Physics-Based Selection of Actions That Maximize Motion for Interactive Perception

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Abstract— Interactive perception methods exploit the correlation between forceful interactions and changes in the observed signals to extract task-relevant information from the sensor stream. The amount of information that can be derived from a single interaction depends on the trade-off between two factors: the skillfulness of the interacting agent and the accessible sensor modalities of the observer. When observer and interactor are the same the contact with the environment generates a richer sensor stream, but the stream only contains relevant information if the interaction is meaningful. On the other hand, observing a knowledgeable agent ensures meaningful interactions but limits the available types of observations (e.g. haptic information from contact). We propose a method that incrementally builds up models of articulated objects that allow generating and selecting optimal exploratory manipulations for interactive perception. Our iterative method reduces the need of predefining motion for interactive perception: the robot can select autonomously the contact-involving action that reveals most information, which lead to improved models that enable better manipulations.

I. INTRODUCTION

A robot that interacts and manipulates the physical world around it must possess knowledge about the objects it possibly encounters during its lifetime. Rather than equipping the agent with all required object knowledge a priori, a more reasonable approach is to provide a skill that allows it to acquire object models as needed. A family of methods subsumed under the term *interactive perception* describes ways to implement such a perceptual skill. The core idea behind all those methods is to make interactions part of the perceptual process by exploiting knowledge about a forceful interaction and the sensory signals it generates and would otherwise not be present [1]. This idea has proven successful in perceptual tasks like object segmentation [2], [3], classification [4] and recognition [5].

An important characteristic of interactive perception is that the interaction can be performed either by the perceiving agent itself or any other agent. In the first case the interaction provides a richer set of sensory signals making it easier to infer haptic or dynamic object properties. However, it also assumes a meaningful interaction is known to the agent who is learning about the novel object. In contrast, when observing an experienced agent haptic or dynamic properties are hard or even impossible to infer.
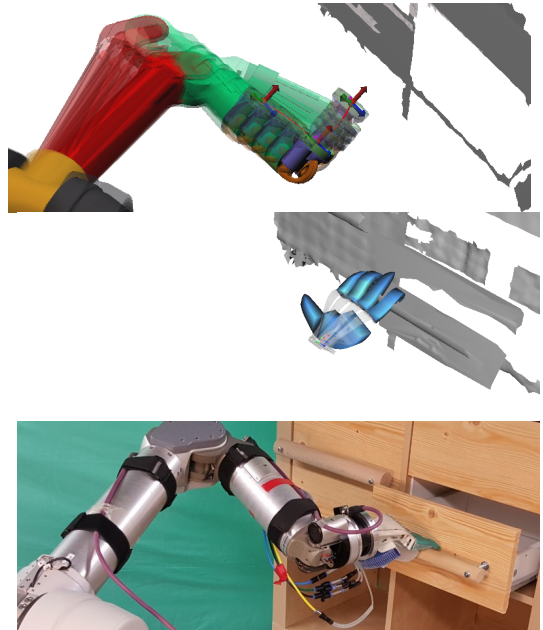
Fig. 1. The selection of desired motions for articulated objects in the context of interactive perception is split into two subproblems: (1) Constraints due to robot kinematics, collisions, and kinematics of the articulated object are satisfied via sequential convex optimization [6] on a kinematic model (*top*). (2) The complex contact interactions between end-effector and object (*center*) are evaluated with a dynamic physics simulation [7]. The execution of the selected motion (*bottom*) reveals information about the object, which in turn affects the next action selection.

In this work, we overcome the dichotomy between being in the driver's seat of the interaction and not being in the driver's seat, thereby enabling a reduction of the uncertainty about the environmental state. We propose an incremental approach that integrates the generation and selection of contact-rich actions as part of the perceptual process: Based on visually perceiving a skillful agent interacting with an unknown articulated object the robot builds a model that represents the gained knowledge about its different components, kinematic constraints and shape. Using this information the robot plans an informative contact-rich action that satisfies these constraints (kinematics, collisions) and allows to explore and reduce the uncertainty of physical properties that cannot be inferred visually, such as stiffness or friction. We close the loop and use this new information to generate, select and execute safer and more efficient interactions.

