Abstract—Perception-for-grasping is a challenging problem in robotics. Inexpensive range sensors such as the Microsoft Kinect provide sensing capabilities that have given new life to the effort of developing robust and accurate perception methods for robot grasping. This paper proposes a new approach to localizing enveloping grasp affordances in 3-D point clouds efficiently. The approach is based on modeling enveloping grasp affordances as a cylindrical shells that corresponds to the geometry of the robot hand. A fast and accurate fitting method for quadratic surfaces is the core of our approach. An evaluation on a set of cluttered environments shows high precision and recall statistics. Our results also show that the approach compares favorably with some alternatives, and that it is efficient enough to be employed for robot grasping in real-time.

I. INTRODUCTION

Recently, the development of inexpensive range sensing technology such as the Microsoft Kinect has given new life to the effort to develop robust and accurate perceptual capabilities for robot grasping. Perception-for-grasping is a challenging problem because even small localization errors can cause the robot hand to miss the target, resulting in complete grasp failure. One approach to the problem is to attempt to localize all relevant objects in the scene. This can be accomplished by creating a library of object models [1], [2] that contains one model for every object that might need to be grasped. The scene is searched for objects from the library. When a match is found, a manipulation planner decides how to pick up the target object. This method is potentially very robust because it leverages prior information about object geometry, but there are drawbacks. Building and maintaining a suitable library is potentially very challenging and performing the matching process can be computationally expensive. Moreover, the method does not work at all for deformable objects or in natural or unstructured environments where it is impossible to predict object geometry in advance.

An alternative is to localize grasp geometries directly. For example, rather than localizing a particular coffee mug found in a large database and creating a plan to grasp it by the handle, the system might localize the handle directly based on a prior knowledge of what kinds of geometries the robot is capable of grasping. This corresponds with the notion of a grasp affordance: a geometric characteristic of an object that allows it to be grasped by a particular robot hand or gripper.¹

This approach has several potential advantages. First, it is very flexible because there is no need to create the object database and it can be applied to flexible or unmodelled objects. Moreover, it has the potential to simplify grasping because there is no need to do grasp planning. Each localized grasp affordance corresponds directly to a set of hand poses to which the robot can reach and achieve a grasp. In addition, it separates the geometry of grasping from the semantic process of deciding what to do with the object or how to grasp it (which affordance to use).

This paper proposes a new approach to localizing enveloping grasp affordances in 3-D point clouds efficiently. The approach is based on modeling an enveloping grasp affordance as a cylindrical shell that corresponds to the geometry of the robot hand. The surface of the grasp affordance must be contained inside the innermost radius of the shell which must be no larger than the maximum hand aperture. The gap between the inner and outer radii must be empty and sufficiently thick to allow clearance for a robot hand to reach a grasping configuration. We propose a perception pipeline that localizes these cylindrical shells efficiently. The core of our approach is an application of Taubin quadric fitting [4] that makes our algorithm faster and more accurate than alternative methods. Our approach does not depend upon making any assumptions about object separation or ground support planes. Our results indicate that the approach is works well in cluttered environments such as that illustrated in Figure 1. We show high precision and recall statistics and show that the approach compares

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favorsably with some alternatives.

A. Background

Recently, there has been a strong interest in applying the bevy of new range sensing technologies to the problem of perception-for-grasping. One approach is to focus on localizing modeled objects in the scene. After localizing an object with known geometry, a grasp planner can be used to find a suitable grasp. Here, it is increasingly common to use a feature-based approach to localization. Two recent feature representations for use with 3-D point clouds are Fast Point Feature Histograms (FPFH) [5] and the SHOT feature [6]. Both of these encode the local feature geometry in terms of a neighborhood of point locations and normals. After choosing a feature representation, the next step is to align features in the model with features found in the scene. One well-known way to do this is to use iterative closest point (ICP) [7]. More recently, a stochastic generalization of ICP was proposed [8]. Another popular approach is Hough voting [9], [10]. These strategies often require significant pre-processing of the point cloud: voxelization, ground plane extraction, surface normals estimation, etc. State of the art approaches can be expected to achieve precision and recall results of between 70% and 90% for cluttered and occluded scenes [8].

