Physics-Based Selection of Informative Actions for Interactive Perception

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***Abstract*— Interactive perception exploits the correlation between forceful interactions and changes in the observed signals to extract task-relevant information from the sensor stream. Finding the most informative interactions to perceive complex objects, like articulated mechanisms, is challenging because the outcome of the interaction is difficult to predict. We propose a method to select the most informative action while deriving a model of articulated mechanisms that includes kinematic, geometric, and dynamic properties. Our method addresses the complexity of the action selection task based on two insights. First, we show that for a class of interactive perception methods, information gain can be approximated by the amount of motion induced in the mechanism. Second, we resort to physics simulations grounded in the real-world through interactive perception to predict possible action outcomes. Our method enables the robot to autonomously select actions for interactive perception that reveal most information, given the current knowledge of the world. This leads to improved perception and more accurate world models, finally enabling robust manipulation.**

I. Introduction

A robot that interacts with the physical world must possess knowledge about the objects it manipulates. Rather than equipping the agent with all required object knowledge a priori, a more reasonable approach is to provide the robot with the ability to interactively acquire object models from perception. A family of methods, subsumed under the term *interactive perception*, proposed ways to realize such a perceptual skills. The core idea behind all those methods is to make interactions part of the perceptual process by exploiting forceful interactions and the information rich sensory signals they generate [1]. This idea has proven successful in perceptual tasks like object segmentation [2], [3], object classification [4], and object recognition [5].

Interactive perception increases its performance when actions are chosen that reveal most relevant information about the environment. Therefore, action selection must attempt to maximize the expected information gain. Usually, information gain is measured directly by estimating the entropy on the belief state of the environment. In this work, we advocate for the use of induced motion as an simple but effective proxy for information gain in the context of perceiving models of articulated objects. In this problem, motion is a good proxy as it reveals the articulation of the mechanism and the relationship between the motion of rigid bodies and the forces applied to them.

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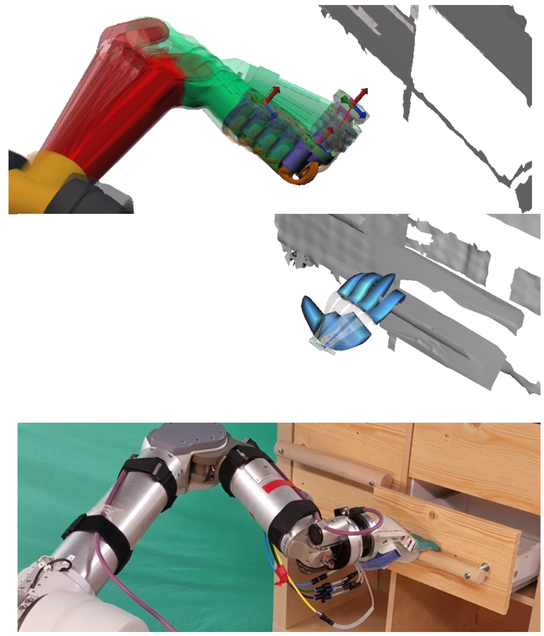

Fig. 1. The selection of informative actions for articulated objects in the context of interactive perception is split into two subproblems: (1) Generating actions that obey the constraints due to robot kinematics, collisions, and kinematics of the articulated object via sequential convex optimization [6] on a kinematic model (*top*); (2) The prediction of the outcome of the complex contact interactions between end-effector and object (*center*) with a dynamic physics simulation [7]; The execution of the selected motion (*bottom*) reveals information about the object enabling new and better manipulations

A crucial bottleneck in selecting informative actions is the model that is used to predict action outcomes. Manipulations of articulated objects are contact-rich interactions. The large variety of possible kinematic structures and their dynamic properties make it difficult to find general predictors of the real world. We therefore propose the use of a physical simulation for predicting and evaluating the outcome of actions. The proposed simulations are grounded in the real world because they are based on estimated articulated models obtained during interactive perceptual. To alleviate the accompanied computational costs of such simulations, we compare different sampling methods to select informative actions.

