Analytic Grasp Success Prediction with Tactile Feedback

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Abstract—Predicting grasp success is useful for avoiding failures in many robotic applications. Based on reasoning in wrench space, we address the question of how well analytic grasp success prediction works if tactile feedback is incorporated. Tactile information can alleviate contact placement uncertainties and facilitates contact modeling. We introduce a wrench-based classifier and evaluate it on a large set of real grasps. The key finding of this work is that exploiting tactile information allows wrench-based reasoning to perform on a level with existing methods based on learning or simulation. Different from these methods, the suggested approach has no need for training data, requires little modeling effort and is computationally efficient. Furthermore, our method affords task generalization by considering the capabilities of the grasping device and expected disturbance forces/moments in a physically meaningful way.

I. INTRODUCTION

Many robotics applications require robust grasp acquisition and subsequent object manipulation which remain difficult to achieve in real environments. One reason lies in the inevitable uncertainties in modeling and perception. In general, these uncertainties make it impossible to realize hand configurations and contact locations exactly as planned. Consequently, unplanned movements occur frequently when making contact with the target object. These potentially negate the grasp quality guarantees made during offline planning. In turn, this may lead to grasp failure which can result in dropping the object. This problem can be addressed by re-evaluating grasp success online using sensory feedback. In case a grasp is predicted to fail, this allows to initiate early countermeasures such as adjusting the hand pose and/or contact locations [1], [2]

Grasp success depends on whether the hand is able to exert wrenches (i.e., concatenated force/moment vectors) suitable to counterbalance disturbances, such as gravity wrenches, occurring during task execution. Therefore, if all relevant modeling parameters are known accurately, the grasp success prediction problem can be solved by forward simulation. As this is not the case in real world applications, most current approaches rely on learning techniques which have the potential to address uncertainties in a principled manner. However, as training data is typically limited, it is difficult for learning-based systems to generalize to unknown objects and/or task disturbances.

A. Our Approach to Grasp Success Prediction

A meaningful task description should involve the wrenches which a grasp needs to exert in order to counter the disturbance forces/moments occurring during task execution [3], [4], [5]. Our approach relies on the following core concept: given a set of task wrenches, the grasp success prediction problem boils down to checking whether this set is contained in the wrench set that can be applied by the hand. To this end, we use the quality criterion by Haschke et al. [6] which, loosely speaking, constitutes a continuous measure of set containment. While widespread in offline grasp planning, analytic reasoning in wrench space has been largely abandoned in application scenarios since it requires good knowledge of contact locations and orientations. We use tactile feedback, obtained after the hand contacts the target object, to alleviate contact placement uncertainties [7], [8]. This allows us to build a computationally efficient grasp success predictor with little modeling effort and no need for training data. Explicitly accounting for expected disturbance wrenches affords a clear physical interpretation and enables generalization to arbitrary tasks. The contributions of this work are:

i) we address the open question of how well analytic grasp success prediction with tactile feedback can work in

Fig. 1. Platform: (Left) The utilized platform comprises a 3-fingered Schunk SDH hand† mounted on an industrial KUKA manipulator. (Right) Each finger of the hand has 2 tactile sensor arrays which are composed of 6 x 14 taxels on proximal phalanges and 6 x 13 taxels on distal phalanges.

http://www.mobile.schunk-microsite.com/
practice and provide a rigorous evaluation using the platform shown in Fig. 1.

ii) we propose an efficient approximation of the quality criterion in [6] as the solution of a Linear Program (LP);

iii) we elucidate potential sources of uncertainty and suggest appropriate counter strategies.

The remainder of this article is organized as follows: below we briefly discuss related work in the context of our approach. In Section III we detail the utilized grasp contact model, while Section IV is dedicated to the proposed analytic grasp success predictor. An evaluation of our method is given in Section V before we conclude with a discussion in Section VI.

II. RELATED WORK

An often overlooked consequence of wrench-based reasoning is the implicit assumption of ideal force control, i.e., the ability of the hand controller to command appropriate grasp wrenches instantaneously without contact displacement. Simulation potentially allows to loosen this assumption by accounting for the full mechanism, controller and environment dynamics in the grasp success prediction problem [9]. However, the large modeling effort and computational cost make it impractical for real-world applications. Although some recent progress has been made [10], it is in general not possible to eliminate modeling uncertainties to a degree which makes a full dynamic simulation accurate enough to be meaningful.

