A Survey of Unknown Object Grasping and Our Fast Grasping Algorithm-C Shape Grasping

Qujiang Lei
TU Delft Robotics institute
Delft University of Technology
Delft, Netherlands
e-mail: q.lei@tudelft.nl

Jonathan Meijer
TU Delft Robotics institute
Delft University of Technology
Delft, Netherlands
e-mail: J.G.J.Meijer@student.tudelft.nl

Martijn Wisse
TU Delft Robotics institute
Delft University of Technology
Delft, Netherlands
e-mail: m.wisse@tudelft.nl

***Abstract*—Grasping of unknown objects with neither appearance data nor object models given in advance is very important for robots that work in an unfamiliar environment. In recent years, extensive research has been conducted in the domain of unknown object grasping and many successful grasping algorithms for unknown objects are created. However, So far there is not a very general fast grasping algorithm suits various kinds of unknown objects. Therefore, choice among different grasping algorithms becomes necessary for users. In order to make it more convenient for users to quickly understand and choose a suitable grasping algorithm, a survey about the latest research results of unknown object grasping is made in this paper. We compared different grasping algorithms with each other and obtained a table to clearly show the result of comparison. The comparison could give researchers meaningful information in order to quickly pick a grasping approach with their requirements. Meanwhile, we briefly showed our latest fast grasping algorithm which employs only a partial point cloud of the target object as input, and the grasping algorithm can quickly work out a suitable grasp for most objects within 2 seconds on a common personal computer. Simulations are used to examine the performance of our algorithm and successful results are obtained.**

Keywords-robot; unknown object grasping; survey; fast grasping; C-shape grasping; Partial point cloud

I. INTRODUCTION

In 2015, the number of professional service robots sold increased by 25% than that in 2014. It is forecasted that this increase will continue for the upcoming years [1]. To help people with household tasks, grasping and manipulation are key functions for service robots. However, finding a suitable grasp is a complex task. Grasping approaches are designed to find meaningful grasp on a target object. However, due to the amount of research of the past decade in this field, there are an abundance of different grasping approaches.

As explained by Bohg et al. [2], empirical grasping methodologies rely on sampling grasp candidates for an object and ranking these candidates with the use of a metric. In the study of Bohg et al. [3], the empirical grasping methodologies are divided into three categories: known, familiar and unknown object grasping approaches. Known object grasping approaches rely on the available information of the object to perform stable grasps. Familiar object grasping approaches also rely on available object information. However, they are able to grasp an object when the object is similar to the known ones. Unknown object grasping approaches do not need any prior information of the object to perform grasps.

In human environments, a great variety of different kinds of objects exist. Providing detailed information about all these objects would be a time-consuming task. The use of familiar object grasping approaches could help simplifying the aforementioned task. However, if these approaches pick a wrong similar object, grasps can become unreliable or imprecise. Since unknown object grasping approaches do not rely on available information, they are suitable to grasp a great variety of objects.

The survey by Bohg et al. [3] already focuses on the use of different unknown object grasping approaches. However, this survey did not compare the different approaches. Moreover, after the publication of this survey, more grasping approaches have been developed. For the survey part in this paper, we aim to give an updated overview on the existing unknown object grasping approaches and provide a simple comparison. This will be done by collecting meaningful data found in the corresponding literatures, for example success rate and execution time.

In this paper, we divide the existing unknown object grasping approaches into two groups, namely global and local grasping approaches. Global grasping approaches try to represent the full 3D model of the unknown object to find suitable grasps, which can be done by recreating the model with the use of multiple views of the object, symmetries, decomposition into 3D shapes or by closing the surface area of the retrieved data. Local grasping approaches only use the data available to work out suitable grasps, which use information in particular like edges, boundaries or silhouettes of the unknown object.

In above paragraphs, we explained what is unknown object grasping and why we do the survey about the existing approaches of unknown object grasping. Additionally in this paper, we will briefly introduce our latest fast grasping algorithm of unknown objects.

Due to the difficulties associated with the increasing complexity of design and control of fully actuated robotic hands, under-actuated gripper is becoming increasingly popular in recent years. Fig. 1 (b) shows a good example of under-actuated gripper. In order to make our grasping algorithm being widely used, in another word, in order to make our grasping algorithm more general for most unknown objects, we specially designed a grasping algorithm for under-actuated gripper shown in Fig. 1 (b).