From a practical perspective, it is often the case that not all objects in a given scene can be identified with a modeled object from a database. Recently, a growing body of work has focused on localizing and modeling unknown objects. Some approaches work by representing unknown objects using shape primitives. For example, Rusu et al. represent kitchen environments using planes, boxes, cylinders, etc. [11] and Biegelbauer and Vincze describe complex shapes by fitting superquadrics [12]. Other work includes strategies for modeling and grasping unknown objects [13], [2]. These strategies often make strong assumptions about ground support planes and object separation in order to make object segmentation easier.

Recent work has also focused on learning to detect graspable geometries in a scene. For example, Jiang et al. propose a learning approach that predicts the “graspability” of parts of an object [14]. A potential grasp is represented as a rectangle and a feature representation is proposed that enables a classifier to achieve good prediction performance. Recently, related work has achieved similar goals using an unsupervised approach [15]. While the objectives of the above work are similar to our own, our current work is based on geometric modeling rather than learning. In fact, it is notable and a bit surprising that our work achieves such good performance (see Section V) without learning. Other recent work closely related to our own has focused on localizing and learning to localize grasp affordances in point clouds [16], [17].

II. GRASP AFFORDANCE GEOMETRY

We derive the geometry of an enveloping grasp affordance from the robot hand geometry (see Figure 2). In an enveloping grasp [18], the “thumb” opposes one or more “fingers” and the hand wraps most or all of the way around the object. The plane in which this opposition occurs is the opposition plane [19]. The axis perpendicular to this plane is the opposition axis [19]. The space in the opposition plane contained between the thumb and fingers will be known as the capture region [20]. The radius of the largest inscribed circle in the capture region will be known as the capture radius. The maximum thickness of the thumb or fingers in the opposition plane will be known as the finger thickness.

In order for an object in the environment to be grasped, two conditions must be met: 1) a portion of the object surface must fit within the capture region of the robot hand, and 2) the object must be partially surrounded by a gap comprised of sufficient free space to allow the gripper to pass. These two conditions can roughly be translated into the following geometric characterization of a point neighborhood in the 3-D cloud:

1) points that lie on the object surface must be contained within a cylinder with radius no larger than the capture radius;
2) this cylinder must be contained within a cylindrical shell that is clear of points and at least as thick as the finger thickness.

These two conditions on a point neighborhood will be referred to as the enveloping grasp affordance (EGA) conditions. Notice that the EGA geometry is parameterized by the characteristics of the robot hand. Any point cloud neighborhood satisfying the EGA conditions for the given hand must be graspable in the sense that it is possible for the robot hand to close around whatever object material is contained within the shell.

III. LOCALIZING CANDIDATE GRASP AFFORDANCES USING TAUBIN FITTING

Localizing environmental geometries that satisfy even the simple EGA conditions can be challenging. A key idea in this paper is to sample a large set of local neighborhoods from the point cloud and to use Taubin quadric fitting to see if they contain any potential EGA geometries. For each neighborhood, Taubin fitting is used to calculate a smooth
approximation of the local surface(s) efficiently. Then, we
evaluate whether the surface is likely to lie within the capture
radius of the hand by thresholding on median curvature and
normal covariance.