II. RELATED WORK

The task of selecting informative actions for interactive perception has been previously addressed. 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 search only for the best pulling direction. Otte et al. [8] proposed a similar method based on a physics simulator. Different to these methods, ours selects autonomously complete actions –including grasping pose and manipulation trajectory– and incrementally incorporates and exploits information including dynamic properties.

Previous work 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 [9], [10], [11], [12]. 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. [13] 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. Finally, the idea of using a physics simulator as a model for motion planning or action selection has been previously explored ([8], [14]). We think our approach is essentially different 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

The proposed approach alternates between estimating a (partly) probabilistic model of an arbitrary articulated object and selecting an action that improves 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 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 model of its shape s_i. A joint $j_k \in J$ is represented with random variables of its kinematic and dynamic properties:

$$j_k := (jt_k, jp_k, q_k, F_k^{Stiction}, F_k^{KinFriction}),$$

where jt_k is a discrete random variable over possible first-order joint types ($jt_k \in \{Prismatic, Revolute, Rigid, Disconnected\}$), jp_k is a continuous random variable of the joint-specific parameters (the drawer of our experiments is parametrized with a variable for the joint axis orientation in spherical coordinates, $jp_k = j_k^{ori} = (\phi_k, \theta_k)$), q_k is a continuous random variable of joint's configuration, $F_k^{Stiction}$ is a random variable of the force to overcome stiction (force required to initiate joint motion), and $F_k^{KinFriction}$ is a random variable of the kinetic friction (force required to maintain joint motion).

The joint type, parameters and configuration are estimated online from 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 point features in the image stream, of motion of rigid bodies from features, and of the kinematic properties from motion constraints in the rigid bodies [15].

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 the previous estimated shape to segment the RGB-D images into areas occupied by each link. The accumulated point clouds are then used to generate a triangular mesh per link [16].

The force to overcome stiction and kinetic friction of a joint are estimated combining force-torque signals at the end-effector, its pose and the estimated kinematic properties [17].

B. Selecting Actions for Articulated Objects

We would like 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. The planned actions also need to satisfy the robot's and the object's kinematic constraints, i.e. we are looking for action

$$a^* = \arg\max_{a \in A} \Delta q(a)$$
$$s.t. \quad robot\_kinematics(a),$$
$$object\_kinematics(q),$$
$$collision\_free(a)$$

where $\Delta q(a)$ is the change of the object's kinematic configuration induced by the robot action a. We parameterize a by assuming three phases: reach towards a grasping pose, close the hand and move it along the estimated DoF of the mechanism. The first part is fully characterized with a grasping frame and an approach vector. The last phase is just a motion of the hand along the dimension of allowed motion of the articulated object. Therefore, an action a is defined as:

$$a \in \mathbb{S}^2 \times SE(3) \times \mathbb{R}^3$$

We calculate the motion $\Delta q_k(a)$ of the articulated object given the robot's action a using the dynamic simulation SOFA [7]. SOFA is a simulator that provides physically

coherent interactions between an articulated object and a soft-manipulator like the RBO Hand 2. 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 jt_k, jp_k (ensuring the constraint $object_k inematics(q)$), poses, 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. We enforce that the robot's, object's kinematic constraints and collision constraints are fulfilled using a sequential convex optimization [6]. After running the simulations for a fixed amount of time we can calculate an expectation of $\Delta q_k(a')$.

To approximate a^* we implemented two sampling schemes: a systematic mesh-based sampling and a resampling with Gaussian moves. Both schemes start with the same set of $N_{actions} = 100$ uniformly distributed actions. But while the systematic schema keeps adding new uniformly distributed samples (pure exploration), the resampling with Gaussian moves selects a fraction of the best actions and perturbs their parameters with Gaussian noise.