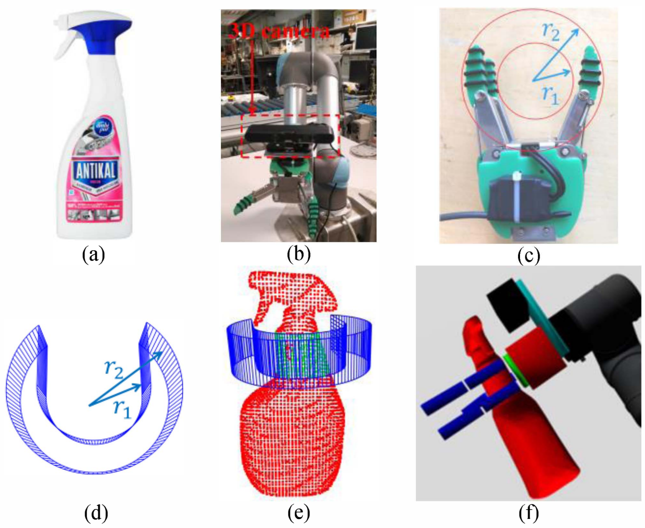


Figure 1. The outline of our fast grasping algorithm for unknown objects. (a) shows an example of an unknown object. (b) shows a robot arm equipped with a 3D camera and an under-actuated gripper. (c) and (d) show the inspiration of this paper, the under-actuated gripper is simplified as a two layer C-shape cylinder. (e) shows an example grasp found by our algorithm. (f) demonstrates the grasp execution in the simulation environment.

The outline of our fast grasping algorithm is shown as Fig. 1. We simplify the under-actuated gripper as a two-layer C-shape cylinder (shown as Fig. 1 (c) and Fig. 1 (d)) with radius r_1 and r_2 respectively, after that, the algorithm will do C-shape cylinder searching on the partial point cloud of the target object to quickly synthesize an executable grasp. Specifically, Fig. 1 (b) shows a setup consisting of a robot arm equipped with a 3D camera and an under-actuated gripper. A spray bottle in Fig. 1 (a) works as an example of an unknown object. Fig. 1 (c) and (d) shows the inspiration of this paper. The gripper in Fig. 1 (b) is described as a two-layer C-shape cylinder with radius r_1 and r_2, which is used to compute suitable grasps on the partial point cloud of the target object. Fig. 1 (e) shows an example of executable grasp found by our algorithm. The green points on the object stand for the corresponding grasp area. Fig. 1 (f) shows the grasp execution for the spray bottle. Details about our algorithm will be explained in section III.

II. Survey About Unknown Object Grasping

Grasping of unknown objects can be done in a variety of ways. In this section, the existing grasping approaches are classified and shortly explained, followed by the comparison part. The different approaches will be compared with each other by looking at characteristics that the approaches have in common. In the end of this section, the comparison outcome is discussed.

A. Existing Unknown Object Grasping Approaches

Unknown object grasping approaches can be categorized into two groups: global grasping approaches and local grasping approaches. Global grasping approaches consider the whole object in order to find the best grasp. Local grasping approaches only work with partial data of the object to find a suitable grasp.

To segment the unknown object from the scene, grasping approaches usually only consider objects placed on flat surfaces. In a point cloud representation of the scene, a RANSAC (Random Sample Consensus) can help to distinguish flat surfaces. Isolating a point cloud cluster that represents the unknown object is done by removing all the points on the found flat surface.

1) Global grasping approaches

a) Multiple views

A way to consider the whole object is to look at the unknown object from multiple locations. From these locations, either 2D or 3D data can be retrieved in order to get accurate information of the model to successfully grasp the object.

In the work by Bone et al. [4], 2D images and structured-light data from multiple views are being used to create a 3D model of the unknown object. From the 2D images, silhouettes are extracted to create a 3D visual hull, which is merged with the more precise 3D shape data retrieved from the structured light technique. The approach in turn analyzes the model and generates a robust force closure grasp.

Dune et al. [5] determine the quadric that best resembles the shape of the object, which is done by using multiple view measurements. The quadric is estimated in each 2D view. The robot arm will already start moving towards the unknown object after the first quadric estimation is obtained, which results in a fast real-time grasping algorithm.

Similar work is presented by Yamazaki et al. [6]. In this approach, the 3D model of the unknown object is retrieved through SFM, which stands for ‘structure from motion’. By considering the gripper’s width, a good grasp is said to be found in a short amount of time.

Lippiello et al. [7] place a virtual elastic surface around the point cloud of the object, then this surface is shrunk at every iteration step (new image acquisition) until this intercepts with some points of the object. Attractive forces of points on the object will make an equilibrium with the elastic forces of the virtual surface in order to present the 3D model. During the construction of the virtual surface, the grasp planner is already active thus moving the end effector towards the unknown object.

b) Symmetries

When working with one 3D camera and without changing the angle on a specific object, the obtained point cloud contains occlusions. For instance, when the camera is in front of an object, no information of the back of the object can be given. The approach of Bohg et al. [2] overcomes this problem by considering symmetries found in human-made objects. Their algorithm first tries to determine the planar symmetry on which the detected point cloud of the object will be mirrored about. After the mirroring of the points, a surface approximation is applied, this closes the object in order to find grasping locations on the object.

c) Decomposition

The decomposition with respect to the object, it means that the object is factorized into different parts. Factorizing into simple parts will decrease computation times when trying to grasp complex models.

