

Value of Assistance for Grasping

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Abstract. In multiple realistic settings, a robot is tasked with grasping an object without knowing its exact pose and relies on a probabilistic estimation of the pose to decide how to attempt the grasp. We support settings in which it is possible to provide the robot with an observation of the object before a grasp is attempted, but this possibility is limited, and there is a need to decide which sensing action would be most beneficial. We support this decision by offering a novel *Value of Assistance* (VOA) measure for assessing the expected effect of a specific observation will have on the robot’s ability to complete its task. We evaluate our suggested measure in simulated and real-world collaborative grasping settings.

1 INTRODUCTION

Task-driven agents often need to decide how to act based on partial and noisy state estimations which may greatly compromise performance. We consider settings in which an agent is tasked with grasping an object based on a probabilistic estimation of its pose. Before attempting the grasp, another agent may assist by performing a sensing action and sending its observation to the grasping agent. In our settings of interest, sensing and communication may be costly or limited and there is a need to support the decision of which observation to perform by offering principled ways to assess the expected benefit.

To demonstrate, consider the simplified automated manufacturing setting depicted in Figure 1. One agent, denoted as the *actor*, is a robotic arm with a parallel-jaw gripper that is tasked with grasping an object (here, an adversarial object from [1]). After a successful grasp, the object drops unexpectedly. Since the actor does not have a functioning sensor it can attempt to grasp the object based only on its estimation of the current position of the object. Alternatively, it can attempt the grasp after receiving an observation from another agent, the *helper*, that is equipped with a functioning sensor (here, an OnRobot 2.5D Vision System). The question that we pose is whether the helper can provide valuable assistance and what is the best position for the helper from which to provide the sensor reading among the possible options. Of course, the same question arises in single-agent settings in which it is the agent itself that needs to decide whether to perform a costly sensing action.

Beyond this illustrative example, grasping is an essential task for a wide range of robotic applications, including industrial automation, household robotics,

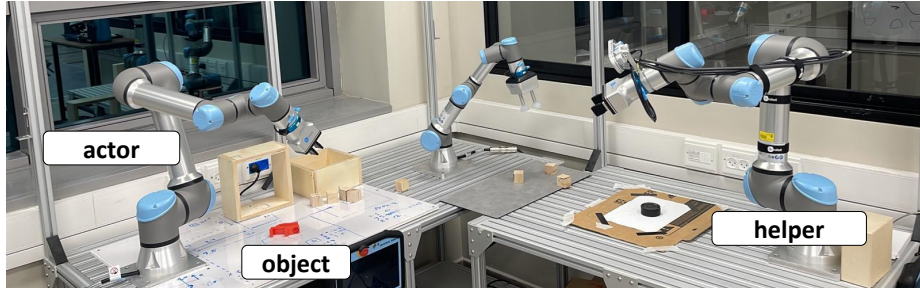


Fig. 1: Collaborative Grasping Example.

agriculture, and more [27, 13]. Accordingly, research on effective grasping capabilities has resulted in many solution approaches that can be generally divided into two main categories [43, 13]. In analytical approaches, a representation of the physical and dynamical models of the agent and the object are used when choosing a configuration from which to attempt a grasp [21, 41, 40, 12]. In contrast, data-driven approaches rank labeled samples to come up with grasping policies. The ranking is usually based on a heuristic or on experiences collected from simulated or real robots [14, 10, 39, 37, 25].

We assume the actor is associated with a procedure for choosing a grasp given its *belief* which represents its knowledge about the position of the object. To support the decision of which observation would be most beneficial, we formulate *value of assistance (VOA) for grasping* and offer ways to compute it for estimating the benefit a sensing action will have on the probability of a successful grasp. This involves accounting for how the actor’s estimation will change based on the acquired observation and assessing how this change will affect the actor’s decision of how to attempt the grasp.

VOA is used to assess the informative value an observation will have and is therefore closely related to the well-established notions of *value of information (VOI)* and *information gain (IG)* [22, 42, 50, 45, 16], which are widely used across multiple AI frameworks to assess the impact information will have on agents decisions and expected utility. We adapt these ideas to robotic settings. While in [7] we used VOA for assessing the effect localization information would have on a navigating robot’s expected cost, here we use it in the context of a grasping task.

