Relaxed-Rigidity Constraints: In-Grasp Manipulation using Purely Kinematic Trajectory Optimization

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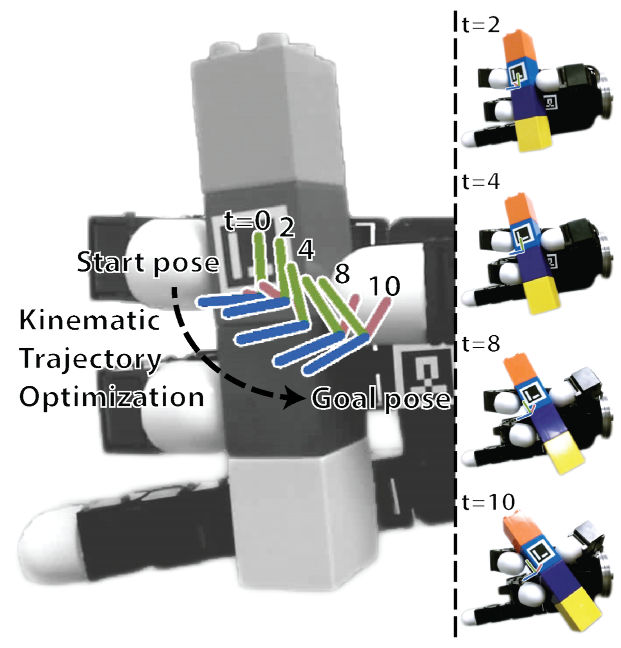
PROBLEM



In-grasp manipulation

Obtain a joint trajectory which moves an object with respect to the palm, under grasp to a desired object pose without breaking or making new contact.

Motivation:

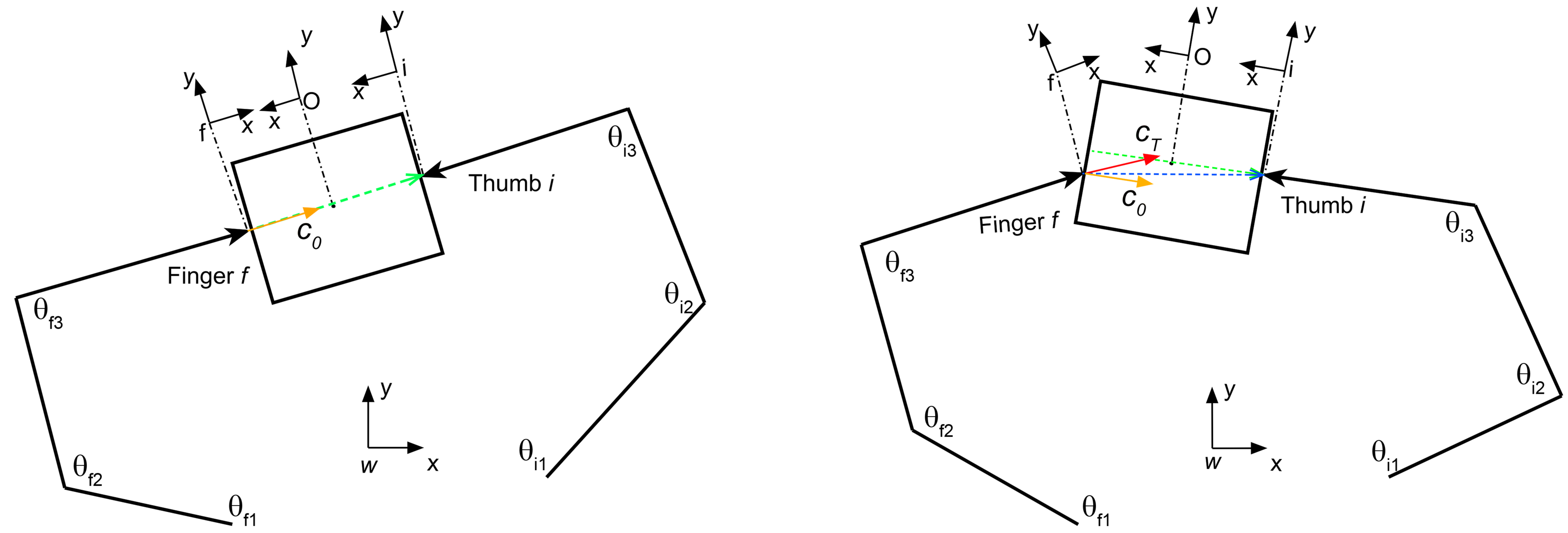
1. Current analytic methods require extensive object information [1, 2] and decouple inverse kinematics from trajectory planning [1].
2. Learning based methods require significant experience with robot or learn a single behavior to transfer between objects [3, 4].

