Mirroring without Overimitation: Learning Functionally Equivalent Manipulation Actions

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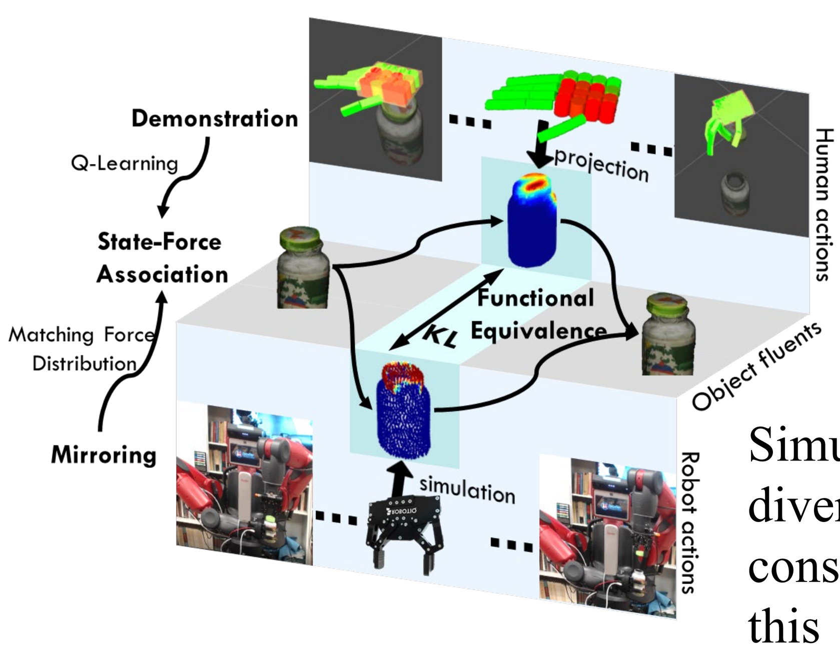
Motivation

Inspired by the mirror neurons, we propose a *mirroring* approach that extends the current LfD, through the physics-based simulation, to address the correspondence problem. Rather than overimitating the motion controls from the demonstration, it is advantageous for the robot to seek *functionally equivalent* but possibly visually different actions that can produce the same effect and achieve the same goal as those in the demonstration.

1. **Force-based**: Use a tactile glove to collect human demonstration with fine-grained manipulation forces.
2. **Goal-oriented**: Learn a grammar model to represent the action sequences as state changes and the causing forces.
3. **Mirroring without overimitation**: Reasons about the motion to achieve the goal in simulation.

Framework

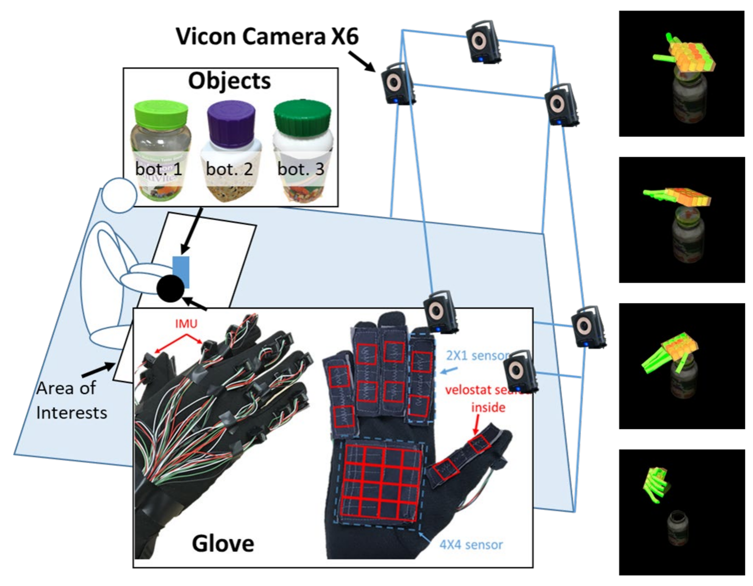


We explicitly model the forces on the object exerted by the hand in the demonstration with a pose and force sensing tactile glove. The distribution of the forces on the object is compared to a set of the force distributions exerted by the robot gripper on the same object in a physics simulator.