The contributions of this work are threefold: We show that motion can be used as a proxy for information gain and that the gained knowledge allows for riskier and more tailored manipulations. Second, we present a method to find informative actions by sampling physics simulations and splitting the search into kinematic and dynamic aspects. Finally, we integrate our proposed action selection method into a real-world robot system that perceives and interacts with articulated objects. This paper is based on a previous workshop contribution [8].

II. Related Work

Previous methods that select actions for interactive perception differ in *1)* how they assess the information gain of an action (some kind of cost or objective function), and *2)* how they explore the space of possible interactions to find the most informative one. One of the first methods in interactive perception (Tsikos and Bajcsy [9]) proposed an approach to map the content of a tray into a graphical representation that encodes the spatial distribution of objects. This representation is directly mapped into the best next action (e.g. shake the tray, pick and remove) to clear the tray. In a similar vein, Gupta and Sukhatme [10] proposed an approach to perceive the "amount of clutter" of objects on a table. The amount of clutter maps directly into the best next action (e.g. pick an object, push the clutter) to clear the table. Hermans et al. [11] presented an action selection method to push objects on a table and singulate them. Their method is based on the insight that pushing along the direction of visual edges between image regions would maximally help to separate objects. These methods generate an intermediate representation that maps heuristically to the most informative action. The set of possible actions is predefined and their outcome is not explicitly predicted. Differently, we do not use a representation tailored for the action selection task. Also, when interacting with articulated objects to perceive them, the complexity of the manipulation does not allow for a simplification of the outcome and requires to predict the effect of the interaction.

A second group of action selection methods use entropy-based information gain criteria to select the action of (expected) largest reduction on the uncertainty about the environment. Van Hoof et al. [2] presented a method to select the best pushing action to segment a cluttered scene. Their probabilistic model contains hypotheses about the regions that belong to the same object and serves as simple forward model. Our model contains more detailed kinematic and dynamic information that we use to obtain more descriptive action consequences and to generate and select more complex grasp-and-interact sequences. Hausman et al. [4] presented a method to select the best action to gain knowledge about the kinematic constraints of an articulated object. Similar to our approach, they require an initial human interaction. They assume a known grasping pose and select the best pulling direction. Otte et al. [12] proposed a similar method based on a physics simulator. Their method considers several single-joint articulated objects and selects to interact with the one that will reveal more information about the overall structure of the environment. Different to these methods, ours generates and autonomously selects complete actions—including grasping pose and manipulation trajectory—and incrementally incorporates and exploits information including dynamic properties.

Entropy-based methods require to predict 1) the outcome of an action, and 2) the influence of the outcome on the belief (through a perceptual system). Because both predictions are costly to compute, previous approaches generate a finite set of possible actions from the continuous space of action parameters based on a heuristic, and computes the most informative one. Our method addresses differently the challenges of searching for the most informative action: First, given that our perceptual system reduces entropy by accumulating motion evidences about the articulated object, we avoid the costly computation of the exact belief change for each action and predict instead the amount of actuation of the articulated mechanism. Second, we do not predefine a discrete set of actions but explore on the space of action parameters for the most informative.

The motion planning community has also addressed the problem of generating and planning interactions with articulated objects using knowledge about its kinematic constraints. These methods exploit the definition of the task (the manipulation of an articulated object) to simplify the generation and/or selection of actions [13], [14], [15], [16]. We also aim to obtain task-aware actions but do not rely on given models; on the contrary, our method integrates the action generation, selection and the perceptual problem into a single process and provides interactions that reveal more information to build a richer model. Stilman et al. [17] use the constraints of the articulated object to guide the search of robot trajectories in joint space. Instead of searching in the space of joint trajectories, we search in a simpler task-related action space and enforce the feasibility of the manipulation using trajectory optimization. Our goal is not to find one solution for the overly constrained motion planning problem, but rather to find the optimal solution to actuate the mechanism *and* reveal information about it.

