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Grasping of Unknown Objects from a Table Top^{*}

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Abstract. This paper describes the development of a novel vision-based grasping system for unknown objects based on range images. We realize a synthesis of the calculated grasp points with a 3D model of a hand prosthesis, which we are using as gripper. We locally find grasp point candidates based on the shape of the object and validate the globally by checking collisions between the gripper and surrounding objects and the table top. Our approach integrates a robust object segmentation and grasp point detection for every object on a table in front of a 7-DOF robot arm. The algorithm analyzes the top surface of every object and outputs the generated grasp points and the required gripper pose to grasp the desired object. Additionally we can calculate the optimal opening angle of the gripper. The first experimental results show that the presented automated grasping system is able to generate successful grasp points for a wide range of different objects.

1 Introduction

“People have always been fascinated by the exquisite precision and flexibility of the human hand. When hand meets object, we confront the overlapping worlds of sensorimotor and cognitive functions [1].” The grasping task was studied from a psychological, biological and engineering focus but still remains unresolved. There exist partial solutions for certain cases, however there is still no general valid solution. This paper presents an approach that detects potential grasp points to realize the task of grasping arbitrary objects in arbitrary poses. Our vision is to find a fully autonomous way to detect, grasp and manipulate any kind of object. The human has a sophisticated system, which allows him to grasp a wide range of different objects in different cases. Human hands are characterized by five soft fingers with high dexterity and the humans know the shape, dimension and properties of their hands. Additionally humans have as yet unmatched visual capabilities. In this work we try to realize this combination of the human abilities with a laser range scanner and a 3D model of the used

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gripper, which is a prosthetic hand from the company Otto Bock¹. Humans are also able to grasp unknown objects. They learn different shapes from early on and people are able to generalize to new objects. We present an algorithm that automatically segments a 2.5D point cloud, calculates practical grasp points and checks the validity of the grasp points with a 3D model of the hand prosthesis. Thereby the algorithm finds the best gripper pose for the used hand prosthesis to grasp the desired object without any collision.

1.1 Problem Statement and Contribution

We operate on a 2.5D point cloud of a typical table scene, where every object is scanned from the same laser range scanner position. All considered objects have mostly horizontal planar top surfaces. Fig. 1² shows seven different objects, where object no. 1 to 6 have a convex shape and object no. 7 has a concave shape. We define what we consider as grasp points, the blue lines represent the optimal positions for grasp points. The first goal of this work is a robust detection of the grasp points of any kind of object in the point cloud, see fig. 3. This including robustness despite to noise, outliers and shadows, which can be caused by specular or reflective surfaces. Fig. 2 gives an overview of our proposed method.

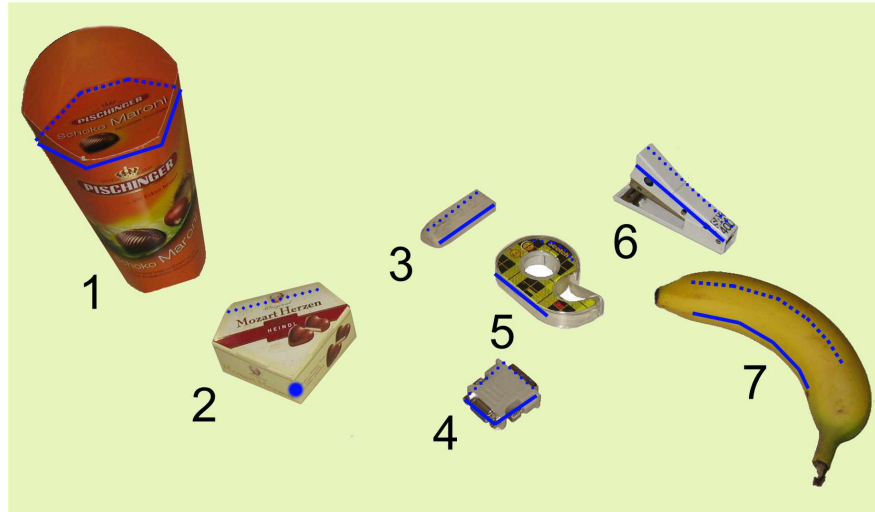


Fig. 1. Table scene with seven different objects (from left: 1. chocolate package, 2. package Mozart, 3. eraser, 4. plug, 5. adhesive foil, 6. stapler, 7. Banana). The blue lines represent the optimal positions for grasp points.