Simulated actions with sufficiently small KL divergence with respect to the demonstration are considered *functionally equivalent*, thus hinting this action would be the best robot action to accomplish the task.

Discover hidden force in Human Demonstration

The hand pose and force data is collected using an open-sourced tactile glove.

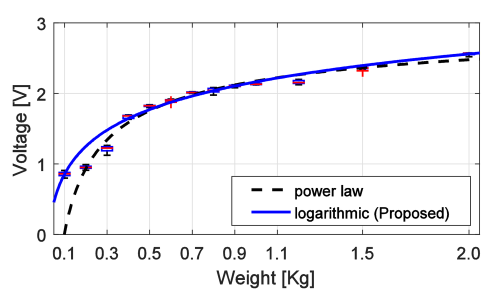


- 15 IMUs for pose sensing
- Piezoresistive material for force sensing

Hardware

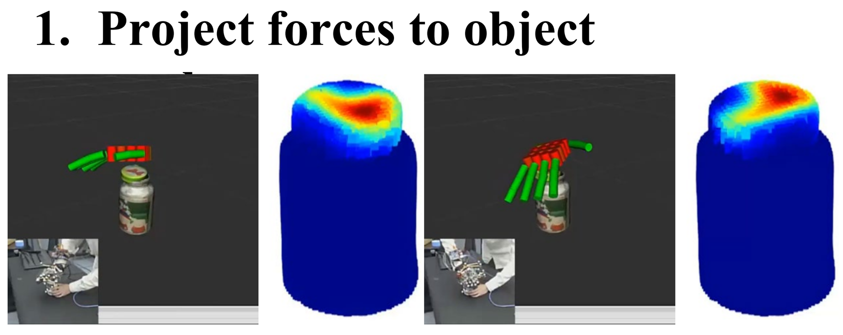
Parameter	Value
BNO055 IMU	N = 15
Sampling Frequency	20 [Hz]
Velostat sensor	N = 26
Sampling Frequency	40 [Hz]
Raspberry Pi 2	N = 1
Quad-core CPU	900 [MHz]
RAM	1 [GB]