A. Taubin Quadric Fitting

Taubin fitting approximates the least-squares fit of a
quadric surface in three variables to a set of points in
Cartesian space. A quadric can be described in implicit form
by \( f(\mathbf{c}, \mathbf{x}) = 0 \), where
\[
 f(\mathbf{c}, \mathbf{x}) = c_1 x_1^2 + c_2 x_2^2 + c_3 x_3^2 + c_4 x_1 x_2 + c_5 x_2 x_3 + c_6 x_1 x_3 + c_7 x_1 + c_8 x_2 + c_9 x_3 + c_{10},
\]
and \( \mathbf{c} \in \mathbb{R}^{10} \) denotes the parameters of the quadric and \( \mathbf{x} \in \mathbb{R}^3 \)
denotes the Cartesian coordinates of a point on the surface.
In principle, we would like to solve for the parameters that
minimize the sum of squared geometric distances between
the points and the quadric surface. Unfortunately, it turns
out that this is a non-convex optimization problem with no
known analytical solutions. Instead, a standard approach is to
solve for an algebraic fit, that is to solve for the parameters
\( \mathbf{c} \) that minimize
\[
\sum_{i=1}^{n} f(\mathbf{c}, \mathbf{x}_i)^2 = \mathbf{c}^T M \mathbf{c},
\]
where \( M = \sum_{i=1}^{n} l(\mathbf{x}_i)/|l(\mathbf{x}_i)| \). \( \mathbf{x}_1, \ldots, \mathbf{x}_n \in \mathbb{R}^3 \) are the points to
which the curve is fitted, and
\[
l(\mathbf{x}) = (x_1^3, x_2^3, x_3^3, x_1 x_2, x_1 x_3, x_2 x_3, x_1, x_2, x_3, 1)^T.
\]
This problem is slightly different from the geometric fitting
problem because \( f(\mathbf{c}, \mathbf{x}) \) is not linear in the distance to the
surface. However, \( f(\mathbf{c}, \mathbf{x}) \) is a good approximation to the
geometric distance within a neighborhood about the surface,
and as a result, this general approach can yield good fits.

An important choice that affects the resulting algebraic
fit is how Equation 2 is normalized. Notice that minimizing
Equation 2 directly would yield the trivial solution with \( \mathbf{c} \)
at the origin. This question has been studied extensively in the
literature. Perhaps the simplest solution is to constrain \( |\mathbf{c}|^2 = 1 \). Then, Equation 2 can be minimized by performing an
Eigen decomposition on \( M \). Other possible solutions include
setting \( c_{10} = 1 \) [21] and setting the constraint \( c_1^2 + 1/2 c_2^2 +
\]
c_3^2 = 1 [22]. Unfortunately, both of the above normalization
methods can cause the algebraic fit to diverge significantly
from the solution to the geometric least squares problem and
produce poor fits. One normalization method that has been
found to work well in practice [23] is Taubin’s method [4].
This method sets the constraint \( |\nabla_x f(\mathbf{c}, \mathbf{x})|^2 = 1 \) and
can be solved as follows. Let
\[
N = \sum_{i=1}^{n} I_x(\mathbf{x}_i) l_x(\mathbf{x}_i) I_x(\mathbf{x}_i) + I_y(\mathbf{x}_i) l_y(\mathbf{x}_i) I_y(\mathbf{x}_i) + I_z(\mathbf{x}_i) l_z(\mathbf{x}_i) I_z(\mathbf{x}_i),
\]
where \( l_x(\mathbf{x}) \) denotes the derivative of \( l(\mathbf{x}) \) taken with respect
to \( x_1 \) and the other derivatives are defined similarly. Then,
solve the generalized the generalized Eigen decomposition,
\( (M - \lambda N) \mathbf{c} = 0 \). The best-fit parameter vector is equal to
the Eigenvector corresponding to the smallest Eigenvalue.

Figure 3 shows two examples of surface fits that were found
using Taubin’s method. The point data in these two examples
come from a 3-D point cloud measured using an Asus Xtion
Pro sensor. Figure 3(a) shows a section of a quadric fit to a set
of points that lie on the side of a cylinder. Figure 3(b) shows
a section of a fit to points on a right angle corner. The ability
of the Taubin fit to measure this kind of local neighborhood
surface geometry makes it a good tool for detecting target
geometries in point clouds.

B. Identifying Candidate Grasp Affordances

Quadric fitting is a convenient method for efficiently
finding object surfaces that could potentially fit within the
capture radius of the robot hand and thereby satisfy the first
EGA condition (Section II). Although the object surface may
be non-convex, there must be a smoothed version of that
surface that is convex and is sufficiently curved in order
to fit inside the capture radius. The fitted quadric can be
used to detect this condition because it smooths out high-
frequency content in the points to which it has been fit. Given
a quadric that has been fit to a point neighborhood, we can
evaluate the general shape of the neighborhood by looking
at the curvature of the quadric. A sufficiently large curvature
over much of the quadric indicates that it could potentially
fit within the capture radius.

