AA 598B Special Topics

Decision-Making & Control for Safe Interactive Autonomy

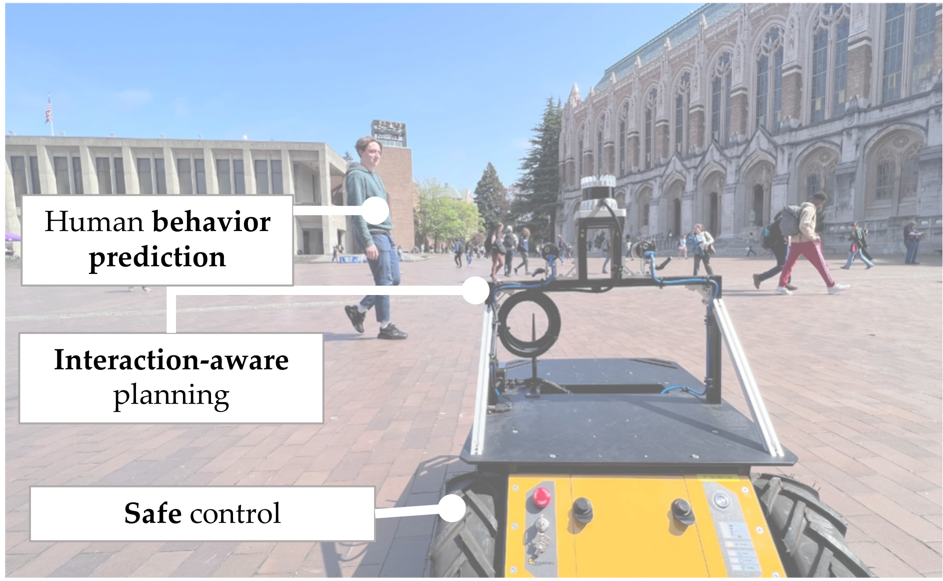
Instructor: Prof. Karen Leung

Autumn 2024

https://faculty.washington.edu/kymleung/aa598/

Reminders and announcements

- Course website:
  - https://faculty.washington.edu/kymleung/aa598/
  - Long paper discussion sign up sheet
    - Current enrollment: 14
  - Homework 1 out
- OH moved to 12



Last time

- “How to skim a research paper”
- Dynamical systems for human-robot systems
  - Recapped state space models
  - Types of dynamics models (control affine will be handy in Module #3)
  - Posed a joint human-robot system
  - Highlighted the interaction/coupling effects
  - Derived relative dynamics

