Reflective Learning of Stochastic Physical Models of Objects for Manipulation
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Objectives
- Robust robotic manipulation of novel objects through the use of stochastic friction and mass models of objects.
- Building upon prior models instead of starting from scratch with each new object.
- Correcting the prior models on the fly.
- Efficient use of physics engines for black-box model identification and correction.
- Lifelong online learning.

Examples

Figure 1: To grasp the pair of pliers from the tabletop, the robot needs to push the object to the table’s edge and grab it easily from there. To avoid dropping the pliers, a good model of the mass and friction properties of the clippers needs to be learned on the fly. The learned model is used in a physics engine to simulate the motion of the clippers.

Figure 2: Planar Pushing Dataset [1] (MCUBE lab, MIT). The data consist of recorded poses of a planar object being pushed by a robot. The goal is to identify the unknown friction factors and mass of the object in order to predict its motion.

Notations
- $\theta$ is a $d$-dimensional vector corresponding to the unknown mass and static and kinetic friction coefficients of each subpart of a given object.
- $P_t$ is a probability distribution of $\theta$ at time-step $t$.
- $x_t$ is the observed 6D pose (position and orientation) of the manipulated object at time $t$.
- $\mu_t$ is a vector describing a force applied by the robot’s fingertip on the object at time $t$.
- $f$ is the transition function of a physics engine, such that $f(x_t, \mu_t, \theta) = \tilde{x}_{t+1}$.

Problem
- Given $P_t$, a prior of model $\theta$ before starting to interact with the object, and a sequence of actions and observed poses $(x_0, \mu_0, x_1, \mu_1, \ldots, x_t, \mu_{t-1}, x_t)$.
- Calculate $P_t$, the probability distribution of $\theta$.

Method
- Empirical error on observed data:
  \[ E(\theta) = \frac{1}{N} \sum_{i=1}^{N} |f(x_i, \mu_i, \theta) - \tilde{x}_{i+1}| \]
- Best model that explains observed data:
  \[ \theta^* = \arg \min_{\theta} E(\theta) \]
- We do not know the analytical form of error function $E$ because $E(\theta)$ is obtained from simulation with a physics engine.
- Use black-box Bayesian optimization [2, 3] to find $P_t$, the probability distribution of $\theta^*$.
- Following the entropy search technique [4],
  \[ P_t(\theta) \overset{d}{=} P(\theta = \arg \min_{\theta} E(\theta)) \]
  \[ = \int_{\Theta} P(\theta) p_\text{emp}(\theta) H(E(\theta)) - E(\theta) \text{d}E, \]
  where $H$ is the Heaviside step, i.e.
  \[ H(E(\theta)) = 1 \text{ if } E(\theta) \geq E(\theta) \text{ and } H(E(\theta)) = 0 \text{ else, and } p(E) \text{ is the probability of error function } E. \]
- $p(E)$ is a Gaussian Process, and $P(\theta)$ is evaluated by Monte Carlo samples from $p(E)$.
- $p(E)$ is computed by evaluating $E$ from several simulations with different hypothesized models $\theta$.

Preliminary Results

Figure 4: Error in predicting poses of pushed planar objects as a function of simulation time. Bayesian optimization refers to the greedy entropy search approach.

Figure 5: Pose prediction error as a function of the number of training samples with three different objects.

References