¹ <http://www.ottobock.de/>

² All images are best viewed in color.

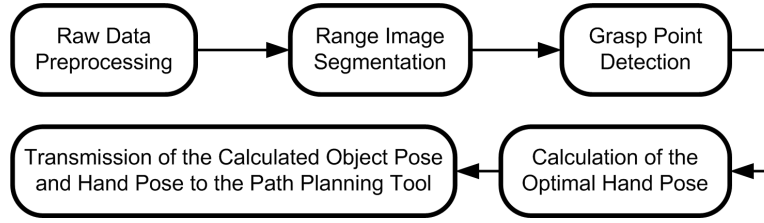


Fig. 2. Overview of our grasp point detection and synthesis algorithm.

The algorithm consists of five main steps:

- Raw Data Preprocessing: The raw data points are preprocessed with a geometrical filter to reduce noise and outliers.
- Range Image Segmentation: This step identifies different objects based on a 3D DeLaunay triangulation.
- Grasp Point Detection: Calculation of possible grasp points based on the top surfaces of the objects.
- Validity Check of the Grasp Points: Considering surrounding objects and the table surface as obstacles, find optimal gripper pose, which maximizes distances to obstacles.
- Path Planning Tool: Transmission of the calculated object pose and hand pose to the path planning tool.

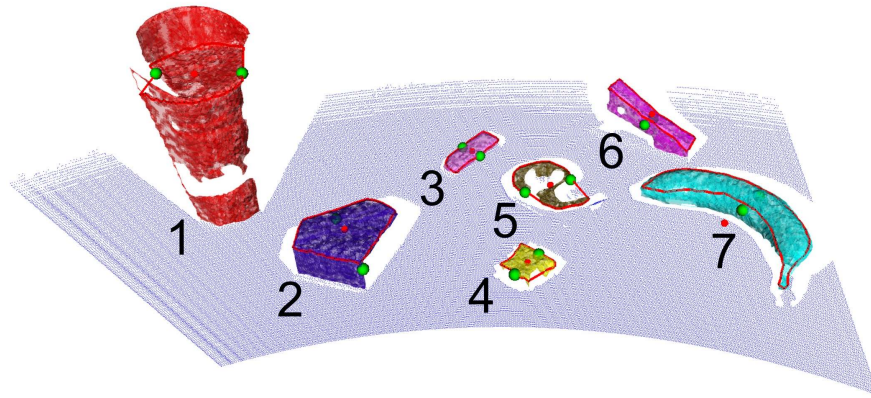


Fig. 3. The figure shows the generated meshes with 12.437 object points and 81.691 plane points from originally 100.843 points. The two shadows from laser and camera and the grasp points (green colored) and the rim line (red colored) are clearly visible. The red points represent the calculated center of mass of the different top surfaces.

The second goal of our work is to analyze the calculated grasp points with the help of a 3D model of the hand prosthesis, which we are using as gripper,

see fig. 4. It has three active fingers, the thumb, the index finger and the middle finger. The last two fingers are just for cosmetic reasons. So the proposed algorithm is based on two grasping points between the thumb and index finger. The 3D model of the gripper is realized with a Minolta VIVID 700 range scanner³. This 3D model enables it to calculate the optimal position and orientation of the gripper to successfully grasp the desired object. Furthermore it affords to consider all surrounding objects to identify potential obstacles. As well the opening angle can be observed to detect a possible collision with the table. All these information is important for the path planner to calculate a successfully path to grasp the desired object.

