Estimating Tactile Data for Adaptive Grasping of Novel Objects

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Abstract—We present an adaptive grasping method that finds stable grasps on novel objects. The main contributions of this paper is in the computation of the probability of success of grasps in the vicinity of an already applied grasp. Our method performs adaptions by simulating tactile data for grasps in the vicinity of the current grasp. The simulated data is used to evaluate hypothetical configurations and thereby guide the robot in the right direction.

We demonstrate the applicability of our method by constructing a system that can plan, apply and adapt grasps on novel objects. Experiments are conducted on objects from the YCB object set, \([1]\), and our method increases the robot's success rate from 71.4\% to 88.1\%. Our experiments show that the application of our grasp adaption method improves grasp stability significantly.

I. INTRODUCTION

In this paper we present a method to evaluate and correct grasps on novel objects.

It is essential to develop robust robotic grasping capabilities to be able to achieve autonomous robots that can help humans with a wide variety of tasks. The main challenge for a robot grasping novel, real-world objects is to be able to handle noisy and incomplete information. Typically the robot will not have any prior information about the object and limited and noisy sensor capabilities, making grasp planning difficult and the resulting grasp unreliable. The imperfect information used for grasp planning creates a need for sensory feedback to achieve and verify successful grasps.

To this end, tactile sensing is a crucial tool for grasping, as shown in \([2]\), \([3]\), \([4]\), \([5]\), \([6]\). Tactile sensory feedback can be used to estimate grasp stability \([5]\), \([7]\), \([8]\), \([9]\), \([10]\), \([11]\), \([12]\), \([13]\), \([14]\): the robot first learns a mapping from tactile data to the probability of success of a grasp, then in turn uses this mapping to decide whether a grasp is safe before lifting the object. Tactile data can also be used to find corrective actions to improve grasps \([15]\), \([10]\), \([16]\), \([17]\), \([18]\), \([13]\), \([14]\).

In this paper we present a method to find and apply grasp corrections based on tactile sensing. Our method considers grasp corrections when the probability of success of the current grip is below a certain threshold. The probability of success of the current grip is computed by comparing sensor data to previous experience, via a classifier based on tactile features and the shape of the object around the grasping point. The estimation of the probability of success of a grasp from tactile data was discussed in our previous work \([19]\). Our method chooses grasp corrections by estimating and comparing the probability of success of neighboring grips, i.e. gripper poses that are in the vicinity of the current grip. Executing multiple grasp attempts to collect multiple tactile signatures is a costly process – consuming both time and computational resources. To avoid this expensive tactile data collection phase, we proceed by predicting the effect that small gripper displacements are likely to have on the pressure measured by the tactile sensors. The probability of success of each new gripper pose is then computed with the classifier discussed above.

The main contributions of this paper is in the computation of the probability of success of neighboring grasps. Our method is explained in more detail in section III and our experimental setup and results are presented in section IV.

II. RELATED WORK

Some groups have used tactile sensing to improve grasping by detecting and countering slip \([20]\), \([21]\), \([22]\), \([23]\). We are however considering the problem of finding grasp adaptions that lead to successful grasps based on tactile sensor data under the more static conditions present before an object is lifted. Touch based grasp adaptions in a similar static fashion have been carried out by several research groups \([15]\), \([10]\), \([16]\), \([17]\), \([18]\), \([13]\), \([14]\), \([24]\).

Hsiao et al. \([15]\) used tactile sensing to apply contact servoing to acquire successful grasps. They translate the hand according to the sensed pressure to center the object in the middle of the hand.

Sommer et al. \([24]\) used tactile exploration to find grasps on unknown objects. The authors’ method identifies the objects through tactile exploration then applies a predefined grasp. The experiment ran on a two-armed robot; during the exploration the object was held with one hand, which helped prevent object perturbations.

Dang et al. \([9]\) used the 3D locations of object-hand contacts to estimate grasp stability. In \([16]\), \([17]\) they extended their work to include finding corrections for unstable grasps based on tactile data. Corrective actions were synthesized by comparing the contact locations of the current grasp to grasp in a tactile experience database. The stability of grasps in the database is evaluated based on common quality measures, the epsilon quality \(\epsilon\) and the volume quality \(v\), achieved in simulation. The authors also implemented corrective actions based on local tactile exploration. Miao et al. \([10]\) used a similar approach as Dang et al. \([17]\), although their method
were based on other tactile features and applied different corrections. Their corrections were synthesized by comparing to similar data in a database consisting of only stable real-world grasps. The grasp adjustments consisted of adjusting the stiffness of the fingers and/or slightly move one finger. By contrast to our work, neither Dang et al. nor Miao et al. take object shape information into account when assessing stability.

