in the actual environment model for collision avoidance has to be transmitted to the path planning tool. This 3-d mesh is generated by using all objects besides the target object, based on the triangles calculated by a DeLaunay triangulation (O'Rourke, 1998) This step is important to enable a collision free robot trajectory.

5 OBJECT GRASPING AND MANIPULATION

The task of this part of our work is to calculate a collision free robot path and to execute the grasping activity safely. The first step is performed by the path planning tool from AMROSE. The input to this tool is the detected object pose, the environment model and a transformation between the robot coordination system and the range scanner coordinate system. The output is a collision free trajectory to the desired object. Before the robot execution is approved, the user can check a simulation of the calculated trajectory and decide, if it is safe enough to handle the object (see Fig. 7 and Fig. 8). After the robot approaches the user

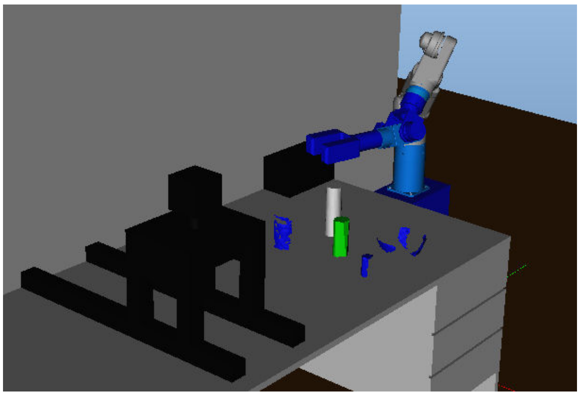

Figure 7: Visualization of the trajectory by a simulation tool. The white cylinder is the grasping object. The green cylinder (= $2.^{nd}$ grasping object) and the blue objects are the obstacles. Images are best viewed in color.

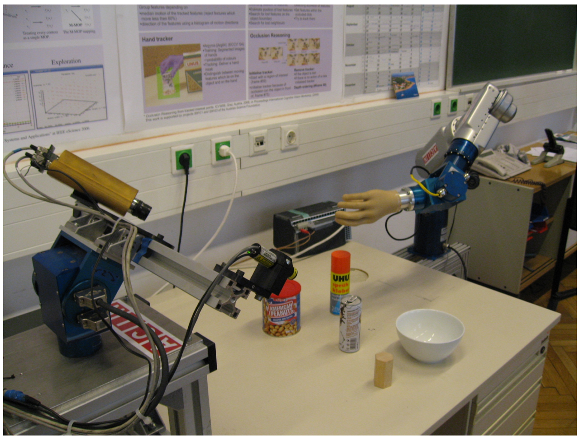

Figure 8: Real position of the robot arm after the approach trajectory.

can initiate the closing of the gripper. As soon as the gripper encloses the object, the robot motion to the transfer point starts. Finally the desired object can be placed at a defined position or directly handed over to the user.

The calculation of the object detection and localization is performed by a PC with 1.8GHz Pentium IV processor and takes less than 12sec. depending on the range image size. The reliability depends on the ambient light, object surface properties, laser beam reflections and vibrations. Therefore, the laser-range scanner must be configured to the respective environment. By using an additional red-light filter the impact of light or reflections can be minimized.

6 EXPERIMENTS

The entire system exhibits its robust behavior and has been evaluated at a live demo presentation[7] in front of more than 1000 college students. During the demonstration day about 50 runs were performed. The main problem that rarely appeared was a malfunction of the path planning tool, because no suitable trajectory could be found. Whereby the path planning had to be restarted. Sometimes the last two fingers, which reduce the grasping radius (see Fig. 1), shift the grasp object, but without a final effect on the success of the grasping process. Tab. 1 shows a short analysis of the arisen problems within 50 runs. The recoginition of the cylindrical objects fails at strong environmental influences by the ambient light.

The autonomous grasping function should be able to find and grasp a cylindrical object in a defined area. When objects are positioned closer to each other, the autonomous grasping function show up difficulties to find the correct object. A minimum distance of 20*mm* (this distance is equal to the diameter of the thumb of the hand prothesis) has to be observed between the objects.

Table 1: Evaluation of the arisen problems in percent [%] at 50 runs.

Arison Problems	Number of Events	Percent [%]
Path Planning	11	22%
Hand Prosthesis	4	8%
Object Recognition	2	4%
Sum	17	34%

7 CONCLUSIONS AND FUTURE WORK

This paper presents an approach of a robot system equipped with a laser-range scanner to get high accuracy table scene sensing. It shows that feature detection, in our case we only consider cylindrical objects, is a faster way (12sec.), than usual object segmentation (more than 30sec.) by a flood-filling recursive function. The presented method performs with very high reliability. Thus the approach for object detection and localization is well suited for use in related applications under difficult conditions.

A seven degrees of freedom arm manipulator and an arm prothesis as gripper are used to grasp and deliver the desired object. The goal of this system is

[7]http://www.yo-tech.at/

to analyze the feasibility and reliability of object detection, which could be shown at a live demo. The cylinder detection approach can be extended to detect any type of object, since it is based on a grouping of high curvature points. This grasping approach can be applied for any kind of geometrical figures. This will expand the application to other tasks.

In the future, the robot arm will be installed on a mobile robot and for the object detection we calculate the grasping points of novel objects. This includes the revision of the path planning tool and a segmentation of sharp curvature points to speed up the method. Summarizing, this work illustrates that the concept of a 3-d vision guided robot arm can be adopted to many applications and has high potential to enable a more complex system. We will also deal with the development and the prototypes integration of a new laser range sensor with additional two cameras for stereovision to increase the robustness and predictability of the object detection system.

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