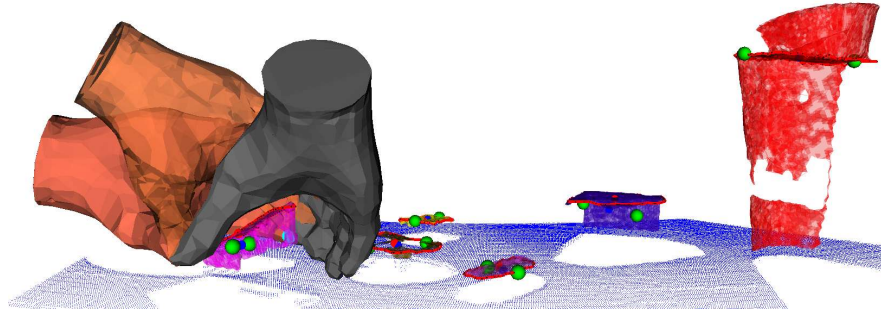


Fig. 4. This figure shows on the left side three different hand configurations to grasp the stapler. The left 3D model of the hand (red colored) shows the maximum positive hand orientation by 90° , the right hand (black colored) shows the maximum negative hand orientation by -30° and the hand model in the middle (orange colored) shows the optimum orientation by 60° .

We simulate the complete grasping process with a commercial path planning tool from AMROSE⁴. The input is the detected object pose, the gripper pose, the environment model, the grasp points and a transformation between the robot coordinate system and the laser range scanner coordinate system. The output is a collision free robot trajectory to the desired object. Before the robot executes the trajectory, the user can check a simulation of the calculated trajectory.

The outline of the paper is as follows: The next Section 2 details the analysis of the objects and describes the calculation of possible grasp points. Section 3 describes the implementation of a 3D model of the gripper. Section 4 shows our results and Section 5 finally concludes the paper.

³ <http://www.konicaminolta.com/sensingusa/products/3d>

⁴ <http://www.amrose.dk/>

1.2 Related Work

Fagg and Arbib [2] developed the FARS model, which focuses especially on the action-execution step. Nevertheless, no robotic application has been yet developed following this path. Saxena et al. [3] developed a supervised learning algorithm that is able to predict the grasp position of novel objects as a function of 2D images. The work focuses on the task of identifying grasp positions. In our work we do not use learning, but we believe a priori that we consider possible grasp points. Saxena also defines for every object only one grasp point, in some cases objects can be grasped slanted. In our approach we calculate two grasp points to realize a more stable grasp. Stansfield [4] developed a system for grasping objects with unknown geometry. At the beginning every object was placed on a rotary disc. Then the object was rotated and translated under a laser range scanner to generate a 3D model of the object. The scanned 3D model formed the input to an expert system that planned the grasping process. This system was tested for several objects. Miller et al. [5] specify an automatic grasp planning system “GraspIt!” for hand configurations using shape primitives, by modeling an object as a sphere, cylinder, cone or box. They use a set of rules to generate possible grasp positions. In our case the vision task is to detect edges and surfaces of objects that are analyzed to calculate grasping points. We use a 3D model of the hand prosthesis, which we are using as gripper to find an optimal grasping angle to grasp the object. Wang et al. [6] developed a framework of automatic grasping of unknown objects by using a laser scanner and a simulation environment. Boughorbel et al. [7] aid industrial bin picking tasks and developed a system that provides accurate 3D models of parts and objects in the bin to realize precise grasping operations, but their superquadrics based object modeling approach can only be used for rotationally symmetric objects. Bone et al. [8] presented an interesting approach, which combines online silhouette and structured-light 3D object modeling with online grasp planning and execution with parallel-jaw grippers. Their algorithm analyzes the solid model, generates a robust force closure grasp and outputs the required gripper pose for grasping the object. We analyze the validity of the calculated grasping points with a 3D model of the hand, thereby our algorithm also outputs the required gripper pose to grasp the object. Borst et al. [9] show that it is not necessary in every case to generate optimal grasp positions, however they reduce the number of candidate grasps by randomly generating hand configuration dependent on the object surface. Their approach works well if the goal is to find a fairly good grasp as fast as possible and suitable. Kragic and Birkman [10] developed another vision-guided grasping system. Their approach was based on integrated monocular and binocular cues from five cameras to provide robust 3D object information. The system was applicable to well-textured, unknown objects. A three fingered hand equipped with tactile sensors was used to grasp the object in an interactive manner. Recatalà et al. [11] developed a framework for the development of robotic applications on the synthesis and execution of grasps. Li et al. [12] presented a data-driven approach to grasp synthesis. Their algorithm uses a database of

captured human grasps to find the best grasp by matching hand shape to object shape.