Miller et al. [8] and Goldfeder et al. [9] use shape primitives to simplify the object, however they consider knowing the model before. The principle can still be implemented to use it for unknown objects as shown in the work of Eppner and Brock [10]. The grasping approach transforms the point cloud into shape primitives and a grasp is chosen depending on these shapes.

Huebner and Kragic [11] also use shape primitives to represent an unknown object. The point cloud of the object is transformed into a minimum volume bounding box (MVBB). This MVBB is split into multiple MVBBs and fitted in order to get more resolution of the actual model. The splitting is continued until more splits are not beneficial.

In the work of Hsiao et al. [12], a bounding box is placed around the available point cloud of an unknown object. Heuristics are applied to find the most suitable grasp. This approach also incorporates a local grasping approach.

d) Surface

A more straightforward approach to grasp an unknown object is to look at the available point cloud of the object and reconstruct a fitting surface of the object using those points.

In the work of Lee et al. [13], a 3D model is retrieved by using stereo matching. From the matching, a dense map is created. A three-dimensional interpolation (the triangular mesh method) is applied on the dense map. Suitable grasps can be located on the triangular mesh of the target object.

2) Local grasping approaches

a) Edges

A grasping approach with the use of edges of an object has been used by Jiang et al. [14]. The algorithm finds grasping locations by fitting a so-called “grasping rectangle” on an image plane. The rectangle describes the configuration of the gripper. The grasping approach also includes a learning algorithm in order to select the best grasping location depending on the object shape. The use of the learning algorithm increases the success rate of the grasp but increases the computation time.

Lin et al. [15] extends the principle of the grasping rectangle by looking at the contact area of the grasping rectangle. For instance, if the contact area is too small, the grasp is likely to fail and a better grasp can be picked. The success-rate when incorporating this technique is higher than Jiang et al. [14].

In Popovic et al. [16], grasps are generated based on edge and texture information of the unknown object. Baumgartl and Henrich [17] use Hough transformation to find edges in a 2D image. A check has been done to verify if the edges are long enough to be grabbed by the gripper. Another check is done to verify if the parallel edges fit into the gripper’s width. The two quick checks result in a fast grasping approach.

Richtsfeld and Vincze [18] detect grasp points on top surfaces of unknown objects. Firstly a 3D mesh generation is applied on the segmented point cloud, and then the top surface can be extracted using a 2D DeLauney triangulation. Only information of the rim points and feature edges are left. One grasp point is found by finding the minimum distance from the center of mass to the edge. The second grasping point can be selected by extending the line of the first grasp point to the center of mass to the edge on the other side.

Similarly, Bodenhagen et al. [19] use machine learning to find suitable grasp on 3D edges of the unknown object. They refine an initial grasping behavior based on the 3D edge information by learning. A prediction function is used to compute likelihood for the success of a grasp using either an offline or an online learning scheme.

b) Boundary

The proposed grasping approach of Ala et al. [20] retrieves graspable boundaries and convex segments of an unknown object. From a 3D camera, the scene is segmented and a point cloud of the unknown object is left. With the use of blob detection, the boundaries of the object are retrieved. These boundary lines are then transformed into straight lines. The grasp planner tries to find parallel contact points in order to execute an envelope grasp. When an unknown object has a desirable thickness, then one contact point can be retrieved in order to execute a boundary grasp.

Maldonado et al. [21], ten Pas and Platt [22] try to fit the shape of the gripper on the available point cloud of the object(s). The latter uses a detailed segmentation to be able to pick objects from dense scenes and incorporates learning that significantly improves the grasp success rate.

In the grasping approach of Navarro [23], the unknown object center is estimated with the available point cloud cluster. Only round objects are considered with this approach and the objects are tracked on a conveyer belt. The gripper is aligned above the object to grasp it.

The work of Suzuki and Oka [24] estimate the principal axis and centroid of the unknown object on the retrieved point cloud to produce a stable grasp. The approach is shown to produce a high success rate for a set of household objects.

c) Silhouette

In the work of Calli et al. [25], the grasping algorithm uses curvature information of the silhouette of an unknown object. Using elliptic Fourier descriptors (EFD), the silhouette of the object can be modeled from a 2D image. To find grasping points, local minima and maxima curves of the silhouette are evaluated. Force closure tests are applied onto the grasping points to get the final, likely stable, grasping points. The grasping points are 2D points to help align the gripper.