Perhaps closest to our work is *active perception* and *sensor planning* [44, 38, 17, 23, 24, 48, 26, 11, 34] which refer to the integration of sensing and decision-making processes within a robotic system. This involves actively acquiring and utilizing information from the environment and selecting viewpoints or trajectories likely to reveal relevant information or reduce uncertainty [46, 9]. While these include work on active perception in manipulation tasks they mostly focus on assessing the effect various perspectives will have on the ability to correctly locate and classify objects [44, 30]. We offer a general formulation of VOA for

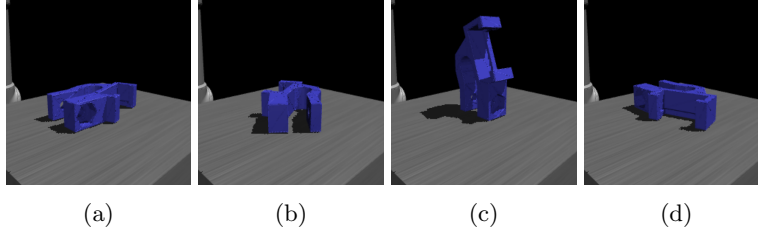


Fig. 2: Example stable poses.

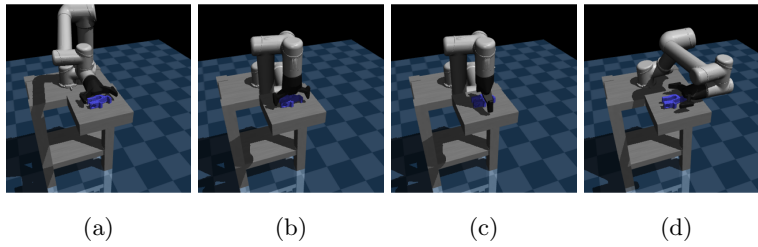


Fig. 3: Example grasp configurations from which the actor can attempt to grasp the object - each configuration is associated with a score, i.e., probability of success.

grasping and novel ways to estimate the effect an observation will have on the probability of accomplishing a grasp.

Since our focus is on settings in which information acquisition actions are limited and may be performed by another agent, our work is also highly related to *decision-theoretic communication* in particular, where agents communicate over a limited-bandwidth channel and messages are chosen to maximize the utility or effectiveness of the communication [19, 11, 26, 20, 32]. Our novelty is in offering measures that account for the manipulation and sensing capabilities of robotic agents when assessing the value of communicating an observation within a collaborative grasping setting. Our key contributions are the following:

1. We introduce and formulate *Value of Assistance* (VOA) for grasping.
2. We instantiate VOA for a collaborative grasping setting with a robotic arm equipped with a gripper and another agent equipped with either a lidar or a depth camera.
3. We empirically demonstrate in both simulated and real-world robotic settings how VOA predicts the effect an observation will have on performance and how it can be used to identify the best assistive action.

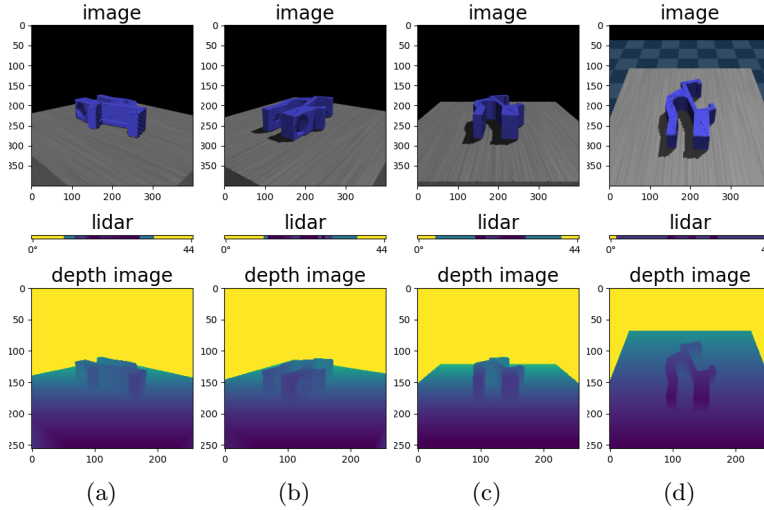


Fig. 4: Example sensor configurations. Each column represents the RGB image [top] lidar reading [middle] and depth image [bottom] for a sensor configuration-object pose pair.

