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Engineering

Educating Leaders. Creating Knowledge. Serving Society.



New Vistas in Robotics at Berkeley

S. Shankar Sastry

Professor of EECS, BioEng., Mech Eng.

Director, Blum Center for Developing Economies

Director, C3.ai Digital Transformation Institute

Univ of California Berkeley

An Overview of the Telesurgical Workstation Project

S. Shankar Sastry, Cenk Cavusoglu, Michael Cohn,
Winthrop Williams, Matt Danning, Dimitry Derveyanko,
Lara Crawford, Jeffrey Wendlandt, Curt Deno

Key Collaborators: Frank Tendick, Ron Fearing

Department of Bioengineering
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Berkeley, CA 94720

Telesurgical Workstations



Minimally invasive—small incisions: millirobotic tools: surgeon is remote!

Robotic tools give surgeon dexterity and tactile sensations of force, hardness, etc.

Improved imaging, 3D displays: AR/VR Environments



Shankar Sastry

Laparoscopic Manipulators



Two stage design

- First, for gross positioning of the end effector is a Stewart platform-like parallel manipulator, driven by electric motors, giving 4 degrees of freedom.
- Second, the 3 DOF millirobot has a 2 DOF wrist and gripper, driven by hydraulic actuators. The millirobot's design is optimized to provide enough dexterity to perform suturing and knot-tying tasks.

Telesurgical Workstation



ANIMAL LAB TRIALS 1998

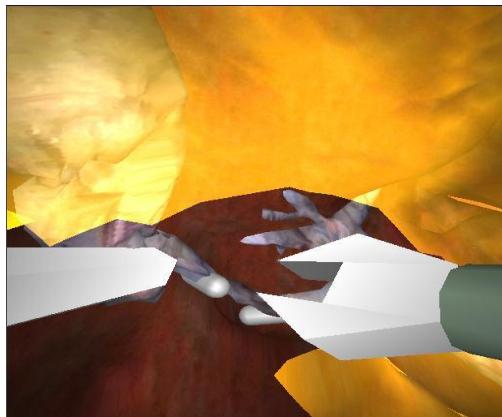
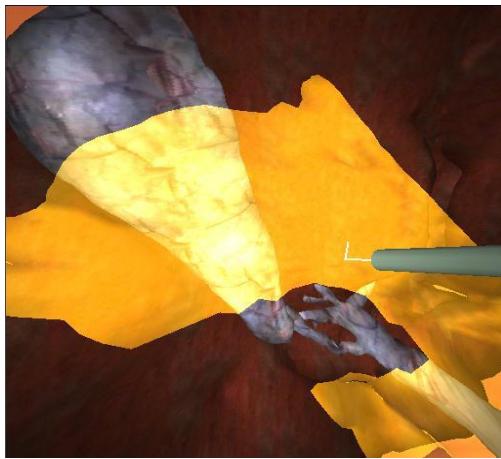
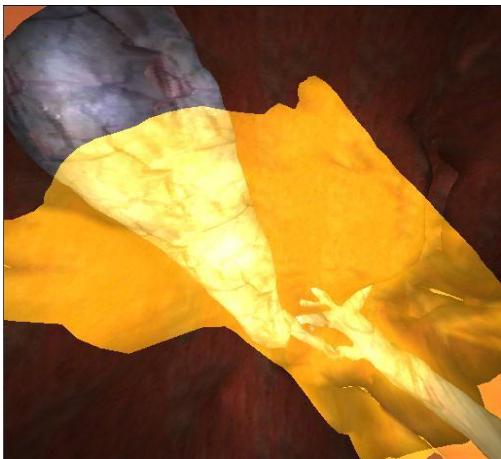


Suturing with Unimanual System, 1998



Laparoscopic Cholecystectomy VR Simulation

Frank Tendick, Michael Downes, M. Cenk Cavusoglu, Shankar Sastry,
and Lawrence Way UC San Francisco and UC Berkeley



Future

- Telesurgery
 - Smaller scale manipulators for **cardiac** and **fetal** surgery
 - Critical look at the **mechanical design** of teleoperation systems from **control point of view**
 - Surgery on the **beating heart**
- Surgical Simulation
 - **Deformable tissue models** for dynamic simulation
 - **Bridging the gap** between finite element, finite difference, and lumped element models, i.e. computer scientists and mechanical engineers

Robotic Surgery Companies Today

- Intuitive Surgical, 2014, Da Vinci
- Stryker, 2013, MAKO (knee and hip surgery)
- Accuray, Cyberknife, partnered with Kuka (radiation therapy)
- Smith & Nephew, NAVIO, knee replacement
- Mazor Robotics, 2012, Mazor X, neurosurgery
- Auris Health, MONARCH robotic bronchoscopy (now J&J)
-

Intuitive Surgical Da Vinci System

<https://intuitive.com>



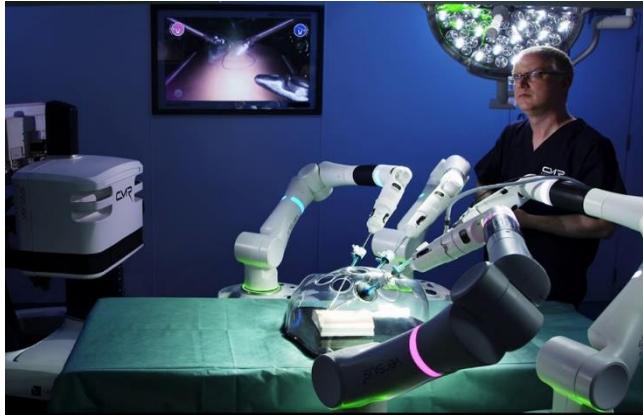
- As minimally invasive surgery expands, Academic Medical Centers will continue to play a large role in preparing the surgeons of tomorrow for its latest modalities, including da Vinci robotic-assisted surgery.
- There are currently 350+ da Vinci systems spread across 140 robotics programs in U.S. Academic Institutions, which help 90,000+ patients every year.¹

Auris Monarch J&J Bronchiboscopy System



- For remote insertion of Bronchioscopes.
- Especial need for Covid
- Can it be made less expensive?

Newer Companies



Clockwise from bottom left

1. ActivSight by ActivSurgical:
soft tissue suturing
2. Versius by CMR Medical,
laparoscopic procedures
3. Dexter by Distal Motion,
laparoscopic procedures



The Berkeley Aerial Robot Project (BEAR)

<http://robotics.eecs.berkeley.edu/bear>

David Shim, Jin Kim, Hoam Chung, Peter Ray, Omid Shakernia, Jonathan Sprinkle, Mike Eklund, Todd Templeton, Travis Pynn, Cory Sharp, Cedric Ma, Rene Vidal, Perry Kavros, Shahid Rashid, Tulio Celano, Bruno Sinopoli, Shawn Shaffert, Andrew Godbehere and Sam Burden **with Shankar Sastry**

University of California, Berkeley



BEAR Fleet: rotorcraft





Conflict Detection and Resolution

Berkeley UAV Collision Avoidance Experiment

David H. Shim, H. Jin Kim
May 25, 2003

University of California, Berkeley



Vision Based Landing

Vision-Based Landing of a UAV

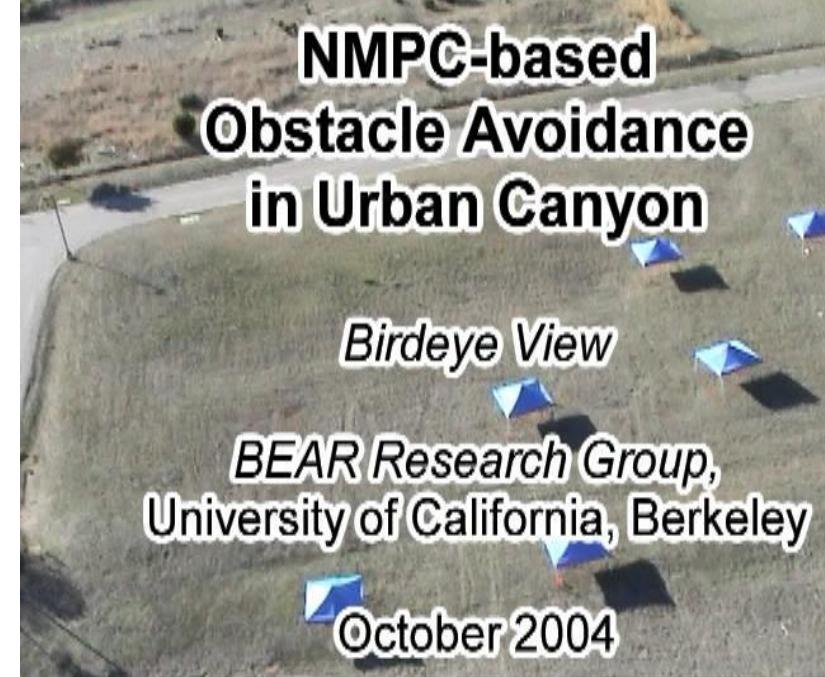
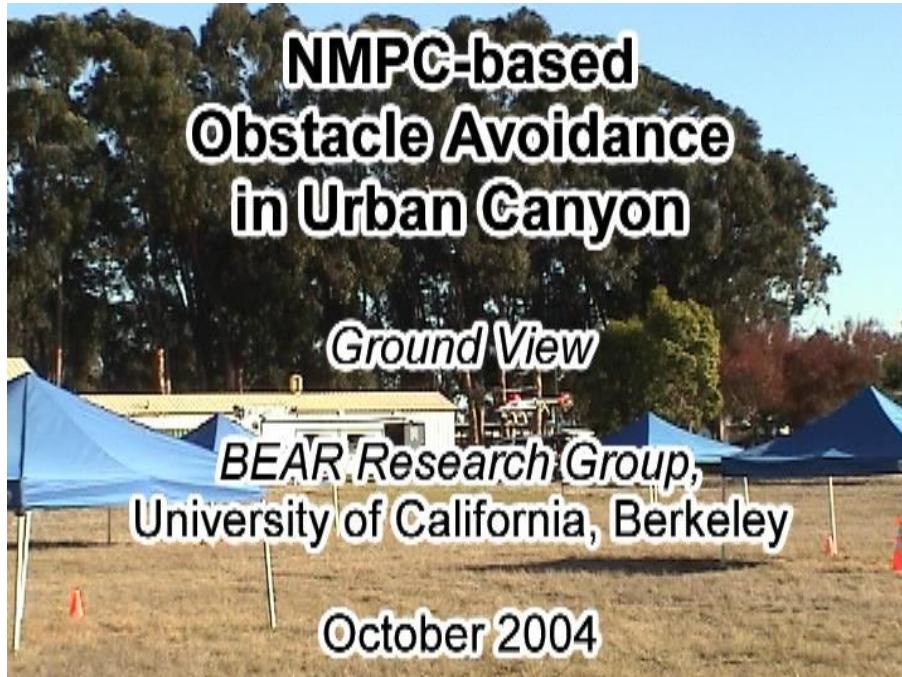
Omid Shakernia