Tackling the grasp success prediction problem with supervised learning reduces the modeling effort for the price of data collection. The underlying feature representations and machine learning methods have been evaluated by Laaksonen et al. [11] with respect to their performance in determining grasp stability. Most existing approaches build probabilistic classifiers based on various grasp quality metrics [12], [13], [14]. Recent works also include features derived from tactile feedback. For example, Bekiroglu et al. use tactile image moments in their classifiers which are based on Kernel Logistic Regression [15] and Bayesian Networks [1] respectively. Similarly, Dang and Allen [2] utilize Support Vector Machines and a Bag-of-Features model containing tactile information.

In essence, grasp success depends on the physical capabilities of the grasping device in relation to the expected task disturbance wrenches. In our opinion, this is insufficiently reflected in current learning-based approaches which either use high-level task definitions [1] only, or rely on ad hoc descriptions such as the minimum-norm wrench that can be exerted by scaled contact forces [16]. Especially the latter, while used frequently, has been shown to be of limited practical value [17]. In general, current methods relying on learning require a large amount of training data to synthesize a predictor able to generalize with respect to the actual task disturbances.

III. GRASP CONTACT MODELING

A grasp is given as $i = 1, \ldots, n$ soft contacts which touch the target object surface at contact areas $C_i \subset \mathbb{R}^3$ with pressure-weighted centers $p_i \in \mathbb{R}^3$. The corresponding inward-pointing surface unit normals are denoted as $n_i \in \mathbb{R}^3$. Our approach relies on the knowledge of the set of wrenches that can be applied to the object. Let us therefore express a generalized contact friction force $f = [f_x, f_y, f_z, \tau_z]^T$ in a local contact frame with origin at $p_i$ and $z$-axis pointing along $n_i$ as illustrated in Fig. 2. Here, $f_x, f_y$ and $f_z$ respectively indicate tangential and normal contact force components, while $\tau_z$ stands for the frictional moment about the contact normal. We build upon the work by Howe and Cutkosky [18], who formulate an ellipsoid limiting the set of frictional forces/moments that can be transmitted by a deformable finger contact onto a flat surface with friction coefficient $\mu \in \mathbb{R}^+$.

$$F_i = \{ f \in \mathbb{R}^4 \mid f_x^2 + f_y^2 + (\mu f_z, \tau_z)^2 \leq (\mu f_z)^2 \},$$

In (1), $g_i^* \in \mathbb{R}^4$ and $\tau_i^* \in \mathbb{R}^4$ respectively denote the total normal force and the maximum frictional moment that the soft contact can apply under this normal force. If subjected to additional forces/moments, a deformable finger contact will change in response and ultimately limit this motion as noted by Ciocarlie et al. [19]. Therefore it has been recognized, that the set of exertable forces/moments should be augmented accordingly [19], [20]. In this work, we follow the approach in [20] and apply generalized frictional forces, constrained by (1), at points $c \in C_i$ lying in the contact surface area. We
can now denote the wrench set a contact can apply as
\[ \mathcal{W}_i = \left\{ w \in \mathbb{R}^6 \mid \begin{array}{c}
    w = G(c) f, \\
    c \in C_i, \\
    f \in F_i
\end{array} \right\}, \]  
(2)
where the matrix \( G(c) \in \mathbb{R}^{6 \times 4} \) maps generalized forces to wrenches expressed in an object coordinate frame [21]. In the following, we discretize \( \mathcal{W}_i \) in (2) by a total of \( l_i \) samples and collect them in matrix
\[ W_i = [w_{i,1}, \ldots, w_{i,l_i}]. \]  
(3)
The wrenches in (3) are formed by applying forces/moments, corresponding to a discretization of the friction ellipsoid as shown in Fig. 3 [18] at each taxel center \( c_i(x_i, y_i) \) with non-zero tactile readings (cf. Fig. 2). This allows to formulate the set of wrenches that a grasp can apply as the discrete Grasp Wrench Space (GWS)\(^2\) which is found by forming the convex hull over the Minkowski sum of the \( n \) single contact wrench sets
\[ GWS = \text{conv} \left( \bigoplus_{i=1}^{n} \{ w_{i,1}, \ldots, w_{i,l_i} \} \right). \]  
(4)
Note, that we assume that target objects are rigid which precludes hand-relative motion of contact centers \( p_i \) due to object deformation and corresponding distortion of the wrenches spanning the GWS in Fig. 4.