Lei and Wisse [26] perform a force balance calculation in order to find suitable grasping points. Once a point cloud cluster of an unknown object is retrieved with the use of one or two 3D cameras, the coordination system of the object is created. After that the cloud points are projected on the XOY plane and a concave hull method is applied to extract the contours of the object. A graspable zone is calculated from this contour and then the force balance is computed on the XOY plane to find the maximum force balance. In order to match the gripper's angle with the angle of the object, a force balance is also computed on the XOZ plane. This is a robust grasping approach which is faster than for example [10].

In Lei and Wisse [27], this is built upon [26]. The difference is that the new approach uses data from two 3D cameras to build virtual object coordination systems (VOCS) from different virtual viewpoints. From these coordination systems, multiple XOY and XOZ planes can be created. Force balance can be computed on all these planes. The maximum force balance resembles the best possible grasp. This grasping approach is robust and finds favorable grasps.

d) Saliency

In the work of Bao et al. [28], saliency is being used to segment the scene and find unknown objects. The algorithm is mainly useful for dealing with multiple unknown objects.

e) Tactile feedback

As for global grasping approaches, there can also be local grasping approaches that use tactile sensory data to find a suitable grasp. This is shown by the work of Haschke [29] where with the use of tactile servoing, it can, for example, establish and maintain grasping.

The approach of Hsiao et al. [12] also includes a local grasping approach part. The grippers in this approach are fitted with tactile sensors to help to adjust the grasp when collisions are found during the execution of the grasp found by the global grasping approach part.

B. Comparison

In this subsection, we will make comparisons about the different grasping approaches investigated in subsection A.

1) Comparison table

The approaches described in part A have been added to Table I. This aids in comparing the different approaches by highlighting chosen approach characteristics. The following characteristics are chosen:

- Object-grasp representation: as explained in the beginning of subsection A, existing unknown object grasping approaches can be categorized into two groups: global and local grasping approaches. This can show if one group in particular is better performing than the other.
- Object features: the data given to the approach can be 2D, 3D or a combination called 'multi' in the table. This information helps determining which data is most suitable for grasping.
- Vision-based only: if an approach is not using vision data only, the approach can be more difficult to implement and likely more expensive since more hardware are needed. A good example of this is the approach of Hsiao et al. [12] in which tactile sensors are mounted on the gripper.
- Camera-position: the camera-position can be of great importance for retrieving valuable information about the object. Approaches using an eye-in-hand camera can view the objects from multiple viewpoints [2], [4], [5].
- Multi-fingered: when using approaches with multiple fingers (more than two), a grasp can be more stable since there are more places the object is grasped. This assumption can be checked with this comparison.
- Grasp closure: there can be two kinds of grasp closures: form and force closures. Form closures depend on the shape of the target object, these grasps usually place the fingers of the gripper in such a way that the object cannot fall out of the hand easily. This closure is for instance being used by Calli et al. [25]. Force closures press the fingers of the grippers (using force) on the object in order to keep it in the gripper.
- Non-grasping movement of arm: some approaches have to perform an extra motion of the arm to get more data of the unknown object. This can be time consuming.
- Cluttered-scene handling: this means that the approach is able to distinguish multiple unknown objects and is able to grasp them separately.
- Rate of success: from the literature, an estimate can be given on the success rate of the grasping approach. Lower than 70%, between 70% - 80%, between 80% - 90% and higher than 90% success rate is marked with --, -, + and ++ respectively. When no information about the success rate is given it is marked with ?.
- Execution time: to identify fast performing approaches we looked in the literature to find meaningful information about execution times. Since different processing power is used in the approaches, we limit ourselves to the presented execution times in the corresponding paper. Approaches in the literature which can finish the grasping process within 4 seconds are marked with +++. Between 4-8 seconds with ++, between 8-12 seconds with +, between 12-16 seconds with - and approaches that take longer than 12 seconds are marked with a --. When no information is given in the literature, a ? has been given instead.

2) Comparison discussion

From Table I, it can be noted that among the eight global grasping approaches, five of them are designed for multi-fingered grippers (62.5%). Comparing this to the 2 of the 16 local grasping approaches (12,5%), it can be noticed that global grasping approaches are more suitable for multi-fingered grippers. Grasps found by Global grasping approaches are mostly with a force closure.