Algorithm 1 Physics-Based Action Selection

Input: x_{ao} ▷ The current estimate of the articulated object.
1: $A \leftarrow \emptyset, Q \leftarrow \emptyset$ ▷ The set of all available actions and the corresponding induced articulated object motion.
2: **for** $i = 1..10$ **do**
3:    $A^{new} \leftarrow \text{sample}(A)$ ▷ Sample actions, either in Cartesian space based on the mesh or by perturbing past successful samples.
4:    $A^{new} \leftarrow \text{constrain}(A^{new})$
5:    **for** $a \in A^{new}$ **do**
6:       **for** $j = 1..N_{model}$ **do**
7:          $o \leftarrow \text{sample}(x_{ao})$
8:          $\Delta q_k^j \leftarrow \text{simulate}(a, o)$ ▷ Simulate an action on a sampled instance of the current articulated object estimate using SOFA.
9:       $A \leftarrow A \cup \{a\}, Q \leftarrow Q \cup \{\frac{1}{N} \sum_j \Delta q_k^j\}$
10:    $a^* \leftarrow \underset{a \in A}{\text{argmax}} \, Q_a$
11: **return** a^*

IV. EXPERIMENT WITH DRAWER

We evaluate our approach to perceive and manipulate a drawer connected to a cabinet. We use a 7-DoF Barrett WAM with the soft-manipulator RBO Hand 2 [18] as end-effector (Fig. 1). The robot is equipped with an Asus RGB-D sensor and an ATI FTN-Gamma force-torque sensor on the wrist.

1. Perceiving Kinematic Model from Human Demonstration

Initially, the robot does not possess any knowledge about the articulated object and assumes its environment to be a single static rigid body. In this condition our method cannot generate a skillful and informative interaction and has to wait
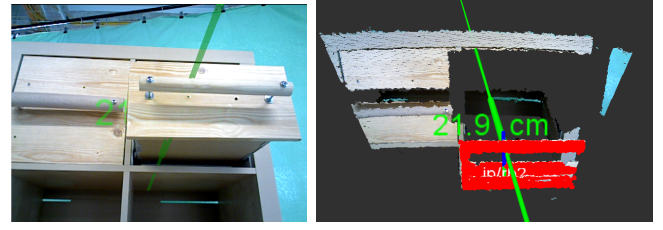

Fig. 2. Left: robot view at the end of a human interaction with the articulated object (estimated kinematic structure in green overlay); Right: 3D visualization of the interaction and the estimated kinematic model (estimated shape of the drawer in red)
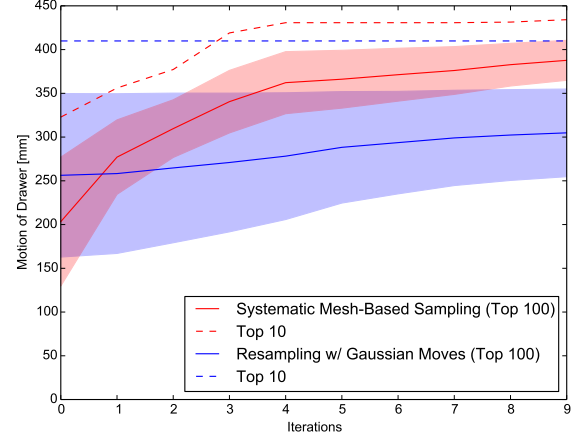

Fig. 3. Comparison of two sampling schemes of the presented algorithm and the resulting motion of the drawer in the first run of the action generation and selection (uncertain dynamics)

for a human to interact and reveal information about the drawer.

Once a human demonstration has been observed, a second rigid body (drawer) is estimated; the motion of the drawer is sufficient to estimate the joint type and axis with significant certainty. In contrast, the estimates for the force required to overcome stiction and kinetic friction are very uncertain. Fig. 2 depicts the model of the drawer the robot acquired at this point in time.