Dept of EECS, UC Berkeley

<http://robotics.eecs.berkeley.edu/~omids>



Model Predictive Control Based Path Planningg





Smart Bird takes flight

Smart Bird

"Single Man Aerial Reconnaissance Technology"

Battlefield Information Reconnaissance Deployment"



Press Coverage of BEAR

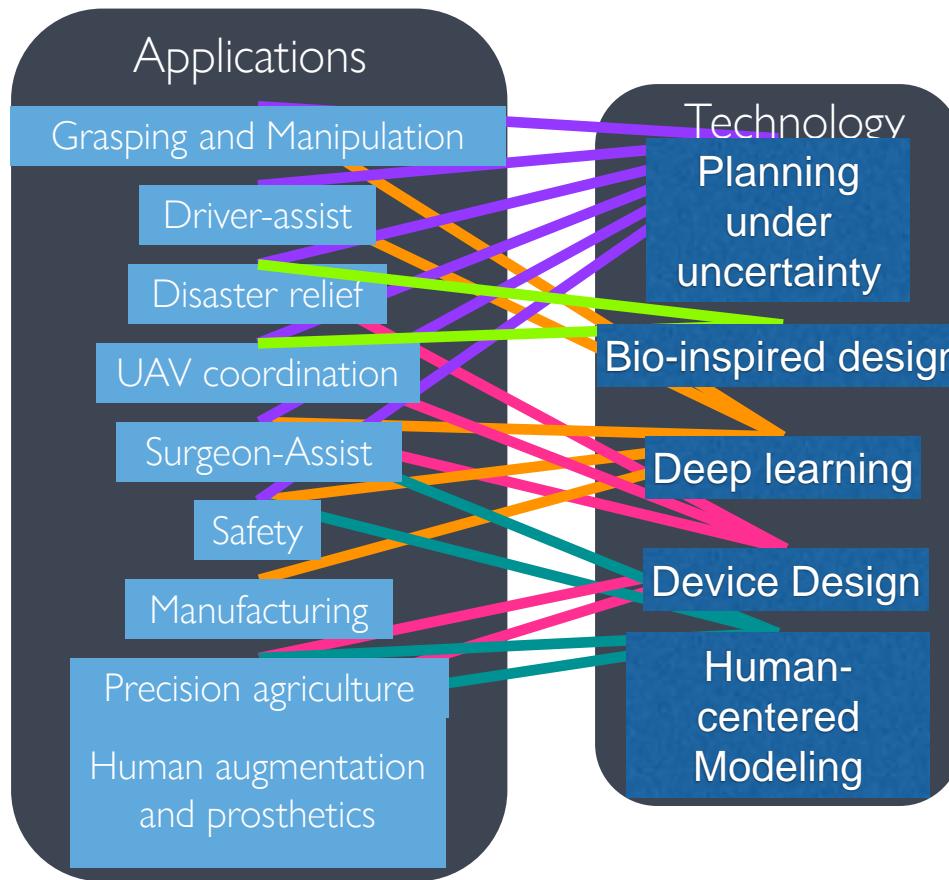


BEAR UAV Research Test bed: A Legacy of Innovation and Transition

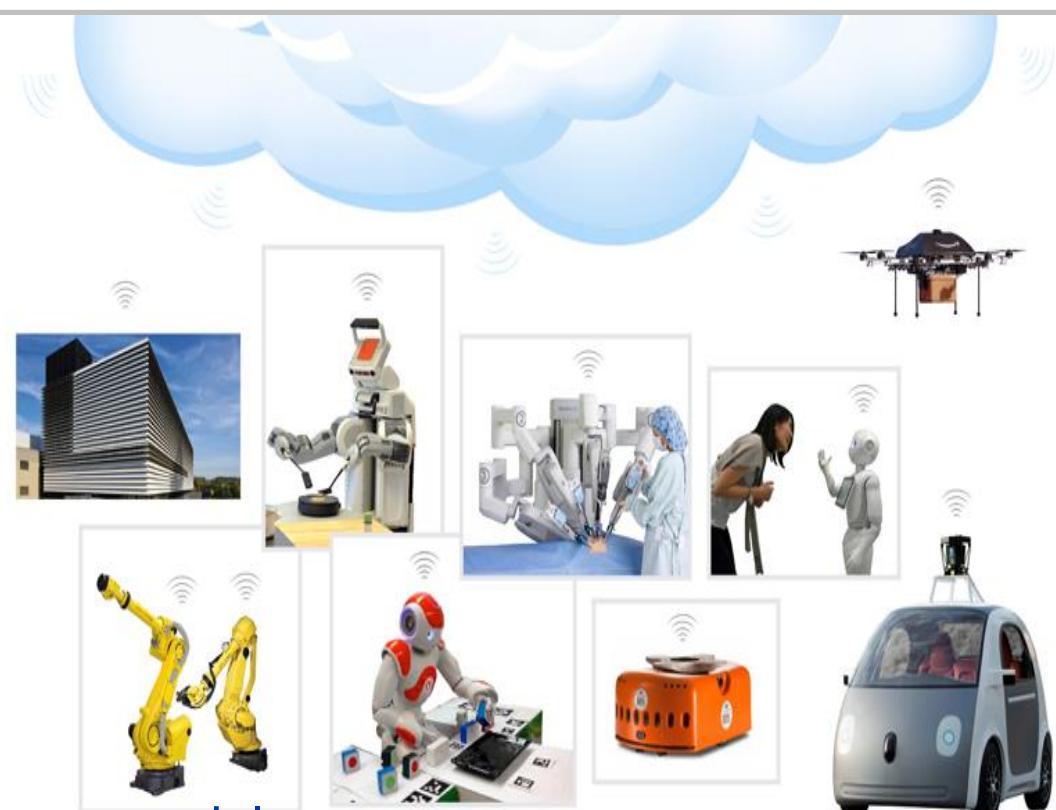
- ▶ Architecture for multi-level rotorcraft UAVs 1996- to date
- ▶ Pursuit-evasion games 2000- 2002 (transitioned to AFRL/Darpa/Boeing UCAV program)
- ▶ Vision Based landing on pitching decks 2001- to date (transitioned to Socom Boeing-Frontier Systems Maverick/A-160)
- ▶ Multi-target tracking 2001- to date (transitioning to 1st MEP, Camp Pendleton)
- ▶ Formation flying and formation change 2002-4 (transition begun to Army Socom, 160th SOAR, Sikorsky)
- ▶ NMPC Based Acrobatic Flying, conflict resolution 2003 (transitioned to DARPA UCAR, Lockheed, Northrup Grumann)
- ▶ Aerial Pursuit Evasion Games 2003 (transitioned to Boeing UCAV program, demo at Edwards AFB, June 2004)
- ▶ Automated Landing transitioned to Northrup Grumann (demo at Edwards AFB, June 2004)
- ▶ Sensor Webs (low bandwidth air dropped sensor webs demonstrated at China Lake, Feb 04): now Smart Bird personal UAVs
- ▶ Personal back pack sized UAVs (Smart Bird), April 2004-ongoing
- ▶ Perch and Move Electric UAV Vehicles, August 2004
- ▶ Map Building and Collision Avoidance, November 2004
- ▶ Vision Based Landing transitioned to Boeing Frontier, demo first autonomous landing Dec 2005



CITRIS “People and Robots” Initiative

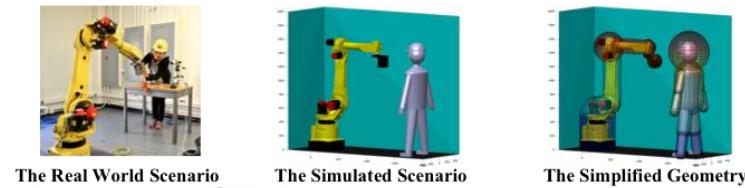


Cloud Robotics



1. Big Data: Images, maps, models
2. Cloud Comp.: Statistical learning
3. Open-Source: Sharing code, data, designs
4. Robot Learning: Robots sharing code, data
5. Crowdsourcing: Input from remote humans

