Data-Driven Statistical Modeling of a Cube Regrasp

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Abstract— **Regrasping is the process of adjusting the position and orientation of an object in one's hand. The study of robotic regrasping has generally been limited to use of theoretical analytical models and cases with little uncertainty. Analytical models and simulations have so far proven unable to capture the complexity of the real world. Empirical statistical models are more promising, but collecting good data is difficult. In this paper, we collect data from 3300 robot regrasps, and use this data to learn two probability functions: 1) The probability that the object is still in the robot's hand after a regrasp action; and 2) The probability distribution of the object pose after the regrasp given that the object is still grasped. Both of these functions are learned using kernel density estimation with a similarity metric over object pose. We show that our data-driven models achieve comparable accuracy to a geometric model and an off-the-shelf simulator in classification and prediction tasks, while also enabling us to predict probability distributions.**

I. INTRODUCTION

Humans are experts at reorienting objects in their hands. They use this skill to adjust their grip of a pencil to write with it, or to change their grasp of a key from its teeth to its head to unlock a door. By contrast, once a robot has picked up an object, it generally maintains the same grasp as long as the object is in contact with the hand. If a robot does adjust an object grip, it is generally a predetermined operation with deterministic results, and only applicable for a constrained set of initial and desired final grasp poses. In contrast, humans can adapt to different objects with arbitrary initial and desired final poses. One possible explanation of this discrepancy is that humans have better models of how the object pose changes as a function of their actions. In this paper, we show how robots can build better models of regrasp actions.

By a regrasp action, we mean any sequence of movements that results in a change of the object pose with respect to the hand. Often, the final pose of an object is critical to a task.

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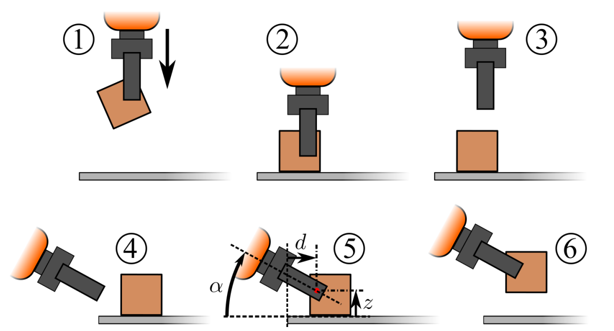

Fig. 1. Place and pick regrasp action studied in this paper. Initially, the robot is holding a block between its fingers. Then, it moves downwards to a specific pose above the platform, where the block may move to conform to the new contact. It then opens its fingers and repositions itself at a certain position and orientation with respect to the edge of the platform. It then closes its fingers and moves upwards, completing the regrasp. There are several scenarios where the robot will not be holding the block in step 6. In step 1, the object could slip out of the hand. In step 2, the object-hand system could collide with the table. In step 5, the robot could miss the block and fail to pick it up.

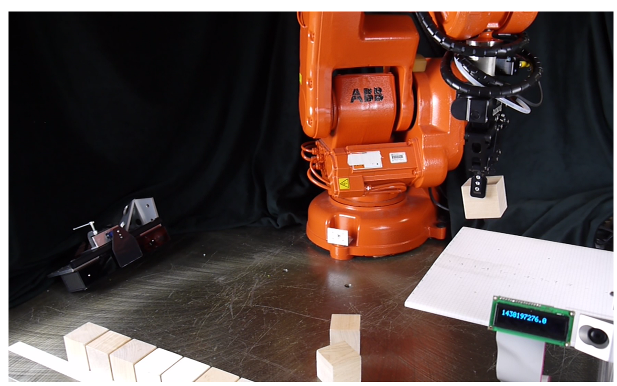

Fig. 2. Place and pick regrasp data collection setup. We use an industrial arm with a parallel jaw gripper and place an pick objects. A three dimensional vision system based on point clouds is used to record the object position before and after a regrasp. In the event of a failure, the robot either picks up the dropped block from on top of the platform or retrieves a new block from a stack of fresh blocks. With this setup, the robot performed over 3000 regrasp experiments. We use this data to fit models for predicting the probability of not dropping the object, and estimating the final pose of the block after a regrasp.

