Lecture 24: Professor Goldberg

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24.1 Grasping Overview

Humans can grasp general objects from a very young age, but robots cannot. Robots are clumsy. Presented with an unusual object, deciding where to place grippers is a very subtle problem that humans and animals can solve but robots cannot yet do.

Grasping is very important. One big application: e-commerce warehouse sorting.

24.2 Three Ingredients

Error and uncertainty in physics, perception, and control underlie the fundamental difficulty in grasping.

24.2.1 Control

The two finger jaw gripper is reliable, low-cost, elegant, and functional. We should understand the jaw gripper first before extending to more complex hardware such as adding more fingers. Minimalist hardware can have high capability if we solve the control problem. Proof-of existence: very simple surgical manipulators, and chopsticks as used by humans.

24.2.2 Perception

There has been significant recent advancement in computer vision, particularly in depth sensing via LIDAR. We can reconstruct the structure of an object as a pointcloud. This is not perfect: the pointcloud has holes. Depth sensing has trouble with transparency and reflectivity which causes light to behave non-ideally. This is common in warehouses as many objects are plastic-wrapped.

24.2.3 Physics

We cannot necessarily accurately predict the outcome of a manipulation due to uncertainly in microscopic surface topology. Introduce a grain of sand, and the motion of an object being pushed might deviate significantly. This might be a fundamentally undecidable problem.

24.3 First wave: Analytic Grasp Planning

Given state X (e.g. shape, friction), plan a grasp U (e.g. contact points and maybe pose) to maximize a reward function R:

$$\pi(x) = \underset{u \in U}{\operatorname{argmax}} R(x, u)$$

There has been lots of research on the analytic methods from the past 30 - 40 years.

24.4 First wave+ (Dex-Net 1.0): Stochastic Analytic Methods

(Plato)

Idea for DexNet 1.0 (started in 2016): model all the variables in a probability network and have all the variables be random variables with stochastic noise.

That is, instead of having the state x be a fixed constant, we have a random variable $\tilde{x} = \hat{x} + \epsilon$. Similarly, for the control input u, we have $\tilde{u} = u + \delta$.

Then, the 'quality' or robustness of a grasp, $Q(x, u) = E[R(\tilde{x}, \tilde{u})]$

Diagram:

Robust grasp planning now becomes maximizing the expected robustness $Q(x, u)$:

$$\begin{aligned} u^* = \pi(\hat{x}) &= \underset{u \in U}{\operatorname{argmax}} Q(\hat{x}, u) \\ &= \underset{u \in U}{\operatorname{argmax}} E[R(\tilde{x}, \tilde{u}) \mid \hat{x}, u] \\ &= \underset{u \in U}{\operatorname{argmax}} \int R(\tilde{x}, \tilde{u}) p(\tilde{x}|\hat{x}) p(\tilde{u}|u) \, d\tilde{x} \, d\tilde{u} \end{aligned}$$

Intuitively, when you want to grasp an object, you need to choose where to grasp the object. You look at each potential grasp and sample from a distribution perturbations, center of mass, friction. For each particular choice of values, we can analytically check if the grasp succeeds or fail. Note this approach is resembles a foundation of wrench theory (Robust Force Closure).

Example of a Dex-Net 1.0 grasp estimate:

The idea is that we have an observation y (e.g. image or point cloud) and map it to a state x:

$$x = f^{-1}(y)$$

Roughly, the pipeline is:

1. Sensor Data
2. State Inference
3. Grasp Planning

The result is a system that sometimes works, but sometimes makes a lot of mistakes due to perception noise.

24.5 Second Wave

(Aristole: looking at the real world, roughly corresponds to collecting data)

Lots of related work: mostly end-to-end. Example is google's arm farm with results:

Summary: this is a log plot and it might take a really really long time.

Perception Uncertainty

The idea was to generate a large data set of 3D object labelled with quality computed analytically using Monte Carlo integration.

Adversarial objects generated in a similar way to generating adversarial images.

24.6 New Wave: Simulation and Dexnet 1.0

For each object, attempt 1 million grasps in simulation with 1 thousand perturbations per graps: a total of 1 billion evaluations per object. For 10 thousand objects, this 10 trillion grasp evaluations. This is an embarassingly parallel problem, so we can compute this on a lot of hardware in parallel.

Use multi-arm bandits to evaluate similarity between pairs of objects. Use deep learning to learn similarity. Multi-view Deep CNN: Generate many views of the same object and train the network to recognize them as the same object. This network will compute a similarity metric between objects. The similarity is used as a strong prior for the likelihood of grasp transferred from another object. We can start searching for grasps by bootstrapping from the prior. Having the priors allows convergence to a high quality grasp much faster.

24.7 Crossing the Reality Gap

We have to move from simulation to physical reality. The learned policy has to be robust.

Noise injection: During training, introduce noise to simulate noise in physical reality and increase the robustness of the policy. We can strategically inject noise that simulates real-world noise rather than naive uniform noise.

24.8 Dex-Net 2.2: Bin picking

Given a heap of object in a grasp, generate candidate grasps with cross-entropy. Iterate and run the candidate grasps through the network to narrow down grasps that have high probability of success.

24.9 Dex-Net 3.0: Suction grasps

The industry uses suction-based manipulators. A physical model for suction grasps was developed. The network is trained to evaluate candidate points for suction grasping, then apply perturbations to evaluate robustness.

24.10 Dex-Net 4.0: Composite Policies

Goal: Use a policy that selects between end effectors to increase the diversity of objects

$$\pi(y) = argmax\left(max_{u \in U_g)} Q_g(y, u_g), max_{u_s \in U_s} Q_s(y, u_s)\right)$$

Different modalities were good for different tasks, so the system needed to have memory so that it wouldn't keep trying with the same approach and failing again and again. Note there are some pathological objects that just cannot be picked up by either the suction cup or gripper.

24.11 Ambi Robotics

Company formed in 2018.

24.12 New Projects

1. Optimizing the motion of the arm (Deep learning can accelerate grasp-optimized motion planning, Nov 2020) Main idea: Combine the classical technique of minimal jerk motion planning to generate optimal trajectories
2. Untyping dense knots
3. Robots of the Lost Arc: Learning to dynamically manipulate fixed-endpoint ropes and cables
4. Robot-Assisted Surgery (suturing)
5. Gardening (alphagarden.org)