Nikandrova et al. [25] iteratively estimated grasp stability and applied corrections. A probabilistic framework was used to represent uncertainties in object attributes. After applying a grasp the object attributes were updated and the stability of the grasp estimated. If the grasp was deemed unstable a new grasp was planned to either maximize the predicted stability or the predicted information gain. Their method used proprioceptive sensors and the object attribute that was considered uncertain was the object’s position.

Chebotar et al. [13] used time series of tactile data represented with ST-HMP to implement a grasp stability estimator in the same fashion as Madry et al. [7]. This grasp stability estimator was used to learn a regrasping behavior through reinforcement learning, whose applicability was demonstrated on two objects. They later extended their work to generalize better to other objects, through the use of a more complex regrasping policy [14].

In [26], Bekiroglu et al. learned a probabilistic model of the relationships between grasp related features, using both successful and unsuccessful grasps. Their representation consisted of both tactile data, a 7-dimensional object relative gripper pose, object identity and gripper orientation. They demonstrated their model on several tasks; object recognition, estimating tactile imprints, and correcting grasps. They correct grasps by using their model to find a relation between the current grasp and a nearby configuration corresponding to a successful grasp.

Recently data-driven methods for grasp synthesis have become common, a survey of these are available in [27].

III. Method

The aim of the work presented in this paper is to optimize hand-object contacts before lifting the object. The only information available to the robot prior to grasping are 3D images from one point-of-view.

Our solution consists of three parts: a grasp planner, a stability estimation method and a grasp adaption method. The planner is used to plan initial grasps and extract a notion of shape that characterize the region around the grasping point. After an initial grasp has been found, tactile and finger-configuration data can be combined with shape information to assess grasp stability and find successful grasps.

To physically execute dozens of grasps on the object in search for a successful grasp is both time consuming and risks perturbing the object. Our solution reduces the need for physical exploration by simulating grasps in the vicinity of the current grasp. This way successful grasps can often be found through only one corrective movement.

We combine a stability estimation method and a grasp adaption method. The stability estimation method is used to estimate the grasp stability and the grasp adaption method is used to find and apply actions that increase the probability of success. Our solution use these two methods iteratively until either a successful grasp is found or no corrective actions that improve grasp stability can be found. This is illustrated in Figure 1.

We explain more about the planner and the used notion of shape in section III-A, about our stability estimation module in section III-B and about our grasp adaption module in section III-C.

A. Planner

We use the planner presented by Detry et al. [28] to plan and apply initial grasps. The planner uses grasping prototypes learned from experience. The prototypes contain both information about the shapes of objects in the vicinity of the grasping point and how to grasp it. A grasp is planned by fitting the shapes of the prototypes to the available 3D image and choosing the best match. The shapes of the prototypes contain information gathered from more than one direction. Therefore only part of the prototypical shapes are aligned with the available 3D image, the other part implicitly represents the planner’s hypothesis about the shape of the unseen part of the object. The grasp parameters encoded in the chosen prototype are then used to execute the grasp.

Therefore information about which prototype is used encodes information about the general shape of the current object around the grasping point. This information constitutes the notion of shape used by the methods presented in this paper.

For further information on the planner and the prototypes, we refer the reader to the work of Detry et al. [28].

B. Stability estimation

Our stability estimation method uses tactile and finger-configuration data together with the notion of shape described in III-A to predict if a grasp is successful. Many tactile clues might indicate a successful or unsuccessful grasp, for example a tactile pad with no registered contacts are likely to indicate an unsuccessful grasp. Instead of trying to define hand written rules for grasp stability we can let the robot learn these rules from experience. The notion of shape is used by learning a separate model for each prototype. The models are trained with kernel logistic regression.

These classifiers estimate the stability of a grasp based on one tactile and finger-configuration readings, which can be written as

$$p_{\rho}(y = \text{stable}|x)$$

where $\rho$ is the currently used prototype, $y$ is a binary stability label $y \in \{\text{stable, unstable}\}$ and $x$ is a vector containing the tactile and finger-configuration readings. The stability estimation method is described in more detail in our previous work [19].