If the initial pose of an object is arbitrary, then the robot must use models to determine what regrasp actions to take to move the object to the desired pose. Physics-based models can only take us so far. Modeling multiple contacts along with impact, friction, and uncertainty in object size, mass, finger shape, dirt, etc can make it difficult to compute models a priori. In this paper, we encapsulate this real-world noise and uncertainty in the model as a probability distribution. A simple Gaussian is not a good model of the probability distribution for manipulation. Flipping a coin, or the difference in object pose based on whether or not contact occurs cannot be represented as a unimodal Gaussian distribution. In this paper, we use kernel density estimation to estimate a multi-modal probability distribution from collected data to model regrasps.

We study a place and pick regrasp of a cube (Figure 1) as a first step to understand the challenges involved in statistical modeling of regrasp actions. We collected data from 3300 robot regrasps, and used this data to learn two models: 1) Given an initial object pose and regrasp action, how likely is it that the object remains grasped? and 2) Given an initial pose and action, where do we expect the object to end up? We show that our learned model, despite not having any prior knowledge of the task, achieves comparable accuracy to a physics simulator and a geometric model.

The rest of the paper is outlined as follows. In Section II we look at prior work in this area. In Section III we outline our method for modeling regrasps. In Section IV we explain the data collection process and experiments performed. In Section V we compare our model with an off-the-shelf simulator and geometric model, and in Section VI we summarize our work and discuss future directions.

II. PRIOR WORK

Regrasping has been studied for a long time, starting with Paul [1], Tournassoud et al. [2], Fearing [3], and Brock [4]. Early regrasping work assumed a known world model with deterministic actions. Most regrasping work falls under three categories: pick and place [2], [5], [6], closed-loop dynamic regrasping [7][8][9], or what is generally referred to as dexterous manipulation or finger gaiting [3], [10][11][12][13][14][15]. Chavan Dafle et al. [16] present work on "extrinsic dexterity", which uses gravity, inertia, and external contacts to vary the pose of the object within the hand.

Uncertainty during manipulation has been represented using two approaches: "possibilistic" and probabilistic. The "possibilistic" approach [17][18] maintains a set of possible object poses, and the robot makes motions that reduce the size of the set. Brost [19] uses pushing, squeezing and offset grasping with a parallel jaw gripper to reliably grasp objects with high position uncertainty. Dogar and Srinivasa [20] explicitly propagate object uncertainty regions to plan robust grasp plans. Probabilistic approaches [21][22][23][24] maintain a probability distribution of object poses in order to plan the best action. Bayesian estimation [25][26] and particle filters [27][28] are the most common ways to deal with the non-Gaussian, multi-modal probability distributions inherent in manipulation tasks.

To model manipulation actions, researchers often use simulation[29][30], imitation learning[31], or models learned with collected robot data [32][33]. In this paper, we expand on prior work by using real data to model uncertain manipulation actions.

The most similar work to ours comes from Kopicki et. al. [34]. They use regression to learn the resulting motions of real robotic push actions. They also fit multi-modal probability distributions to their data and show improvement over regression. Our work focuses on learning both the probability of maintaining a grasp after a regrasp and the resulting probability distributions of robotic regrasp actions, along with paying closer attention on how to collect a large amount of robot manipulation data.

III. METHOD

A. Task Description

The place-and-pick regrasp action we will learn is shown in Figure 1. The robot moves down vertically to a fixed height above a platform, releases the object, and then attempts to grasp it again at a specified position in the workspace. Note that in step 2, the object pivots and slides in the fingertips when it comes into contact with the platform, which we expect to be difficult for physics-based models to capture. Our regrasp action $\boldsymbol{a}$ is parameterized by three continuous variables, d, z, and α, which represent the pose of the hand frame with respect to the edge of the platform. The parameters of action $\boldsymbol{a}$ are not relative to the object pose on the platform, because this data may be unavailable to the robot while it is performing a regrasp.

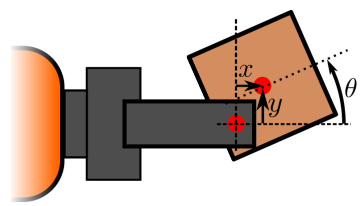

Fig. 3. State space used in this paper. While the world is six-dimensional, because we are grasping a cube with a parallel jaw gripper, we can reduce the state space to three dimensions. Note that as the cube is symmetric, we restrict θ to be between $-\pi/4$ and $\pi/4$.