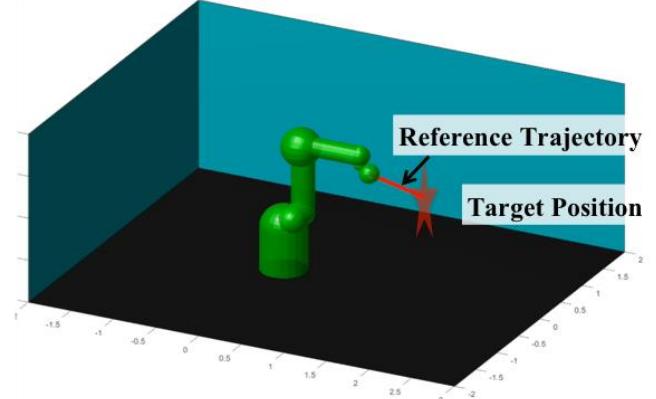
Manufacturing



The Real World Scenario

The Simulated Scenario

The Simplified Geometry



Masayoshi
Tomizuka



Ken
Goldberg



Paul
Wright

Data-Driven Grasping and Manipulation

DexNet: A cloud-based network of 3D objects for robust grasp planning

Algorithms for efficient grasp quality evaluation

Energy-bounded caging

Topological motion planning for grasping and manipulation

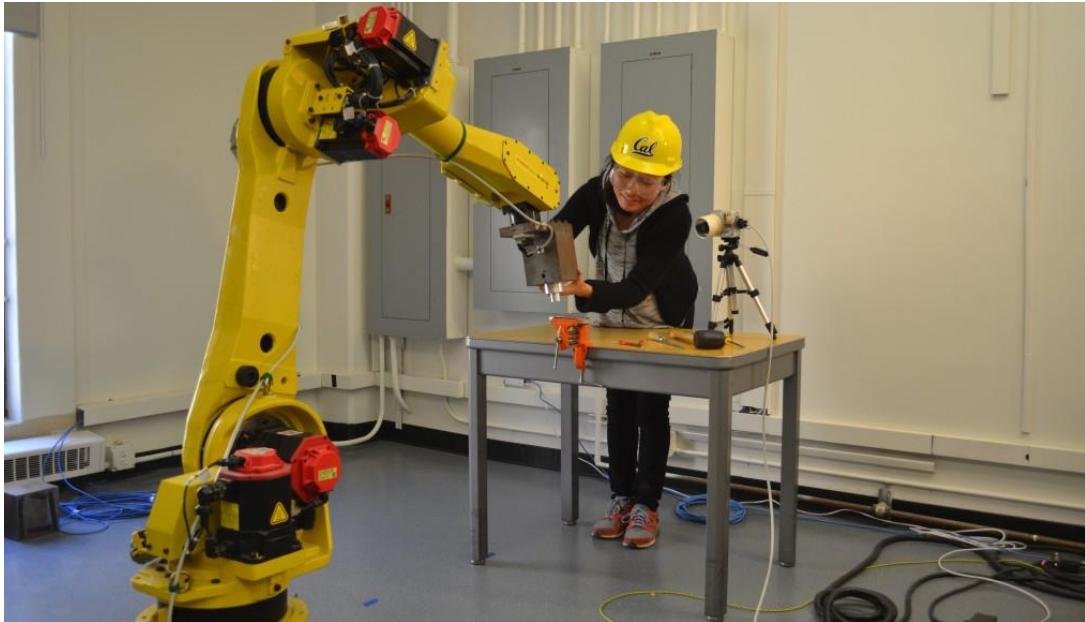


Ken Goldberg



Pieter Abbeel

Safety in Human-Robot Interaction



Safety-constrained motion planning for efficiency in factory human-robot interaction

Learning and prediction for safety in HRI

Provably safe human-centric autonomy



Claire Tomlin



**Masayoshi
Tomizuka**

Deep Learning

- [N] Neural Network
- [P] Probabilistic Model
- (●) Supervised learning
- (○) Unsupervised learning

Traditional models
Deep models

[H] Neural Nets
[McCulloch & Pitts 1943]

[N] Perceptron
[Rosenblatt 1958]

Decision Tree(CLS)
[Hunt 1966]

SVM
[Vapnik 1979]

[N] RNN
[Grossberg 1973]

[N] Conv. Net
[Fukushima 1979]

Boosting
[Schapire 1990]

[N] AI
[Hinton 1989]

[N] ZN(P)
[Hoerik 1989]

RBM (P)
[Hinton 1999]

[N] GMM (P)
[Reynolds 1992]

[N] Sparse Coding (P)
[Olshausen 1996]

[N] DBN (P)
[Hinton et al 2006]
[N] D-AE
[Vincent 2008]

[N] BayesNP (P)
[Teh & Jordan 2009]

[N] DBM (P)
[Salakhutdinov & Hinton 2009]

Algorithms authors and dates often unclear. Oldest citations were assumed.
Classifications based on Yann LeCun's Deep Learning class at NYU – spring 2014.

Deep Learning for Robotics



Learning deep visuomotor policies: enable robots to autonomously acquire new skills by learning from human demonstrations

Simultaneous transfer across domains

Deep learning for locomotion

Unsupervised Trajectory Segmentation of Multi-Modal Surgical Demonstrations with Deep Learning



Trevor Darrell



Pieter Abbeel



Ken Goldberg

Reducing Supervisor Burden for Robot Learning



Learning from demonstrations

Learning deep visuomotor policies:
enable robots to autonomously
acquire new skills by learning from
human demonstrations

Cooperative inverse reinforcement
learning: understanding value
alignment between humans and
machines