2 Grasp Point Detection

At the beginning the recorded point cloud from the laser range scanner should be filtered with a low pass filter to reduce any noise and outliers. The range data segmentation starts by detecting the surface of the table with a RANSAC [13] based plane fit. The segmentation of the remaining points is achieved with a 3D mesh generation, based on the triangles calculated by a 3D DeLaunay triangulation [14].

The algorithm for grasp point detection finds the top surface of all objects with a defined threshold of $3mm$ and generates a 2D DeLaunay triangulation, with this 2D surface information the rim points and feature edges of every object can be detected, see fig. 5. Then we calculate the center of mass for every objects top surface (red colored points in fig. 5). For convex shapes the center of mass is inside the surface, but for concave shapes the center of mass may be outside as illustrated in fig. 5 by object no. 7.

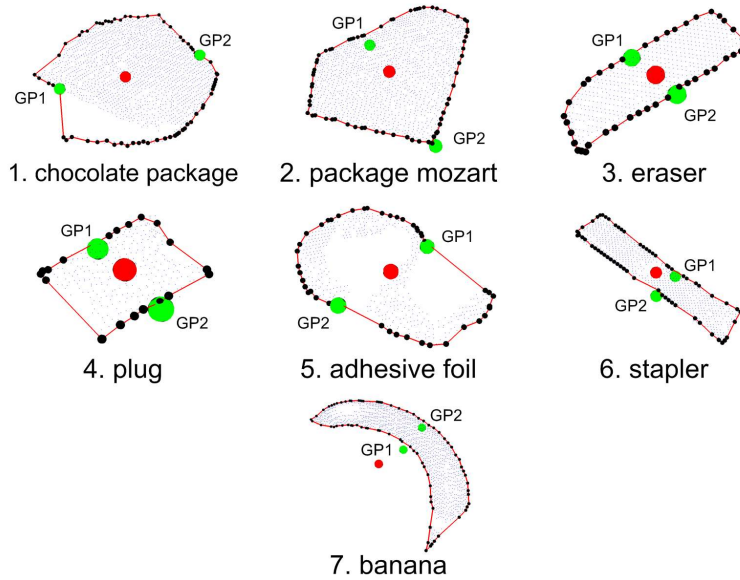


Fig. 5. Top surfaces of the seven objects from fig. 1. The red lines represent the form of the top surfaces, the red point represents the center of mass. The green points are the calculated grasp points, GP1 is the first grasp point with the shortest distance to the center of mass and GP2 is the second grasp point.

The first grasp point (GP1) is that point along the rim line (red line), which has the shortest euclidian distance to the center of mass (red point). The second grasp point (GP2) is on the opposite rim line. Thereby, the first grasp point (GP1) should have with the second grasp (GP2) and the center of mass should lie on a line. To grasp an object on the top rim line can create a possible slipping through the fingers of the hand prosthesis. To avoid that, the height of the top surface is calculated and both grasp points are shifted down. The shifting distance in our case is maximal $30mm$, this distance is pretended through the gripper. Additionally we check that at least one of the shifted grasp points lies on a visible surface, i.e. is not shifted into thin air.

3 Feasibility of Objects Grasp Points

In order to successfully grasp an object it is not sufficient to find locally the best grasp points, the algorithm must also decide like humans from which angle it is possible to grasp it. Moreover the algorithm checks the validity of the grasp points. For that approach we rotate the 3D model of the hand prosthesis around the rotation axis, which is defined through the grasp points. The rotation axis of the hand is defined by the thumb and the index finger of the hand as illustrated in fig. 6 with the cyan colored points. At the beginning the hand is placed accurately over the grasping object. This start position is defined with a grasping angle of 0° . Furthermore the opening angle of the hand is set to its maximum. The algorithm checks for a collision of the hand with the table or other objects. If there is no collision our approach calculates the maximum and minimum possible rotation angles. We find the best gripper position and orientation by an averaging of the maximum and minimum possible rotation angles. Through that, the algorithm calculates the best gripper pose to grasp the desired object for the path planning tool. If there is a collision the grasp point detection algorithm calculates new grasp points for the desired object. Then the algorithm takes for the first grasp point (GP1) the second shortest euclidian distance between the center of mass and the rim line and all other calculations are repeated.