A. Contact Parametrization

We exploit tactile feedback to estimate the geometrical contact quantities. For each contact we fit a 3-d normal distribution \( N(\mu_i, \Sigma_i) \) to those taxel center points which have non-zero tactile readings. Then, we approximate the contact surface area \( C_i \) by projecting the taxel grid from the curved finger pads onto a plane defined by point \( \mu_i \) and normal \( n_i \). The latter is obtained as the eigenvector corresponding to the smallest eigenvalue of \( \Sigma_i \).

Let \( q \in \mathbb{R}^6 \) denote the hand joint configuration and let \( \bar{\tau} \in \mathbb{R}^6 \) be the vector containing the maximum joint torques.

Joint torques can be expressed as the product of the total contact force and the transpose of the hand jacobian \( J_i(q) \in \mathbb{R}^{3 \times k} \) formed with respect to \( p_i \). Using this relation, we obtain the maximum normal force magnitude exertable at the \( i \)th contact as the solution of the Linear Program (LP)
\[ g_i^* = \arg \max_{g_i \in \mathbb{R}^+} g_i, \]  
(5)
such that
\[ -\bar{\tau} \leq J_i(q)^T n_i g_i \leq \bar{\tau} \]
Note that \( g_i^* \) in (5) is hand configuration dependent and, in general, differs between contacts. We acquire the maximum moments \( \tau^*_i \) as the apices of the limit surface in Fig. 4 corresponding to pure torsional load. Let \( a = \sum_{c_i} \hat{g}_i(x_i, y_i) \) denote the sum of raw tactile readings over contact area \( C_i \). Following [18], \( \tau^*_i \) can be computed by adding the frictional moment contributions made by the local tangential forces acting at individual taxel centers \( c_i(x_i, y_i) \)
\[ \tau^*_i = \frac{\mu g_i^*}{a} \sum_{c_i} (\hat{g}_i(x_i, y_i)||c_i(x_i, y_i) - p_i||_2). \]  
(6)
Equation (6) implies that the measured tactile readings \( \hat{g}_i(x_i, y_i) \) correspond to the maximal possible normal force magnitude \( g_i^* \), which is not the case in general. Since the actual contact area resulting from \( g_i^* \) will be larger or equal than \( C_i \), (6) constitutes a conservative approximation of \( \tau^*_i \).

IV. Task-Based Grasp Success Prediction

Given a grasp, the core concept of our success prediction scheme is to evaluate the containment of a set of task wrenches in the GWS. We assume the availability of a task description as a set formed by the mirror image of expected disturbance wrenches that need to be resisted
\[ T = \{ t_j \in \mathbb{R}^6 \mid j = 1, \ldots, m \}. \]  
(7)
A. Measuring Grasp Quality

To measure the aforementioned set containment we use the quality criterion in (6) which, essentially, constitutes the maximum task wrench set scaling factor \( q^* \) such that the GWS in Fig. 4 contains the task set in (7) as illustrated in Fig. 4.

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\( ^2 \) We adhere to the naming convention made in the literature, although the GWS is not a vector space because the identity- and inverse elements of addition axioms do not hold in general.
Therefore, $q^* > 1$ constitutes the decision boundary at which we expect a grasp to be successful since it should be able to counterbalance all expected disturbance wrenches. Opposed to the similar $Q$ distance criterion by Zhu and Wang [22], the utilized criterion does not require the task wrench set to contain the origin. Also, it does not necessitate the force-closure property and is defined for non-prehensile grasps. Computation of $q^*$ in [6] requires, for each wrench in (7), the solution of a (convex) determinant maximization problem with linear matrix inequality constraints as discussed in [23]. Here, we compute $q^*$ such that each of the scaled task wrenches in (7) can be expressed by convex combinations of the discrete grasp contact wrenches in (7) summed over all $n$ contacts. This can be formulated as a single LP

$$q^* \in \arg \max_{q \in \mathbb{R}_+^n, \lambda_{i,j} \in \mathbb{R}_+^n} q,$$

subject to

$$\sum_{i=1}^{n} W_i \lambda_{i,j} = q t_j, \quad j = 1, \ldots, m,$$

$$\|\lambda_{i,j}\|_1 = 1, \quad i = 1, \ldots, n, \quad j = 1, \ldots, m,$$

for which highly efficient solvers exist. Note, that the sum of convex wrench combinations in (8) can express each element contained in the discrete GWS in (4). Therefore, the actual construction of the GWS is not required. Opposed to the original formulation in [6], the LP in (8) operates on a discrete representation of the contact wrench set in (2). However, as evidenced by our experiments reported in Section V, the introduced discretization error proved to be negligible.