Finally, the idea of using a physics simulator as a model for motion planning or action selection has been previously explored ([12], [18]). We think this is the best approach to avoid having to assume simplified action effects that cannot be predicted for complex objects. However, our approach is essentially different to the literature because we integrate a perceptual algorithm to ground the simulation to the real world, leading to more realistic simulated action effects.

III. Physics-Based Action Selection

Our approach estimates a (partly) probabilistic model of an unknown articulated object and selects the action that reveals most information to improve this estimate. In the following we describe what exactly is represented in the model, how it is updated, and how informative actions are generated and selected.

A. Representing and Estimating Articulated Objects

We represent an articulated object (*ao*) as an undirected graph, $x_{ao} := (L, J)$, where the set of nodes L are links and the set of edges J represent joints. A link $l_i \in L$ is represented with a triangular mesh of its shape s_i. A joint

$j_k \in J$ is represented with random variables of its kinematic and dynamic properties:

$$j_k := (t_k, \theta_k^{prism}, \theta_k^{rev}, \theta_k^{rig})$$

where $t_k \in \{Prismatic, Revolute, Rigid, Disconnected\}$ is a discrete random variable over possible single-DoF joint types and $\theta_k^{prism}, \theta_k^{rev}, \theta_k^{rig}$ are independently updated multi-dimensional random variables of the kinematic (ϕ_k, q_k) and dynamic $(F_k^{Stiction}, F_k^{KinFriction})$ properties for prismatic, revolute and rigid joint hypotheses (disconnected joints are parameter-free). ϕ_k is a multi-dimensional random variable of the joint-specific parameters: a drawer ($t_k = Prismatic$) is parametrized with a two dimensional Gaussian distributed variable for the joint axis orientation in spherical coordinates, and a door ($t_k = Revolute$) is parametrized with a similar variable for axis orientation and an additional three dimensional Gaussian distributed variable for axis position. q_k is a Gaussian distributed variable of joint's configuration, $F_k^{Stiction}$ is a Gaussian distributed variable of the force to overcome stiction (force required to initiate joint motion), and $F_k^{KinFriction}$ is a Gaussian distributed variable of the kinetic friction (force required to maintain joint motion).

The parameters of the distributions over joint type, joint parameters and configuration are estimated online from the motion perceived in the RGB-D stream of an interaction with the articulated object. The estimation is factorized into three subproblems that are solved via Bayesian recursive estimation: the estimation of motion of salient point features in the image stream, of motion of rigid bodies from assigned sets of features, and of the kinematic properties from motion constraints in the rigid bodies [19]. This perceptual algorithm uses observations of the motion of the mechanism as source of information to reduce the uncertainty about the kinematic model, becoming more accurate the more actuation is observed.

We estimate the shape models s_i of the links also from RGB-D data. The estimation of the shape models exploits the estimated rigid body motion and, in a recursive manner, the previously estimated shape to segment the RGB-D images into areas occupied by each link. These areas are accumulated as point clouds and used to generate a triangular mesh of the surface of each link [20].

The force to overcome stiction and kinetic friction of a joint are estimated combining force-torque signals at the end-effector, the end-effector pose and the estimated kinematic constraints [21]. The applied wrench is projected into the dimensions where the actuation of the articulated mechanism is kinematically allowed or constrained. The tangential component (working wrench) is combined with the perceived change in the kinematic state of the object (the velocity of the joints) to estimate the force necessary to initiate the actuation from a resting state (stiction) and the minimum force to maintain the actuation (kinetic friction). We deem the effect of other dynamic processes (e.g. damping, viscous friction,…) to be negligible for the objects and the contact interactions we consider. This method reduces further the