We decide to use the power crust algorithm for the surface reconstruction [15] of the 3D model of the hand prosthesis, because this algorithm delivers very good results and is quite fast. It realizes a construction which takes a sample of points from the surface of a 3D object and produces a surface mesh and an approximate medial surface axis. The approach approximates the medial axis transform (MAT) of the object. Then it uses an inverse transform to produce the surface representation from the MAT.

This approach allows it to change the start position and orientation of the gripper online depending on the grasping object. The grasping pose depends on the grasping object itself, surrounding objects and the calculated grasp points. The advantage of this novel implementation is that it realizes a alleviation for the path planner to grasp an object fast and successfully, as illustrated in fig. 6.

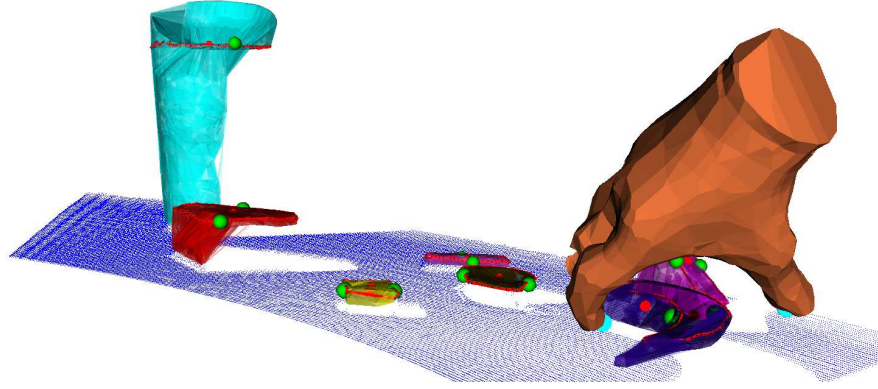


Fig. 6. The rotation axis of the hand is defined through the thumb and the index finger of the hand with the cyan colored points. This rotation axis must be aligned with the axis defined by the grasp points.

4 Experiments and Results

In our work, we demonstrate that our grasp point detection algorithm for objects with flat top surfaces shows promising results, see tab. 1. We evaluated the detected grasp points by comparing them to the optimal grasp points as defined in fig. 1. The object segmentation and grasp point detection is performed by a PC with 3.2GHz dual-core processor and it takes about 30sec. to compute the grasp points and to syntheses the calculated grasp points takes about 51sec., this calculation depends on the number of the surrounding objects and their shape. The algorithm is implemented in C++ using the Visualization Tool Kit (VTK)⁵. In testing of 10 different point clouds with the seven objects, the algorithm shows very good results, see tab. 1. For the objects no. 1, 2 and 7 in some cases the algorithm can not detect the pre-defined grasp points, because of shadows of the laser range scanner. The difference of object no. 7 to all other considered objects is that it has a concave and not a convex shape, which represents a problem for many published methods.

Tab. 2 shows the maximum positive grasping angle of every object and tab. 3 shows the maximum negative grasping angle. These tables show also the reason of the collision, which can be caused by the table, other surrounding objects or the grasping object itself. Using these values we calculate the optimal 3D hand pose to grasp the desired object, see tab. 4. The final grasping angle results as average from the maximum positive and negative grasps, where minimum and maximum angles are $\pm 90^\circ$. The first object illustrates that it is not ideal in every case use a vertical gripper orientation as starting position to grasp an object. The second object can be grasped with a reduced opening angle. In this

⁵ Open source software, <http://public.kitware.com/vtk>.

Table 1. Grasping rate of different objects.

No.	Objects	Grasp-Rate [%]
1	chocolate package	70%
2	package mozart	70%
3	eraser	100%
4	plug	100%
5	adhesive foil	80%
6	stapler	100%
7	banana	80%
Overall		85.71%

case the distance between the grasp points is about $75mm$, so the opening angle must reduced to $75mm$ with a safety distance of $5mm$ to avoid a possible collision with the object itself at the beginning. After that step the optimal hand pose can be calculated again.