2 Preliminaries

To support a grasping task, where the object is assumed to be in a stable pose, we use a function that assigns a score to a grasping configuration - object stable pose pair.

Definition 1 (Grasp Score). *Given a set of object poses \mathcal{P} and a set of grasp configurations \mathcal{G} , a grasp score function $\gamma : \mathcal{G} \times \mathcal{P} \mapsto [0, 1]$ specifies the probability that an actor applying grasp configuration $g \in \mathcal{G}$ will successfully grasp an object at pose $p \in \mathcal{P}$, i.e. $\gamma(p, g) = P(s|p, g)$, where s is the event of a successful grasp.*

The grasp score function may be evaluated analytically, by considering diverse factors such as contact area, closure force, object shape, and friction coefficient [36, 13] or empirically, by using data-driven approaches such as [31] where a deep learning model is trained to predict the quality of grasps based on depth images of the objects.

The actor’s choice of a grasp configuration relies on a *pose belief* which describes the perceived likelihood of each object pose within the set of possible stable poses \mathcal{P} .

Definition 2 (Pose Belief). *A pose belief $\beta : \mathcal{P} \mapsto [0, 1]$ is a probability distribution over \mathcal{P} .*

The pose belief is affected by different factors, including the model of the object and its dynamics and the collected sensory information. We formulate the initial belief after the object is dropped (Figure 1) using a joint probability

model that captures the prior probability of stable poses, a von Mises PDF for the angle [33], and a multivariate normal distribution for the position on the plane. See Section 1 of our online appendix for the formulation¹.

Definition 3 (Expected Grasp Score). *For grasp configuration g and pose belief β , the expected grasp score $\bar{\gamma}(g, \beta) = \mathbb{E}_{p \sim \beta}[\gamma(g, p)]$ is the weighted aggregated grasp score over the set of possible poses. A maximal grasp of β , denoted $g^{max}(\beta)$, maximizes the expected grasp score, i.e., $g^{max}(\beta) = \arg \max_{g \in \mathcal{G}_a} \bar{\gamma}(g, \beta)$.*

The actor receives an *observation* from the helper which corresponds to its readings from a specific sensor configuration $x \in \mathcal{X}$ and object pose $p \in \mathcal{P}$. Our formulation of the *observation space* O is general and represents the set of readings that can be made by the sensor that is available in the considered setting. In our evaluations, we used a planar lidar sensor for which a reading is an array of non-negative distances per angle \mathbb{R}^{360} and a depth camera which emits a 2D array $\mathbb{R}^{w \times h}$, where $w \times h$ are the image dimensions.

As is common in the literature, (e.g., [47, 29]), we consider obtaining an observation as a stochastic process.

Definition 4 (Sensor Function). *Given object pose $p \in \mathcal{P}$, sensor configuration $x \in \mathcal{X}$, and observation $o \in O$, sensor function $\mathcal{O}(o, p, x) = P(o|p, x)$ provides the conditional probability of obtaining o from x for p .*

Notably, an agent may not be aware of the actual distribution and may instead only have a *predicted sensor function* $\hat{\mathcal{O}}$ and a *predicted observation probability* $\hat{P}(o|p, x)$, based on a distribution which may be incorrect or inaccurate.

When receiving an observation o , the actor updates its belief using its *belief update function* which defines the effect an observation has on the pose belief.

Definition 5 (Belief Update). *A belief update function $\tau : \mathcal{B} \times O \times \mathcal{X} \mapsto \mathcal{B}$ maps belief $\beta \in \mathcal{B}$, observation $o \in O$ and sensor configuration $x \in \mathcal{X}$ to an updated belief $\beta^{o,x}$.*

The literature is rich with approaches for belief update (e.g., [47, 45, 23, 28]). We use a Bayesian filter such that for any observation $o \in O$ taken from sensor configuration $x \in \mathcal{X}$, the updated pose belief $\beta^{o,x}(p)$ for pose $p \in \mathcal{P}$ is given as

$$\beta^{o,x}(p) = \frac{\hat{P}(o|p, x) \beta(p)}{\int_{p' \in \mathcal{P}} \hat{P}(o|p', x) \beta(p') dp'} \quad (1)$$

where $\beta(p)$ is the estimated probability that p is the object pose prior to considering the new observation o .