Indirect learning from humans:
context and motion from archived
video

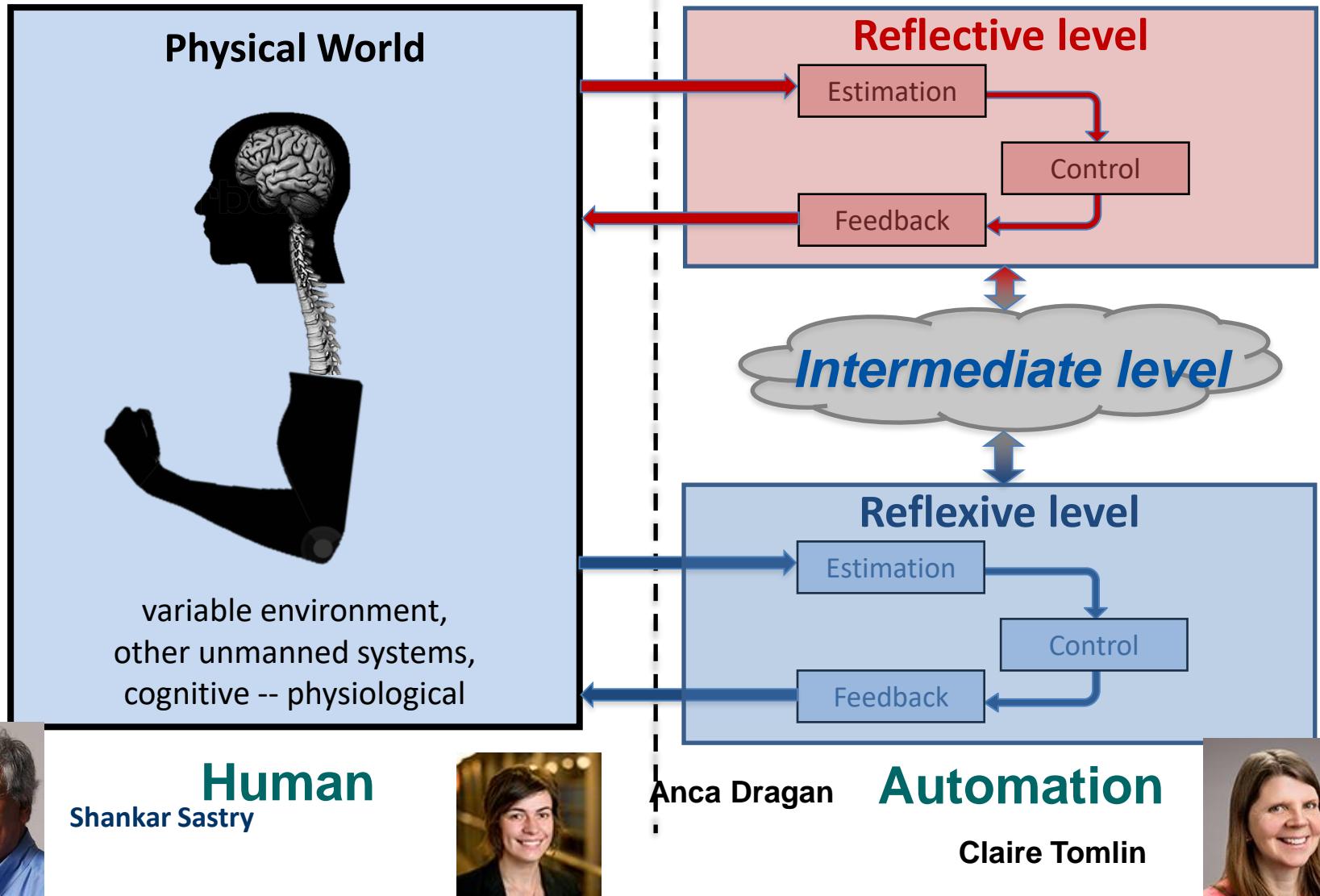


Ken
Goldberg

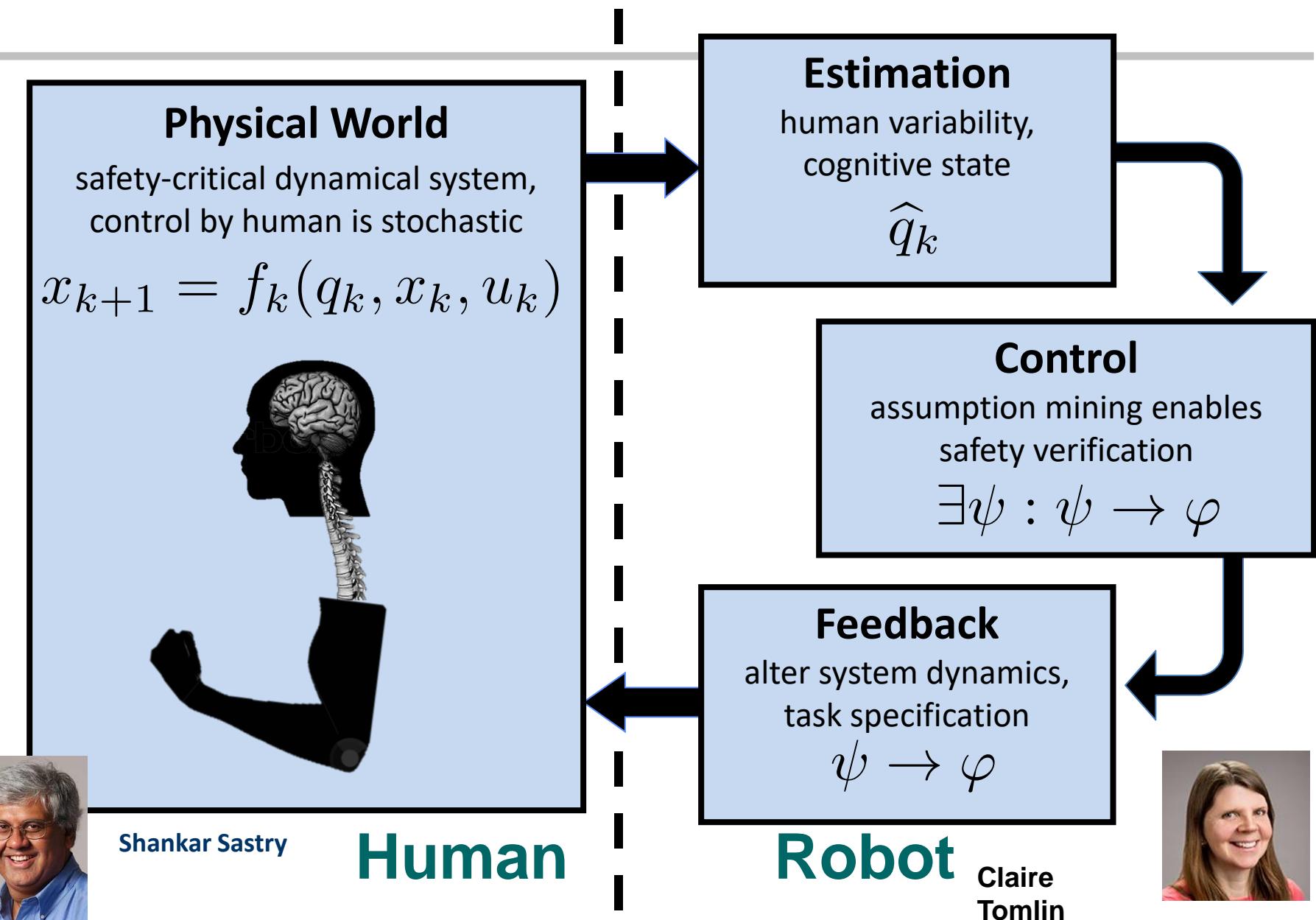


Pieter
Abbeel

Embedding Humans in Automation



High Confidence Robotic Assistants



Interaction with Humans

Google's Driverless Cars Run Into Problem: Cars With Drivers

By MATT RICHTEL and CONOR DOUGHERTY SEPT. 1, 2015

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MOUNTAIN VIEW, Calif. — [Google](#), a leader in efforts to create driverless cars, has run into an odd safety conundrum: Its cars don't make enough mistakes.

Last month, Google's self-driving car approached a supposed pedestrian in a crosswalk, but instead of applying the brakes, as it was programmed to do, the car continued forward, not so much because it was behind the pedestrian but because the pedestrian had stepped off the curb and onto the street. "It's a challenge," says Sebastian Thrun, Google's director of driverless-car research. "One of the biggest challenges facing automated cars is blending them into a world in which humans don't behave by the book."

Google's fleet of autonomous test cars is programmed to follow the letter of the law. But it can be tough to get around if you are a stickler for the rules. One Google car, in a test in 2009, couldn't get through a four-way stop because its sensors kept waiting for other (human) drivers



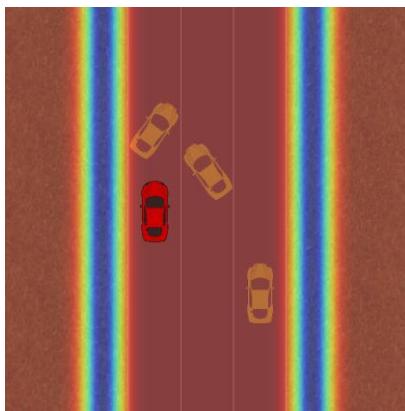
The Google self-driving car, with Eric Schmidt, left, the company's executive chairman, and Transportation Secretary Anthony Foxx. Justin Sullivan/Getty Images

Learning Driver Models

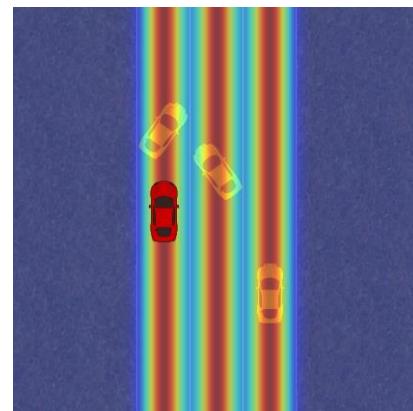
Learn Human's reward function based on Inverse Reinforcement Learning:

$$P(\mathbf{u}_H | x_0, w) = \frac{\exp(R_H(x_0, \mathbf{u}_R, \mathbf{u}_H))}{\int \exp(R_H(x_0, \mathbf{u}_R, \bar{\mathbf{u}}_H)) d \bar{\mathbf{u}}_H}$$

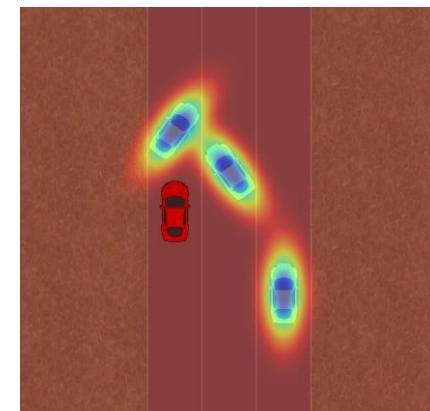
$$r_H(x^t, u_R^t, u_H^t) = w^\top \phi(x^t, u_R^t, u_H^t)$$



(a) Features for the boundaries of the road

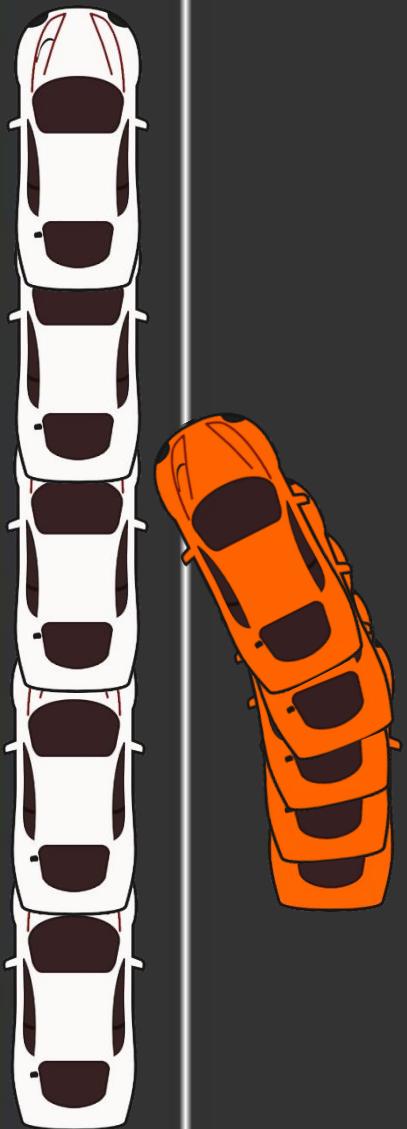


(b) Feature for staying inside the lanes.

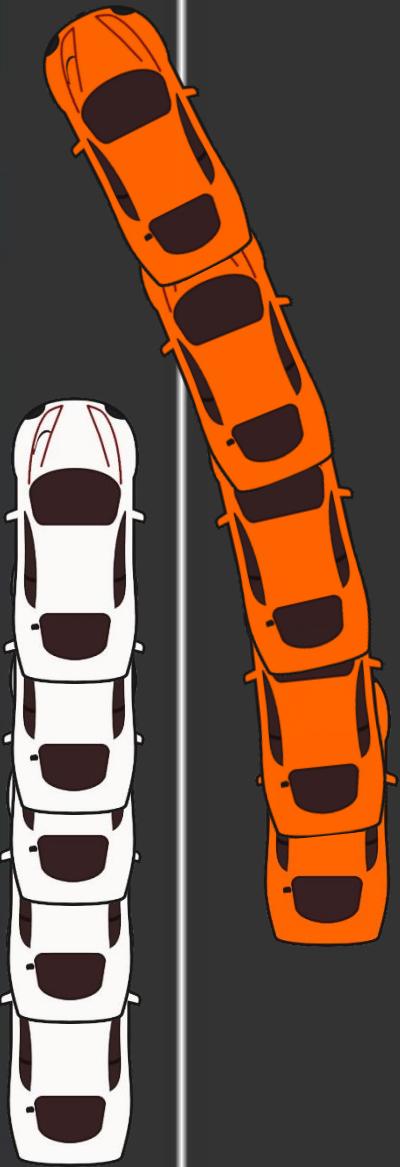


(c) Features for avoiding other vehicles.