Before proceeding, it is necessary to understand some
details about calculating the curvature of an implicit quadric.
The curvature of a quadratic surface at a particular point can
be calculated by evaluating the shape operator \( \mathbf{S} \) on the plane
tangent to the point of interest. The Eigenvectors of the shape
operator describe the principle directions of the surface and
its Eigenvalues describe the curvature in those directions.
This can be calculated for a point, \( \mathbf{x} \), on the surface by taking
the Eigenvalues and Eigenvectors of:
\[
(\mathbf{I} - N(\mathbf{x})/N(\mathbf{x})^T) \nabla N(\mathbf{x}),
\]
where \( N(\mathbf{x}) \) denotes the surface normals of the quadric. It
is calculated by differentiating and normalizing the implicit
surface:
\[
N(\mathbf{x}) = \frac{\nabla f(\mathbf{c}, \mathbf{x})}{||\nabla f(\mathbf{c}, \mathbf{x})||^2}.
\]
\(^2\)In general, the shape operator, \( \mathbf{S} \), can be calculated using the first and
second fundamental forms of differential geometry: \( \mathbf{S} = \mathbf{I} - \mathbf{II} \).
where
\[ \nabla f(c, x) = \begin{pmatrix} 2c_1x_1 + c_4x_2 + c_6x_3 + c_7 \\ 2c_2x_1 + c_4x_2 + c_5x_3 + c_8 \\ 2c_3x_1 + c_5x_2 + c_6x_3 + c_9 \end{pmatrix}. \]

Once a quadric is fit to a point neighborhood, we evaluate the median curvature of the quadric in the point neighborhood. This is accomplished by randomly sampling several points from the local quadric surface and calculating the maximum curvature (maximum of the two principle curvatures) magnitude at each of them. Then, we take the median of these maximum curvature values and accept as grasp affordance candidates all quadrics where the median curvature is larger than that implied by the hand capture radius. This method detects smoothly curving surfaces such as that shown in Figure 3a, where the majority of sampled neighborhood points are sufficiently curved.

IV. Grasp Affordance Perception Pipeline

Algorithm 1

```
procedure GRASP_AFFORDANCE_PERCEPTION(p_cloud, n, r_target)
    list = {};
    for i = 1 : n do
        sample point neighborhood, p_i;
        if !FilterOcclusion(p_i) then
            \( \kappa_{\text{ax}} \) = FitTaubin(p_i);
            if \( \kappa_{\text{ax}} \geq 1/r_{\text{target}} \) then
                found, \( \lambda_{\text{shell}} \) = FitShell(p_i, \( \kappa_{\text{ax}} \));
                if found then
                    list <- {list, \( \lambda_{\text{shell}} \)};
                end if
            end if
        end if
    end for
end procedure
```

The grasp affordance perception pipeline works by sampling a large set of neighborhoods from the point cloud, identifying grasp affordance candidates using Taubin fitting, and then attempting to fit a cylindrical shell with the appropriate capture radius and thickness. Pseudocode is shown in Algorithm 1.

The algorithm works as follows. Step 4 samples neighborhoods from the point cloud. For each point neighborhood, Step 5 eliminates from consideration those neighborhoods that are significantly occluded by objects in the foreground. Step 6 does Taubin quadric fitting and Step 7 filters out those neighborhoods that are not sufficiently curved to satisfy the first EGA condition. For the neighborhoods that remain, Step 8 fits a cylindrical shell in the neighborhood that satisfies the second EGA condition. These steps are discussed in more detail below.

A. Sampling and Occlusion Filtering

Step 4 samples point neighborhoods by randomly sampling a single point from the cloud and setting the point neighborhood equal to the set of points that fall within a sphere with radius equal to the capture radius. This value of the radius ensures that the point neighborhoods are roughly proportional to the size of the robot hand.