2. Perceiving Dynamic Properties from Self-Interaction

Based on this model, the robot plans an opening/closing motion of the drawer (see Fig. 3) that is optimal since the model predict it to generate 44 cm of motion of the drawer. By executing this action the robot gathers haptic and visual sensory data. At each step the force-torque sensor signal acquired by a sensor on robot's wrist is projected into the dimensions where the motion of the drawer is kinematically allowed or constrained. The robot combines the tangential component of the force-torque signal with the perceived change in the kinematic state of the object (the velocity of the joints) to infer the dynamic properties $F_k^{Stiction}, F_k^{KinFriction}$. The parameters of the distribution over dynamic properties of the drawer estimated after the interaction are $\mu_{Stiction} =$
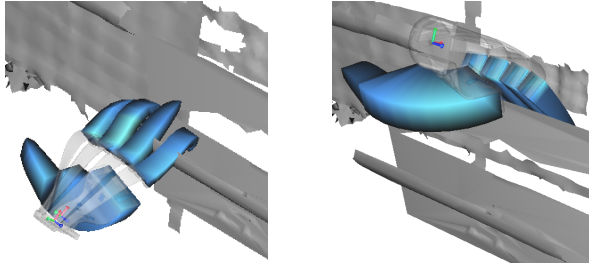
Fig. 4. Grasps that only partly touch handle (*left*) fail to move drawers with high stiction/friction, while grasps that make more contact, e.g. with the inside of the drawer (*right*), succeed even when facing large uncertainties about the drawer's dynamic properties.

2.1 N, $\sigma^2_{Stiction} = 0.3\,\text{N}^2$, $\mu_{KinFriction} = 0.5\,\text{N}$ and $\sigma^2_{KinFriction} = 0.02\,\text{N}^2$.

Fig. 3 shows the result of our two sampling schemes for action generation. The systematic mesh-based sampling generates better actions (actions that cause larger actuation of the articulation) than the resampling with Gaussian moves.

3. Action Generation and Selection for Better Interactions

Interestingly, Fig. 4 shows the best interactions that result from the action generation and selection in the first iteration based on the first model (with highly uncertain dynamic properties) and the second iteration based on the model with low uncertain dynamic properties. We observe that the richer information available in the latter action generation and selection step leads to different best ranked actions. While for the former interaction the robot opts for a conservative manipulation, in the latter interaction it selects actions that are only safe to be successfully executed given the knowledge of the dynamic properties acquired from self-interaction. The effect of the higher certainty in the estimated model of the environment is also observed in Fig. 5. The generation and selection of actions based on certain dynamics lead to more optimal solution that causes larger motion of the articulated object.

V. LIMITATIONS

Our method inherits the need for an initial interaction from our perceptual algorithm for the estimation of kinematic models [15], [16]. 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 to perceive dynamic properties. The method does not show generalization to new drawers; an object classification could help to transfer estimated information and successful interactions between instances of articulated objects. In our method the action generation is initiated with a uniform sampling. This could be improved with a sampling based on heuristics exploiting shape or kinematic information.

VI. CONCLUSION

We presented a method to build incrementally richer models of articulated objects from contact and interaction. The
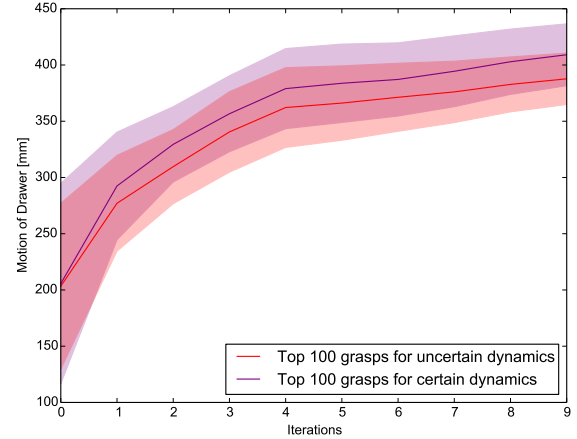

Fig. 5. Comparison of the systematic mesh-based sampling strategy on the model with uncertain (blue) and certain (red) dynamic parameters; after acquiring information about the dynamics the algorithm generates and selects interactions that lead to larger motion

method integrates interactive perception and the generation and selection of information-gathering actions to overcome the trade-off between the skillfulness of the interacting agent and the richness of the sensor-action signals for the interactive perceiver. We demonstrated the validity of our method in a real-world scenario with a drawer.

REFERENCES

[1] J. Bohg, K. Hausman, B. Sankaran, O. Brock, D. Kragic, S. Schaal, and G. S. Sukhatme, "Interactive perception: Leveraging action in perception and perception in action," *IEEE Transactions on Robotics and Automation*, 2017, to appear. [Online]. Available: http://arxiv.org/abs/1604.03670

[2] H. van Hoof, O. Kroemer, H. Ben Amor, and J. Peters, "Maximally informative interaction learning for scene exploration," in *International Conference on Intelligent Robots and Systems*, 2012, pp. 5152–5158.