Our state $\boldsymbol{s}$ is represented by three continuous variables, x, y, and θ, corresponding to the relative pose of the cube with respect to the hand, as shown in Figure 3. Note that this is a planar state space; we will not consider out of plane rotations or grasps. Any grasps of this kind will be considered "not grasped" for the purposes of this paper.

In order for the robot to successfully model this regrasp action, we must learn two probability functions:

1) The probability that the object is in the robot's hand after a regrasp action, $P(\text{grasped}|\boldsymbol{s}, \boldsymbol{a})$
2) The probability distribution of the final state given that the object is still grasped, $P(\boldsymbol{s}'|\boldsymbol{s}, \boldsymbol{a}, \text{grasped})$

Note that if the object is not grasped after a regrasp action, its final state $\boldsymbol{s}'$ does not exist, since $\boldsymbol{s}'$ is the in-hand pose of the object. Learning these two probability distributions enables us to solve planning problems such as: 1) what action maximizes the chance of maintaining a grasp? or 2) what action maximizes the chance of the center of the object being at most $1\,\mathrm{cm}$ away from the center of the fingers? In this paper, we focus solely on learning the above distributions from data, and leave planning with these models as future work.

B. Predicting the Probability of Maintaining a Grasp

To estimate the probability that the object is in the robot's hand after a regrasp action, we use kernel density estimation with Bayes discriminant rule [35], [36]. We estimate the probability of retaining and not retaining the object using kernel density estimation, and then, for a query point, determine which of the two probabilities are greater. That is, we would like to calculate:

$$P(\pi_i|\boldsymbol{s},\boldsymbol{a}) = \frac{p_i P(\boldsymbol{s},\boldsymbol{a}|\pi_i)}{\sum_j^g p_j P(\boldsymbol{s},\boldsymbol{a},\pi_j)}$$

where $p_i = P(\pi_i)$ is the prior probability of a randomly selected observation being in class π_i, g is the total number of classes, and $P(\boldsymbol{s},\boldsymbol{a}|\pi_i)$ is the conditional probability density of an observation given that it is in class π_i. In our case, we have two classes, grasped and not grasped, so we will learn two probability densities using kernel density estimation:

$$P(\boldsymbol{s},\boldsymbol{a}|\pi_i) = \frac{1}{N_i}\sum_j^{N_i} K^s_{h_1}(\boldsymbol{s},\boldsymbol{s}_j)K^a_{h_2}(\boldsymbol{a},\boldsymbol{a}_j)$$

where N_i is the number of training observations belonging to class π_i. Note that we set $p_i = N_i/\sum_j^g N_j$ as our prior probabilities.

We define our kernel functions $K^s_{h_1}$ and $K^a_{h_2}$ by first expressing distances in state and action space, and then use a Gaussian kernel over these distance functions:

$$\begin{aligned}
D_a(\boldsymbol{a}_1,\boldsymbol{a}_2) &= \left\| \begin{bmatrix} d_1 \\ z_1 \\ \rho\alpha_1 \end{bmatrix} - \begin{bmatrix} d_2 \\ z_2 \\ \rho\alpha_2 \end{bmatrix} \right\|^2 \\
D_s(\boldsymbol{s}_1,\boldsymbol{s}_2) &= \left\| \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} - \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \right\|^2 + 2\rho^2(1-\cos(\theta_1-\theta_2)) \\
K^s_{h_1}(\boldsymbol{s},\boldsymbol{s}_j) &= \frac{1}{\eta_s(\rho,h_1)}\exp\left(-\frac{1}{2h_1^2}D_s(\boldsymbol{s},\boldsymbol{s}_j)\right) \\
K^a_{h_2}(\boldsymbol{a},\boldsymbol{a}_j) &= \frac{1}{\eta_a(\rho,h_2)}\exp\left(-\frac{1}{2h_2^2}D_a(\boldsymbol{a},\boldsymbol{a}_j)\right)
\end{aligned}$$

where ρ is the radius of gyration for the object, which allows us to properly trade off distance and angle, while η_s and η_a normalize the kernels so they represent probability distributions. Note that for the state distance function, we use a cosine function to handle angle wrap-around for object pose (i.e. $-\pi = \pi$). Both of the distance functions D_a and D_s represent squared distance in action and state space. The units for d, z, x, and y are mm, while α and θ are in radians. Thus, our distance functions have units of mm^2, and our bandwidths h_1 and h_2 have units of mm.

