Value of Assistance for Grasping - Preliminary Evaluation

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I. Value of Assistance (VOA) for Grasping

We aim to assess the effect sensing actions will have on the probability the gripper agent will successfully grasp an object. Specifically, given the current belief regarding the object's pose and a set of possible grasping actions, we seek a measure that predicts the effect each sensing action will have on the probability of successfully grasping the object.

We start by presenting a general formulation of VOA for grasping using sensing actions. In the following sections, we present how this general idea can be instantiated to support a specific setting and how we examine it empirically.

The settings we support here include a gripper agent and a sensor agent. We note that we use this two-agent model since it clearly distinguishes between the grasping and sensing capabilities. Depending on the application, this model can be used to support the decision-making of a single agent with both manipulation and sensing capabilities.

The gripper agent needs to choose a configuration from which to attempt to grasp an object. While the gripper agent cannot sense the object, it can receive a single sensor reading or *observation* from the sensor agent.

We make the following assumptions.

- The shape of the object is known, and it is assumed to be at a stable pose. However, its exact pose is not known. Formally, we assume the object p is within some known and finite set of stable poses $\mathcal{P}_o$.
- The gripper agent can move to any valid configuration, but cannot acquire on its own new information about the object before it attempts the grasp.
- The gripper agent chooses a single *grasp configuration* x from a finite set of possible configurations $\mathcal{X}_g$.
- Equivalently, the sensor agent can choose a single *sensor configuration* x_s from a set of possible configurations $\mathcal{X}_s$ from which to capture an *observation*.

Our focus here is on assessing the expected benefit of receiving observation and on supporting the decision of which intervention to perform. Accounting for the optimization considerations of the sensor agent is an interesting avenue for future work.

A. Computing Grasp Score

We define a configuration of the gripper agent as a valid configuration of its end-effector. For computing VOA for grasping, we need a score function for a grasping configuration with regards to a particular stable pose of the object.

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Definition 1 (Grasp Score). Given a set of possible object poses $\mathcal{P}$ and a set of possible grasp configurations $\mathcal{X}_g$, a *grasp score function* $Q : \mathcal{X}_g \times \mathcal{P} \mapsto [0,1]$ specifies the probability of successfully grasping an object at pose $p \in \mathcal{P}$ from configuration $x \in \mathcal{X}_g$.

Diverse factors such as contact area, closure force, object shape, and friction coefficient impact grasp score. This function may be evaluated analytically or empirically[1].

In many settings, an agent may need to grasp an object for which the exact pose is not known. Instead, the agent's decision relies on a *pose belief* over a set of possible object poses $\mathcal{P}_o$, which describe the likelihood of each pose.

Definition 2 (Pose Belief). Given a set $\mathcal{P}_o$ of possible (stable) object poses, a *pose belief* $\beta : \mathcal{P}_o \mapsto [0,1]$ is a probability distribution over $\mathcal{P}_o$.

The gripper agent uses the grasp score Q and pose belief β to select a grasping configuration $x \in \mathcal{X}_g$ from which to attempt the grasp. A good choice is a configuration that maximizes the *expected grasp score*.

Definition 3 (Expected Grasp Score). Given a configuration x, and a pose belief β, the *expected grasp score* is

$$\bar{Q}(x, \beta) = \mathbb{E}_{p \sim \beta}[Q\,(x, p)].$$

Based on the definition above, an *optimal grasp* x^* is one that maximizes the probability of success, i.e.,

$$x^* = \underset{x \in \mathcal{X}_g}{\arg\max}\, \bar{Q}(x, \beta) \tag{1}$$

With a slight abuse of notation, we denote the highest expected grasp score $\bar{Q}^*(\beta) = \bar{Q}(x^*, \beta)$.

B. Grasp Belief Update

In our setting, the gripper agent can receive one *observation* o, which corresponds to the sensor agent's readings from a specific sensor configuration $x_s \in \mathcal{X}_s$. We denote these interventions as *sensing actions* $\mathcal{A}^s$. Each sensing action $\alpha \in \mathcal{A}^s$ corresponds to a specific sensor configuration x_s and emits an observation. The possible sensing actions are induced by the sensor agent and the environment, and may be associated with an environment-specific cost.

Given a new observation o, the agent updates its belief using its *belief update* function.