Approach:

1. A purely kinematic trajectory optimization, to solve a large set of in-grasp manipulation tasks with a real robot hand.
2. Directly solve for joint configurations at all time steps, without the need of a separate inverse kinematics solver.
3. Extensive validation on a real robot hand, with multiple objects from the YCB dataset.

APPROACH

Find joint space trajectory $\Theta = [\Theta_1, \ldots, \Theta_T]$, that moves the object from its initial pose X_0 at time 0 to a desired pose X_g at time T.



$$\min_{\Theta} E_{obj}(\Theta_T, X_g) + k_1 \sum_{t=0}^{T-1} E_{obj}(\Theta_t, W_t) + k_2 \sum_{t=0}^{T} E_{pos}(\Theta_t) + k_3 \sum_{t=0}^{T} E_{or}(\Theta_t)$$

s.t.

$$\Theta_{min} \preceq \Theta_t \preceq \Theta_{max}, \forall t \in [0, T]$$

$$-\dot{\Theta}_{max} \preceq \frac{\Theta_{t-1} - \Theta_t}{\Delta t} \preceq \dot{\Theta}_{max}, \forall t \in [1, T]$$

Constraints - joint position and velocity limits of the robot hand.

Cost function terms:

E_{obj} encourages object to the desired pose, assuming the thumb is rigidly attached to the object.

E_{pos} **and** E_{or} define our novel relaxed-rigidity constraint.

E_{pos} maintains the initial relative positions between the thumb and the remaining fingertips.

E_{or} penalizes deviations from the initial relative orientation of the fingertips.

EXPERIMENTAL SETUP

Objects from YCB dataset

Comparison Methods

IK-rigid is a rigid contact model between the object and the fingertips.

Point Contact with friction model for the fingertips.

