EECS C106B / 206B Robotic Manipulation and Interaction **Spring 2022**

Lecture 18: Grasp Stability, Manipulability, Grasp Planning

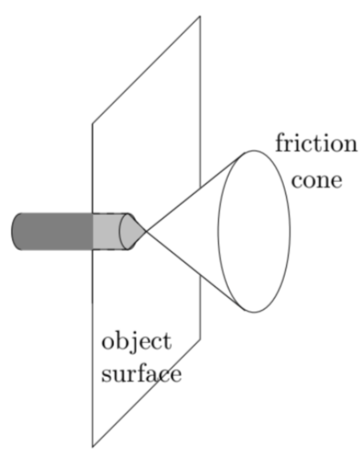
Scribes: Emma Stephan, Mohsin Sarwari

18.1 Overview

In the first half of this lecture, we continue our discussion on the mathematical modeling and conceptualization of grasping. In the second half, we'll overview the incredible ROAR project from the VIVE Center here at Berkeley. In EECS C106A/206A, students gain an understanding of how to model and control a single rigid limb or arm link. In EECS C106B/206B, specifically this lecture and the following lecture, we expand on this modeling, developing mathematical intuition for enabling multiple rigid limbs and arm links to work together. How might we develop mathematical notions of a force control grasp, in which a robot grasps an object in such a way that the object is not easily pulled away or dropped?

18.2 Grasping Continued

In reality, fingers are typically soft and deform upon contact with objects. However, we use point contact as an idealization of grasping to simplify visualization.



Point Contact

In the point contact with friction model, we write our contact force F_c as a wrench:

$$\vec{F}_{C_i} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} f_{c_1} \\ f_{c_2} \\ f_{c_3} \end{bmatrix}$$

A wrench is comprised of both a force and torque component. This contact force is given in terms of the coordinate frame attached to the finger, and it has three forces and no torques. In the above equation, let the vector comprised of the components $f_{c_1}, f_{c_2}, f_{c_3}$ be known as $\vec{x}_i$, and μ_i is the Coulomb coefficient of friction.

$$FC_i = \{\vec{x}_i \in \mathbb{R}^3 : \sqrt{f_{c_1}^2 + f_{c_2}^2} \le \mu_i f_{c_3}, f_{c_3} \ge 0\}$$

.

The soft finger contact model represents the fact that, in addition to generating a normal force, contact also generates a torque.

$$\vec{F}_{C_i} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f_{c_1} \\ f_{c_2} \\ f_{c_3} \\ \tau \end{bmatrix}$$

In the above equation, let the vector comprised of the components $f_{c_1}, f_{c_2}, f_{c_3}, \tau$ be known as $\vec{x}_i$, and μ_{it} is the torsional coefficient of friction. This additional friction coefficient attempts to model the fact that the finger resists rotation because it deforms upon contact.

As seen in the previous lecture, there are two versions of the soft contact model:

The Elliptic Model: $FC_i = \{\vec{x}_i \in \mathbb{R}^4 : \sqrt{\frac{1}{\mu_i^2}(f_{c_1}^2 + f_{c_2}^2) + \frac{1}{\mu_{it}^2}\tau^2} \le f_{c_3}\}$
The Linear Model: $FC_i = \{\vec{x}_i \in \mathbb{R}^4 : \frac{1}{\mu_i}\sqrt{(f_{c_1}^2 + f_{c_2}^2)} + \frac{1}{\mu_{it}}|\tau| \le f_{c_3}\}$

18.2.1 Grasp Maps

18.2.1.1 Single Contact

For each limb or finger, we have a point of contact $c_i \in \mathbb{R}^3$ and a rotation matrix $R_{c_i} \in SO(3)$, we can represent the position and rotation of the i^{th} contact point relative to the object coordinate frame with the following matrix:

$$g_{oc_i} = \begin{bmatrix} R_{c_i} & c_i \\ 0 & 1 \end{bmatrix} \in \mathbb{R}^{4\times 4}$$

The transpose of the inverse of the adjoint of this matrix applied to the contact force at this point gives the force applied to the body's center of mass:

$$F_o = Ad^T_{g_{oc_i}{}^{-1}} F_{c_1} = G_i B_i x_i$$

where $G_i = Ad^T_{g_{oc_i}{}^{-1}} B_i = \begin{bmatrix} R_{oc_i} & 0 \\ \hat{p}_{oc_i} R_{oc_i} & R_{oc_i} \end{bmatrix} \in \mathbb{R}^{6\times 6}$ and B_i is a wrench basis.