Definition 4 (Belief Update). A belief update $\tau : \mathcal{B} \times \mathcal{O} \mapsto \mathcal{B}$ maps a given belief $\beta \in \mathcal{B}$ and a given observation $o \in \mathcal{O}$ to an updated belief.

C. Grasp Belief Update Estimation

A belief update function defines the effect a sensing action has on the pose belief after it is performed. Since we are interested in deciding which action to perform, we seek ways to estimate beforehand the effect the expected observation will have on the belief. Notably, our focus here is not on estimating the effect an observation will have on the ability to identify the object's pose with high certainty. Instead, we are interested in estimating the effect a sensing action will have on the choice of the best grasp configuration and on the probability of the gripper agent successfully grasping the object. Formally, we aim to find a sensing action that maximizes the expected grasp score $\bar{Q}^*(\beta)$.

For this purpose, we define an *observation prediction function*, that generates a (synthetic) observation that is predicted to be generated when the sensor is at a specific configuration and the object is at a certain pose.

Definition 5 (Observation Prediction). Given a set of possible object poses $\mathcal{P}$ and a set of sensing actions $\mathcal{A}^s$, the *observation prediction*, $\tilde{f}_s : \mathcal{P} \times \mathcal{A}^s \mapsto \mathcal{O}$, maps an object pose $p \in \mathcal{P}$ and a sensing action $\alpha \in \mathcal{A}^s$ to an estimated observation $\tilde{o} \in \mathcal{O}$.

D. Computing VOA for Grasping

We define *Value of Assistance* (VOA) as the difference between the highest expected grasp score before and after an observation is used to udpate the pose belief.

Definition 6 (Value of Assistance for Grasping). The VOA of the sensing action $\alpha \in \mathcal{A}^s$ and belief $\beta \in \mathcal{B}$, is

$$U_{voa}(\alpha, \beta) = \mathbb{E}_{p \sim \beta}\left[\bar{Q}^*\left(\beta_p\right)\right] - \bar{Q}^*(\beta), \quad (2)$$

where β_p is the updated belief given pose p.

$$\beta_p = \tau\left(\beta, \tilde{f}_s\left(p, \alpha\right)\right). \quad (3)$$

The above formulation is general and can be used to support various settings, including different observation-prediction and belief-update functions than the ones described in the remainder of this paper.

II. VOA for a Parallel Gripper and Lidar Sensor

We demonstrate our general framework with our specific illustrative system as depicted in figures **??** and 1. The gripper agent is a 6-DOF robotic arm[1] with a parallel-jaw gripper[2]. We programmed the gripper agent to perform a set of grasp configurations $\mathcal{X}_g \subset \mathbb{R}^6$. The sensor agent is a mobile robot[3], with a lidar[4] mounted on its top. We can therefore describe the sensor configuration as its 2D coordinates on the plane parallel to the floor at the lidar's level, and the robot's yaw or orientation, $\mathcal{X}_s \subset \mathbb{R}^3$. Given the sensor agent's configuration $x_s \in \mathcal{X}_s$ and the lidar's reading in the agent's local frame, we can transform the sensor's reading to an observation o as a set of points on the plane in the global frame.

Finally, the object shape $\sigma = (\mathcal{V}, \mathcal{F})$ is represented as a mesh comprised of a set of vertices $\mathcal{V} \subset \mathbb{R}^3$ and faces $\mathcal{F} \subseteq \mathcal{V} \times \mathcal{V} \times \mathcal{V}$. The object pose $p \in \mathbb{R}^6$, defines a local frame for the shape. Given an object with a known shape, we can generate an observation prediction $\tilde{f}_s$ by simulating a sensing action at a configuration defined by x_s and p by tracing rays from the simulated sensor, and recording the first intersection of these rays with the object's faces.

For assessing the grasp score function Q, we adopt an empirical approach to effectively capture the real-world effects of influential factors.

Given an object pose p and sensing action α we want to assess the significance of the estimated observation $\tilde{o} = \tilde{f}_s\left(p, \alpha\right)$. Intuitively, the more distinct the observation is from observations that could be made for other object poses, the more informative it is.

