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 estimate the probability of success of a grasp and to find corrective actions to improve grasps. Our method considers grasp corrections when the probability of success of the current grip is below a certain threshold. The probability of success of each new grip 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 \textsuperscript{III} and our experimental setup and results are presented in section \textsuperscript{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.

Sommel 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 was 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.

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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 module and a grasp adaption method. The planner is used to plan initial grasps and extract a notion of shape that characterizes the region around the grasping point. After an initial grasp has been found, tactile and proprioceptive information 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 grasps 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 measurements from tactile and proprioceptive sensors together with the notion of shape described in III-A to predict if a grasp is successful. Many tactile cues 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 proprioceptive reading, 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 proprioceptive reading. 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 the tactile sensors, instead of working on features extracted from tactile data as it was in our previous work [19].
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. 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 use 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

$$\text{argmax}_\alpha p(y_{n+1} = \text{stable} | x_n, \alpha)$$  \hspace{1cm} (2)

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

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 calculating a probability distribution, whose probability density function can then be written as

$$f_{X_{n+1}}(x) = g(x_n, \alpha),$$  \hspace{1cm} (3)

where $g$ is some function of $x_n$ and $\alpha$. This distribution will represent both the predicted tactile sensor values and the estimated uncertainty for these values. How this prediction is done is explained in section III-D

Next we sample from $f_{X_{n+1}}(x)$ to get a set of tactile readings $x_{i,\alpha}, i = 1, 2, ..., m$. This discretization allows us to use our stability estimation module to predict the grasp stability for each of these samples. Now a prediction of the outcome of an action $\alpha$ can be calculated based on $f_{X_{n+1}}(x)$ as the average grasp stability for all samples $x_{i,\alpha}$:

$$p(y_{n+1} = \text{stable} | x_n, \alpha) = \frac{1}{m} \sum_{i=1}^{m} p(y_{n+1} = \text{stable} | x_{i,\alpha})$$  \hspace{1cm} (4)

We use this to predict the grasp stability, $p(y_{n+1} = \text{stable} | x_n, \alpha)$, for each $\alpha \in A$ and pick the action $\alpha_{\text{best}}$ that predicts the best outcome:

$$\alpha_{\text{best}} = \text{argmax}_\alpha p(y_{n+1} = \text{stable} | x_n, \alpha)$$  \hspace{1cm} (5)

$\alpha_{\text{best}}$ 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 proprioceptive sensor 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 normal axes.
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:

$$f(t_j) = \frac{1}{\sigma_j \sqrt{2\pi}} exp \left\{ -\frac{(t_j - \mu_j)^2}{2\sigma_j^2} \right\}$$ (6)

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 proprioceptive values, $\ell_j$ are also represented with gaussian probability distributions, but here the current joint values are always used as the expected values $\mu_j$, and the variance is always the same $\sigma_j$.

$X_{n+1}$ 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

$$f_{X_{n+1}}(x) = \frac{1}{\sqrt{(2\pi)^k |\Sigma|}} exp \left\{ -\frac{(x - \mu)^T \Sigma^{-1} (x - \mu)}{2} \right\}$$ (7)

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 have been taken and passed to the planner. The grasp suggested by the planner have then been executed. Thereafter the tactile sensors were read once and the grasp stability estimated according to our method described 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 was 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.

<table>
<thead>
<tr>
<th>Total:</th>
<th>Stable</th>
<th>Unstable</th>
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<tr>
<td>With corrections</td>
<td>37 (88.1%)</td>
<td>5 (11.9%)</td>
</tr>
<tr>
<td>Without corrections</td>
<td>30 (71.4%)</td>
<td>12 (28.6%)</td>
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<tr>
<th>Initial grasp predicted to be stable:</th>
<th>Stable</th>
<th>Unstable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stable</td>
<td>22</td>
<td>2</td>
</tr>
<tr>
<td>Unstable</td>
<td>15</td>
<td>3</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>Initial grasp predicted to be unstable:</th>
<th>Stable</th>
<th>Unstable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stable</td>
<td>22</td>
<td>8</td>
</tr>
<tr>
<td>Unstable</td>
<td>3</td>
<td>10</td>
</tr>
</tbody>
</table>

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

In one case were the grasp adaption method were 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 were the grasp adaption method were used, it found a grasp that were 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 were 26.7%. For the final grasps achieved on these objects after grasp adaption, the average estimated grasp stability were 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, $p(y_{n+1} = \text{stable} | x_n, b)$, 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 with 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