When $\hat{\mathcal{O}}$ and \hat{P} describe stochastic processes they can be directly used for belief update using Equation 1. Sometimes, it may be useful to consider deterministic sensor functions where the conditional distribution of an observation is

¹ <https://github.com/CLAIR-LAB-TECHNION/GraspVOA>

replaced by a deterministic mapping $\hat{O} : \mathcal{P} \times \mathcal{X} \mapsto O$. For example, a deterministic sensor model would assign the value of a cell in a lidar reading based on the predicted distance between the lidar and the object surface at a specific angle. A stochastic sensor model would sample from a Gaussian distribution with this value as the mean and the specified error margins as the standard deviation.

In some cases, such as when using a deterministic sensor model, a similarity score $\omega : O \times O \mapsto [0, 1]$ is used to compare the predicted and received observations and to compose a valid distribution function for \hat{P} :

$$\hat{P}(o|p, x) = \frac{\omega(\hat{O}(p, x), o)}{\int_{p' \in \mathcal{P}} \omega(\hat{O}(p', x), o) dp'} \quad (2)$$

The literature is rich with ways to measure ω , which may vary between applications and sensor types. See Appendix 3 for a description of several approaches including using MSE for assessing the similarity between lidar sensor readings and an SSIM-based measure [49] for depth images.

3 Value of Assistance (VOA) for Grasping

We offer ways to assess the effect sensing actions will have on the probability of successfully grasping an object. We formulate this as a two-agent collaborative grasping setting with an *actor* that is tasked with grasping an object for which the exact pose is not known and a *helper* that can move to a specific configuration within its workspace to collect an observation from its sensor and share it with the actor.

We note that we use a two-agent model since it clearly distinguishes between the grasping and sensing capabilities. Depending on the application, this model can be used to support an active perception setting in which a single agent needs to choose whether to perform a manipulation or sensing action if it is capable of both.

The actor chooses a grasp configuration based on its *pose belief* (Definition 2). While the object’s exact pose is unknown, its shape is given and it is assumed to be in a stable pose (see Figure 2). The actor needs to choose a feasible *grasp configuration* $g \in \mathcal{G}$ from which a grasp will be attempted (see Figure 3) based on its pose belief and grasp score function. The helper can choose among a set of *sensor configurations* $x \in \mathcal{X}$ that offer different points of view of the object (Figure 4) and a potentially different effect on the actor’s pose belief.

We aim to assess *Value of Assistance* (VOA) for grasping as the expected benefit an observation performed from a sensor configuration will have on the actor’s probability of a successful grasp. Our perspective is that of the helper and its decision of which sensing action to perform. Accordingly, we seek a way to estimate beforehand the effect an expected observation will have on the actor’s belief and on its choice of configuration from which to attempt the grasp.

Importantly, the helper’s belief may be different than that of the actor. We denote the helper and actor pose beliefs as β_h and β_a , respectively. We note

that when considering a single agent with sensing and grasping capabilities the computation remains the same, with $\beta_a \equiv \beta_h$.

A key element in VOA computation is the expected difference between the utility of the actor with and without the intervention. Here, utility is the grasp score of the configuration chosen by the actor based on its belief.

Definition 6 (Value of Assistance (VOA) for Grasping). *Given actor belief $\beta_a \in \mathcal{B}$, helper belief $\beta_h \in \mathcal{B}$, helper perceived sensor function \hat{P}_h , sensor configuration $x \in \mathcal{X}$ and actor belief update function τ_a ,*

$$U_x^{VOA}(\beta_h, \beta_a) \stackrel{\text{def}}{=} \mathbb{E}_{p \sim \beta_h} \left[\mathbb{E}_{\hat{o} \sim \hat{P}_h(o|p, x)} \left[\gamma(g^{max}(\beta_a^{\hat{o}, x}), p) \right] - \gamma(g^{max}(\beta_a), p) \right] \quad (3)$$

where \hat{o} is the predicted observation and $\beta_a^{\hat{o}, x}$ is the predicted actor's belief after receiving \hat{o} from sensor configuration x and updating its belief, i.e., $\beta_a^{\hat{o}, x} = \tau_a(\beta_a, \hat{o}, x)$.