We note that the stability estimation method used in our current work differs from our previous work in one aspect: the classifier used here directly operates on the data issued by
C. Grasp adaption

If the grasp stability module informs us that the current grasp is unstable we search for an action that leads to a stable grasp. For simplicity, we choose to only consider a discrete set $A$ of possible corrective actions $\alpha$. Since we have an underactuated hand that does not allow individual control of the finger joints we choose to only consider actions consisting of translations of the whole hand. The translations we used are defined in the hand’s coordinate system and are either 11 mm along the hand’s approach axis or 8 mm along the axis that is perpendicular to both the hand’s approach axis and to the tactile pads normal axes, see Figure 2.

Now the problem of finding a suitable grasp adaption is reduced to the problem of estimating which action in our set $A$ has the highest probability of leading to a stable grasp

$$\arg\max_{\alpha} p(y_{n+1} = \text{stable}|x_n, \alpha)$$

where $y_{n+1}$ is a binary stability label $y \in \{\text{stable, unstable}\}$ representing the grasp stability after a gripper translation $\alpha$ has been applied and $x_n$ is a feature vector containing the current tactile and finger-configuration readings.

We start by predicting what tactile reading $x_{n+1}$ we will get if we apply a specific action $\alpha$, given the current tactile reading $x_n$. We do this by constructing a probability density function $f_{x_{n+1}}(x)$ that parametrizes the probability of obtaining a certain tactile measurement if we were to execute action $\alpha$. (The construction of $f_{x_{n+1}}(x)$ is deferred to Section III-D.) Assuming the existence of $f_{x_{n+1}}(x)$, we compute the probability of success of a grasp yielded by action $\alpha$ by sampling several tactile readings from $f_{x_{n+1}}(x)$, and averaging the value of the probability of success (Section III-B) of these readings, as

$$p(y_{n+1} = \text{stable}|x_n, \alpha) = \frac{1}{m} \sum_{i=1}^{m} p(y_{n+1} = \text{stable}|x_i, \alpha)$$

where $x_{i, \alpha}$’s are randomly sampled from $f_{x_{n+1}}(x)$. We use (3) to predict the grasp stability, $p(y_{n+1} = \text{stable}|x_n, \alpha)$, for each $\alpha \in A$ and pick the action $\alpha_{best}$ that predicts the best outcome:

$$\alpha_{best} = \arg\max_{\alpha} p(y_{n+1} = \text{stable}|x_n, \alpha)$$

$\alpha_{best}$ is executed on the robot if it is predicted to give a higher probability of success than the current grasp, otherwise the grasp adaption method stops. After a new action has been carried out the grasp stability is reestimated and if the current grasp is predicted to still be unstable the grasp adaption process starts over to find a new action to apply. The process stops when the current grasp is predicted to be successful or when no available action is predicted to improve the current situation.

D. Predicting tactile sensor data

The prediction of likely tactile and finger-configuration readings arising from applying an action $\alpha$, is calculated as follows. Since our actions consist of pure translations between the hand and the object, we assume that the resulting force readings on the tactile pads will be similar to the current readings, but translated across the tactile pads according to the movement of the hand. Since this behavior is not guaranteed, we model the uncertainty by...
representing the new pressure on each texel, $t_j$, with a gaussian probability distribution centered around the value, $\mu_j$, predicted by assuming a simple translation according to the hand movement. The variance of these gaussians are computed heuristically. If we denote the variance for each texel $t_j$ as $\sigma_j$, the probability density function for a texel can be written as:

$$f(t_j) = \frac{1}{\sigma_j \sqrt{2\pi}} e^{\frac{-(t_j - \mu_j)^2}{2\sigma_j^2}}$$  \hspace{1cm} (5)

For the texels that after the translation will be facing an area previously unexplored by the tactile pads, we use the values from the closest previously explored area as our expected value $\mu_j$. To take the larger uncertainty here into account we use gaussian distributions with a larger variance $\sigma_j$ to represent the pressure on these texels.

The predicted finger-configuration values, $\ell_j$ are also represented with gaussian probability distributions, but here the current joint values are always used as the expected values $\mu_{\ell_j}$ and the variance is always the same $\sigma_{\ell}$.