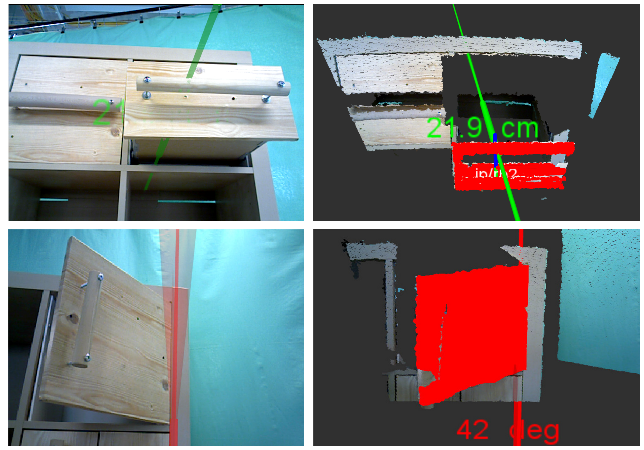

Fig. 2. Left: robot view at the end of a human interaction with the articulated objects (estimated kinematic structure overlaid: prismatic joints in green, revolute joints in red, uncertainty indicated with translucent cones); Right: 3D visualization of the interaction and the estimated kinematic model and state (reconstructed shape of the movable link in red)

uncertainty over the dynamic parameters by integrating more haptic measurements collected during motion.

The prerequisite of these perceptual methods is a forceful interaction with the articulated object that generates *motion* and information-rich sensor-action signals. While kinematic and shape properties can be estimated both from observing another agent interacting or (more easily) from self-interaction, the estimation of dynamic properties requires the robot to contact the object to obtain haptic sensor signals. In previous publications this prerequisite was circumvented by predefining contact-rich interactive manipulations. In this work we address the generation and selection of the most informative interactions to be used by the aforementioned interactive perceptual methods.

B. Selecting Actions for Articulated Objects

Our goal is to generate and select robot actions that learn as much about the articulated object as possible, i.e. decrease the uncertainty of the estimate x_{ao}. To achieve this we use a task-specific objective—maximizing the motion of the articulated object—since this is the main source of information for our interactive perception method. However, when revealing information of articulated objects there are additional (kinematic) constraints that the action needs to satisfy. And because our goal is to generate actions to be executed by a real robot, the specific robot manipulator additionally restricts the actions: they have to be achievable given the kinematics of the manipulator and should not lead to collisions of the robot with the environment. Considering these requirements, we are looking for an action

$$\begin{aligned} a^* = \operatorname*{argmax}_{a \in A} \Delta q(a) & \\ \text{subject to} \quad & \text{valid\_robot\_kinematics}(a), \\ & \text{valid\_object\_kinematics}(q), \\ & \text{collision\_free}(a) \end{aligned}$$

where $\Delta q(a)$ is the change of the object's kinematic configuration induced by the robot action a.

Algorithm 1 Physics-Based Action Selection

Input: x_{ao} ▷ The current estimate of the articulated object.

$A \leftarrow \emptyset$, $Q \leftarrow \emptyset$ ▷ The set of all available actions and the corresponding induced articulated object motion.
$O \leftarrow$sample(x_{ao}) ▷ Sample N_{model} objects
for $i = 1..N_{batches}$ **do**
  $A^{new} \leftarrow$ sample(A) ▷ Sample $N_{batchsize}$ actions
  $A^{new} \leftarrow$ constrain(A^{new})
  for $a \in A^{new}$ **do**
    for $o \in O$ **do**
      $\Delta q_k^o \leftarrow$ simulate(a, o) ▷ Simulate an action on a current articulated object sample (SOFA)
    $A \leftarrow A \cup \{a\}$, $Q \leftarrow Q \cup \{\frac{1}{N_{model}} \sum_o \Delta q_k^o\}$
  $a^* \leftarrow \underset{a \in A}{\text{argmax}}\, Q_a$
return a^*

To maximize the amount of motion and actuation of the mechanism we parametrize a by assuming three phases: reach towards a grasping/pushing pose, close the hand and move it along the estimated DoF of the mechanism. The first part is fully characterized with a grasping/pushing frame (that we assume to be on the surface of the movable link) and an approach vector towards this frame. We use a soft hand (the RBO Hand 2 [22]) in our interactions that simplifies the search problem because it adapts morphologically to the environment during the closing phase and avoids having to define additional grasping parameters. The last phase is a motion of the hand along the dimension of allowed motion of the articulated object. To avoid reaching the joint limits of the mechanism we generate motion between the borders of the joint state range observed so far. Therefore, an action a is defined as $a \in \mathbb{S}^2 \times SE(3)$.