TABLE I. COMPARISON OF EXISTING UNKNOWN OBJECT GRASPING APPROACHES ('NA'= NOT APPLICABLE)

Literature	Object representation		Object features			Vision based only	Camera position		Multi-fingered	Grasp closure		Non-grasping movement of arm	Cluttered scene handling	Rate of success	Execution time
	Local	Global	2D	3D	multi		Overhead	Eye in hand		Form	Force				
Bohg et al. [2]		√		√		√	√		√		√			+	-
Bone et al. [4]		√			√			√			√	√		++	--
Dune et al. [5]		√	√			√		√			√	√		-	+
Eppner and Brock [10]		√		√		√	√		√	√	√		√	-	?
Huebner et al. [11]		√		√		√	√		√		√			-	-
Lee et al. [13]		√		√		√	√		√		√			--	?
Lippiello et al. [7]		√		√		√		√	√		√	√		++	+
Yamazaki et al. [6]		√		√		√		√			√	√		++	-
Ala et al.[20]	√			√		√	√				√		√	++	+
Bao et al. [28]	√			√		√	√				√		√	+	?
Baumgartl and Henrich [17]	√		√			√	√				√		√	++	+++
Bodenhagen et al. [19]	√			√		√	√				√		√	--	?
Calli et al. [25]	√		√			√		√		√				?	?
Haschke [29]	√			√			NA	NA	√		√	√		++	?
Jiang et al. [14]	√			√		√	√				√		√	++	?
Lei and Wisse [26]	√			√		√		√		√	√	√		++	+++
Lei and Wisse [27]	√			√		√		√		√	√			++	+++
Lin et al. [15]	√			√		√		√			√		√	++	+++
Maldonado et al. [21]	√			√		√	√		√		√		√	++	?
Navarro [23]	√			√		√	√				√			?	?
Ten Pas and Platt [22]	√			√		√	√				√		√	++	+++
Popovic et al. [16]	√			√		√	√				√		√	--	?
Richtsfeld and Vincze [18]	√			√		√	√				√		√	+	--
Suzuki and Oka [24]	√			√		√	√				√			+	++
Hsiao et al. [12]	√	√			√		√				√			++	?

Once multiple object features are used for grasping, then the approach is not vision-based only. These approaches use for instance tactile sensor data.

Except for Calli et al. [25], all the approaches use a force closure.

For approaches of non-grasping movements of the arm, all have an eye-in-hand camera position. When the camera is fixed, movement of the arm will not result in any change with respect to the data of the unknown object. When a movement is made with the arm incorporating eye-in-hand camera position, there will be change in the data. Cluttered-scene handling is usually connected to an overhead camera position. This is to be expected since multiple unknown objects can then be identified.

When looking at the rate of success, two things can be noticed. Firstly the overall performance of the global grasping approaches is less than the local grasping approaches. Since global grasping approaches try to represent a full 3D model, resulting in a lot of details of the unknown object are lost, a good example of this is the decomposition of the unknown object into blocks [11]. Secondly an eye-in-hand camera position performs better, likely because the unknown object data obtained by eye-in-hand system is more detailed to perform stable grasps.

From the available information in the literature, local grasping approaches have the lowest execution times. Not all approach literatures include information on execution time. As we mentioned before, the characteristic of execution time is dependent on the computing power.

Some approaches perform well in all the specified areas, which are all local grasping approaches. Take for instance the work of ten Pas and Platt [22], this planner is able to use 3D vision data to perform stable grasps for unknown objects from a cluttered-scene in a short amount of time. The work from Lei and Wisse [27] also shows favorable results like [24] though it does not work in cluttered scenes.

C. Conclusion

This section of the paper presented an overview on the existing unknown object grasping approaches. The approaches were sorted in groups and a short description of each approach was given. With the use of a table that included all the approaches, remarks were given on common grasping characteristics.

III. Our Latest Grasping Algorithm

This section contains a brief explanation of our grasp algorithm. Because of the page restriction, authors will not explain that much details. Part A shows the problem formulation on the base of the inspiration of C-shape grasping. Part B shows our solution and Part C shows the successful simulation results we obtained.

A. Problem Formulation

As mentioned before, we simplify the under-actuated gripper as a C-shape two-layer cylinder. Then, the algorithm will do C-shape searching on the single point cloud of the target object to quickly synthesize an executable grasp. In order to get the parametric equations for an arbitrary C-shape cylindrical in 3D space, we need to know how to obtain the parametric equations for an arbitrary circle on an arbitrary plane. If C is the center of the circle and its coordinate value is (x_0 , y_0 , z_0), and the radius is r . The arbitrary plane is II, and its unit normal vector is N=($\cos a$, $\cos\beta$, $\cos\gamma$). a , β , γ are the direction angles of the unit normal. The arbitrary plane II can be obtained by transforming the XOY plane through the following transformation: rotating around the X axis by a ; rotating around the Y axis by β , then moving along the vector N to (x_0 , y_0 , z_0) . The whole transformation can be summarized as equation (1).