Implication: Efficiency

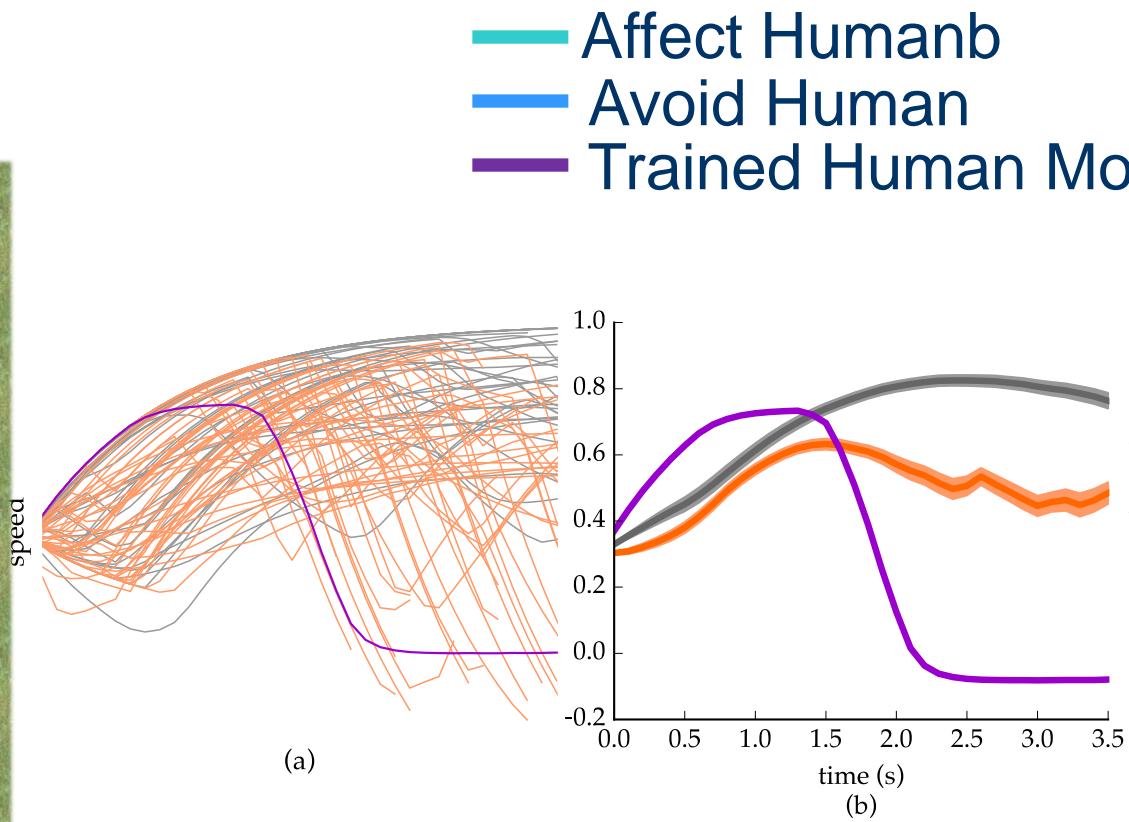
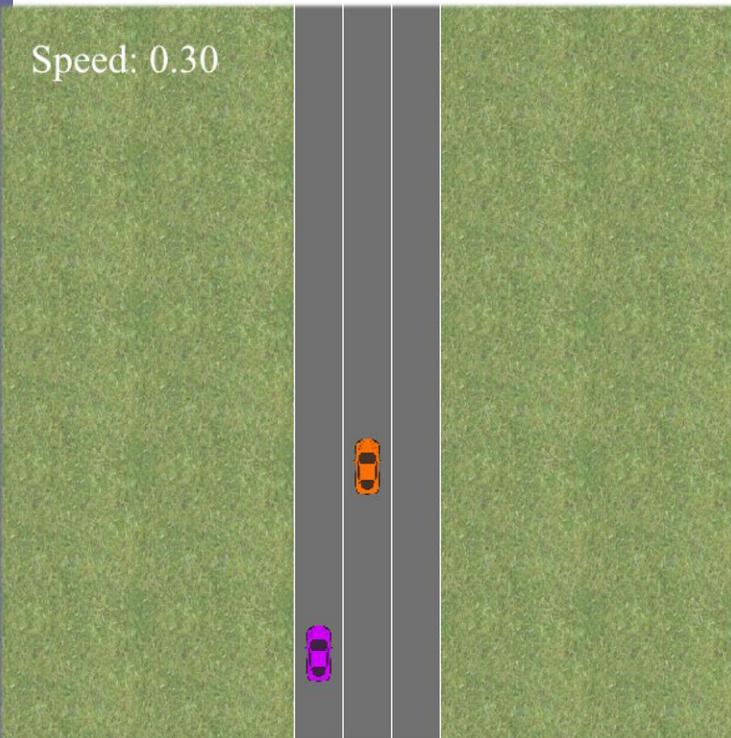


Implication: Efficiency



Make Human Slow Down

Autonomous vehicle optimizes for efficiency, and leverages affects on the human.



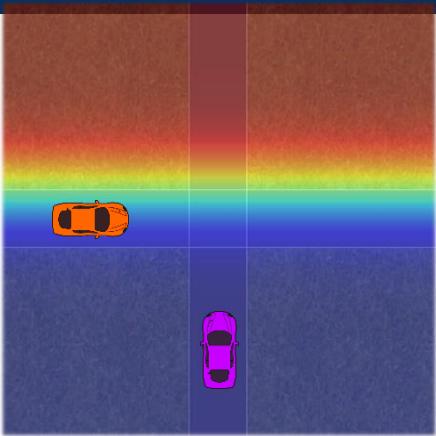
Implication: Coordination



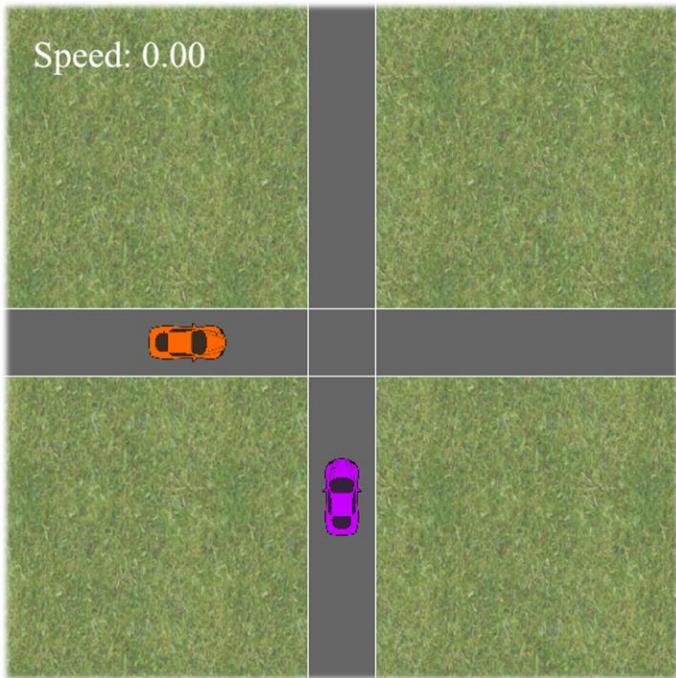
Implication: Coordination



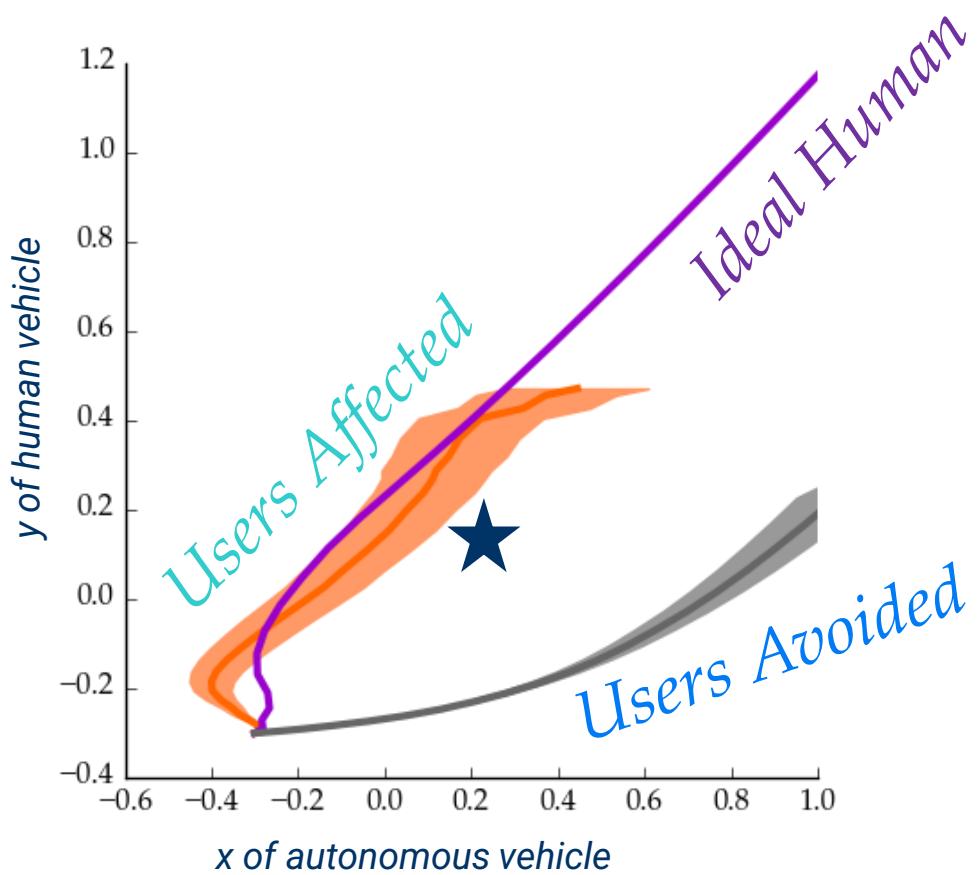
Make Human Cross First



Reward for making the human cross first.



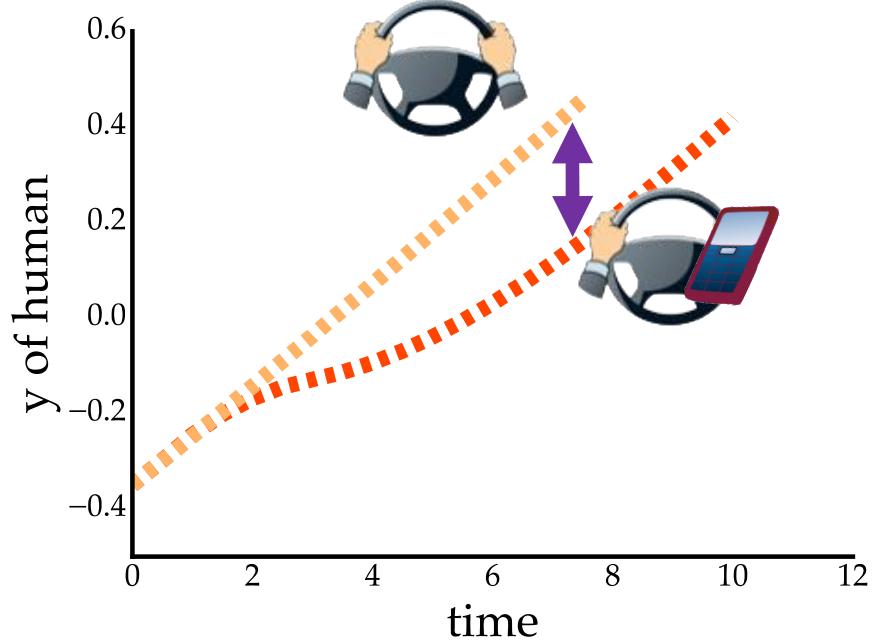
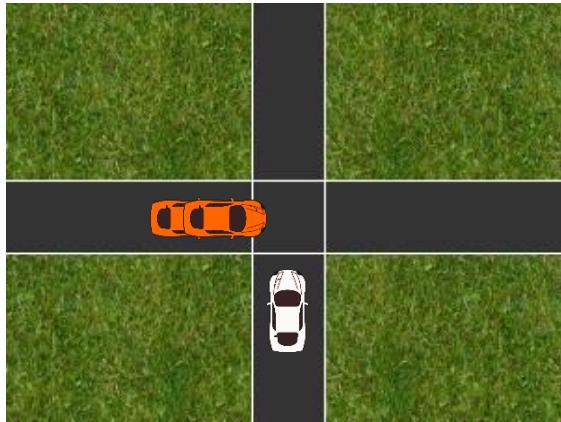
Autonomous vehicle backs up to communicate with the human, and make her cross first.