$X_{n+1}$ has the multivariate gaussian distribution created by combining the distributions for both all the individual texels $t_j$ and all joint values $\ell_j$. This way the probability density function for $X_{n+1}$ is given by

$$f_{X_{n+1}}(x) = \frac{1}{\sqrt{(2\pi)^k |\Sigma|}} e^{\frac{-((x - \mu)^T \Sigma^{-1}(x - \mu))}{2}}$$  \hspace{1cm} (6)

where $x$ is a vector with all $t_j$ and all $\ell_j$, $k$ is the dimensionality of $x$, $\mu$ a vector with all $\mu_j$ and all $\mu_{\ell_j}$, $\Sigma$ is the covariance matrix and $|\Sigma|$ is the determinant of $\Sigma$. The covariance matrix is a diagonal matrix with all values of $\sigma_j$ and $\sigma_{\ell}$ on the diagonal.

IV. EXPERIMENTS

A. Experimental setup

We have evaluated our method on a robotic platform consisting of the robotic arm UR5 from Universal Robots, The 3-finger adaptive robot gripper from Robotiq, the TakkTile Kit for Robotiq Adaptive Gripper from TakkTile and a Kinect sensor. Since we only have tactile sensors on the fingertips of the hand we have limited our work to fingertip grasps.

We have tested our method on a total of 42 objects, all of them taken from the YCB object set [1]. The used objects are shown in Figure 3.

For each object we have used the following procedure; The object has been put on a table in front of our robot, then a 3D image has been taken and passed to the planner. The grasp suggested by the planner has then been executed. Thereafter the tactile sensors were read once and the grasp stability estimated according to our method described in III-B. If the estimated probability for grasp stability was higher than 50% we lifted up the object to evaluate if the grasp was indeed stable or not. If the estimated probability for grasp stability was lower than 50% we first used our grasp adaption method presented in III-C, then we lifted up the object to evaluate the grasp stability.

We also compared this to the performance of the same procedure without applying corrections. It was however impossible to use exactly identical cases for the two procedures, since lifting up the object to evaluate the grasp stability would inevitably somewhat alter the current hand-object configuration. To create test cases as similar as possible without introducing disturbances caused by evaluating the alternate procedure, we instead used separate test cases for the two procedures. Both test cases used the same object placed at, to the best of our ability, identical positions and with identical orientations. However due to small variations in object placements, sensor measurements, grasp execution and stochastic behavior of the grasp planner the resulting grasps in the two cases were not exactly identical, but always very similar. For the cases when the initial grasp was deemed stable the two procedures are completely identical, therefore there is no need to use two separate test cases in this situation, since the only differences would be the differences introduced by the unwanted, unavoidable variances described above. Because of the inability to always use identical test cases the performance comparison presented below should be considered as a strong indication rather than an absolute truth.

B. Results

The rate of stable grasps for the procedure that considered grasp corrections were 88.1%. The corresponding rate for the procedure that did not utilize grasp corrections were 71.4%. We note that both procedures give fairly high success rates, which to a large extent is due to the mechanical design of the Robotiq gripper. The main observation here is the increase in performance with 16.7 percentage points when grasp corrections are considered.

24 out of the 42 objects in our test set had initial grasps that were predicted to be stable and hence did not apply our grasp adaption scheme, making the two procedures described above identical on these test cases. Out of these 24 grasps, 22 grasps were stable and 2 unstable. On another object the initial grasp failed to establish a lasting contact with the object, making our grasp adaption method unable to find corrections and thus failing to achieve a stable grasp. For the remaining 17 objects, contacts were established but
the initial grasps were predicted to be unstable, hence our grasp adaption method were used to improve the grasps. Our grasp adaption method achieved stable grasps on 15 of these 17 objects, which can be compared to the procedure that did not use grasp adaption, which had stable grasps on 8 of these 17 objects. These results are shown in table 1. We can see that the use of our grasp adaption method increases the probability of achieving stable grasps.

|                | With corrections |                      | Without corrections |                      |
|----------------|------------------|----------------------|---------------------|----------------------|
|                | Stable            | Unstable             | Stable              | Unstable             |
|                | 37 (88.1%)        | 5 (11.9%)            | 30 (71.4%)          | 12 (28.6%)           |
| Initial grasp predicted to be stable: |                      |                      |                     |
| Stable         | 22               | 2                    |                      |
| Unstable       | 15               | 3                    |                      |
| Initial grasp predicted to be unstable: |                      |                      |                     |
| Stable         | 8                | 10                   |                      |
| Unstable       | 8                | 10                   |                      |

Table 1. Here we show results achieved with and without using our grasp adaption method to apply corrections.