Table 2. Maximal positive grasping angle.

No.	Objects	Maximal positive Grasping Angle [°]
1	chocolate package	0° (object collision itself)
2	package mozart	23° (object collision itself)
3	eraser	35° (object collision with obj. no. 2)
4	plug	90°
5	adhesive foil	90° (table collision)
6	stapler	90°
7	banana	80° (object collision with obj. no. 6)

Fig. 7 shows the positive influence of the angle adjustment. Through the calculation of the optimized grasping angle we realize a safer grasp. There is a higher distance to the all surrounding objects. Thereby it realizes a faster and safer calculation of the needed robot path with the path planning tool to grasp the desired object.

5 Conclusion and Future Work

In this paper we present a framework to successfully calculate grasp points of unknown objects in 2.5D point clouds from laser range data. The presented method shows high reliability. We calculate the grasp points from the top surfaces. The grasp point detection approach can be applied to a reasonable set of objects. This idea can be applied to every gripper type with a suitable 3D model of the used gripper.

Table 3. Maximal negative grasping angle.

No.	Objects	Maximal negative Grasping Angle [°]
1	chocolate package	-2° (object collision itself)
2	package mozart	-10° (table collision)
3	eraser	-10° (table collision)
4	plug	-5° (table collision)
5	adhesive foil	-15° (table collision)
6	stapler	-30° (table collision and object collision itself)
7	banana	-5° (object collision itself)

Table 4. Optimized grasping angle.

No.	Objects	Optimized Grasping Angle [°]
1	chocolate package	-1°
2	package mozart	16.5°
3	eraser	22.5°
4	plug	47.5°
5	adhesive foil	52.5°
6	stapler	60°
7	banana	42.5°

In the near future we will check the quality of the calculated grasp points directly on the robot, this time we simulate the total grasping process with a commercial path planning tool from AMROSE. We plan to use a deformable hand model to reduce the opening angle of the hand so we can model the closing of a gripper in the collision detection step. Also the rest of the robot arm will be used in the collision detection step. Furthermore most experiments are in simulation and will be carried out to the real robot later.

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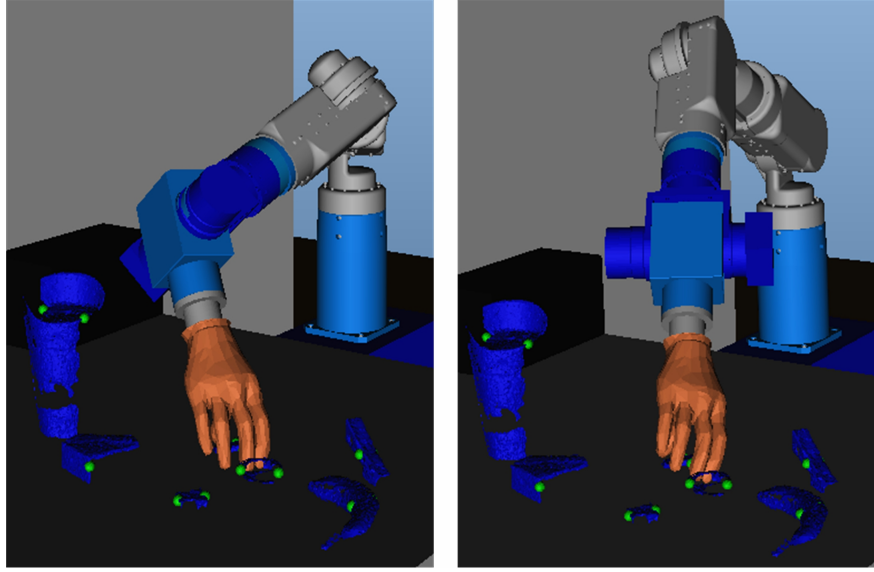


Fig. 7. The left figure shows the calculated grasping angle without an angle adjustment. It shows a higher collision risk with object no. 1 as the right figure with an angle adjustment of 22.5° , as illustrated in tab. 4.

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