Force-resistance relationship

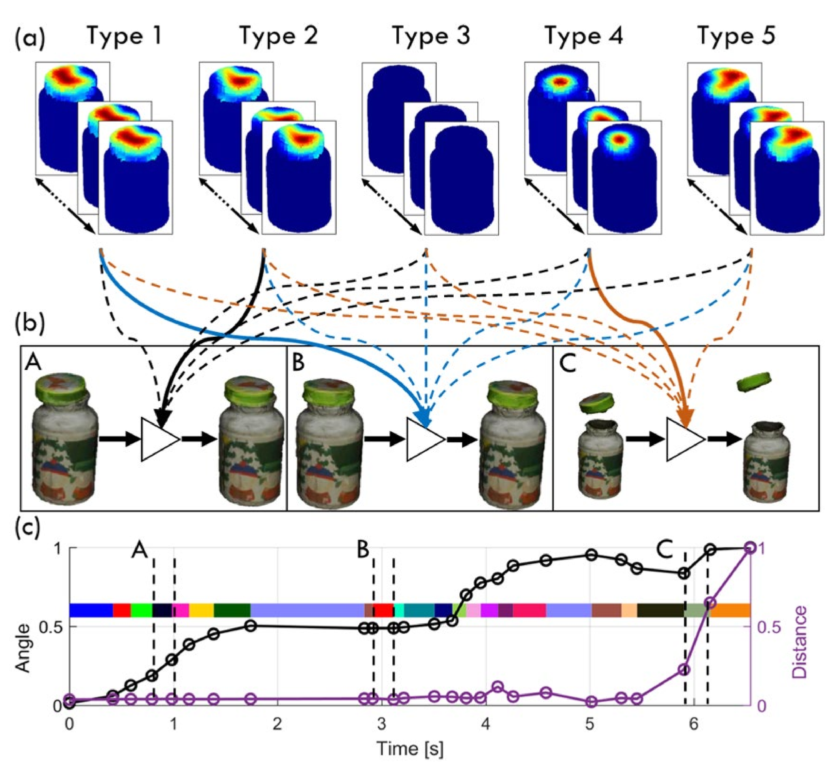


Demonstration Modeling

1. Project forces to object

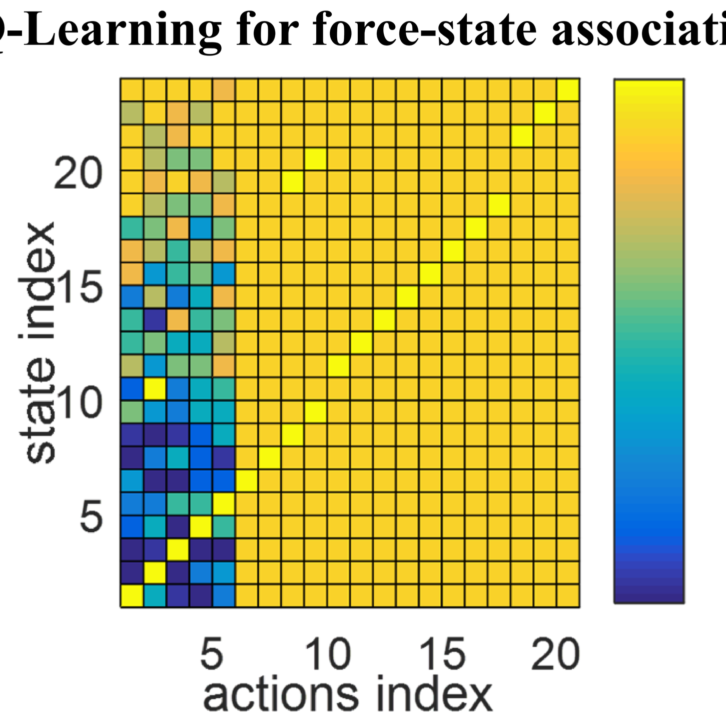


2. Quantize states and segment forces:



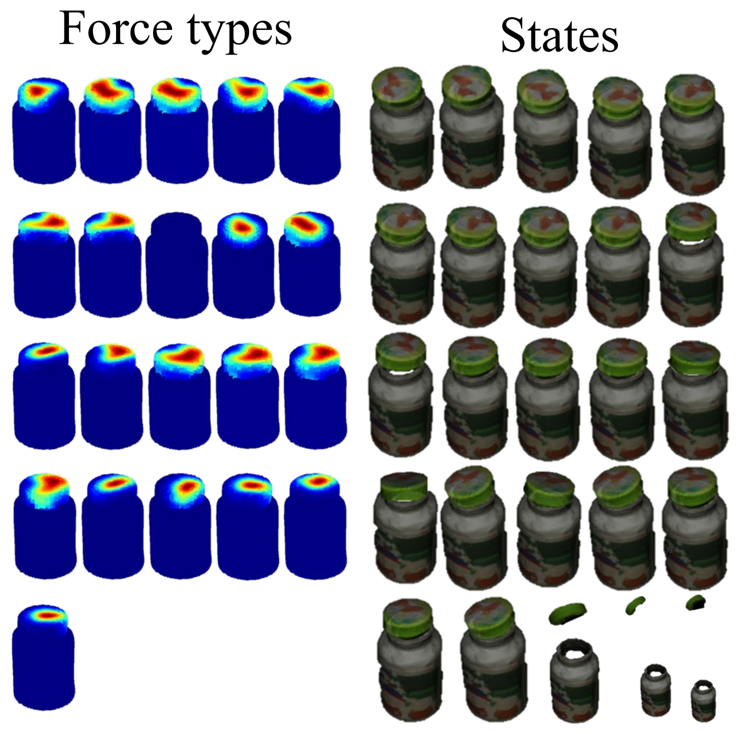
force and state associations as *hoi* units. The manipulation force is clustered into 21 types.