The effect of an action a in terms of the motion $\Delta q_k(a)$ induced on the articulated object is predicted using the physics simulation SOFA [7]. Fingers of the RBO Hand 2 are modelled as Cosserat beams, while the collision geometry is determined via skinnning. A compliance-based method resolves collisions [23]. The simulation is spawned with the current estimate x_{ao} by including the reconstructed triangular meshes for each rigid body, s_i, the estimated kinematic constraints t_k, θ_k, poses q_k, and frictional properties $F_k^{Stiction}, F_k^{KinFriction}$. To account for the probabilistic components of x_{ao}, we draw $N_{model} = 3$ samples for each simulated action. Because the simulation of contact and interaction of the soft-manipulator with the articulated object is computationally expensive we pre-impose the constraints due to the robot manipulator on the action. We enforce that the robot's, object's kinematic constraints and collision constraints are fulfilled using a sequential convex optimization [6]. We simulate the robot-consistent actions on the physics simulator and estimate the expected actuation of the mechanism over the samples of the belief of the environment $\Delta q_k(a')$. The action selection process is summarized in Algorithm 1.

Sampling the space of action parameters and evaluating the induced motion to find a^* is costly. We compare three sampling schemes with increasing exploitation of previous sample quality: a random mesh-based sampling (pure exploration), an evolution strategy with Gaussian moves, and a sequential sampling based on batch Bayesian optimization. The assumption of the exploitative methods is that the similar actions will result in similar outcomes. The goal is to derive a sampling strategy that requires as few samples as possible to find informative actions avoiding costly simulations. To reduce the time required in the simulation of sampled actions, we parallelize them within batches, i.e. we evaluate $N_{batches}$ batches of $N_{batchsize}$ actions. In our experiments we use $N_{batches} = 10$ and $N_{batchsize} = 100$, totalling 1000 actions.

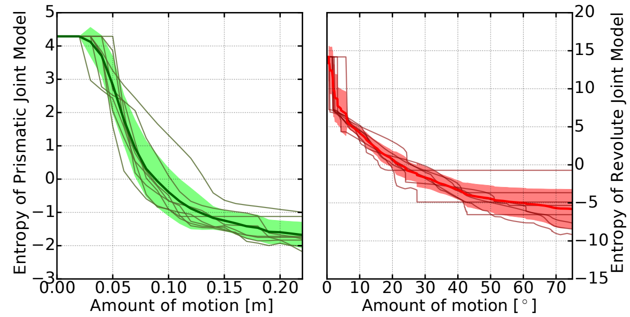

Fig. 3. The entropy of the probabilistic model of the articulated object decreases with the amount of motion in prismatic (*left*) and revolute (*right*) joints (eight interactions, mean and standard deviation are shown). The plots show that the entropy correlates strongly with the amount of actuation.

1) Random Sampling: The random sampling scheme uniformly selects a point on the mesh surface, a hand orientation and approach vector. In contrast to the two other schemes it is a pure exploration strategy, without taking past samples and their performance into account.

2) Evolution Strategy: For each new batch the evolution strategy uses $N_{batchsize}$ of all best performing past actions and mutates them by adding normally distributed noise. The standard deviation of the noise decreases linearly in the number of batch iterations. This creates the effect of going from an initially exploratory behavior towards an exploitative one, similar to the temperature decrease in simulated annealing. The very first batch uses only uniformly distributed random actions, as in the random sampling strategy.

3) Bayesian Optimization: In vanilla Bayesian optimization, samples are drawn sequentially based on an acquisition function which is estimated from known data. We use upper confidence bounds as our acquisition function. Since we want to sample entire batches of actions instead of single ones, we use a batch Bayesian optimization approach [24]. In this approach, samples within one batch are chosen iteratively as maximizers of the acquisition function. In each iteration a penalizing function is applied which discourages new samples in the local neighborhood of existing ones. The influence of the local penalizer depends on an estimate of the Lipschitz constant of the acquisition function which represents the smoothness of the function over the entire domain.