In one case where the grasp adaption method was used the hand accidentally pushed over the object when executing the first correction and hence the hand failed to re-establish contact with the object, making our method unable to find more adaptions and thus failing to achieve a stable grasp. In all other cases where the grasp adaption method were used, it found a grasp that was predicted to be stable. The number of iterations needed by the grasp adaption method to find grasps that were predicted to be stable is shown in Figure 4. For the 17 cases that used the grasp adaption method, the average estimated grasp stability for the initial grasps was 26.7%. For the final grasps achieved on these objects after grasp adaption, the average estimated grasp stability was 70.1%, this is shown in Figure 4.

We can evaluate the performance of the method that predict tactile sensor data by looking at each iteration of the grasp adaption method separately. The average estimated grasp stability for grasps before an action were executed, hereby denoted $a$, is 29.4%. We now consider the grasps that result from executing the chosen actions. For these grasps, the average stability predicted before an action were executed, $p(y_{n+1} = \text{stable}|x_n, a)$, hereby denoted $b_1$, is 62.8% and the average stability estimated after an action been executed, $p(y_{n+1} = \text{stable}|x_{n+1})$, hereby denoted $b_2$, is 55.8%. This difference, 7 percentage points, is visualized in Figure 4. Since our stability estimation method operates the same way on both sensed and predicted tactile readings, this difference indicates the accuracy of our method that predict tactile sensor data. By comparing $a$ and $b_2$ we can see that, on average, each iteration of the grasp adaption method increases the estimated grasp stability by 26.4 percentage points.

However all grasps that were predicted to be stable by our stability estimation method were not stable in reality. If we sum up the 24 initial grasps that were predicted to be stable by the 16 grasps that were predicted to be stable after corrections had been made, we can see that 3 out of 40 grasps that were predicted to be stable did fail in practice. This marks the performance of our stability estimation module. We did however put the threshold for predicting a grasp to be stable at > 50% probability of grasp stability. In fact, the average estimated probability of grasp success for these 40 grasps were 81.1%, which suggests that 7.5 out of these 40 grasps should have failed. We can see that our stability estimation method in general underestimates the grasp stability slightly.

V. CONCLUSIONS

We presented a method that finds stable grasps on novel objects. The method uses a planner to find an initial grasp on objects. Thereafter it estimates the probability of grasp success with a tactile based method learned from experience. If a grasp is deemed unstable the agent utilizes a method for grasp adaption that suggests corrective actions by simulating tactile data in the vicinity of the current grasp. Our experimental results confirms the applicability of our method, by showing that our grasp adaption method significantly increases the grasp stability on novel objects. Our system achieved successful grasps on 88.1% of our test cases and when activated our grasp adaption method increased the estimated grasp stability by, on average, 43.4 percentage points. We conclude that although the grasp adaption method has limited accuracy when predicting new tactile sensor data, the predictions are accurate enough to guide the robot towards grasps with a marked increase in grasp stability.

In future work we plan to improve performance by using sensor feedback during grasp execution. We also plan to integrate vision to be able to recover when contact is lost and to help guide grasp adaptions in a more global way.

REFERENCES

[1] B. Çalli, A. Walsman, A. Singh, S. Srinivasa, P. Abbeel, and A. M. Dollar, "Benchmarking in manipulation research: The YCB object and model set and benchmarking protocols," CoRR, vol. abs/1502.03143, 2015.
[2] R. Johansson, “Sensory input and control of grip,” in Novartis Foundation Symposium, pp. 45–59, 1998.
[3] R. Howe, N. Popp, P. Akella, I. Kao, and M. Cutkosky, “Grasping, manipulation, and control with tactile sensing,” in IEEE International Conference on Robotics and Automation, 1990.
[4] A. Bicchi, J. Salisbury, and P. Dario, “Augmentation of grasp robustness using intrinsic tactile sensing,” in IEEE International Conference on Robotics and Automation, 1989.
[5] Y. Bekiroglu, J. Laaksonen, J. A. Jørgensen, V. Kyrki, and D. Kragic, “Assessing grasp stability based on learning and haptic data,” IEEE Transactions on Robotics, submitted.
[6] L. Jenetof, Q. Wan, and R. Howe, “Limits to compliance and the role of tactile sensing in grasping,” in Proceedings of International Conference on Robotics and Automation (ICRA), 2014.
[7] M. Madry, L. Bo, D. Kragic, and D. Fox, “St-hmp: Unsupervised spatio-temporal feature learning for tactile data,” in Proceedings of International Conference on Robotics and Automation (ICRA), 2014.
K. Hsiao, S. Chitta, M. Ciocarlie, and E. Jones, “Contact-reactive grasping,” in *IROS*, pp. 1554–1560, 2011.