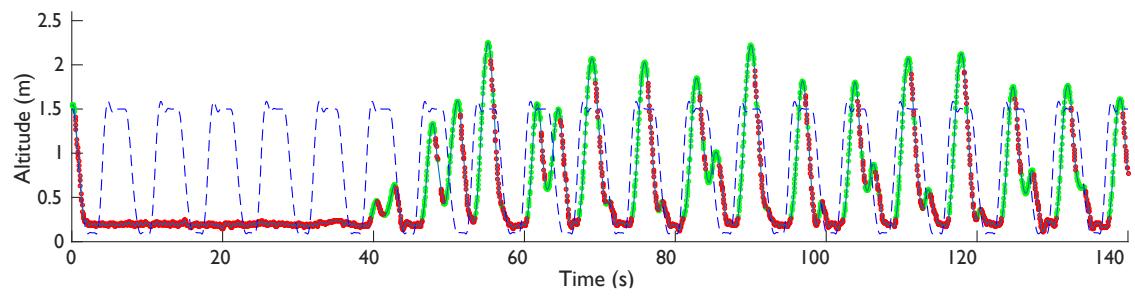
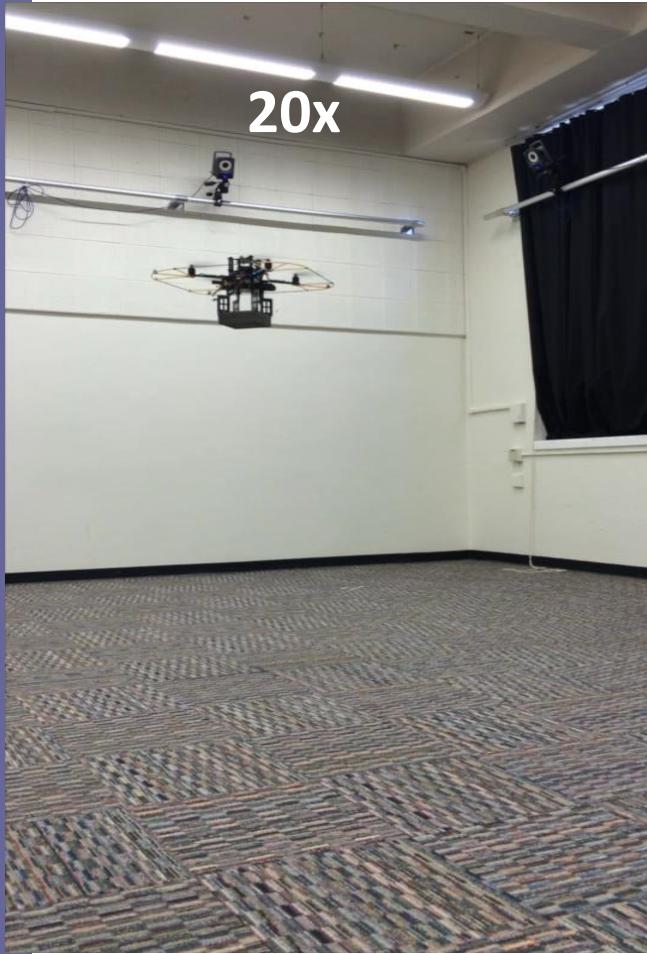
Active Information Gathering

Active information gathering over human's internal state.

Human's internal state:
 φ : *Aggressive vs Timid*
Attentive vs Distracted



Safe Learning



The quadrotor first drops :

After about 1 minute,
it can roughly track the trajectory

Soon, it starts experimenting

...but the safe controller steps in



Claire Tomlin

Safe Learning: UAVs in Flight



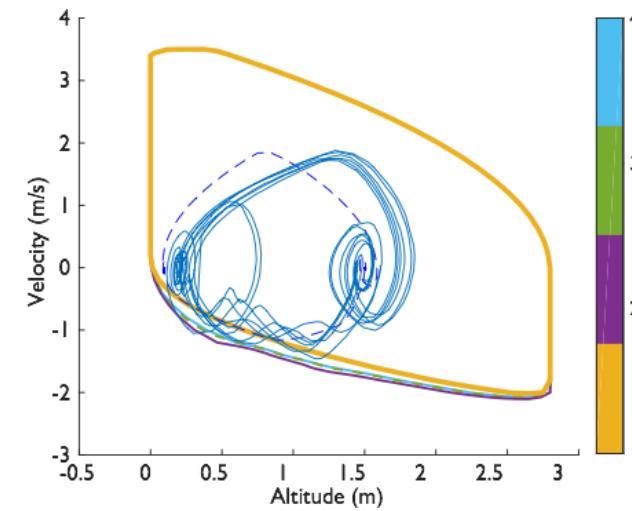
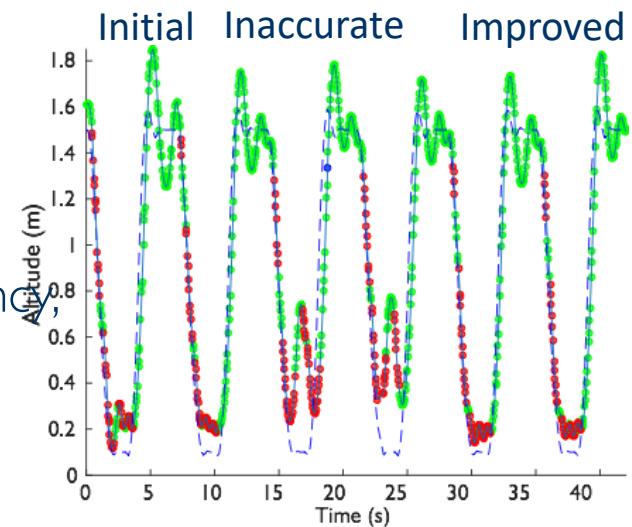
First computed model
is locally inaccurate