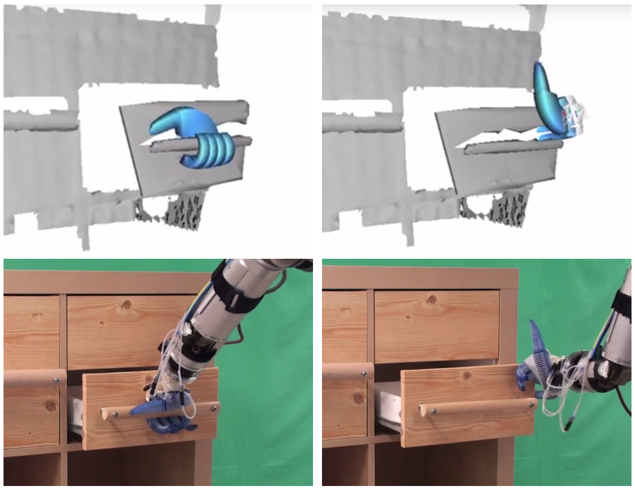

Fig. 4. The selected interaction changes based on the certainty about drawer's frictional properties. High uncertainty leads to a handle grasp (*left*) while knowledge of the low friction allows for a riskier edge grasp (*right*).

IV. Experiments

We evaluate our approach by first supporting our assumption that motion indicates the amount of information gained. Based on this result, we show that the informative actions incrementally improve the estimated model of the environment in real world experiments, and lead to more robust actions. Finally, we find that Bayesian batch optimization is the most efficient sampling strategy.

A. Induced Motion Correlates with Information Gain

The perceptual algorithm we use to update the belief about the state of the environment recursively integrates sensor evidences about the constraints of motion. We analyze the entropy reduction of our estimation algorithm on 16 examples of interactions with drawers and cabinet doors. This data was recorded from different point of views and contains human as well as robot interactions. Fig. 3 depicts the mean and standard deviation of the entropy as a function of the amount of induced actuation. Since all estimations begin with the same prior belief, the initial entropy is always the same. Our experiment confirms that the entropy of the estimate decreases monotonically as more motion of the mechanism is observed.

B. Acquiring Dynamic Information Improves Interactions

To show that our method selects informative actions which allow to plan more robust manipulations, we conduct two experiments with a drawer and a cabinet door, respectively. We use a 7-DoF Barrett WAM, equipped with the pneumatically actuated RBO Hand 2 [22], an Asus RGB-D sensor and an ATI FTN-Gamma force-torque sensor on the wrist (Fig. 1).

Our approach requires an initial human interaction, since it starts with the assumption that the environment is a single static rigid body. Once the mechanism has been articulated by a human, an initial kinematic model with significant certainty can be estimated (see Fig. 2). In contrast, the estimates of stiction and kinetic friction of the joints are still uncertain. Based on this model, our method generates and selects

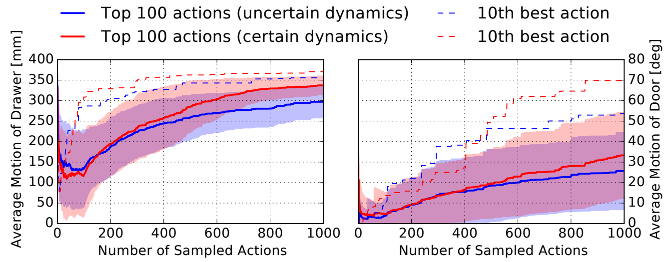

Fig. 5. Comparison of the random mesh-based sampling strategy on the models with uncertain (blue) and certain (red) dynamic parameters; after acquiring information about the dynamics the algorithm generates and selects interactions that lead to larger motion

an interaction that maximizes the expected articulation (see Fig. 6). By executing this action the robot gathers additional visual and haptic data to infer the joint's dynamic properties. In the drawer experiment, the estimated forces to overcome stiction and kinetic friction are 2.1 N and 0.5 N, in the same order of magnitude than the ground truth values measured with a dynamometer (2.9 N and 1.0 N).