We choose the values of bandwidths h_1 and h_2 that minimize the cross-validated negative log likelihood of the observed data:

$$\begin{aligned}
NLL(h_1,h_2) &= -\frac{1}{N_i}\sum_j^{N_i}\hat{P}_{-j}(\boldsymbol{s}_j,\boldsymbol{a}_j|\pi_i) \\
\hat{P}_{-j}(\boldsymbol{s},\boldsymbol{a}|\pi_i) &= \sum_{k\neq j}^{N_i} K^s_{h_1}(\boldsymbol{s},\boldsymbol{s}_k)K^a_{h_2}(\boldsymbol{a},\boldsymbol{a}_k)
\end{aligned}$$

where $\hat{P}_{-j}(\boldsymbol{s},\boldsymbol{a}|\pi_i)$ is the estimator of the conditional probability density with observation j removed.

C. Predicting the Final Object Pose

To predict the resulting probability distribution of the cube after a regrasp action, we will use kernel *conditional* density estimation. We formulate our conditional density estimate using our kernels from above and roughly following Hall, Racine and Li[37]:

$$\begin{aligned}
P(\boldsymbol{s}'|\boldsymbol{s},\boldsymbol{a},\mathrm{gra}) &= \frac{P(\boldsymbol{s}',\boldsymbol{s},\boldsymbol{a}|\mathrm{grasped})}{P(\boldsymbol{s},\boldsymbol{a}|\mathrm{grasped})} \\
P(\boldsymbol{s}',\boldsymbol{s},\boldsymbol{a}|\mathrm{gra}) &= \frac{1}{m}\sum_i^m K^s_{h_3}(\boldsymbol{s}',\boldsymbol{s}'_i)K^s_{h_4}(\boldsymbol{s},\boldsymbol{s}_i)K^a_{h_5}(\boldsymbol{a},\boldsymbol{a}_i) \\
P(\boldsymbol{s},\boldsymbol{a}|\mathrm{gra}) &= \frac{1}{m}\sum_i^m K^s_{h_4}(\boldsymbol{s},\boldsymbol{s}_i)K^a_{h_5}(\boldsymbol{a},\boldsymbol{a}_i)
\end{aligned}$$

where m is the number of experiments where the object was in the robot's hand after a regrasp.

We will choose values for h_3, h_4 and h_5 that minimize the integrated squared error, again using cross validation (see [37] for more details):

$$ISE(h_3,h_4,h_5) = \int\left(\hat{P}_{ssa} - P_{ssa}\right)^2 P_{sa}\,d\boldsymbol{s}\,d\boldsymbol{a}\,d\boldsymbol{s}'$$

where

$$\begin{aligned}
P_{ssa} &= P(\boldsymbol{s}'|\boldsymbol{s},\boldsymbol{a},\mathrm{grasped}) \\
P_{sa} &= P(\boldsymbol{s},\boldsymbol{a}|\mathrm{grasped})
\end{aligned}$$

Note that for both $P(\mathrm{grasped}|\boldsymbol{s},\boldsymbol{a})$ and $P(\boldsymbol{s}'|\boldsymbol{s},\boldsymbol{a},\mathrm{grasped})$, we could have chosen more complex kernels or used different learning algorithms. However, in this paper we select simple models to understand the viability of a data-driven framework for modeling regrasps. In our future work, we plan to evaluate different non-parametric methods for estimating these probability functions.

IV. DATA COLLECTION

Our data collection setup is shown in Figure 2. For our experiments, we use an ABB IRB 140 industrial robot arm and a Robotiq C-85 2-fingered gripper that place and pick an object from a metal platform. We use a $50\,\mathrm{mm}$ wooden cube as our object. Initially, the block is resting on the platform and the robot locates it and picks it up. The vision system records the initial state $\boldsymbol{s}$. Then, the robot places the cube and picks it up again using an action $\boldsymbol{a}$. The $\boldsymbol{a}$ parameters $[d,z,\alpha]$ are sampled uniformly at random and cover the entire range of actions we wish to model for this regrasp.