$$T=\begin{bmatrix}1&0&0&0\\0&\cos a&\sin a&0\\0&-\sin a&\cos a&0\\0&0&0&1\end{bmatrix}\begin{bmatrix}\cos\beta&0&\sin\beta&0\\0&1&0&0\\\sin\beta&0&\cos\beta&0\\0&0&0&1\end{bmatrix}\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\x_0&y_0&z_0&1\end{bmatrix} \quad (1)$$

$$=\begin{bmatrix}\cos\beta&0&-\sin\beta&0\\\sin a\sin\beta&\cos a&\sin a\cos\beta&0\\\cos a\sin\beta&-\sin a&\cos a\cos\beta&0\\x_0&y_0&z_0&1\end{bmatrix}$$

If ($x(t)$, $y(t)$, $z(t)$) are used to sand for an arbitrary points on the arbitrary circle, the parametric equation of the circle can be obtained by the equation (2) and (3).

$$\begin{pmatrix}x(t)\\y(t)\\z(t)\\1\end{pmatrix}=(r\cos t\ \ r\sin t\ \ 0\ \ 1)\begin{bmatrix}\cos\beta&0&-\sin\beta&0\\\sin a\sin\beta&\cos a&\sin a\cos\beta&0\\\cos a\sin\beta&-\sin a&\cos a\cos\beta&0\\x_0&y_0&z_0&1\end{bmatrix} \quad (2)$$

$$\begin{cases}x(t)=x_0+r\cos t\cos\beta+r\sin t\sin a\sin\beta\\y(t)=y_0+r\sin t\cos a\\z(t)=z_0+r\sin t\sin a\cos\beta-r\cos t\sin\beta\end{cases} \quad (3)$$

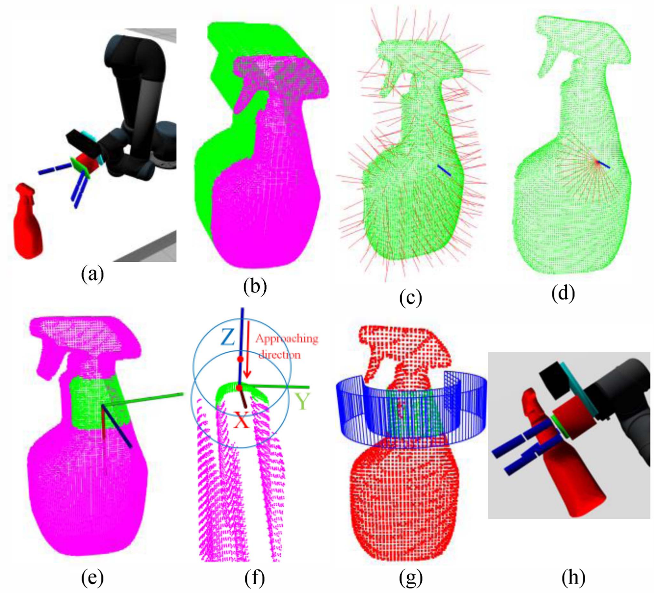
where t satisfies $0\le t\le 2\pi$.

If the cylinder alignment is $r(t)=\{x(t),y(t),z(t)\}$, and the unit normal vector of the cylinder is $N=(\cos a,\cos\beta,\cos\gamma)$, the parametric equations for an arbitrary cylinder in 3D space can be obtained shown as equation (4).

$$\begin{cases}x(s,t)=x_0+r\cos t\cos\beta+r\sin t\sin a\sin\beta+s\cos a\\y(s,t)=y_0+r\sin t\cos a+s\cos\beta\\z(s,t)=z_0+r\sin t\sin a\cos\beta-r\cos t\sin\beta+s\cos\gamma\end{cases} \quad (4)$$

$0\le t\le 2\pi$, $0\le s\le w$, w is the width of the griper.

Then the problem can be formulated as follows: Finding a , β (a and β make up the general rotation of the transformation matrix in equation (1), in another word, a and β play the role of grasp orientation) and the grasp point is P_o (($x(o), y(o), z(o)$)) .



Figrue 2. The outline of our fast grasping algorithm. (a) shows the simulation environment. (b) shows the method to deal with the unseen part of the object, which may lead to grasp uncertainty. (c) shows the down-sampled normal lines. (d) shows how to orientate the gripper. (e) shows an possible grasp area (the green area) obtained from (d). (f) shows how to determine the grasp point along the normal line. (g) shows an good example grasp (the blue stand for the C-shape two layers gripper). (h) shows the grasp execution.