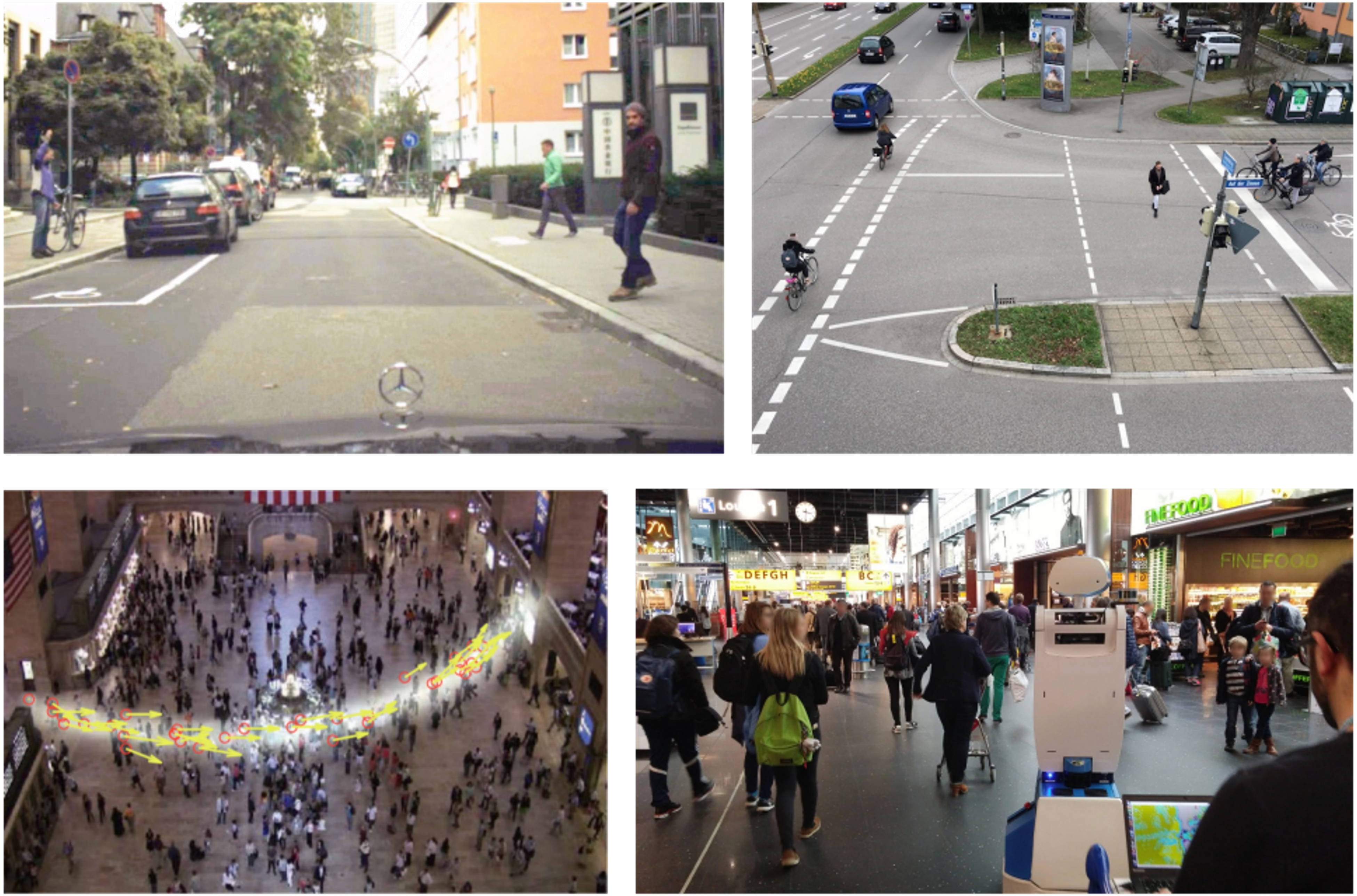
Today

- Start of the prediction module
  - Behavior prediction for HRI
  - Generative modeling
    - Ontological vs phenomenological
    - Latent space models and CVAEs