System detects inconsistency,
slightly contracts safe set

Tracking resumes after a
better model is computed

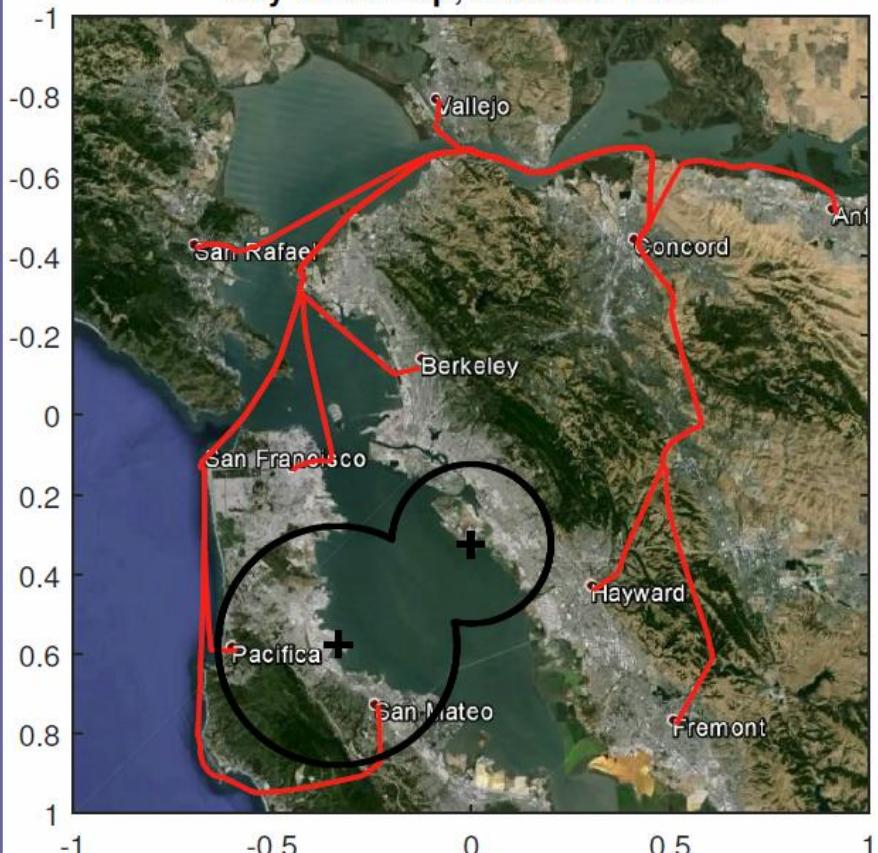


Claire Tomlin

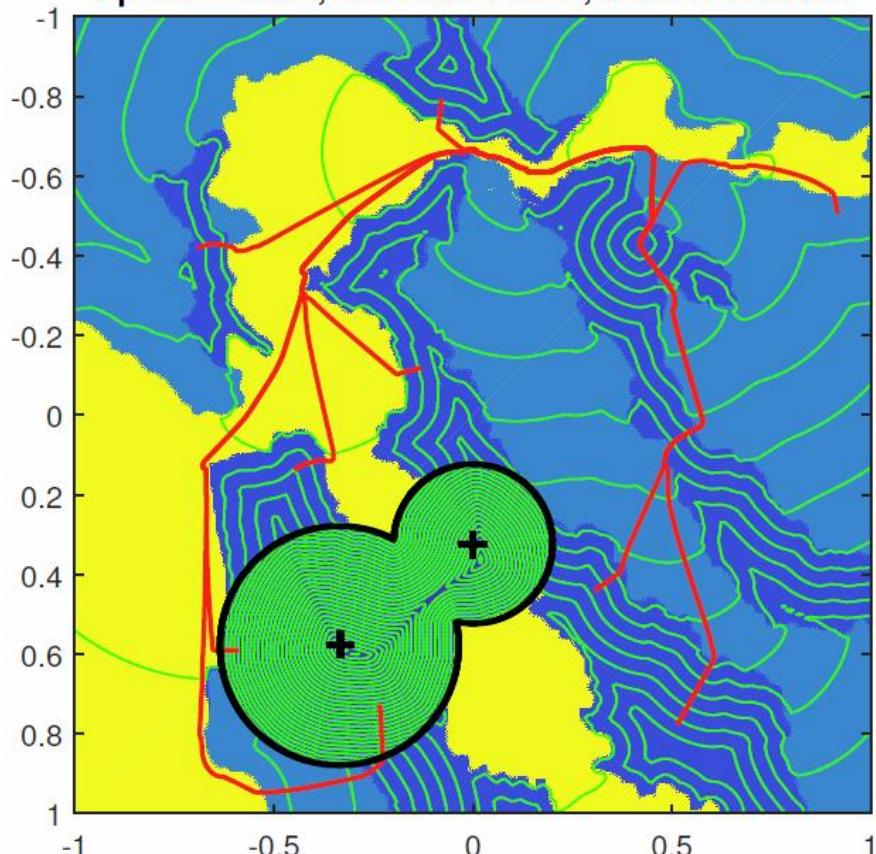


Unmanned Air Traffic Mgmt: Platooning UAVs

Bay Area Map, Shortest Paths



Speed Profile, Shortest Paths, Value Function



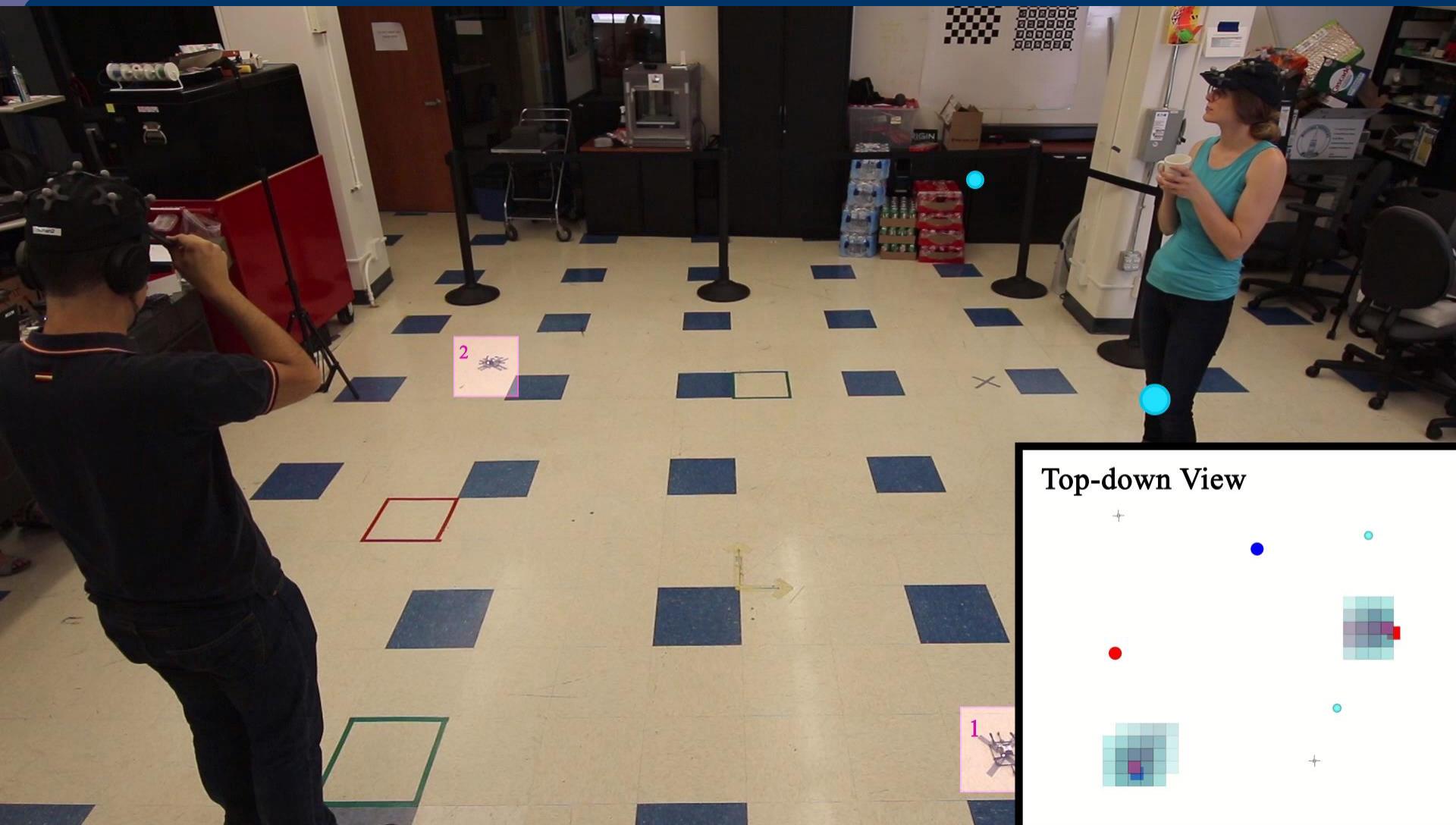
Claire Tomlin

Maneuvering around people

[Bajcsy, Fisac, Fridovich-Keil, Herbert et al., RSS 2018]

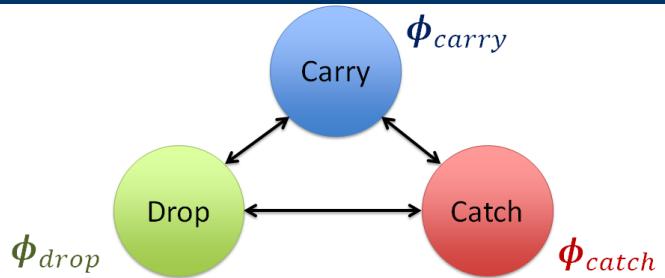


Extending to multiple humans and robots

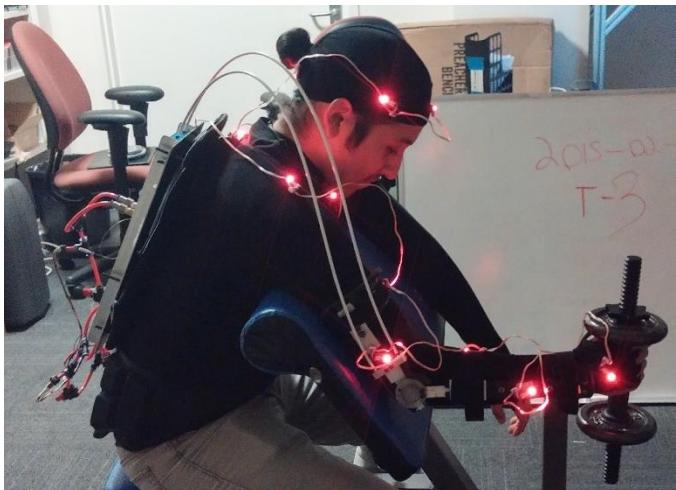


[Bajcsy, Herbert, Fridovich-Keil, Fisac et al.]

Optimal Assistive Device Design



By modelling the individual and the tasks they need to perform, it is possible to generate the design parameters for assistive devices



Actuator selection, and mechanism design can be determined via optimization methods

These devices are lighter, cheaper and more energy efficient than conventionally designed devices



Ruzena Bajcsy

Prosthetics: Sophie's Super Hand



Alice Agogino

Robotic Human Augmentation



Low cost and accessible exoskeleton systems for individuals with mobility disorders.

Exoskeletons for strength and endurance augmentation for emergency personnel

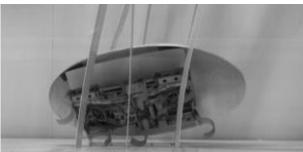
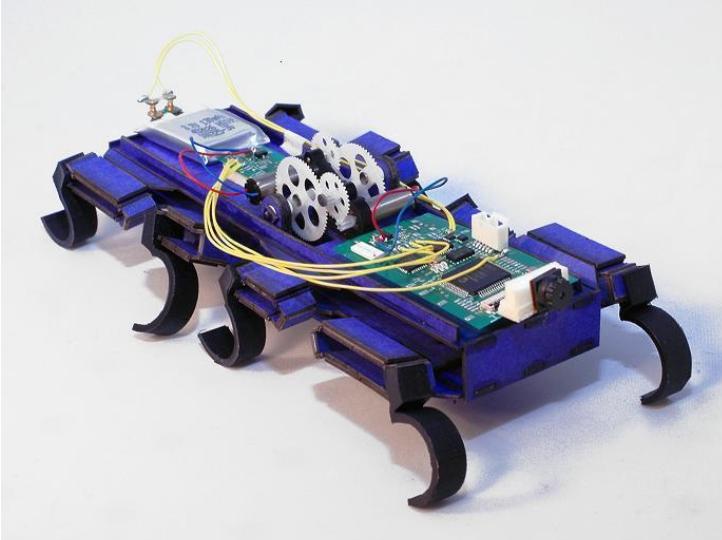
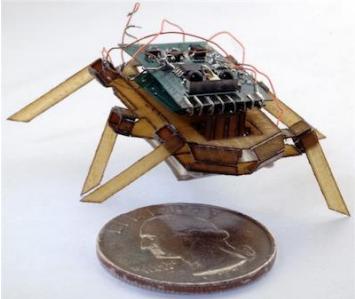
Assistive arms for people with motor impairments