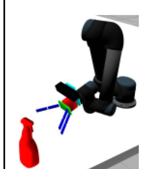
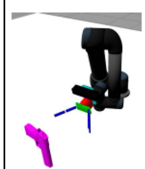
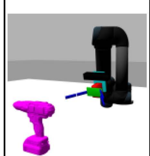
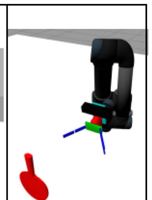
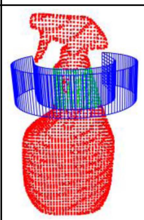
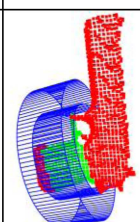
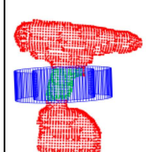
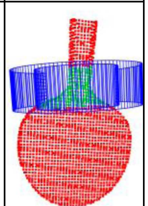
B. Our Algorithm

The outline of our algorithm is shown as Fig. 2. As stated at the above subsection, the grasp problem of unknown object is simplified as the question to find the grasp orientation (a and β) and the grasp point (P_o (($x(o), y(o), z(o)$))). Fig. 2 (b) shows how to deal with the unseen part. The green points are man-made added to the point cloud of target object to remove the uncertainty when the gripper is approaching the target object from the side direction. (c) shows the result of the down-sampled normal lines which are used as the approaching direction of the gripper. (d) shows how to orientate the gripper, a step angle is used to search along one normal line. The green points in (e) stand for one possible grasp. (f) shows how to determine the grasp point for every corresponding orientation in (d). When the gripper tries to approach the target object, the center of the C-shape cylinder with maximum Z value will be used as grasp point. Force balance analysis and local geometry analysis are then used to judge whether a grasp is executable or not. An executable grasp (an example is shown as (g)) is chosen to be executed as (h) shown.

C. *Simulation Results*

In order to verify the effectiveness of our grasping algorithm, several objects are used to do simulations on a personal computer (2 cores, 2.9GHz). Our algorithm can quickly synthesize an executable grasp for the target object within 2 seconds. Specific simulation results are shown as Table II.

TABLE II. SIMULATION RESULTS

Target objects				
Example of executable grasp				
Points	8297	4183	7460	6274
time (s)	1.9	0.8	1.6	1.3

IV. CONCLUSION

A survey about existing algorithms of unknown object grasping is investigated in this paper. Comparisons among different grasping approaches of unknown objects are made. A table is drawn to clearly show the advantage and disadvantage of every grasping algorithm to help the future researchers to quickly pick a suitable grasping approach with their requirements. Meanwhile, we briefly showed our latest fast grasping algorithm which employs a single partial point cloud of the target object as input. Our grasping algorithm can quickly work out a suitable grasp for the tested unknown objects within 2 seconds on a common personal computer, which is faster than recent benchmark [24]. Simulations are used to examine the performance of our algorithm and successful results obtained.

ACKNOWLEDGMENT

The work leading to these results has received funding from the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 609206.

REFERENCES

[1] http://www.ifr.org/service-robots/statistics/ accessed on 12th February 2017

[2] Jeannette Bohg, Matthew Johnson-Roberson, Beatriz León, Javier Felip, Xavi Gratal, Niklas Bergstrom, Danica Kragic, and Antonio Morales. Mind the gap-robotic grasping under incomplete observation. *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, pages 686–693, 2011.

[3] Jeannette Bohg, Antonio Morales, Tamim Asfour, and Danica Kragic. Data-Driven Grasp Synthesis: A Survey. *IEEE Transactions on Robotics*, 30(2):1–21, 2013.

[4] Gary M. Bone, Andrew Lambert, and Mark Edwards. Automated modeling and robotic grasping of unknown three-dimensional objects. *Proceedings - IEEE International Conference on Robotics and Automation*, pages 292–298, 2008.

[5] C. Dune, E. Marchand, C. Collowet, and C. Leroux. Active rough shape estimation of unknown objects. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3622–3627, 2008.

[6] Kimitoshi Yamazaki, Masahiro Tomono, and Takashi Tsubouchi. Picking up an unknown object through autonomous modeling and grasp planning by a mobile manipulator. *Springer Tracts in Advanced Robotics*, 42:563–571, 2008.

[7] V Lippiello, F Ruggiero, B Siciliano, and L Villani. Visual Grasp Planning for Unknown Objects Using a Multifingered Robotic Hand. *Mechatronics, IEEE/ASME Transactions on*, 18(3):1050–1059, 2013.

[8] A T Miller, S Knoop, H I Christensen, and P K Allen. Automatic grasp planning using shape primitives. *Proc. IEEE International Conference on Robotics and Automation ICRA '03*, 2:1824—-1829 vol.2, 2003.

[9] Corey Goldfeder, Peter K. Allen, Claire Lackner, and Raphael Pelossof. Grasp planning via decomposition trees. *ICRA*, pages 4679–4684, 2007.

[10] Clemens Eppner and Oliver Brock. Grasping unknown objects by exploiting shape adaptability and environmental constraints. *IROS*, pages 4000–4006, 2013.