H. Dang and P. K. Allen, “Learning grasp stability,” in *ICRA*, pp. 2392–2397, 2012.

L. Miao, Y. Bekiroglu, D. Kragic, and A. Billard, “Learning of grasp adaptation through experience and tactile sensing,” in *Proceedings of International Conference on Intelligent Robots and Systems (IROS)*, 2014.

Y. Chebotar, K. Hausman, O. Kroemer, G. Sukhatme, and S. Schaal, “Self-supervised regrasping using spatio-temporal tactile features and reinforcement learning,” in *IROS*, pp. 1960–1966, IEEE, 2016.

Y. Chebotar, K. Hausman, O. Kroemer, G. Sukhatme, and S. Schaal, “Generalizing regrasping with supervised policy learning,” in *International Symposium on Experimental Robotics (ISER)*, 2016.

K. Hsiao, S. Chitta, M. Ciocarlie, and E. Jones, “Contact-reactive grasping of objects with partial shape information,” in *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on*, pp. 1228–1235, 2010.

H. Dang and P. K. Allen, “Grasp adjustment on novel objects using tactile experience from similar local geometry,” in *IROS*, pp. 4007–4012, 2013.

H. Dang and P. K. Allen, “Stable grasping under pose uncertainty using tactile feedback,” in *Auton. Robots*, vol. 36, no. 4, pp. 309–330, 2014.

M. Murooika, R. Ueda, S. Nozawa, Y. Kakiuchi, K. Okada, and M. Inaba, “Planning and execution of groping behavior for contact grasping,” in *IROS*, pp. 2717–2722, IEEE, 2015.

sensor based manipulation in an unknown environment,” in *2016 IEEE International Conference on Robotics and Automation, ICRA 2016, Stockholm, Sweden, May 16-21, 2016*, pp. 3955–3962, 2016.

Y. Hyttinen, D. Kragic, and R. Detry, “Learning the tactile signatures of prototypical object parts for robust part-based grasping of novel objects,” in *IEEE International Conference on Robotics and Automation*, 2015.

Z. Su, K. Hausman, Y. Chebotar, A. Molchanov, G. E. Loeb, G. S. Sukhatme, and S. Schaal, “Force estimation and slip detection/classification for grip control using a biomimetic tactile sensor,” in *IEEE-RAS International Conference on Humanoid Robots (Humanoids)*, pp. 297–303, IEEE, 2015.

F. Veiga, H. van Hoof, J. Peters, and T. Herrmanns, “Stabilizing novel objects by learning to predict tactile slip,” in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 5065–5072, Sep 2015.

J. Roberge, S. Rispal, T. Wong, and V. Duchaine, “Unsupervised feature learning for classifying dynamic tactile events using sparse coding,” in *2016 IEEE International Conference on Robotics and Automation, ICRA 2016, Stockholm, Sweden, May 16-21, 2016*, pp. 2675–2681, 2016.

N. Sommer, L. Miao, and A. Billard, “Bimanual compliant tactile exploration for grasping unknown objects,” in *Proceedings of International Conference on Robotics and Automation (ICRA)*, 2014.

E. Nikandrova, J. Laaksonen, and V. Kyrki, “Towards informative sensor-based grasp planning,” in *Robotics and Autonomous Systems, vol. 62, no. 3*, pp. 340 – 354, 2014. Advances in Autonomous Robotics — Selected extended papers of the joint 2012 {TAROS} Conference and the {FIRA} RoboWorld Congress, Bristol, {UK}.

Y. Bekiroglu, A. Damianou, R. Detry, J. A. Stork, D. Kragic, and C. H. Ek, “Probabilistic consolidation of grasp experience,” in *IEEE International Conference on Robotics and Automation*, 2016.

J. Bohg, A. Morales, T. Asfour, and D. Kragic, “Data-driven grasp synthesis - A survey,” *IEEE Trans. Robotics*, vol. 30, no. 2, pp. 289–309, 2014.

R. Detry, C. H. Ek, M. Madry, and D. Kragic, “Learning a dictionary of prototypical grasp-predicting parts from grasping experience,” in *IEEE International Conference on Robotics and Automation*, 2013.