For examining the fit between two observations o and o', we calculate the root mean square deviation, $RMSD\left(o, o'\right)$. Then the significance of $\tilde{o}$ given pose p is assessed accordingly. The pose belief is updated based on the

III. Preliminary Empirical Evaluation

The objective of our evaluation is to examine the ability of our proposed VOA measure to predict the effect interventions in the form of sensing actions will have on the ability of the gripper agent to successfully grasp the object and on finding the best intervention for maximizing that probability.

With this objective in mind, our evaluation is comprised of three parts.

1) **Evaluating grasp score:** measuring the success ratio among the gripper agent's attempts to grasp an object given an object pose from and grasp configuration pair.
2) **Evaluating observation prediction**: examine the ability of our observation prediction to predict the observation generated by the sensor for a sensor configuration and object pose pair.
3) **Assessing VOA** : compare our VOA measure to the *Average Executed Cost Difference* (AECD) achieved in our experiments and which represents the empirical difference between the grasp success probability with and without assistance.

A. Experimental Setting

We perform our evaluation in both a simulated and a real-world two-agent robotic setting. The gripper agent is a UR5e robotic arm[5] with a parallel jaw gripper. The sensor agent is a equipped with a lidar sensor. The object to be grasped is a mug positioned on a table within the reachable workspace of the gripper agent.

For simulation, we used a MuJoCo [2] environment (depicted in Figure **??**). Since the simulator does not include a lidar sensor, we simulated it using the MuJoCo depth camera,

[1]https://www.universal-robots.com/products/ur5-robot/
[2]https://onrobot.com/en/products/2fg7
[3]https://www.turtlebot.com/turtlebot3/
[4]https://emanual.robotis.com/docs/en/platform/turtlebot3/appendix_lds_01/

[5]https://www.universal-robots.com/products/ur5-robot/

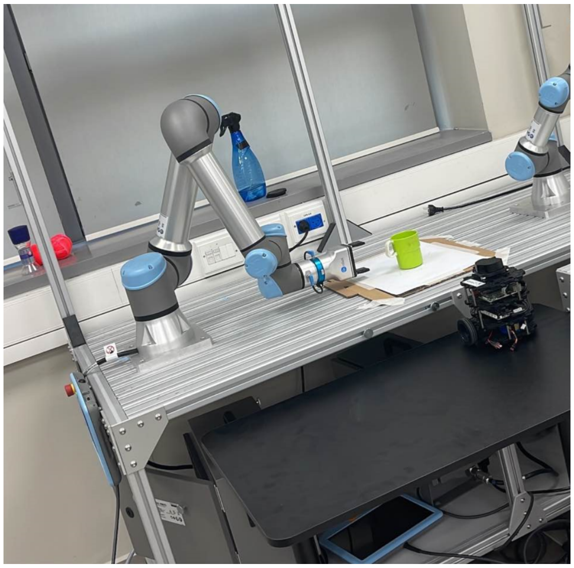

Fig. 1: Lab setup

taking only the row at the height of the simulated lidar. The simulated parallel jaw gripper is a Robotiq 2F-85[6].

In our lab setting, depicted in Figure 1, we use a OnRobot 2FG7 parallel jaw gripper[7]. The sensor agent consists of LDS-01 lidar[8] mounted on a turtlebot3 burger mobile robot. We used a plastic mug to reduce the risk to the robot in the case of unsuccessful grasps. In addition, to increase difficulty, we artificially limited the grasp width to be 18 mm.

B. Evaluating grasp score

In order to evaluate our grasp score function we examined 6 possible object poses and 4 possible grasp configurations. For every pose-configuration pair, we ran 15 grasp attempts.

Figure 2 shows the ratio of successful grasps over the 15 attempts. The rows in the table represent the stable poses and the columns are the grasp configurations.

Results show that configurations TD0 and TD90, corresponding to grasping the mug from its rim, yield a success rate of about 60% if the cup is facing up and the handle is not at the grasping configuration. As expected, grasping the mug at its handle, corresponding to pose-grasp configuration pairs OI90-U_90, OI90-D_90 and TDH0-U_0, yield the highest success rates.