The vision system first checks whether or not the cube is in the robot's hand and then records the final state $\boldsymbol{s}'$. If the object is grasped, it repeats the process with a new action $\boldsymbol{a}$. If the object is not grasped, it enters a recovery procedure and then runs a new regrasp experiment. In this way, we collect a series of $D = (\boldsymbol{s}, \boldsymbol{a}, \text{grasped}, \boldsymbol{s}')$ data points. In this paper, we collected 3304 data points. The robot successfully maintained its grasp of the object after a regrasp 2642 times and failed 662 times.

The vision system consists of four Microsoft Kinect v2 sensors arranged to supply multiple views of the object, both on the platform and in the robot's hand. Depth point clouds are fused together and, after an initialization, Iterative Closest Point is used to find the closest match between our object model and the point cloud. The average positioning error of this system is $5\,\mathrm{mm}$. In the future, we are interested in improving the accuracy of this three-dimensional vision system by using different depth cameras and measuring its effect on our data-driven models.

The recovery procedure reduces the need for human intervention during data collection, and is split into 2 parts. If the object is not in the robot's hand, it is either resting on the platform, or has fallen off the platform. If it is resting on the platform, we command the robot to pick up the object and continue with the next experiment. If the object has fallen off of the platform, we consider the object lost, and grasp a new block from a queue of identical blocks resting on the table. The queue is 11 blocks long, and the robot takes approximately 150 trials to exhaust the entire queue and require human intervention.

V. VALIDATION

We now compare our learned model with an off-the-shelf simulator and a rudimentary geometric model using our data set D. We randomly select a hold-out test set of 1000 data points which we use to compare all three methods. We describe the geometric and simulation models below.

A. Geometric Model

The challenging part of this regrasp to model is what happens during the initial block placement (Step 2 of Figure 1), as there are many possible contact modes including no contact followed by an impact and settling, sliding or pivoting in finger tips, and sliding or rotating against the platform. For simplicity, we assume that during this step, once an object corner contacts the platform, the object rotates about the contact point until it lies flat on the platform. Given an initial object pose $s = [x, y, \theta]$, if c is the distance from the center of the hand to the edge of the platform when placing and w is the width of the block, we can calculate the distance from the edge of the platform to the center of the block q as

$$q = \begin{cases} \theta \geq 0, & c + y + \frac{w}{2}(\sin(\theta) - \cos(\theta) + 1) \\ \theta < 0, & c + y + \frac{w}{2}(\sin(\theta) + \cos(\theta) - 1) \end{cases}.$$

Now, given an action $a = [d, z, \alpha]$, if g is the maximum horizontal distance away from the center of the block that the robot can still grasp the object without missing it, then we will successfully grasp the block if $|d - q| \leq g$, and that final pose will be

$$\boldsymbol{s}' = \begin{bmatrix} x' \\ y' \\ \theta' \end{bmatrix} = \begin{bmatrix} (q-d)\cos(\alpha) + (z - w/2)\sin(\alpha) \\ (q-d)\sin(\alpha) - (z - w/2)\cos(\alpha) \\ \gamma \end{bmatrix}$$
$$\text{with} \quad \gamma = \begin{cases} 0 \leq \alpha \leq \pi/4, & \alpha \\ \pi/4 \leq \alpha \leq \pi/2, & (\alpha - \pi/2) \end{cases}.$$

Creating probability distributions from this kinematic model is difficult, as we do not know the distribution of errors on our parameters. Note that even if we did, even for this rudimentary model, the probability distributions would be multimodal and non-Gaussian.