18.2.1.2 Multifingered Grasp

For multi-fingered grasps, we simply sum these forces applied to the body's center of mass by each individual finger.

$$F_o = \sum_{i=1}^{k} G_i x_i = [Ad^T_{g_{oc_1}^{-1}} B_1, ..., Ad^T_{g_{oc_k}^{-1}} B_k] \begin{bmatrix} f_{c_1} \\ . \\ . \\ . \\ f_{c_k} \end{bmatrix} = Gx$$

18.2.2 Force Closure

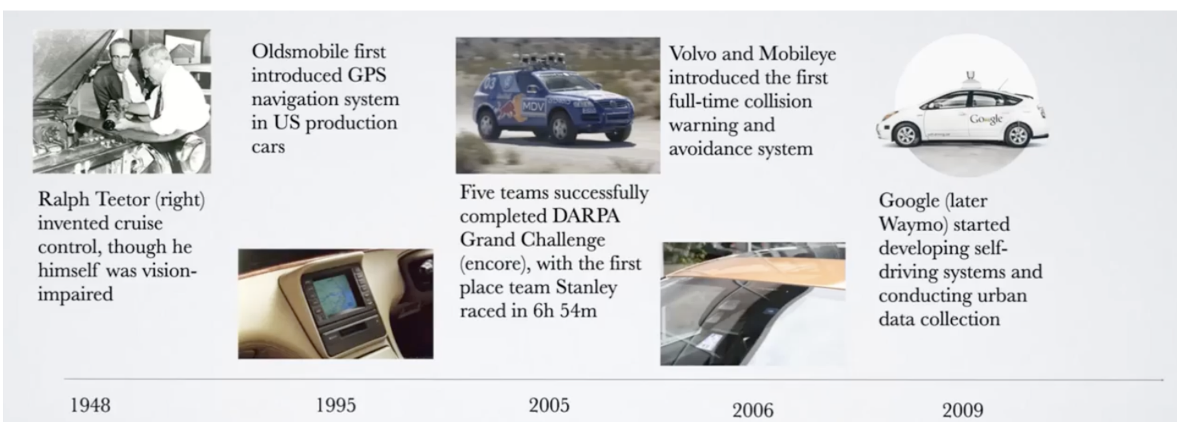
We define a grasp to be force closure if $F_o \in \mathbb{R}^p$ and there exists $x \in FC$, such that $GX = F_o$.

18.3 Berkeley Robot Open Autonomous Racing (ROAR)

In the second half of this lecture, Dr. Allen Yang gave a presentation on ROAR. A project that has been running for three years out of the VIVE Center for Enhanced Reality at Berkeley, ROAR seeks to advance vehicle autonomy in extreme scenarios.

18.3.1 Motivation

Although the hype for self-driving vehicles has certainly shot up over the last decade, the race in this direction has been going on for nearly a century.