B. Addressing Uncertainties

To discuss uncertainty sources in a principled way in the context of our approach, we categorize them as follows.

Contact placement: Uncertainties in contact position and orientation affect the contact wrench set in (2) and therefore distort the GWS. In this work, we alleviate this uncertainties by estimating contact placement from tactile feedback as detailed in Section III-A.

Hand-relative object pose: Since both, grasp wrenches and task wrenches need to be expressed in a common object frame, they are subjected to uncertainties in object pose perception which might result in false positive grasp success predictions. In this work, we build on [5] and reduce the effect of object position uncertainties on the gravity task (used in the evaluation presented in Section V) by augmenting the wrench set in (7), as explained by means of Fig. 5. At present, we are not considering possibilities to reduce object pose uncertainty directly, such as using grasp execution schemes tailored to limit object movement [24] and/or to facilitate perception by incorporating tactile information [25].

Mechanism dynamics and control: While we exploit tactile feedback to aid in contact modeling as explained previously, wrench-based reasoning is blind to robot and controller dynamics (i.e., effects causing unforeseen movement of the grasp contacts due to the inability of computing/commanding appropriate grasp wrenches instantaneously) as stated in Section IV. Therefore, we see no straightforward way to include corresponding uncertainties in our analysis.

Object properties: It is difficult to infer intrinsic object properties, such as mass or friction coefficient, from sensory data. Consequently, if not available a priori, the corresponding parameters should be approximated conservatively (i.e., with a large mass and a low friction coefficient). We provide a respective sensitivity analysis in Section V-C. Also, object deformation during task execution violates the rigid body assumption and can cause unexpected grasp contact movement distorting the GWS in (4).

V. Evaluation

Here, we present an experimental study comparing the proposed analytic grasp success predictor to actual grasp success rates measured from experiments carried out with the platform shown in Fig. 2.
A. Data Collection

We gathered a large data set comprising 584 precision grasps. Half of these grasps remained stable while lifting the grasped object by 5 cm, whereas the other half failed to prevent object slippage and/or rotation. The grasps are distributed over the 4 test objects shown in Fig. 6 and were applied in different object postures (standing/lying). Pre-grasp wrist pose generation was done via sampling from normal distributions centered on manually defined seeds as detailed in [15]. For grasp execution, starting from a fully opened hand configuration, a joint position controller with pre-defined setpoints was used to simultaneously close the fingers. Upon equilibrium, a tactile snapshot was recorded and the hand-relative object pose was estimated with a monocular vision system using a textured CAD model [26].

B. Results

The presented methods were implemented in Matlab and the following results were generated on a standard PC with 6 GB RAM and an Intel i7-2600 CPU. For all test grasps we computed the quality criterion in (8) as summarized in Fig. 7. To this end, we drew 14 samples from the friction ellipsoids in (1) (see Fig. 3) in order to generate the necessary contact wrenches in (3). The discretization parameter was chosen based on Fig. 8 which shows that the corresponding discretization error becomes negligible above 14 samples. To formulate the task wrench set in (7), we modeled the object lifting procedure in a quasi-static manner by augmenting the gravity task with 20 wrenches placed on a radius of $\sigma = 20/3$ mm around the perceived CoM (see Fig. 5). We observed an approximate maximum perception error of 20 mm. Therefore, under the assumption of a normally distributed error, the choice for $\sigma$ was motivated by the 3-sigma rule since it corresponds to an 68% probability of the task wrench set containing the actual gravity wrench, which was deemed sufficient. Based on experiments, the maximum hand joint torques $\bar{\tau}$ in (5) were respectively set to 1.6 Nm for proximal joints and 1.1 Nm for distal joints. An off-the-shelf solver was used to solve the LP’s in (5) and (8).