In the definition above, the maximal grasp g^{max} is the one that maximizes the expected grasp score $\bar{\gamma}$ as in Definition 3. Since VOA estimation is performed by the helper, observation \hat{o} is extracted from its predicted observation probability \hat{P}_h . In contrast, the actor's belief update is based on τ_a and uses Equation 1 with its own perceived observation probability \hat{P}_a .

For simplicity of presentation, we hereon assume that the actor and helper share an initial pose belief β before the grasp attempt. In addition, we assume the predicted observation \hat{o} is generated using a deterministic sensor function such that $\hat{o} = \hat{\mathcal{O}}(p, x)$. The updated belief is then a function of p and x and is denoted as $\beta^{\hat{o}}$. We note that our evaluation and analysis can be adapted to the more general settings in which these assumptions are relaxed, but this allows us to use a simplified VOA formulation as follows

$$U_x^{VOA}(\beta) \stackrel{\text{def}}{=} \mathbb{E}_{p \sim \beta} \left[\gamma(g^{max}(\beta^{\hat{o}}), p) - \gamma(g^{max}(\beta), p) \right] \quad (4)$$

Algorithm 1 in Appendix 2 describes how VOA can be used for supporting the helper's decision of which sensing action to perform. The algorithm includes the ComputeVOA function for computing VOA for a sensor configuration. We also provide a complexity analysis for the algorithm.

4 Empirical Evaluation

The objective of our evaluation is to examine the ability of our proposed VOA measures to predict the effect sensing actions will have on the probability of a successful grasp and on finding one that maximizes this probability. With this objective in mind, our evaluation is comprised of three parts.

1. **Evaluating grasp score:** measuring the success ratio $\gamma(p, g)$ for grasping an object at pose p from grasp configuration g for different objects.
2. **Evaluating $\hat{\mathcal{O}}$:** examining the difference between the predicted sensor function $\hat{\mathcal{O}}$ and the readings of the actual sensor \mathcal{O} .
3. **Assessing VOA:** assessing how well VOA estimates the effect observations will have on grasp score and its ability to identify the best sensing action.

4.1 Experimental Setting

We performed our evaluation in a two-agent robotic setting, both at the lab and in simulation. In our lab setting, depicted in Figure 1, the actor is a UR5e robotic arm [6] with an OnRobot 2FG7 parallel jaw gripper [3]. We used two implementations for the helper with two different sensors that might be available, depending on the setting: a LDS-01 lidar [5] that could be moved on the x-y plane and a 2.5D Onrobot vision system [3] mounted on an adjacent UR5e arm. For simulation, we used a MuJoCo [2] environment (depicted in Figure 3) [18]. We simulated a lidar sensor using the MuJoCo depth camera, taking only one row of the camera’s readings. The simulated gripper was a Robotiq 2F-85 parallel jaw [4]. We used five objects for the simulation and lab experiments (Figure 5). Objects meshes are based on the Dex-Net dataset [1].

We sampled a set $\tilde{\mathcal{P}} \subseteq \mathcal{P}$ of stable poses and considered four possible grasps g indexed 1 – 4 (see Figure ??). We used both the lidar and depth camera. For each object pose $p \in \tilde{\mathcal{P}}$, we recorded the observation o and the predicted observation \hat{o} received from each sensor configuration, indexed $I - IV$ for the lidar and $I - VI$ for the depth camera.

We empirically evaluated grasp score by examining a set of pose-grasp pairs for each object in both simulated and lab settings. Due to space constraints, the full details and results can be found in Section 4 of our online appendix.