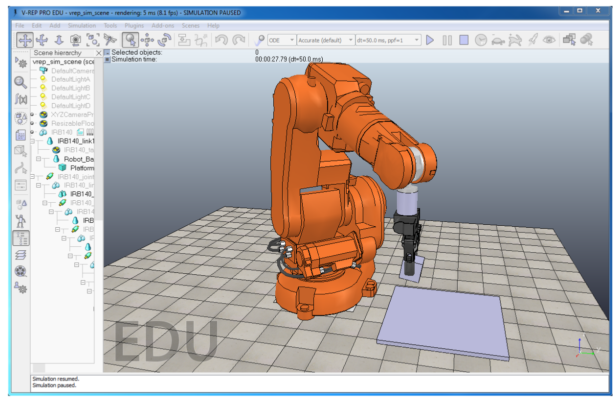

Fig. 4. Simulation environment used in the paper. Using VREP, we have modeled the same industrial robot arm and gripper used in our physical experiments, and placed the platform in the same relative location. We place the block in the simulated robot's hand in the same initial pose as our real trials, and record whether or not the object is still grasped after the regrasp in simulation. If so, we record the final pose of the block.

B. VREP with ODE as a Simulation Model

Using the simulation environment VREP [38], we have modeled an ABB IRB 140 robot with a Robotiq C-85 two-fingered gripper just as in our physical experimental setup. The simulation environment is shown in Figure 4. The platform is placed in the same location, and we use a $50\,\mathrm{mm}$ cube with the same density and frictional properties as our real wooden cube. We can now place the object into the simulated robot's hand at a given initial state $\boldsymbol{s}$, ask the robot to perform the regrasp action $\boldsymbol{a}$, and then observe whether the object was grasped. If so, we record the final state $\boldsymbol{s}'$.

Note that setting up the simulator was a challenge in and of itself. Even the well-tuned ODE in VREP still cannot handle parallel grasping well, and once the block is also made to slide against the table and in the hand, it is difficult to get stable results. The two most difficult phenomena to model in simulation with physics are 1) how the contact patch between the parallel jaws and the cube changes as the hand slightly loosens its grip on the object, and 2) what happens to the cube at the onset of contact with the platform.

Like the geometric model, creating probability distributions using a simulator is difficult as the simulation is deterministic. We could vary initial parameters slightly and fit the resulting data using the probabilistic model described in this paper. However, it is unclear which parameters to vary and how much to perturb them by in order to get plausible results. Moreover, if the underlying physics model is wrong, even this may not give a realistic distribution.

TABLE I
CLASSIFICATION ACCURACY OF PREDICTING WHETHER THE OBJECT REMAINS GRASPED

Setting	Geometric	Simulation	Data-Driven
In Hand	74.8 %	72.8 %	76.2 %
Platform	89.3 %	-	90.7 %

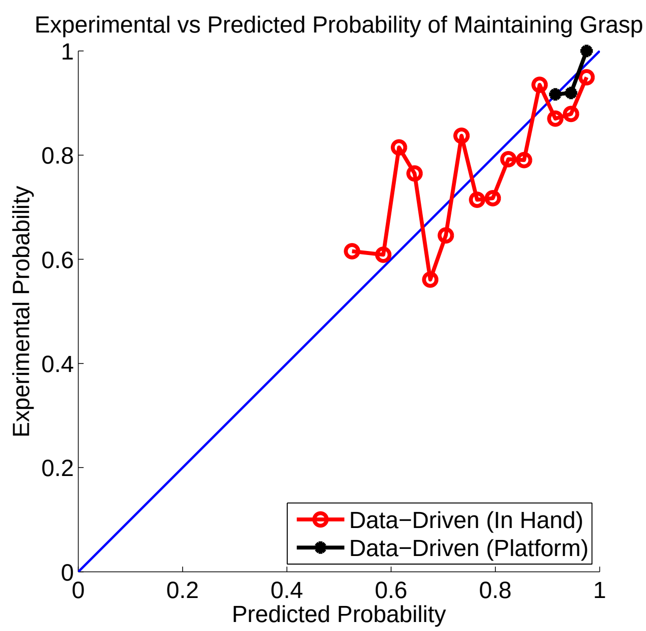

Fig. 5. Comparison between the experimental and predicted probability of maintaining the object after a regrasp. Each data point is the average experimental grasp probability for 5%-wide bins of predicted probability.