3. Q-Learning for force-state association:



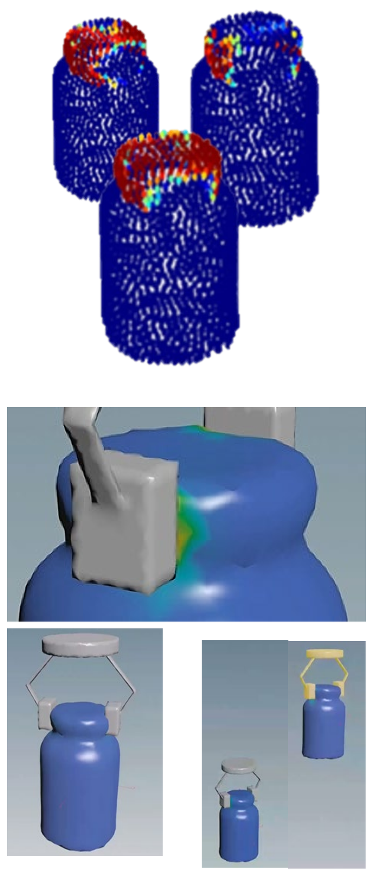
Force types

States



Bridge Human and Robot Embodiments

Force Simulation in Houdini



1. Convert the rigid object to deformable
2. Obtain the mechanical stress under deformation using the Neo-Hookean model (Macosko 1994).

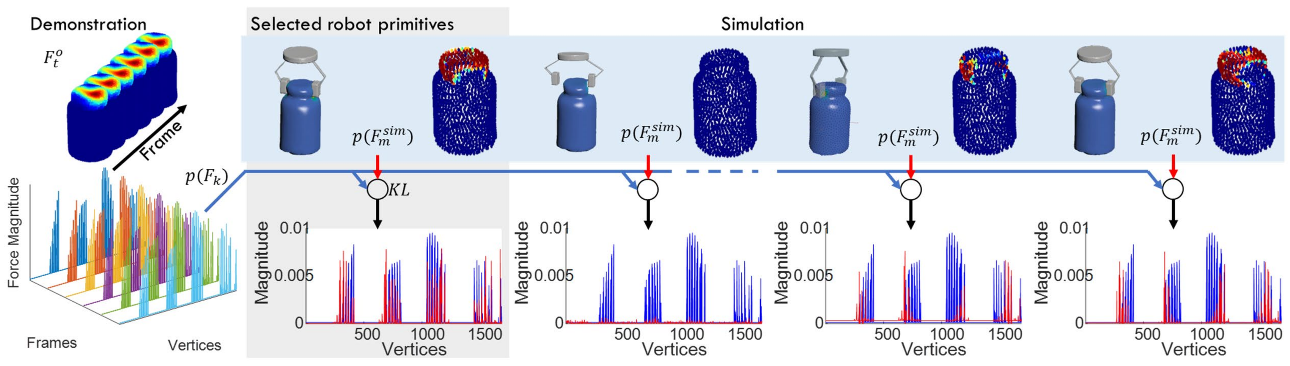
$$P = \mu(F - F^{-T}) + \lambda \log(\det(F))F^{-T}$$

F: strain at each point as the deformation gradient tensor
P: elastic mechanical stress as first Piola-Kirchoff stress tensor
μ, λ : friction coefficient

