Discover hidden force in Human Demonstration

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

Hardware

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Piezoelectric</td>
<td></td>
</tr>
<tr>
<td>Sampling Rate</td>
<td>20 [Hz]</td>
</tr>
<tr>
<td>Sampling Frequency</td>
<td>4 [Hz]</td>
</tr>
<tr>
<td>Network</td>
<td>5.1 (1x)</td>
</tr>
<tr>
<td>Quad-core CPU</td>
<td>800 MHz (1x)</td>
</tr>
<tr>
<td>RAM</td>
<td>1 GB (1x)</td>
</tr>
</tbody>
</table>

| Force-resistant relationship | 0 | 5 | 10 | 15 | 20 |

Demonstration Modeling

1. Project forces to object
2. Quantize states and segment forces:
3. Q-Learning for force-state association:

Ablative Analysis

Robot execution to open Bottle 1

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

Bridge Human and Robot Embodiments

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.

Experiment Results

Comparing the similarity of forces for motion synthesis

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.

Simulations of the robot actions' force responses.

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

The manipulation force is clustered into 21 types.

The forces:

\[ F_{\text{sim}} = \arg\min_{F_m} KL(P(F_m) || P(F_{\text{sim}})) \]

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

Motivation

Learning Functionally Equivalent Manipulation Actions

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