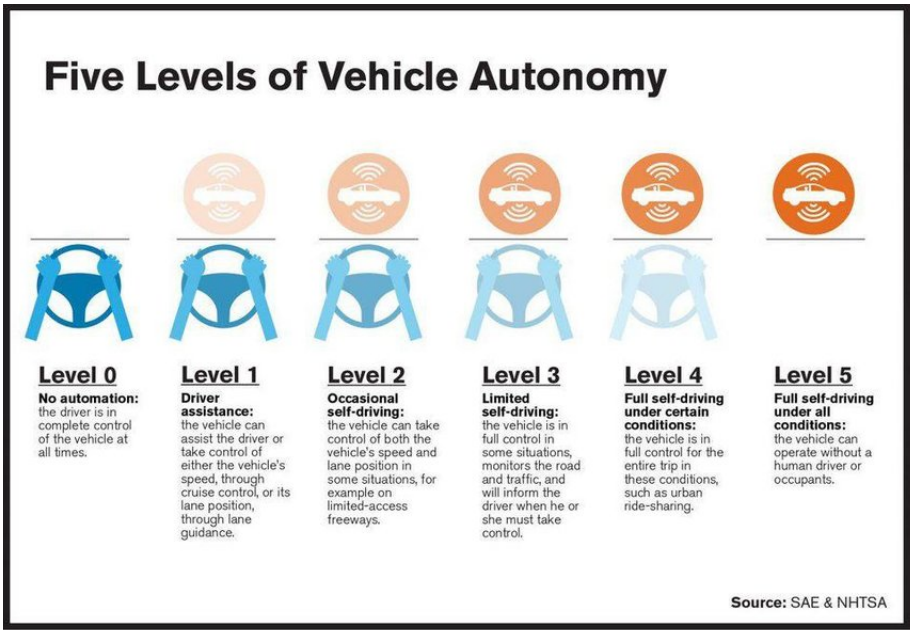


Self-Driving Timeline

However, as the popularity of companies like Tesla and Waymo have risen, so have discussions about when (if ever) fully self-driving technologies will be available for the average consumer.

There are big players on both sides of the debate. For example, Dieter Zetche, former head of Mercedes-Benz, is hopeful. With regards to cars as a consumer product, he says "the best times are still ahead." The most important luxury goods in life are private space and quality time and autonomous vehicles offer an increase in both. Similarly, Elon Musk is unrelenting in his chase, promising that Tesla will have a fully functional robo-taxi fleet very soon. Folks like Steve Wozniak, however, are hesitant about the validity of claims that self-driving is right around the corner, believing that the dream is still a lifetime away.

Although, self driving is not a binary switch. In fact, the automotive industry has worked to break down the landscape into 5 levels.



Levels of Self-Driving

Consumer available self-driving currently exists between Level 2 and Level 3, with the goal of reaching 4 and 5 soon. Problems like Adaptive Cruise Control (which takes care of speed regulation, collision avoidance with the car in front, and lane keeping) are considered closed, as almost all companies have a fixed strategy to address them. However, some crucial pieces of getting self-driving cars in the hands of the consumers are still missing.

18.3.2 Major Issues

There are three main issues when talking about the future of self-driving:

- **Commerical Viability**: Companies, like Waymo, have incredibly impressive performance, but the costs of developing the vehicle are simply too high for a commerical market.
- **Public Reputation**: For self-driving to be accepted by the consumer market, there are going to be ridiculously high performance benchmarks. The public will not be easy to convince even if the basis for the technology is there.
- **Corner Cases**: Probably the toughest problem in the self-driving space. When self-driving on scale, it is impossible to avoid corner cases, like weird roads, harsh weather, and unpredictable behavior from humans. How can you get a model to learn of every possible corner case?

18.3.3 Simulation

One way to continue moving forward despite these constraints, is to train in simulation. Simulation will help us avoid each of the above issues and give us a platform on which we can keep training and testing out algorithms. There are several simulation platforms out there including, Baidu Apollo Database, CARLA, and OpenAI Gym.

The biggest downside of simulation however, is the lack of the human component. You cannot solve a software corner case in software. There is simply no way to implement the unpredictable pedestrians and human drivers exhibit in real life.

18.3.4 Racing

Similar to simulations, racing provides a good incubator for self-driving algorithms. Not only does racing have a constrained environment, but also, mistakes made in racing draw much less attention than those made in the real world. ROAR goes one step further and removes the human risk by working with remote controlled cars.