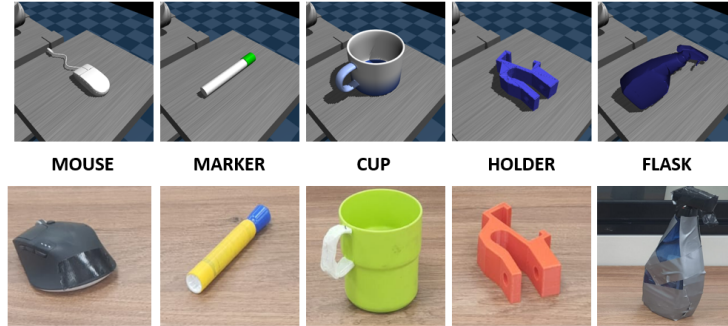


Fig. 5: Evaluation objects

4.2 Evaluating the Predicted Sensor Function $\hat{\mathcal{O}}$

We evaluated our predicted sensor functions $\hat{\mathcal{O}}$ for both the lidar and depth camera by comparing their predicted observations to the readings collected from the sensor (Figure 6). For each sensor configuration-object pose pair, we recorded the mean error of the difference between the measured and predicted readings. For the lidar, the set $\tilde{\mathcal{X}}$ included four sensor configurations for each cardinal direction and $\hat{\mathcal{O}}$ computed the closest intersection between the simulated lidar ray

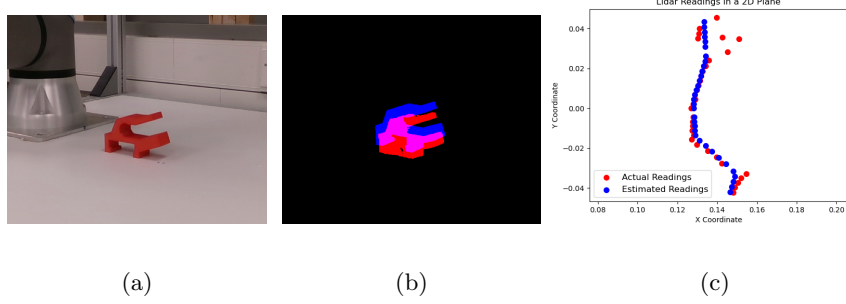


Fig. 6: Observations of HOLDER (a) Actual scene. (b) Comparing the predicted depth image (blue) and the lab-recorded image (red). (c) Comparing the predicted (blue) and lab-recorded (red) 2D representation of the lidar reading.

and the object meshes for the relevant FoV. The actual observations generated by \mathcal{O} for this setup were collected in simulation and the lab. However, while in the lab the lidar was able to capture all objects, in simulation MOUSE and MARKER, could not be captured.

For the depth camera, $\hat{\mathcal{O}}$ rendered synthetic images using the pyrender library [35] which involved projecting the 3D model of an object (transformed into a specific pose), onto a 2D plane using the camera’s intrinsic and extrinsic parameters. We evaluated our observation prediction accuracy compared to the actual image using the Intersection over Union (IoU) measure: we preprocessed the RGB images to extract the object masks and computed IoU between these and the corresponding synthetic images. The set \mathcal{X} of sensor configurations was generated by randomly sampling robot configurations $q \in (-\pi, \pi]^6$ and translating them into camera poses using forward kinematics i.e. $x = FK(q)$. Each sensor configuration $x \in \mathcal{X}$ was ranked using a heuristic

$$H(x) = \left(1 - \frac{D(x)}{D_{max}}\right) + V(x) \quad (5)$$

where $D(x)$ is the Euclidean distance between the camera’s center and the Point of Interest (PoI), representing the mean landing position after the object is dropped, D_{max} is a maximum acceptable distance used for normalization, and $V(x)$ is a visibility score, which assesses how centered the PoI is within the camera’s FoV and is computed as the distance between the projection of the PoI onto the image plane and the center of the image divided by R_{ref} , a reference radius within the image plane that represents the boundary of acceptability.

Results: In appendix 5 the table presents results per sensor for HOLDER (results for all objects are in our online appendix). For each sensor configuration x of the lidar, the table shows the average, minimal and maximal error (Avg. Err., Min. Err. and Max. Err., respectively) in mm over object poses $\tilde{\mathcal{P}}$. Similarly, for the depth camera, we computed the average, maximal, and minimal IOU values.