The forces: $f^{ext} = \nabla P$

Obtain force responses of different robot motion for physics-based simulator

Comparing the similarity of forces for motion synthesis



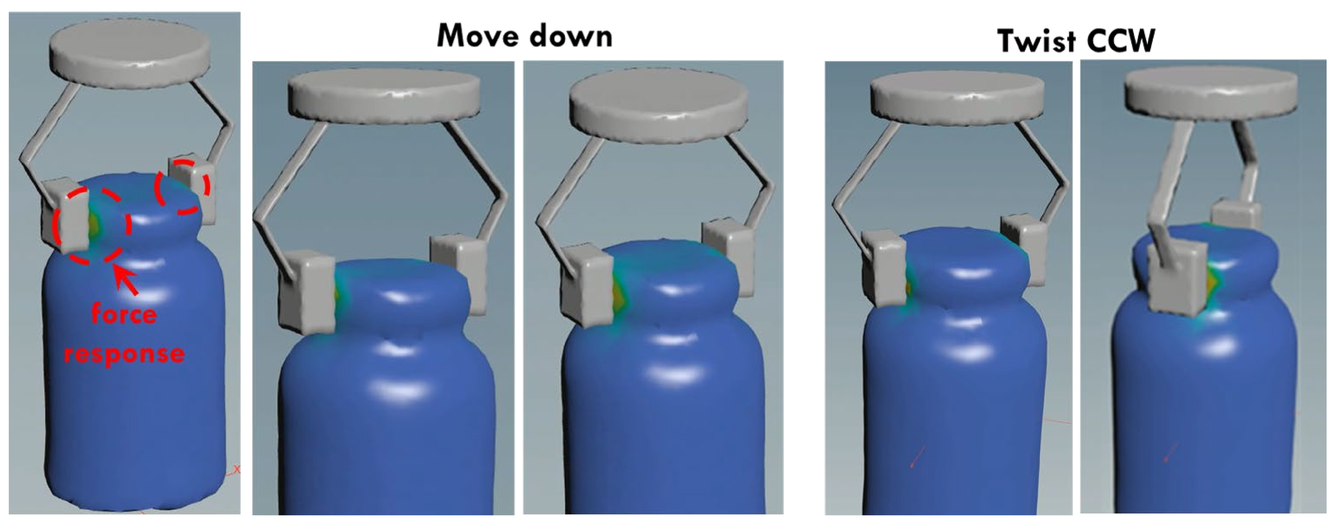
$$P(F_k) = \frac{1}{Z_k} F_k$$

$$P(F_m^{sim}) = \frac{1}{Z_m^{sim}} F_m^{sim}$$

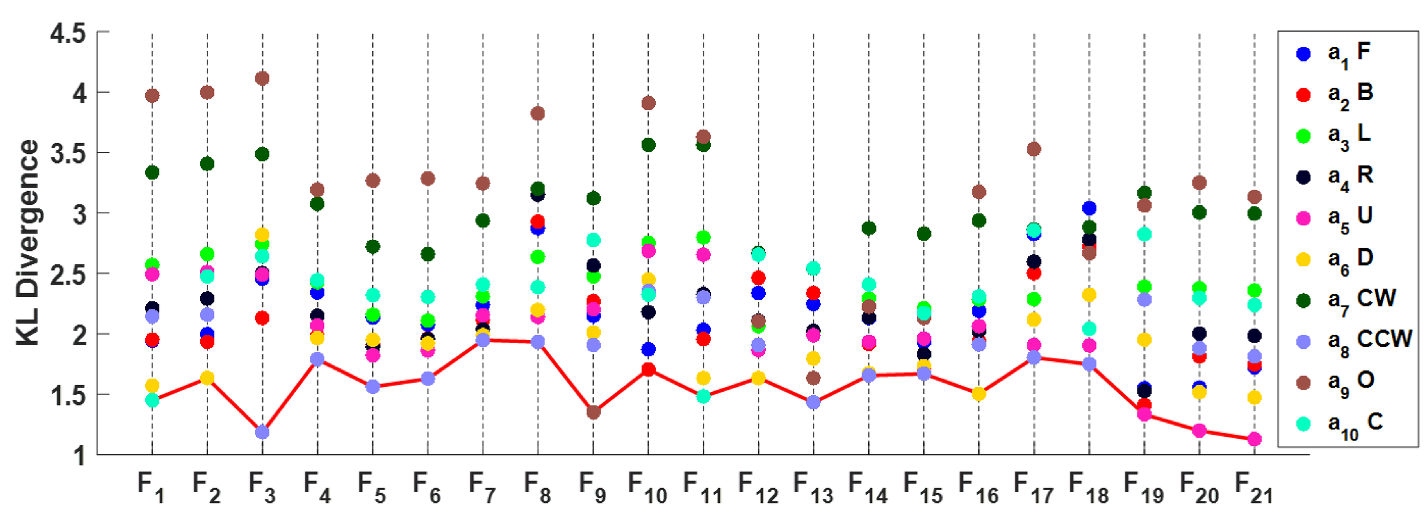
$$F_*^{sim} = argmin\, KL(P(F_k) \,||\, P(F_m^{sim}))$$