The ROAR project is on a track to develop Extreme Intelligence, with four features at the base of its setup:

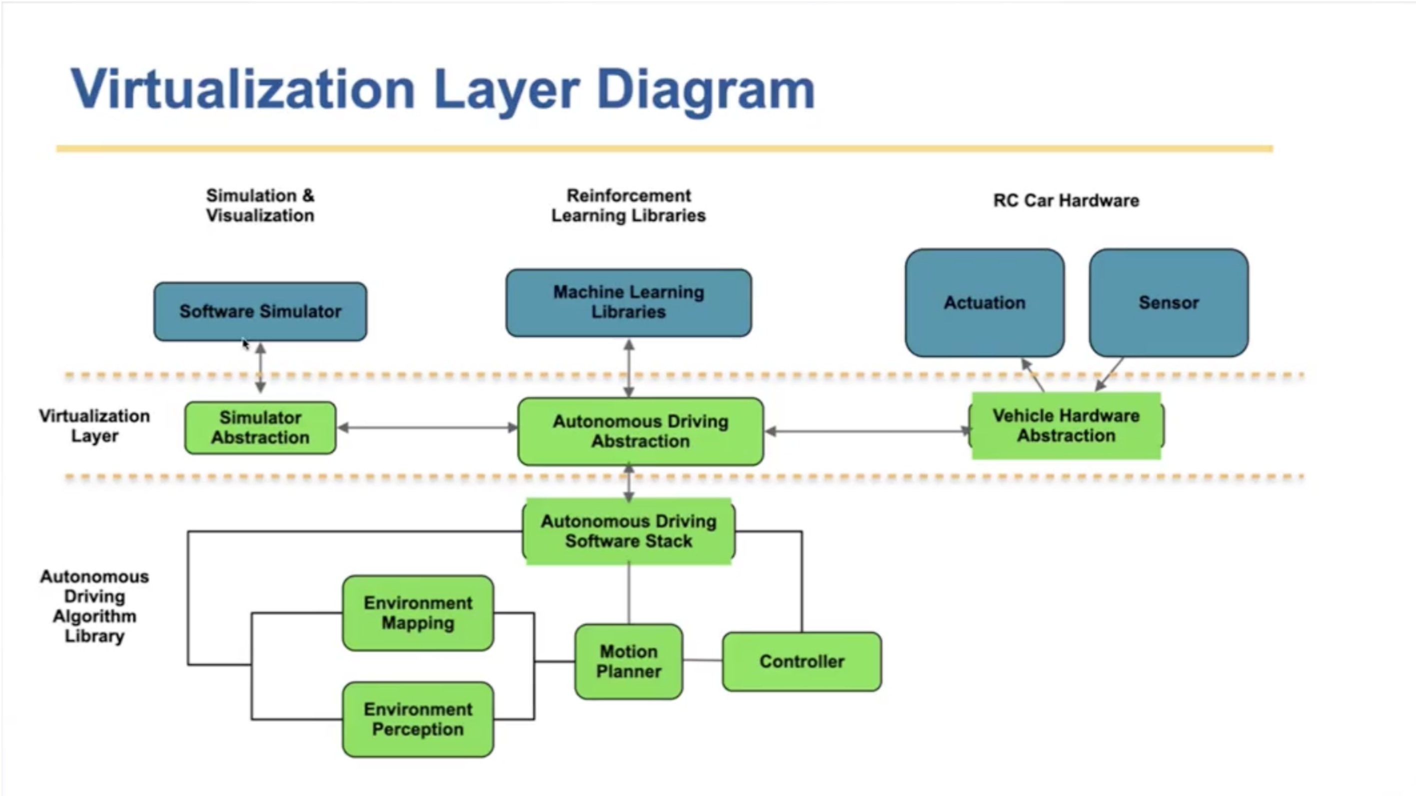
- **Extremely Low Cost**: the entire ROAR hardware is targeted to remain under $1000

- **Extreme Compatibility**: the software is designed to work with most popular simulators and prototype vehicles

- **Extreme Performance**: ROAR maintains the speed and racing aspect of its self driving

- **Extreme Safety**: There is no risk to humans or property

For the algorithms, ROAR uses Reinforcement Learning and Machine Learning techniques to develop self driving capabilities. Below, you can see the architecture used for the project.



ROAR Architecture

If you want to see more of ROAR, or are interested in joining the team, check out https://roar.berkeley.edu/