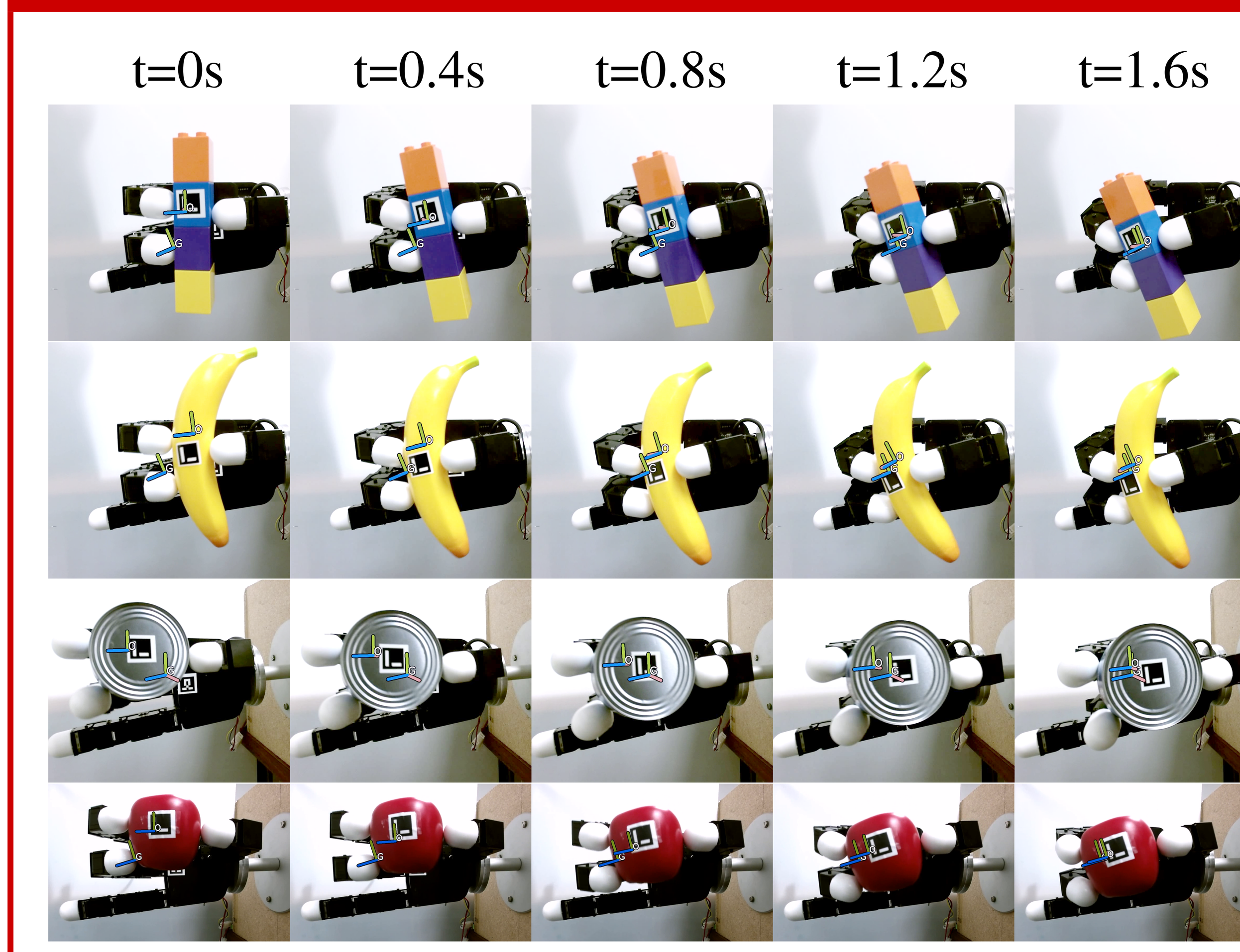
Cost term formulations

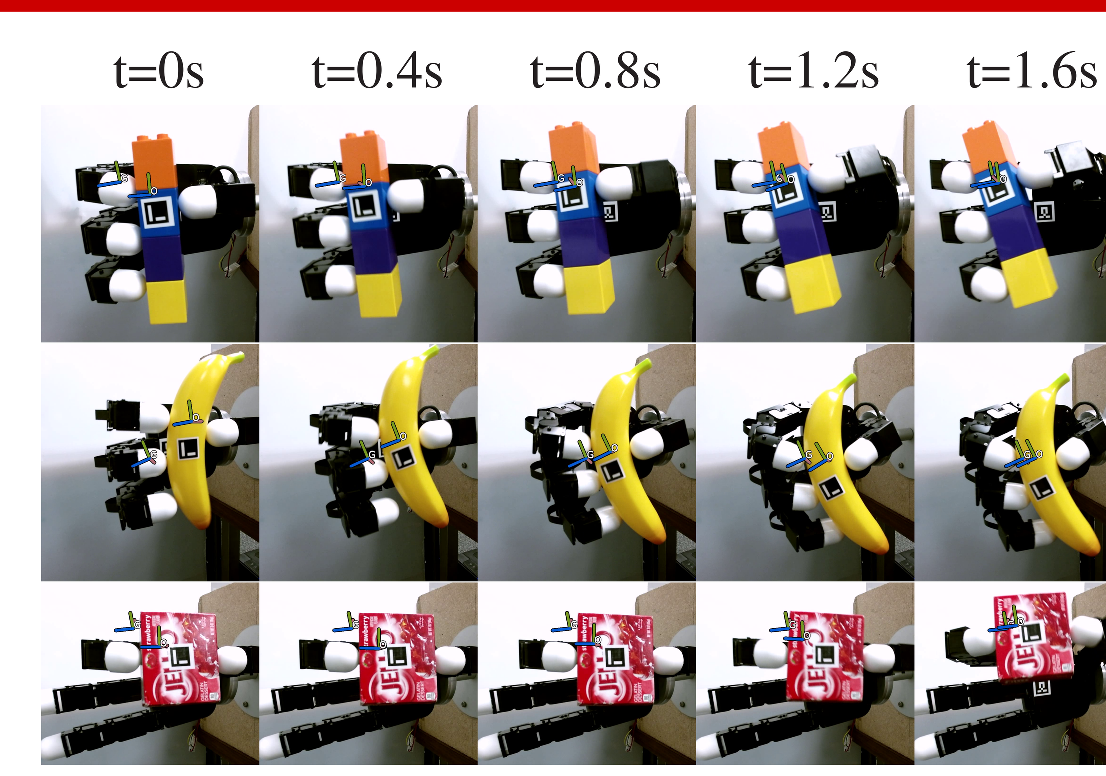
relaxed-position uses only our proposed relaxed-rigidity position cost.

relaxed-position-orientation uses only the relaxed-rigidity position and orientation costs.

Relaxed-Rigidity uses all our costs.

SAMPLE TRAJECTORIES





G- Desired object pose.
O- Current object pose.
Aruco markers only used for error analysis