Experiment Results

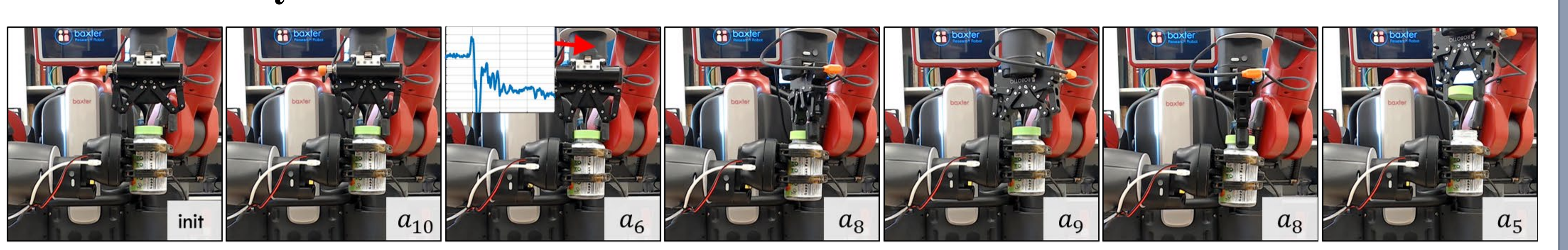
Simulations of the robot actions' force responses.



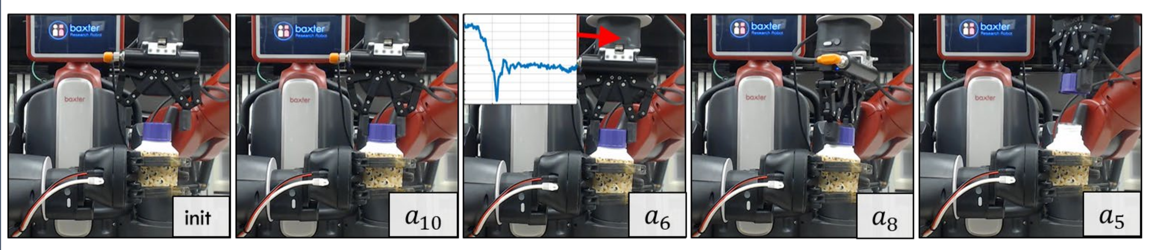
The KL divergence for all action primitives in a *pt*. In this case, the primitives are a_1: *move forward*, a_2: *move backward*, a_3: *move left*, a_4: *move right*, a_5: *move up*, a_6: *move down*, a_7: *rotate clockwise*, a_8: *rotate counter-clockwise*, a_9: *open gripper*, a_{10}: *close gripper*. The solid red line is the sequence of actions for a robot to execute.



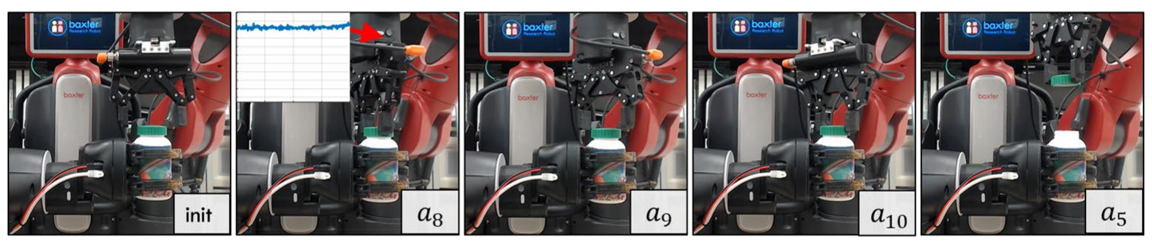
Ablative Analysis



Robot execution to open Bottle 1



Robot execution to open Bottle 2



Robot execution to open Bottle 3

	Bot. 1	Bot. 2	Bot.3
B.	38.5%	30.8%	76.9%
M.	69.2%	53.8%	73.1%

The success rate for opening 3 bottles using the baseline model (B) and the proposed approach (M)

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