Step 5 eliminates from consideration point neighborhoods that are significantly occluded by points in the foreground. This is an important step because when a point cloud is constructed from a single range image, occlusions can introduce significant ambiguity into background parts of the cloud. If the foreground shadows items in the background, shapes can appear in the background that do not really exist. This is a particular problem for our grasp affordance detector because foreground shapes can easily introduce shadows that cause the EGA conditions to be erroneously satisfied. Fortunately, this kind of occlusion is easily detected. For each neighborhood, we project the sphere that defines the neighborhood onto the range image (forming a circle in the range image). We take all points within this circle and evaluate their range. If more than a threshold number of these points are closer than the closest point in the neighborhood, then we assume that we have detected a potential occlusion and discard the neighborhood. When a point cloud is constructed by registering data from two or more range images together, it is more difficult to use the above method to identify occlusions. A simple extension is to label a point neighborhood as unoccluded when the neighborhood is not occluded in any range image. However, we have not tested this extension.

B. Fitting the Cylindrical Shell

After doing Taubin fitting (Step 6) and filtering out neighborhoods without a sufficiently large curvature (Step 7), we fit the cylindrical shell. We are searching for a shell that contains a large number of points inside the inner radius but contains very few points within the thickness of the shell itself. Unfortunately, fitting a cylindrical shell as described above is a non-convex problem and cannot be solved directly using regression. Moreover, a brute force search in the five-dimensional search space (four dimensions of pose plus one dimension of radius) is computationally too expensive. Instead, we reduce the size of the search space by setting the axis of the cylindrical shell to be equal to the axis of maximum curvature found during Taubin fitting. This reduces the search space from five dimensions down to three (two position dimensions and one radius). Since even a three-dimensional search is prohibitive when executed for a large number of candidate neighborhoods, we simplify the search further by: 1) performing a cylinder fitting step to establish a centroid for the inner cylinder of the shell, and 2) searching over the 1-D space of shell radii for the smallest radius that satisfies the EGA conditions.

1) Cylinder Fitting: The purpose of doing the cylinder fit is to find the shell centroid. We assume that the cylinder fit will find a close approximation to the inner cylinder of the shell and that we will be able to find a good shell fit by subsequently increasing the shell radius. In order to perform the cylinder fit, we first set the orientation of the axis of
the cylinder to that of the axis of maximum curvature at the median point on the fitted quadric (see Section III). Once the cylinder axis is fixed, we can calculate the closest fitting cylinder by projecting the point neighborhood onto the plane orthogonal to the axis and finding the best-fit circle. Let $W = (w_1, w_2) \in \mathbb{R}^{3 \times 2}$ be a basis for the orthogonal plane. Then the projection of point $x'$ onto the plane is calculated: $\tilde{x}' = W^T x'$, where $\tilde{x}' = (\tilde{x}'_1, \tilde{x}'_2)^T$. As was done with the quadric fitting, we calculate the best-fit circle by using algebraic distance. We want to find the parameters, $h_x, h_y$, and $r$ that minimize:

$$
\sum_{i=1}^{n} \left( (\tilde{x}'_1 - h_x)^2 + (\tilde{x}'_2 - h_y)^2 - r^2 \right)^2
$$

$$
= \sum_{i=1}^{n} \left( (\tilde{x}'_1)^2 + (\tilde{x}'_2)^2 + a\tilde{x}'_1 + b\tilde{x}'_2 + c \right)^2,
$$

where $a = -2h_x$, $b = -2h_y$, and $c = h_x^2 + h_y^2 - r^2$. Equation (3) can be solved for $w = (a, b, c)^T$ using standard calculus. The result is:

$$
w = - \left( \sum_{i=1}^{n} l_i l_i^T \right)^{-1} \sum_{i=1}^{n} \lambda_i l_i,
$$

where $\lambda_i = (\tilde{x}'_1)^2 + (\tilde{x}'_2)^2$ and $l_i = (-\tilde{x}'_1, -\tilde{x}'_2, 1)^T$. After solving Equation (3) for $w$, we back out the circle center, $(h_x, h_y)$, and radius, $r$.