C. Validation Results: Predicting if the Object Remains Grasped

Table I shows our results for predicting if the object is still grasped after a regrasp action. We compared the classification accuracy of the three models for two separate conditions. First, we consider the condition where we are given the pose of the object in the robot's hand and the parameterized regrasp action to perform. Second, we consider the condition where we know the pose of the object on the platform and

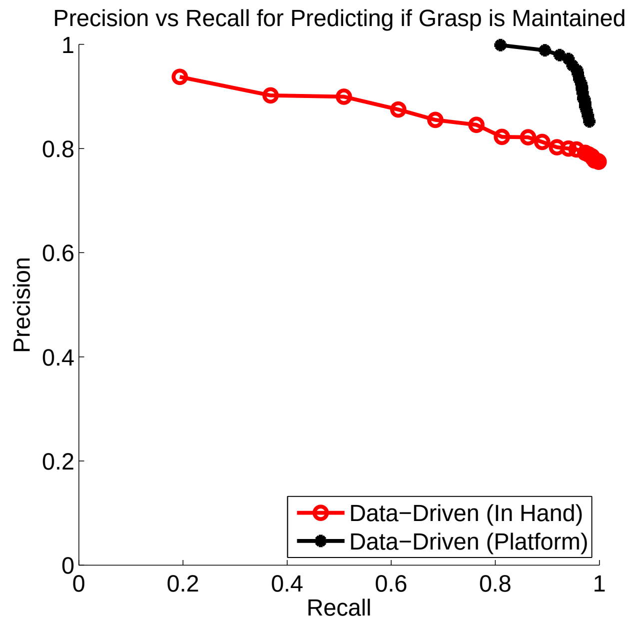

Fig. 6. Precision-recall curve for predicting whether the robot is still holding the object after a regrasp

predict the probability that the robot will be able to successfully pick it up. All three models perform comparably, even though our data-driven model is given no prior information about the task.

In Figure 5, we binned our predicted probability in 5% increments, looked at the percentage of those points where the object was still grasped, and plotted the results. If our predictions are good, the mean of the true grasp probability should follow the straight line. Our predicted probabilities for the platform condition match better than the in-hand condition, which is expected.

If we can predict the probability of maintaining the object after a regrasp, this means we can adjust the decision boundary to achieve different precision and recall values. This is plotted in Figure 6. Note that the platform case gives us a much better precision-recall curve, and that these precision-recall curves are not easily achievable without a data-driven model.

TABLE II
MEAN POSE ESTIMATION ACCURACY (MM)

Setting	Geometric	Simulation	Data-Driven
In Hand	11.7	10.8	13.0
Platform	5.7	-	6.3

D. Validation Results: Final Pose Estimation

To evaluate the predictive power of our pose estimation models, we looked at the mean pose estimation accuracy. We used the square root of our distance function $D_s(\boldsymbol{s}_1, \boldsymbol{s}_2)$ as

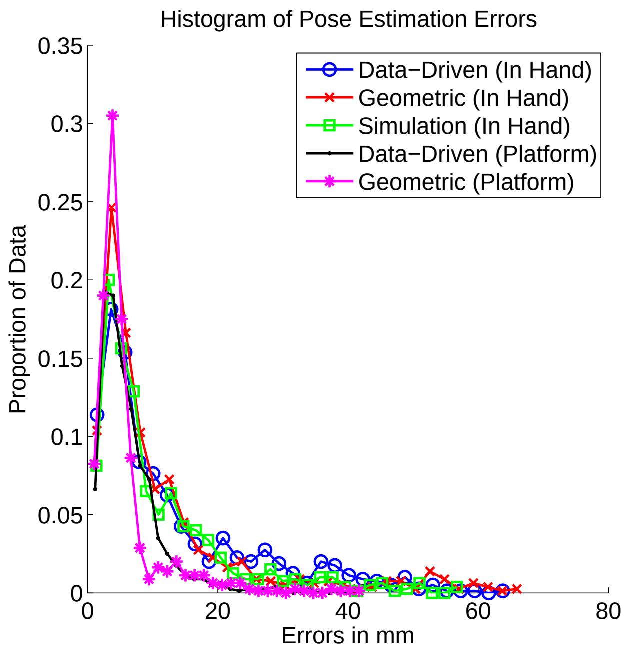

Fig. 7. Histogram of prediction errors. Note that most of the error is less than 10mm, and the data-driven approach achieves comparable accuracy to the other approaches.