Results for the lidar show that the prediction errors are negligible given the dimensions of the objects examined. In contrast, for the depth camera, errors are

more substantial with a maximal average of 0.6. At the same time, results show varying performance across different configurations, depending on the object and its pose. For example, configuration *I* gives high accuracy for some objects, while configuration *IV* excels for others.

Inconsistencies between the observations are the result of several factors including the noise of the sensor itself, inconsistent scaling of the meshes with regard to the real objects, mismatches between objects and the meshes used for estimation, and inaccuracies in the placement of the objects in the lab (while the observation prediction is based on perfect object positioning). In addition, as the distance between the sensor and the object increases, the object occupies less of the sensor’s FoV and the readings include fewer and less informative data points. Specific to the depth camera is the confusion caused by the reflection of bright light on shiny surfaces which may distort object shape.

Figure 6 demonstrates inconsistencies between the predicted and actual observation of HOLDER at the lab. Here, this is due to the misplacement of the object. As we show next, despite these inconsistencies, the estimated observations are still useful for VOA computation.

4.3 Assessing VOA

We estimate the benefit of using VOA as a decision-making tool by assessing the benefit of choosing which sensor configuration to apply based on VOA values. Our evaluation uses the setting depicted in Figure 1 and assumes the initial pose belief (after the object drops) is shared by the actor and helper. The model of the initial belief is described in Section 2.

We used three belief update functions per sensor, each based on a different similarity metric. For the lidar, τ_1 uses a deterministic update rule that considers two observations o_i, o_j as equivalent if for all angles the values are within a margin of 8 mm, τ_2 uses the similarity metric $\omega(o_i, o_j) = e^{-\|o_i - o_j\|}$ to update the belief based on Equation 2, while τ_3 uses a multidimensional Gaussian over one observation while the other observation is the mean vector and the covariance matrix is the identity matrix. For the depth camera, τ_4 is based on the structure element of SSIM [49], τ_5 is based on IoU between the two observations, and τ_6 employs the cv2 library [15] for contour matching to quantify the similarity between two masks by detecting their primary contours and comparing their shapes through a shape-matching algorithm.

Results: Table 1 presents our evaluation for the different objects at the lab². For each setting, we consider three grasps: g^* is an optimal grasp, g_i is the grasp chosen by the actor based on its initial belief, and g_f is its post-intervention choice, i.e., after receiving an observation from a sensor configuration with the highest VOA value (see Figure 7). For each belief update function and object, the table reports the average values of:

- $\delta = \mathbb{E}_{p \sim \beta} [\gamma(g_f, p) - \gamma(g_i, p)]$: the weighted score difference between the chosen grasp after and before the intervention.

² Complete results as well as our implementation, are in our online appendix.

- $\delta^* = \frac{\mathbb{E}_{p \sim \beta}[\gamma(g_f, p) - \gamma(g_i, p)]}{\mathbb{E}_{p \sim \beta}[\gamma(g^*, p) - \gamma(g_i, p)]}$: the ratio between δ and the weighted score difference between the best configuration and the configuration chosen before the intervention.
- $\mathcal{A} = \delta^*(x) - E_{x' \sim \tilde{\mathcal{X}}}[\delta^*(x')]$: the difference of choosing the maximal VOA sensor configuration defined as the ratio between δ^* and the average over all configurations. This represents the difference between choosing a sensor configuration using VOA to choosing randomly.

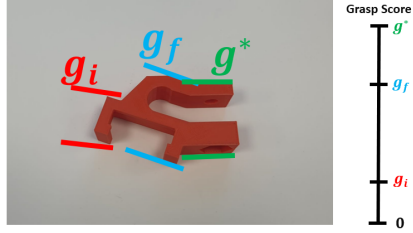


Fig. 7: Grasps for HOLDER: best grasp g^* , initial chosen grasp g_i and chosen grasp after the intervention g_f .

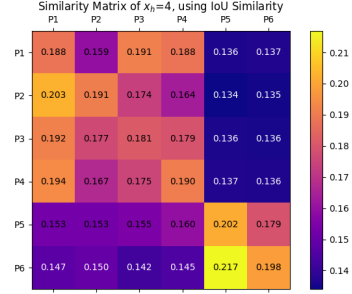


Fig. 8: Similarity score between actual observation (rows) for each pose and predicted observations (columns).