2) Finding the Shell: After fitting the cylinder to the point neighborhood, we seed the search for the cylindrical shell by setting the position and orientation of the shell axis equal to that of the fitted cylinder axis. The only remaining unknown shell parameter is the radius. Starting with the radius of the fitted cylinder, we iteratively increase the shell radius in small steps while keeping the shell thickness constant and equal to the finger thickness. We increase the shell radius until we find a radius where few or no points are contained within the shell thickness. This process is illustrated in Figure 4. Figure 4(a) shows the best fit cylinder. Figure 4(b) shows the cylindrical shell found by increasing the cylinder radius until the affordance surface is contained.

V. EXPERIMENTS

Figure 1 illustrates the typical performance of our approach. In this example, we assume that the robot has a maximum capture radius of 2.9 cm. At this radius, there are seven enveloping grasp affordances (the apple, the end of the banana, the neck of the squirt bottle, the dustpan handle, the jug handle, the jug cap, and the broom handle) that could potentially be grasped by an enveloping robot hand. Figure 1(a) shows the affordances circled manually in an RGB image. Figure 1(b) shows the EGA geometries found automatically by our algorithm. Notice that there is an exact correspondence between the affordances found in the two images. In addition to evaluating the absolute precision and recall of our method, we compare our approach to two possible alternative algorithms. To our knowledge, there are no other algorithms in the literature that address the grasp affordance localization problem in a way that can easily be compared to our work. Therefore, we propose two variations on our algorithm that replace our use of Taubin’s method with alternative shape estimation techniques that are often found in the 3-D point cloud literature. Our results indicate that Taubin-based fitting does have better recall (with the same precision) than the alternative methods, but that all the methods we considered can have very good performance on some datasets.

A. Comparisons

The key feature of our proposed algorithm is the Taubin quadric fitting in Step 6 of Algorithm 1. This step does two things: it enables the algorithm to filter out low-curvature neighborhoods from further consideration and it enables us to decrease the dimension of the prismatic annulus search space by fixing the axis of curvature. In order to evaluate the significance of this step, we compare the Taubin fit version of the algorithm with two variations on the algorithm.

1) The PCA Variation: The first alternative is to do standard PCA on each point neighborhood instead of doing the Taubin fit: calculate the $3 \times 3$ covariance matrix for the points in the neighborhood and perform an Eigen decomposition. In this scenario, “curvature” of the point neighborhood would be approximated (in some sense) by taking the ratio of the second and third smallest Eigenvalues of the covariance matrix. The axis of curvature would be calculated by taking the Eigenvector associated with the largest Eigenvalue of the covariance matrix. Unfortunately, we were unable to improve overall localization performance by placing any threshold on the ratio of Eigenvalues. Therefore, in this alternative algorithm scenario, we omitted the filtering step (Step 7 of Algorithm 1) entirely and just take the direction of the principle Eigenvector as the axis of curvature. The rest of the algorithm is the same as shown in Algorithm 1. We will refer to this variation on our algorithm as the “PCA variation”.

2) The Normals Variation: The second alternative is to calculate a covariance matrix on surface normals for points within each point neighborhood rather than doing the Taubin fit. In this scenario, we assume that the point cloud data has been pre-processed by estimating the surface normal for each point in the cloud using PCA on a 3cm radius about each point. Then, for each point neighborhood, we calculate the $3 \times 3$ covariance matrix, $M = \sum_{i=1}^{k} n_i n_i^T$, where $n_1, \ldots, n_k$
describe the surface normals for points in the neighborhood. The “curvature” of the point neighborhood can be estimated by taking the ratio of the second largest and the largest Eigenvalues of \( M \). The axis of curvature for the neighborhood can be estimated by taking the Eigenvector corresponding to the smallest Eigenvalue. As before, we were unable to improve algorithm performance by doing any thresholding on this value. Instead, this alternative algorithm omits curvature filtering (Step 7, Algorithm 1) and sets the axis of curvature as described above. We will refer to this variation on our algorithm as the “Normals variation”.