We classified grasp success based on a decision boundary of $q^* > 1$ and evaluated the prediction rates by comparing to ground-truth obtained from the experiments. To solve the prediction problem in (8), our proof-of-concept implementation required overall computation times of 12 ± 5 ms (mean and standard deviation). The obtained grasp quality distribution is shown in Fig. 9. It is evident, especially for the case of the Spray Bottle, that there exist some failed grasps with quality $q^* > 1$ which results in false positive prediction.

http://www.gurobi.com/
We observed that false positive grasps usually had one or more contacts close to the borders of the corresponding finger pads. These grasps then failed due to contact loss caused by finger motions occurring during the object lift phase. We therefore hypothesize that the main reason for false positive prediction lies in the controller dynamics which are not modeled in our wrench-based approach. A false positive example ($q^* = 1.97$) is shown in Fig. 2. One source of the relatively few false negative predictions are contacts occurring on unsensorized hand surfaces which apply wrenches that are not accounted for in $\mathbf{\Omega}$. The overall classification accuracy in the experiments was 74%, a breakdown is presented in Fig. 10. On the more uniformly shaped objects which, on average, allow for larger finger contact areas the prediction results are better. We attribute this observation again to unmodeled controller dynamics, since larger contact patches afford more finger movements during task execution. Figure 11 highlights the effect of the task parameter $\sigma$ in Fig. 5 which captures pose uncertainty stemming from object perception. Although the overall classification accuracy remains relatively stable, it can be seen that neglecting pose uncertainty increases false positive predictions. This is because the likelihood that the actual gravity wrench is contained in the task wrench set in (7) decreases with decreasing $\sigma$, which may cause the actually acting disturbance to remain unconsidered by the predictor in $\mathcal{P}$.

Additionally, we evaluated the influence of uncertainties in friction coefficient and object mass. Table II summarizes the obtained overall classification accuracies, as well as true positive and true negative rates under varying object properties. As it could be expected, the results indicate that it is prudent to approximate these properties conservatively if they are uncertain in order to avoid false positive predictions.

<table>
<thead>
<tr>
<th>$\Delta m$</th>
<th>$\Delta m = -0.3\text{kg}$</th>
<th>$\Delta m = 0.0\text{kg}$</th>
<th>$\Delta m = 0.3\text{kg}$</th>
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<tbody>
<tr>
<td>$\Delta \mu$</td>
<td>75</td>
<td>69</td>
<td>69</td>
</tr>
<tr>
<td>$\Delta \mu = 0.0$</td>
<td>67</td>
<td>94</td>
<td>39</td>
</tr>
<tr>
<td>$\Delta \mu = 0.2$</td>
<td>62</td>
<td>96</td>
<td>27</td>
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C. Sensitivity Analysis

While the suggested analytic predictor has no intrinsic parameters which need to be chosen, we want to investigate the effect of uncertainties in those extrinsic parameters which characterize object pose and object properties. Figure 12 highlights the effect of the task parameter $\sigma$ in Fig. 5 which captures pose uncertainty stemming from object perception.

VI. DISCUSSION

This work concerns the open question of how well analytic grasp success prediction works if tactile feedback is used to mitigate contact placement uncertainties. To this end, we developed a wrench-based classifier and evaluated it on a large data set of real grasps where it achieved an overall accuracy of 74%, a ROC AUC of 0.82 and a success rate of 90%. We gained the key insight that exploiting tactile
information allows wrench-based reasoning to perform comparable with recent methods based on learning or simulation. This is a remarkable result in our opinion, since the proposed approach requires little modeling effort, is computationally light and needs no training data. Grasp outcome is fundamentally linked to the grasping device’s physical capabilities in relation to the expected disturbance forces/moments. The suggested method handles this factuality in a direct manner by incorporating wrenches that need to be resisted, and thus affords generalization to arbitrary tasks.

**Limitation analysis:** An implicit assumption when using wrench-space reasoning, is that the hand controller is able to command grasp wrenches instantaneously without contact displacement. Consequently, we identify the sensitivity to unmodeled controller dynamics, which can cause false positive predictions, as the main limitation of the presented approach. This issue could be addressed by exchanging the utilized simplistic position controlled grasping routine with a more advanced force/impedance controller and/or explicitly solving the force optimization problem [27]. We think that such controller improvements would reduce finger movements during task execution and further boost the performance of our predictor.

Also, the presented method requires to approximate a task in form of discrete disturbance wrenches. This is straightforward for quasi-static gravity tasks as shown in this work. However, encoding general dynamic tasks can be difficult depending on the application context. One way to address this issue was recently proposed by Lin and Sun [28], who use human demonstrations to construct probabilistic task representations in wrench space.

**Future work:** Besides addressing the aforementioned limitations, we think that a promising avenue for future research lies in bridging the gap between analytic and data-driven approaches to grasp success prediction. If training data is available, it can be used to reduce the negative impact that unmodeled controller dynamics have on our approach. As a first step, we plan to build a probabilistic model for grasp success prediction [15], [14] involving the same task-oriented criterion [6] which we use in the presented work.

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