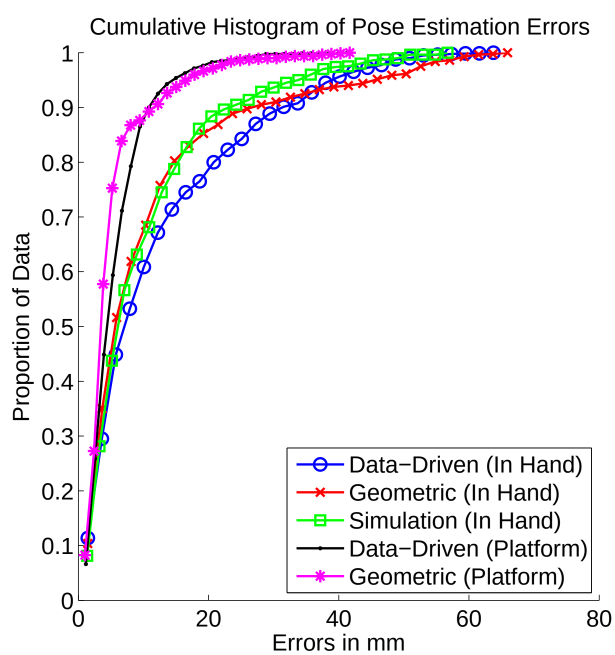

Fig. 8. Cumulative histogram of prediction errors. Over 80% of the data has an error of less than 10mm for the platform case. The data-driven method achieves comparable accuracy to the other approaches.

a measure of accuracy. Note that if the distribution is multi-modal, this measure does not reward capturing that multi-modality. However, since we do not have the true underlying distribution, we use the mean pose estimation accuracy as a baseline. Our results are shown in Table II, Figure 7 and

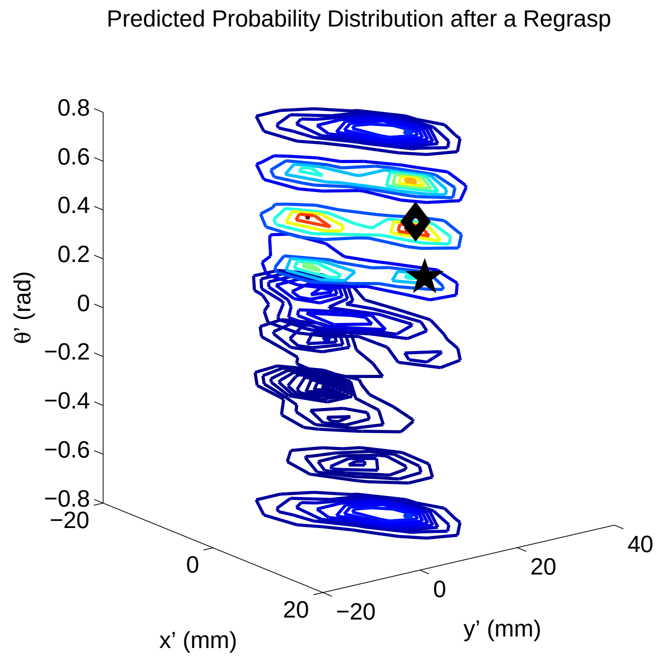

Fig. 9. Predicted probability distribution of a final pose after a regrasp. The most likely predicted pose is the diamond and the true pose is the star. Note the multi-modal nature of the distribution.

Figure 8. Again, our data-driven model achieves comparable accuracy with no prior information.

With our data-driven model, we can also calculate the entire resulting probability distribution in pose space, which is shown in Figure 9. Note the multi-modal nature of the distribution.

VI. CONCLUSIONS

In this paper, we introduced a way to model robotic regrasping using a large amount of real data. First, we briefly discussed how we collected the real robot manipulation data needed for our models. We then showed how to predict the probability of maintaining the grasp of an object given an initial position and robot regrasp action using this data. In addition, we showed how to estimate the probability distribution of where the object will end up in the robot's hand given an initial pose and a robotic regrasp action. We compared our models with a simulator and a rudimentary physics model and showed that our data-driven models have comparable performance even with no prior knowledge of the task.

In the future, we are interested in extending these models to other objects, regrasp actions, and hands. We are especially interested in extending our models to SE(3) space to handle three dimensional rigid body transformations. We are also interested in improving the accuracy of our vision system to improve model accuracy. Finally, we are interested in exploring other non-parametric models to achieve higher fidelity.

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