- Next lecture, bring your laptops

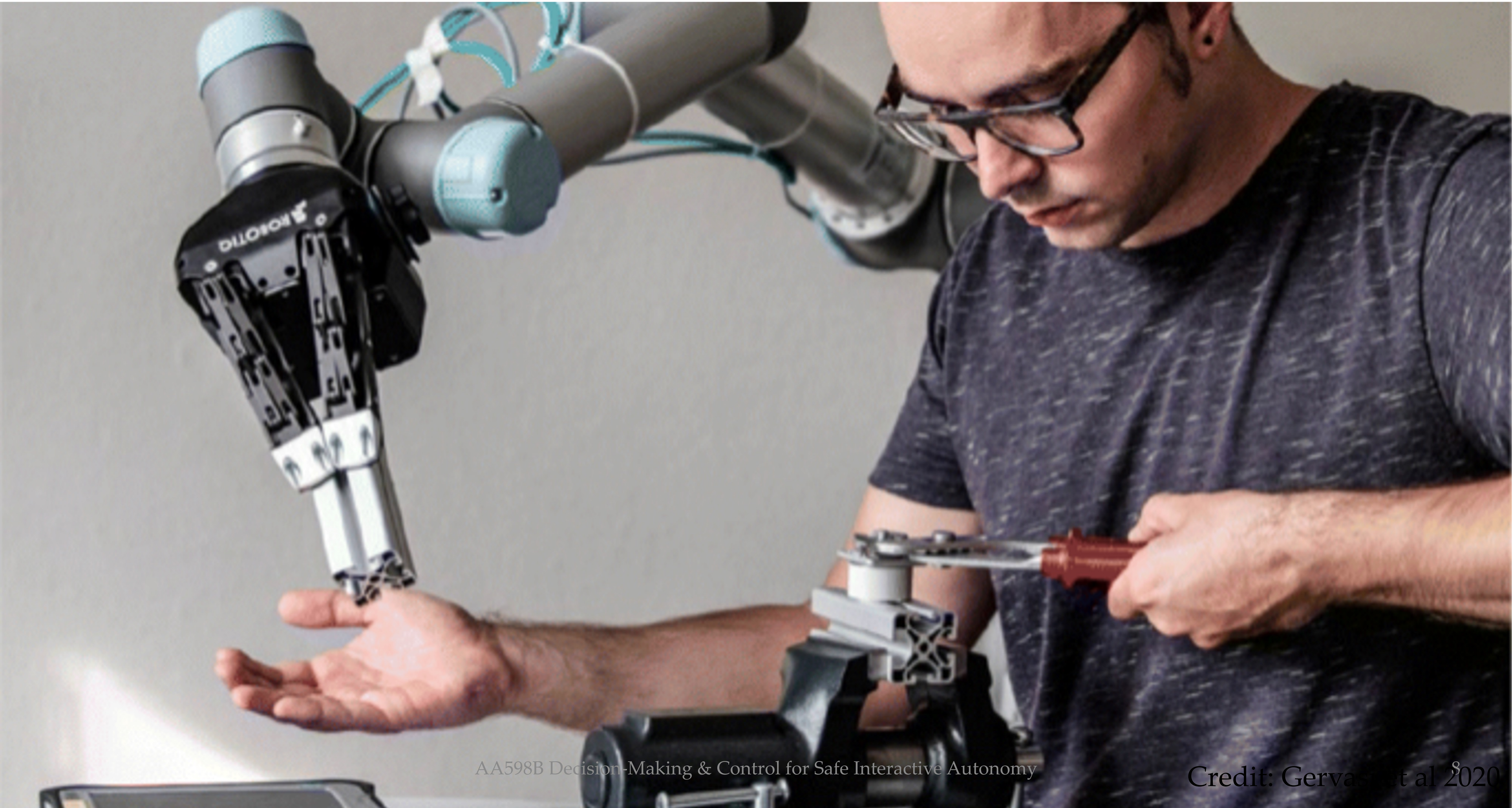
Human behavior prediction

Module #1



Rudenko et al 2019

Credit: MIT News 2022



Credit: Gervasi et al 2020

Why is human behavior prediction important?

(Discussion)

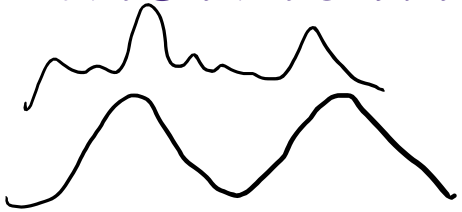
- humans can have very erratic behavior; physics based may not be enough.
- SAFETY vs. performance +1, avoid over conservatism
- multiagent systems -> coordination
- modeling influences between humans & robots.
- Trust, can help make ~~human~~ robot more "human-like"
- learning human preferences can help improve "interaction quality"

Challenges with human behavior prediction

(Discussion)

- **Uncertainty and variability**: Human behavior is highly variable, influenced by individual preferences, emotions, and situational contexts. This variability makes it difficult to create models that generalize across different individuals or settings.
- **Decision-making is complicated**: How humans make decisions is complex and often depend on variables that are not directly observable.
- **Nonlinear and time-varying**: Human actions exhibit nonlinear patterns and may change over time
- **Limited data**: Collecting high-quality data is expensive
- **Social and cultural factors**: Behaviors are shaped by social norms, and vary across individuals and locations.
- **Output representation**: Predict actions? Goals? States? High-level actions?
- **Constraints on the output space**: Obstacles, road rules, speed limits.

In general, we want to learn a *distribution*



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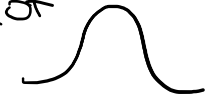


$$\text{Learn} \quad x \sim P(x \mid c)$$

x: some variable representing human behavior.

- position
- states
- images
- controls
- goals / waypoints
- high-level actions
- ...
- can include multiple agents $(x_1, x_2, \ldots, x_n)$

c: conditioning variable ← or ~~obs~~ observations / controls

- history of states (eg. last 15 time steps of info)
- goal
- environment (eg map, weather, time)
- current ~~ac~~ robot actions (eg. ~~to~~ indicators)
- future ~~robot~~ actions.

⋮

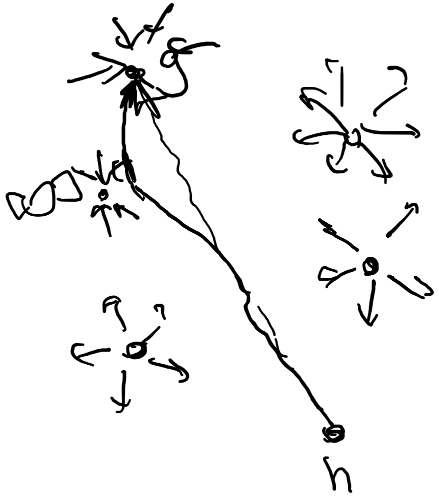
Human Motion Trajectory Prediction: A Survey