[11] K. Huebner and D. Kragic. Selection of robot pre-grasps using box-based shape approximation. *IROS*, pages 1765–1770, 2008.

[12] Kaijen Hsiao, Sachin Chitta, Matei Ciocarlie, and E. Gil Jones. Contact-reactive grasping of objects with partial shape information. *IROS*, pages 1228–1235, 2010.

[13] Hyun-ki Lee, Myun-hee Kim, and Sang-ryong Lee. 3D optimal determination of grasping points with whole geometrical modeling for unknown objects. *Sensors And Actuators*, 107:146–151, 2003.

[14] Yun Jiang, Stephen Moseson, and Ashutosh Saxena. Efficient grasping from RGBD images: Learning using a new rectangle representation. *IEEE International Conference on Robotics and Automation*, pages 3304–3311, 2011.

[15] Yu-chi Lin, Shao-ting Wei, and Li-chen Fu. Grasping Unknown Objects Using Depth Gradient Feature With Eye - in - hand RGB - D Sensor. pages 1258–1263, 2014.

[16] Mila Popovic, Gert Kootstra, Jimmy Alison Jorgensen, Danica Kragic, Norbert Kruger, Jimmy Alison Jørgensen, and Norbert Krueger. Grasping unknown objects using an Early Cognitive Vision system for general scene understanding. *IROS*, pages 987–994, 2011.

[17] Johannes Baumgartl and Dominik Henrich. Fast Vision-based Grasp and Delivery Planning for unknown Objects. *7th German Conference on Robotics (ROBOTIK 2012)*, pages 1–5, 2012.

[18] Mario Richtsfeld and Markus Vincze. Grasping of Unknown Objects from a Table Top. *Workshop on Vision in Action: Efficient strategies for cognitive agents in complex environments*, 2008.

[19] Leon Bodenhagen, Dirk Kraft, Mila Popovic, Emre Ba¸seski, Peter Eggenberger Hotz, and Norbert Krüger. Learning to grasp unknown objects based on 3D edge information. *Proceedings of IEEE International Symposiumon Computational Intelligence in Robotics and Automation, CIRA*, pages 421–428, 2009.

[20] Rajesh Kanna Ala, Dong Hwan Kim, Sung Yul Shin, ChangHwan Kim, and Sung-Kee Park. A 3Dgrasp synthesis algorithm to grasp unknown objects based on graspable boundary and convex segments. *Information Sciences*, 295:91–106, 2015.

[21] Alexis Maldonado, Ulrich Klank, and Michael Beetz. Robotic grasping of unmodeled objects using time of flight range data and finger torque information. *IEEE/RSJ 2010 International Conference on Intelligent Robots and Systems, IROS 2010 - Conference Proceedings*, pages 2586–2591, 2010.

[22] Andreas ten Pas and Robert Platt. Using Geometry to Detect Grasps in 3D Point Clouds. 2015 International Symposium on Robotic Research. 2015.

[23] Stefan Escaida Navarro. Tracking and Grasping of Known and Unknown Objects from a Conveyor Belt. 41st International Symposium on Robotics. 2014.

[24] T. Suzuki and T. Oka. Grasping of unknown objects on a planar surface using a single depth image. *AIM*, pages 572-577. IEEE, Jul. 2016

[25] Berk Calli, Martijn Wisse, and Pieter Jonker. Grasping of unknown objects via curvature maximization using active vision. *IROS*, pages 995–1001, 2011.

[26] Qujiang Lei and Martijn Wisse. Fast grasping of unknown objects using force balance optimization. *IROS*, pages 2454–2460, 2014.

[27] Qujiang Lei and Martijn Wisse. Unknown object grasping using force balance exploration on a partial point cloud. *AIM*, pages 7–14. IEEE, Jul 2015.

[28] Jiatong Bao, Yunyi Jia, Yu Cheng, and Ning Xi. Saliency-Guided Detection of Unknown Objects in RGBD Indoor Scenes. *Sensors*, 15(9):21054–21074, 2015.

[29] Robert Haschke. *Motion and Operation Planning of Robotic Systems*, volume 29 of *Mechanisms and Machine Science*. Springer International Publishing, Cham, 2015.

[30] Qujiang Lei, Martijn Wisse. Object Grasping by Combining Caging and Force Closure. 14th International Conference on Control, Automation, Robotics and Vision (ICARCV 2016), 2016.

[31] Qujiang Lei, Martijn Wisse. Unknown object Grasping by Using Concavity. 14th International Conference on Control, Automation, Robotics and Vision (ICARCV 2016), 2016.

[32] Qujiang Lei, Martijn Wisse. Fast grasping of unknown objects using cylinder searching on a single point cloud. The 9th International Conference on Machine Vision (ICMV 2016), 2016.