B. Methods and Results

To our knowledge, there are no datasets in the literature designed to test enveloping grasp affordance detection. Therefore, we obtained a dataset of our own. Each of the scenes in our dataset is a point cloud created using a range image captured using an Asus XTion Pro sensor. Figure 5(a – e) shows the RGB images associated with the data sets. The points in each point cloud corresponding to an enveloping grasp affordance (for the most part, handles in the scene) were manually labeled. We labelled every surface in each scene that had a radius smaller than the capture radius (2.6cm), had sufficient clearance around it (at least 0.8cm), and was at least three centimeters long. Many of the labelled enveloping grasp affordances were handles (such as the handle on the top of the tea-kettle in Kitchen2) but some of them were “handle-like” surfaces on objects (such as the topics of the salad dressing bottles in Kitchen2).

The algorithm that was executed is exactly as it appears in Algorithm 1. The point clouds in our dataset were each comprised of approximately 250k valid depth points. In general, our algorithm does not require any pre-processing of the point cloud. There is no voxelization step. We did a surface normals calculation step (with a 3cm neighborhood size) only for the purpose of implementing the Normals Variation version of our algorithm. There is no ground plane separation step. There is no object segmentation required. There are no assumptions about objects pointing in the direction of the gravity vector. In all of our experiments, we parameterized the algorithm with a capture radius of 2.6cm and a required shell gap of 0.8cm. Each run of the algorithm sampled the cloud 4000 times (i.e. the value for \( n \) in step 3 of Algorithm 1 was 4000).

Figure 6 illustrates the results of our comparison. For each of the ten scenes, we ran each of the three algorithms and averaged the results over ten different runs. The recall (percent of ground truth affordances found by the algorithm) was 100% on nearly every run for every algorithm, so we do
not report that result. However, precision (percent of labeled affordances that were correct) varied significantly. Perhaps the most striking result is that all of the algorithms performed very well on many of the datasets. On many of the scenes, the Taubin method had very similar precision to the Normals method (at least 90% on eight out of ten datasets). In nearly all the scenes, the PCA method performed slightly worse. Two of the scenes deserve particular attention. First, notice that while the Taubin method performed well on Cleaning1, PCA and Normals did not. The reason for this difference is that PCA and Normals both detected the side of the dust pan as a handle whereas the Taubin method did not because it was not sufficiently curved. Second, notice that all three methods perform relatively badly on the Kitchen1 scene. This is a result of false handle detections on the side of the lotion bottle in the middle of the scene, on the horizontal box at the right, and inside the glass French press at the left of the scene.

C. Practical Running Time

In order to evaluate whether the algorithm is efficient enough to be employed on a real robotic system, we implemented the algorithm in C++ for the robot operating system ROS, and compare the practical runtime of the three variations of the algorithm. The code is parallelized, and a k-nearest neighbor search is used instead of the spherical radius search (k-nearest neighbor search is used instead of the spherical variations of the algorithm. The code is parallelized, and a system ROS, and compare the practical runtime of the three variations. The low time consumption of the PCA and the Taubin variation emphasizes the practical applicability of the algorithm to the perception-for-grasping problem on a real robotic system.

VI. CONCLUSION

The main contribution of this paper is a perception pipeline that solves the grasp-perception problem in a robust and computationally cheap way. Our method works well for localizing enveloping grasp affordances in cluttered environments, and it is fast enough to be applied to real-world scenarios.

The algorithm presented in this paper can be applied "out of the box" to a supervised autonomy scenario in which a human operator selects which grasp affordance is to be grasped by the robot. By virtue of selecting the affordance, the human has a great deal of control over exactly how the robot will perform the grasp.

Other applications are completely autonomous scenarios where the robot itself needs to decide where to grasp. Grasp affordances allow to decouple the process of controlling the robot’s actions from the grasp planning process.

The next step for our work is to use the grasp affordances provided by our algorithm for grasp planning. Our vision is to implement this algorithm on a robot and to use it in a real-world grasping application.

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