C. Evaluating observation prediction

To evaluate the accuracy of our observation prediction, we compared the measurements collected by our lidar sensor and the corresponding synthetic observation generated using our observation prediction function described in Section II. We positioned the object 30 to 40 cm away from the sensor. We examined 17 stable poses, recording the readings for the sensor range within which the object is sensed. For each relevant angle, we calculate the mean and variance of the

[6]https://robotiq.com/products/2f85-140-adaptive-robot-gripper
[7]https://onrobot.com/en/products/2fg7
[8]https://www.robotis.us/360-laser-distance-sensor-lds-01-lidar/

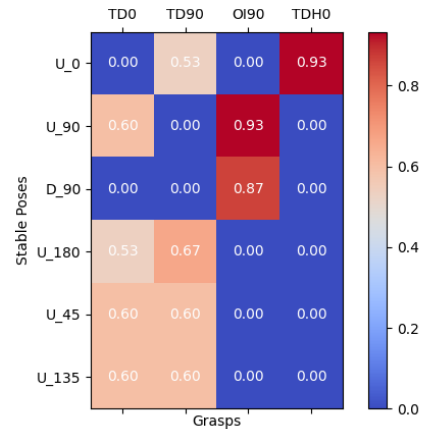

Fig. 2: Evaluating Grasp Score

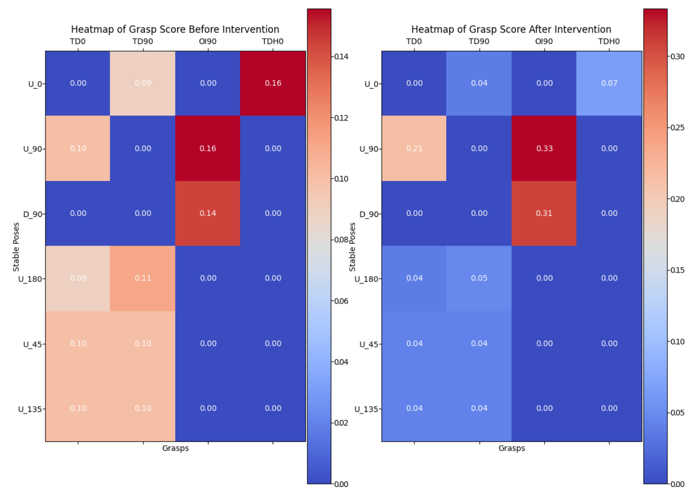

Fig. 3: Assessing grasp VOA.

difference between the measured distance and the estimated distance over the different poses.

Results (omitted due to space considerations) show that for most angles the error is 1-3 mm with negligible variance.

D. Assessing VOA

According to Equation 2 VOA is computed based on the grasp score of the maximal configuration.

The belief update function (used in Equation 3 after the sensing action is performed) is the one we describe in Equation **??**. The grasp score of a configuration is based on the values presented in Figure 2. In all computations, we assumed the initial belief is a uniform distribution over the stable poses.

Figure 3 displays VOA results by showing the weighted grasp score before (left) and after (right) a sensing action is performed. Each row corresponds to a stable pose and each column represents a grasp configuration. The value of each cell represents the grasp score weighted by it probability according to the belief. Formally, the value of a cell is

$$\beta(p) \cdot Q(x, p) \tag{4}$$

where p indicates the row and x indicates the column. Now let's fix x and sum equation 4 over every $p \in \mathcal{P}$:

$$\sum_{p \in \mathcal{P}} \beta(p) \cdot Q(x,p) = \mathbb{E}_{p \sim \beta}[Q(x,p)] = \bar{Q}(x,\beta)$$

As we can see this is equivalent to sum over the corresponding column of x. Now if we take the maximum sum in the sums of each column, this would be $\bar{Q}^*(\beta)$

Noticeably, before the intervention the best grasp to take was TD90 (corresponding to grasp from the rim), since it has moderate success rate for many possible poses. After the intervention the gripper agent is more confident that the handle is at 90 degrees, so the grasp OI90 becomes best grasp as expected. Also, the gripper agent doesn't have a high belief regarding one pose only, there are two poses with high belief, but that doesn't matter since we want to help the agent to choose a grasp with high success rate rather than provide an observation to induce a low entropy belief. The next step is to conduct trials to check which grasp of the two is the best for the pose of the object.

REFERENCES

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[2] E. Todorov, T. Erez, and Y. Tassa, "Mujoco: A physics engine for model-based control," in *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2012, pp. 5026–5033.