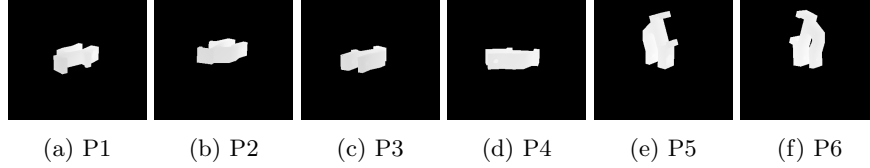


Fig. 9: Observations for different object poses of HOLDER

Results show that for all objects and for 4 of our examined belief update functions (τ_1 - τ_4), selecting the sensor configuration with the highest VOA value is beneficial in terms of the three examined measures. The smallest benefit is for MOUSE for which the initial grasp is optimal for all poses except one for which the optimal grasp has only a slight advantage. This subtlety is captured only by τ_4 .

Notably, belief update functions τ_5 and τ_6 which rely on IOU and contour matching, respectively, did not perform well on average for any of the objects. We associate this with the fact that the objects examined are small relative to their distance from the sensor, which is something these update functions are sensitive to. Figure 8 presents the similarity scores between the actual (rows) and predicted (columns) observations for τ_5 that relies solely on the IoU of the

		δ	δ^*	\mathcal{A}			δ	δ^*	\mathcal{A}
<i>HOLDER</i>	τ_1	0.19	0.23	0.23	<i>CUP</i>	τ_1	0.30	0.33	0.30
	τ_2	0.15	0.23	0.29		τ_2	0.30	0.33	0.41
	τ_3	0.2	0.26	0.28		τ_3	0.37	0.63	0.37
	τ_4	0.03	0.15	0.13		τ_4	0.24	0.38	0.27
	τ_5	0.0	0.0	0.0		τ_5	0.00	0.00	0.00
	τ_6	0.0	0.0	0.0		τ_6	0.00	0.00	0.00
<i>EXPO</i>	τ_1	0.29	0.31	0.29	<i>FLASK</i>	τ_1	0.25	0.25	0.25
	τ_2	0.29	0.31	0.29		τ_2	0.25	0.25	0.25
	τ_3	0.29	0.31	0.29		τ_3	0.25	0.25	0.25
	τ_4	0.04	0.37	0.29		τ_4	0.02	0.25	0.25
	τ_5	0.00	0.00	0.00		τ_5	0.00	0.00	0.00
	τ_6	-0.00	0.29	0.29		τ_6	0.00	0.00	0.00
<i>MOUSE</i>	τ_1	0.00	0.06	0.04	AVG	τ_1	0.19	0.23	0.23
	τ_2	0.00	0.05	0.04		τ_2	0.19	0.23	0.29
	τ_3	0.00	0.07	0.00		τ_3	0.20	0.26	0.28
	τ_4	0.04	0.44	0.53		τ_4	0.08	0.22	0.34
	τ_5	0.00	0.00	0.00		τ_5	0.00	0.00	0.00
	τ_6	0.00	0.00	0.00		τ_6	0.00	0.00	0.00

Table 1: Results per belief update rule (best results per criteria are highlighted)

masks without considering depth values. This makes it hard for τ_5 to differentiate between object poses that occupy the same area across multiple poses, as depicted in Figure 9. The matrix shows a clear distinction between the standing positions 5 and 6 and the laying positions 1 – 4, but the distinction within these two groups is challenging. Another critical issue is demonstrated by the values on the diagonal that show the low similarity scores between the predicted and actual observations. These indicate the sensitivity of τ_5 to noise in the actual image, where even slight distortions can dramatically impact prediction quality. Similar results were observed for τ_6 where noise dramatically distorts contours.

5 CONCLUSION

We introduced *Value of Assistance* (VOA) for grasping and suggested ways to estimate it for sensing actions. Our experiments in both simulation and real-world settings demonstrate how our VOA measures predict the effect an observation will have on performance and how it can be used to support the decision of which observation to perform.

Future work will account for optimization considerations of the helper and for integrating VOA in long-term and complex tasks. Another extension will consider multi-agent settings in which VOA can be used not only for choosing which assistive action to perform but also for choosing which agent to assist.

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