Ontological vs Phenomenological approaches

https://ai.stanford.edu/blog/trajectory-forecasting/

- **Ontological**: "Theory of mind", "first principles", explicit model that describes the interactions in a very interpretable way
  - Social forces model (SFM) [Helbing & Molnar 1998]
  - Optimal reciprocal collision avoidance (ORCA) [van den Berg et al 2011]
  - Intelligent driver model (IDM) [Treiber, Hennecke, Helbing, 2000]
  - MOBIL lane changing models [Kesting, Treiber, Helbing 2006]
  - Game theory [von Neumann 1928]
  - Optimal control, assume agents are optimal planners
  - Rationality model (maximum entropy inverse reinforcement learning) [Ziebart et al 2008, Levine & Koltun 2012, Sadigh et al 2016]

Social forces model



$$\vec{e}_\alpha(t) := \frac{\vec{r}_\alpha^{\,k} - \vec{r}_\alpha(t)}{\|\vec{r}_\alpha^{\,k} - \vec{r}_\alpha(t)\|},$$

Vector toward goal

$$\vec{F}_\alpha^0(\vec{v}_\alpha, v_\alpha^0\vec{e}_\alpha) := \frac{1}{\tau_\alpha}(v_\alpha^0\vec{e}_\alpha - \vec{v}_\alpha).$$

Speed towards goal

$$\vec{f}_{\alpha\beta}(\vec{r}_{\alpha\beta}) := -\nabla_{\vec{r}_{\alpha\beta}} V_{\alpha\beta}[b(\vec{r}_{\alpha\beta})].$$

Repulsive force from other humans

$$\vec{F}_{\alpha B}(\vec{r}_{\alpha B}) := -\nabla_{\vec{r}_{\alpha B}} U_{\alpha B}(\|\vec{r}_{\alpha B}\|)$$

Repulsive force from walls

$$\vec{f}_{\alpha i}(\|\vec{r}_{\alpha i}\|, t) := -\nabla_{\vec{r}_{\alpha i}} W_{\alpha i}(\|\vec{r}_{\alpha i}\|, t)$$

Attract force to points of interests

$$w(\vec{e}, \vec{f}) := \begin{cases} 1 \ \text{ if } \vec{e} \cdot \vec{f} \geq \|\vec{f}\| \cos\varphi \\ c \ \text{ otherwise.} \end{cases}$$

View cone

*Popular model for human crowd simulation

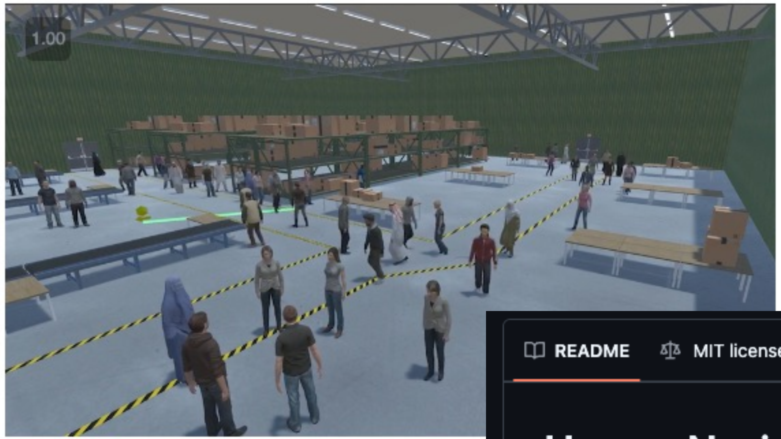
Human simulation environments using SFM

Social Environment for Autonomous Navigation 2.0

The Social Environment for Autonomous Navigation (SEAN) 2.0 is a high fidelity, extensible, and open source simulation platform designed for the fair evaluation of social navigation algorithms.

INSTALL SEAN 2.0 | CODE | PAPER | CITE

https://sean.interactive-machines.com/



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Human Navigation behavior Simulator (HuNavSim)

A controller of human navigation behaviors for Robotics based on ROS2.

This is a work in progress version

Tested in ROS2 Humble

The simulated people are affected by the obstacles and other people using the Social Force Model. Besides, a set of human reactions to the presence of robots have been included.

If you use this simulator in your work, please cite:

N. Pérez-Higueras, R. Otero, F. Caballero and L. Merino, "HuNavSim: A ROS 2 Human Navigation Simulator for Benchmarking Human-Aware Robot Navigation," in IEEE Robotics and Automation Letters, vol. 8, no. 11, pp. 7130-7137, Nov. 2023, doi: 10.1109/LRA.2023.3316072.

https://github.com/robotics-upo/hunav_sim

Nice review paper on social navigation algorithms and simulators:
https://arxiv.org/pdf/2306.16740