[3] K. Hausman, F. Balint-Benczedi, D. Pangercic, Z.-C. Marton, R. Ueda, K. Okada, and M. Beetz, "Tracking-based interactive segmentation of textureless objects," in *Proceedings of the IEEE International Conference on Robotics and Automotion (ICRA)*, 2013, pp. 1122–1129.

[4] K. Hausman, S. Niekum, S. Osentoski, and G. S. Sukhatme, "Active Articulation Model Estimation through Interactive Perception," in *International Conference on Robotics and Automotion*, 2015.

[5] N. Bergström, C. H. Ek, M. Björkman, and D. Kragic, "Scene Understanding through Autonomous Interactive Perception," in *Computer Vision Systems*, ser. Lecture Notes in Computer Science, J. L. Crowley, B. A. Draper, and M. Thonnat, Eds. Springer Berlin Heidelberg, Jan. 2011, no. 6962, pp. 153–162.

[6] J. Schulman, J. Ho, A. X. Lee, I. Awwal, H. Bradlow, and P. Abbeel, "Finding locally optimal, collision-free trajectories with sequential convex optimization." in *Robotics: Science and Systems*, vol. 9, no. 1, 2013, pp. 1–10.

[7] J. Allard, S. Cotin, F. Faure, P.-J. Bensoussan, F. Poyer, C. Duriez, H. Delingette, and L. Grisoni, "SOFA—An Open Source Framework for Medical Simulation," in *MMVR 15 - Medicine Meets Virtual Reality*, ser. Studies in Health Technology and Informatics, vol. 125. Palm Beach, United States: IOP Press, Feb. 2007, pp. 13–18. [Online]. Available: https://hal.inria.fr/inria-00319416

[8] S. Otte, J. Kulick, M. Toussaint, and O. Brock, "Entropy-Based Strategies for Physical Exploration of the Environment's Degrees of Freedom," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Chicago, Illinois, USA, 2014.

[9] M. Prats, P. J. Sanz, and A. P. del Pobil, "Task-oriented grasping using hand preshapes and task frames," in *Proceedings 2007 IEEE International Conference on Robotics and Automation*, April 2007, pp. 1794–1799.

[10] G. I. Boutselis, C. P. Bechlioulis, M. V. Liarokapis, and K. J. Kyriakopoulos, "Task specific robust grasping for multifingered robot hands," in *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Sept 2014, pp. 858–863.

[11] N. A. Tovar and R. Surez, "Grasp synthesis of 3d articulated objects with n links," in *2016 IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA)*, Sept 2016, pp. 1–6.

[12] M. Pflueger and G. S. Sukhatme, "Multi-step planning for robotic manipulation," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*, May 2015, pp. 2496–2501.

[13] M. Stilman, "Task constrained motion planning in robot joint space," in *2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct 2007, pp. 3074–3081.

[14] M. Dogar, K. Hsiao, M. Ciocarlie, and S. Srinivasa, "Physics-based grasp planning through clutter," in *Robotics: Science and Systems VIII*, July 2012.

[15] R. Martín-Martín and O. Brock, "Online Interactive Perception of Articulated Objects with Multi-Level Recursive Estimation Based on Task-Specific Priors," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Chicago, Illinois, USA, 2014.

[16] R. Martín-Martín, S. Höfer, and O. Brock, "An Integrated Approach to Visual Perception of Articulated Objects," in *Proceedings of the IEEE International Conference on Robotics and Automotion (ICRA)*. Stockholm, Sweden: IEEE, 2016.

[17] R. Martín-Martín and O. Brock, "Building kinematic and dynamic models of articulated objects with multi-modal interactive perception," in *AAAI Symposium on Interactive Multi-Sensory Object Perception for Embodied Agents*, AAAI, Ed., 2017.

[18] R. Deimel and O. Brock, "A novel type of compliant and underactuated robotic hand for dexterous grasping," *The International Journal of Robotics Research*, vol. 35, no. 1-3, pp. 161–185, 2016. [Online]. Available: http://dx.doi.org/10.1177/0278364915592961