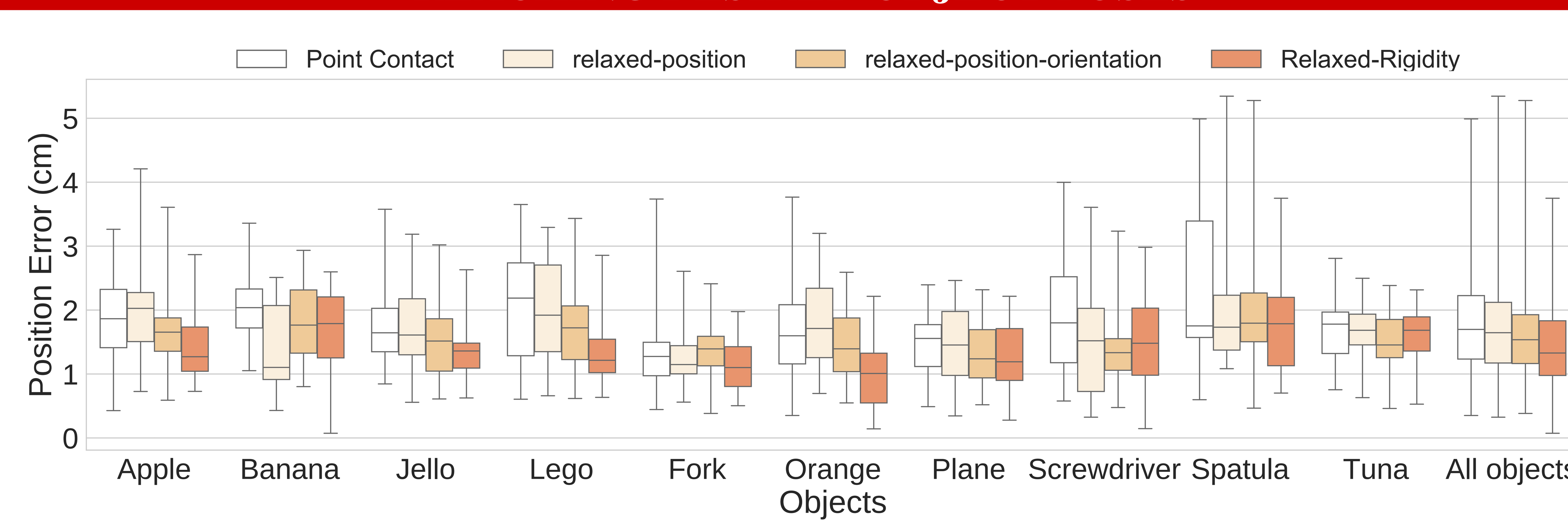
CONCLUSIONS

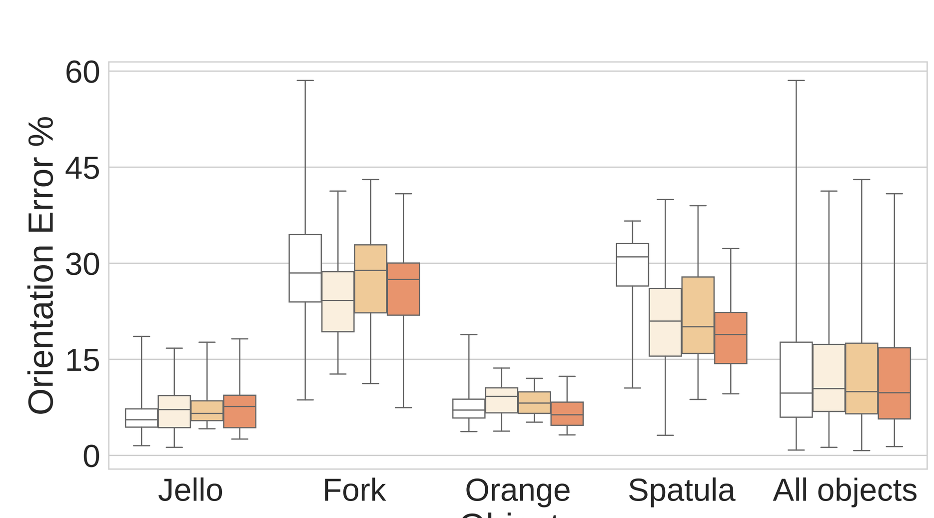
Point-Contact obtains position error% greater than 100% for several trials, showing the object is moving further away from the desired pose than at the initial pose. It also resulted in dropping the object on 25 out of 500 trials, while our proposed method never dropped an object.

Relaxed-Rigidity is closer to the desired pose than the initial pose for all trials with a maximum error of 75% and never drops the object.

All our experiments were run in **open-loop** with no feedback of the object pose. A median position error of 1.32 cm is obtained across all the experiments.

REACHING DESIRED OBJECT POSES





Median errors

	Point-Contact	Relaxed-Rigidity
Dropped Trials	25 of 500	**0 of 500**
Position Error(cm)	1.69	**1.32**
Position Error%	36.81	**28.67**
Orientation Error%	**9.74**	9.86

REFERENCES

[1] Igor Mordatch, Zoran Popović, and Emanuel Todorov. Contact-invariant optimization for hand manipulation. In *ACM SIGGRAPH/Eurographics SCA*, 2012.

[2] Sheldon Andrews and Paul G Kry. Goal directed multi-finger manipulation: Control policies and analysis. *Computers & Graphics*, 37, 2013.

[3] Vikash Kumar, Emanuel Todorov, and Sergey Levine. Optimal control with learned local models: Application to dexterous manipulation. In *ICRA*. IEEE, 2016.

[4] Herke van Hoof, Tucker Hermans, Gerhard Neumann, and Jan Peters. Learning Robot In-Hand Manipulation with Tactile Features. In *Humanoids*, 2015.