Fig. 4 shows how certainty in the estimation of the drawer's dynamic parameters affects the selected interaction. During the first interaction our method finds a rather conservative handle grasp to generate the most motion in the face of unknown joint stiction and friction. After the first action, a riskier but more tailored manipulation is selected. Actuating the drawer by pulling the edge of its front part only works because of the low known joint resistance. This action would fail if the drawer was filled (see attached video). The effect of higher certainty in the estimated model of the drawer and cabinet door is also shown in Fig. 5. In both cases known dynamics lead to more solutions that cause large motions of the articulated object. In the cabinet door experiment the robot's haptic observation was noisier, leading to a less pronounced benefit compared to the drawer experiment.

C. Comparison of Action Sampling Schemes

We compare our three proposed action selection strategies (random sampling, an evolution strategy, and batch Bayesian optimization) to evaluate how many samples they require to approximate the optimal action. We ran those strategies on the drawer example and selected a total of 1000 actions in ten consecutive batches. The results in Fig. 6 show that focussing the search on promising actions—as done by the evolution strategy and Bayesian batch optimization—helps to find informative actions more quickly. The Bayesian optimization already finds multiple good solutions after 5 batches, while the evolution strategy becomes overly exploitative in the later stages.

V. Limitations

Our method can be applied to articulated objects with single-DoF joints, but it inherits the need for an initial interaction from our perceptual algorithm for the estimation of kinematic models [19], [20]. Without any initial information the amount of possible actions is too large to be searched randomly. However, the integration of action selection removes the need of a predefined robot interaction

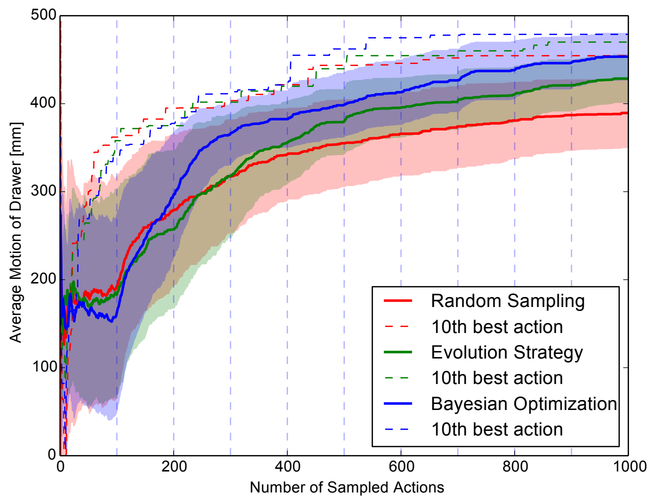

Fig. 6. Comparison of three sampling schemes, showing the mean (solid) and standard deviation of the induced motion of the top 100 actions and the 10th best action (dashed); dashed vertical lines depict ten batches; exploitative methods find an optimal set of actions more efficiently (with less samples).

to improve the initial model and perceive dynamic properties. The current method does not transfer knowledge to new articulated objects. This transfer could be realized by using an object classification that generalizes estimated information and successful interactions between instances of articulated objects. All three evaluated sampling schemes are initialized with a uniform sampling. An initial sampling based on heuristics exploiting shape or kinematic information, or by the same object classification to transfer information about object classes would reduce the amount of initial exploration. Another drawback is the high computational cost of the simulations. Although our methods parallelize the execution of multiple simulations, a single simulation takes on average 15 minutes.

VI. Conclusion

We presented a method to generate and select actions for interactive perception, exploiting the insight that for a class of interactive perception methods information gain correlates with the magnitude of the resulting motion (i.e. actuation of the articulated mechanism). Based on the proposed action selection, the robot incrementally builds increasingly rich and accurate models of articulated objects through interactions. We presented and evaluated different action sampling schemes to reduce the costly step of predicting the effects of the contact-based interactions while still finding the optimal action parameters. We validated our approach in real-world experiments with two articulated objects of different joint types, demonstrating that the method applies to both revolute and prismatic joints.

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