Human power extenders for repetitive lifting in warehouse workers



Homayoon
Kazerooni

Bioinspired Milli-Robots



Ron
Fearing



Bob Full

Bio-inspired design

Locomotion and mobility
inspired by biology

DIY millirobot rapid
prototyping

Micro mechanical flying
insects for disaster
response

Predictive Models of Human Behavior



Desk Simulator:
Motion capture/ stereo camera



Force Dynamics Vehicle/Flight Simulator

- High speed multi-axis motion
- Motion capture/ stereo camera



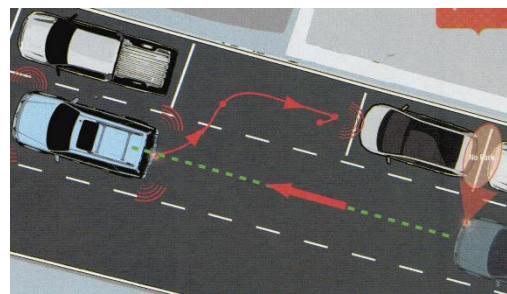
- Vehicle Dynamics
- No Scene Complexity



Jaguar
AFS, Ice test



Hyundai
Fully autonomous capability



- Non-holonomic Constraints
- Static Obstacle Avoidance



- Some Scene Complexity
- Decision Making + Speed

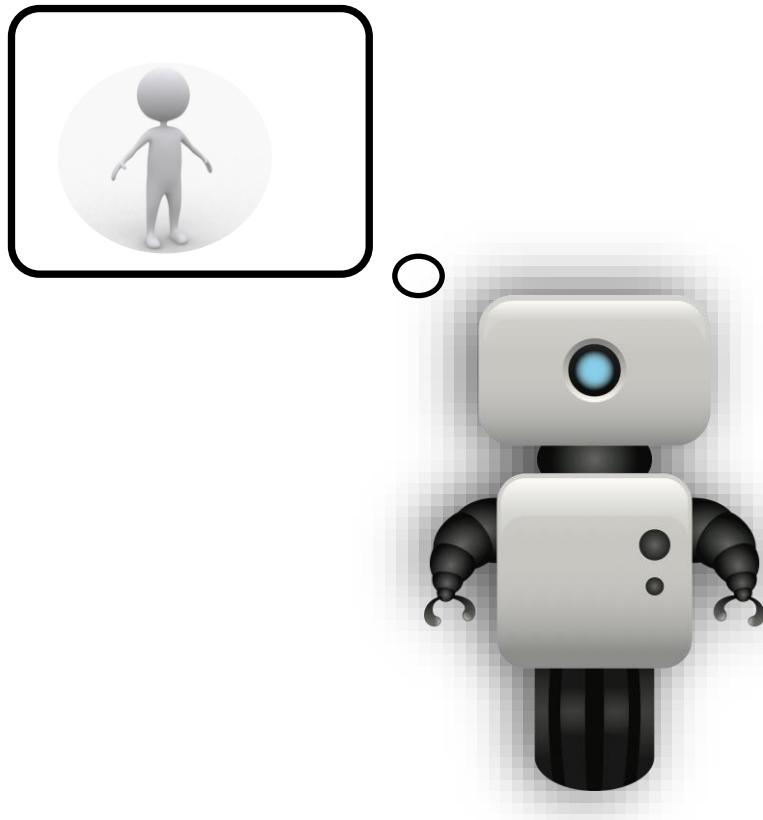
Humans and Robots Cooperating



Shankar Sastry



Anca Dragan



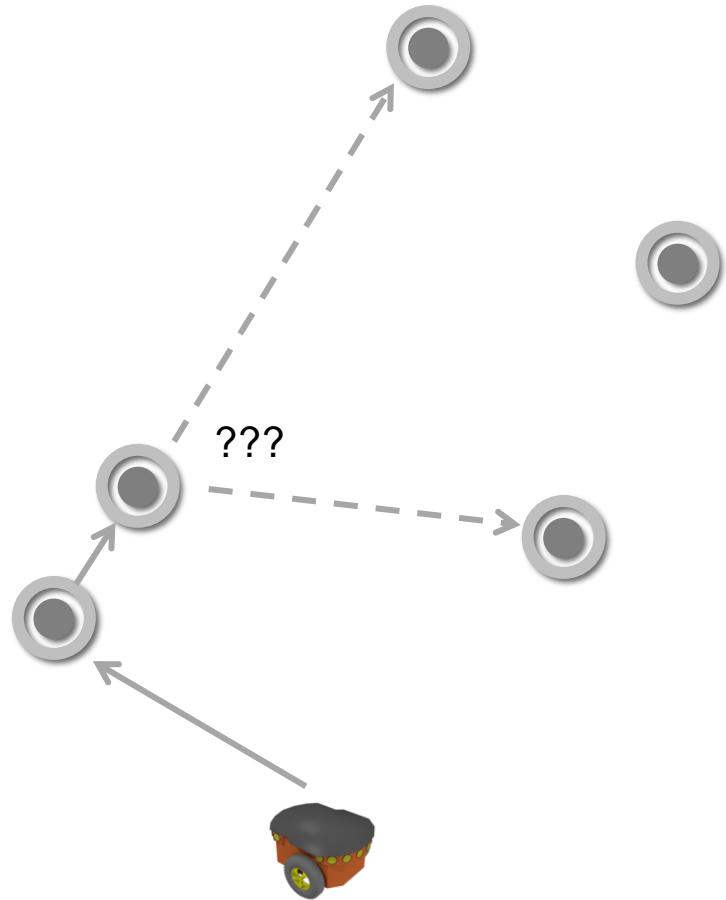
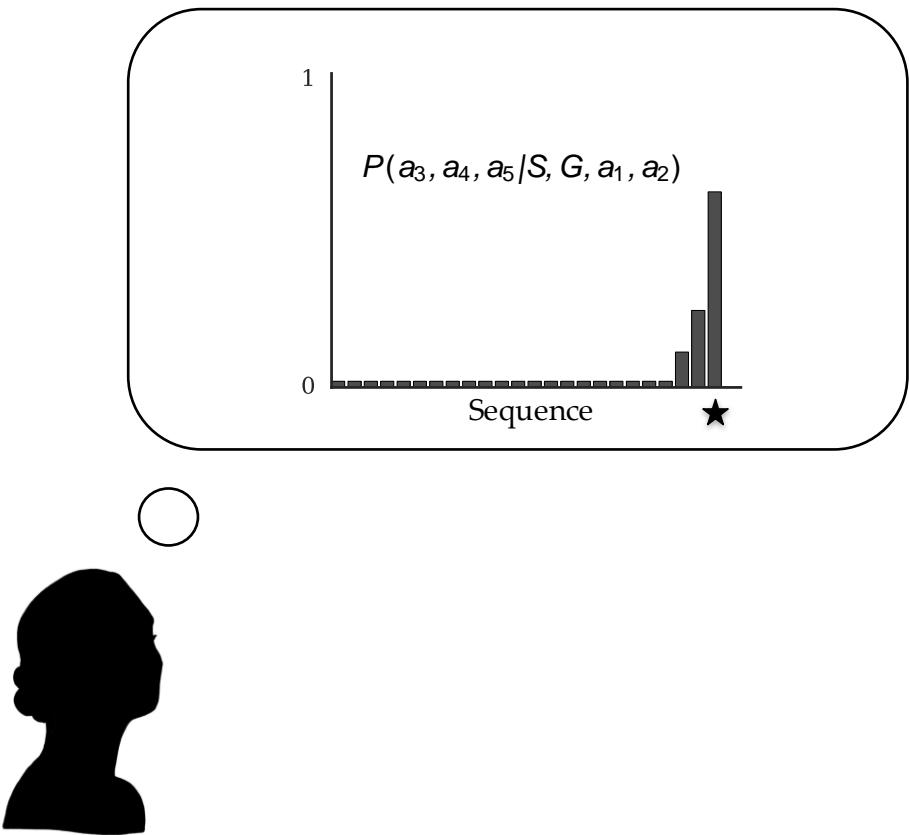
user

robot

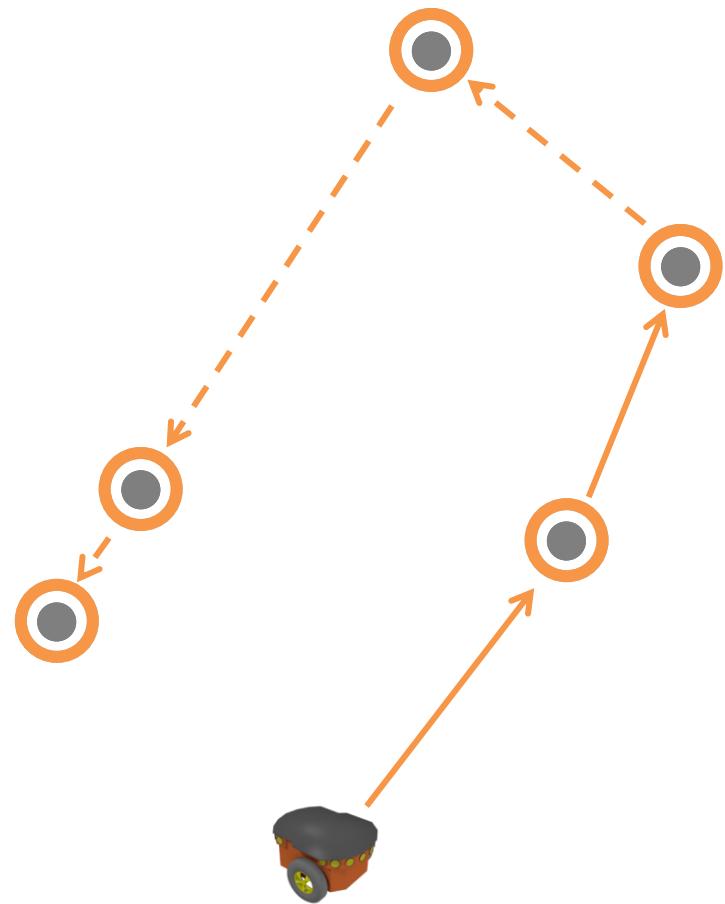
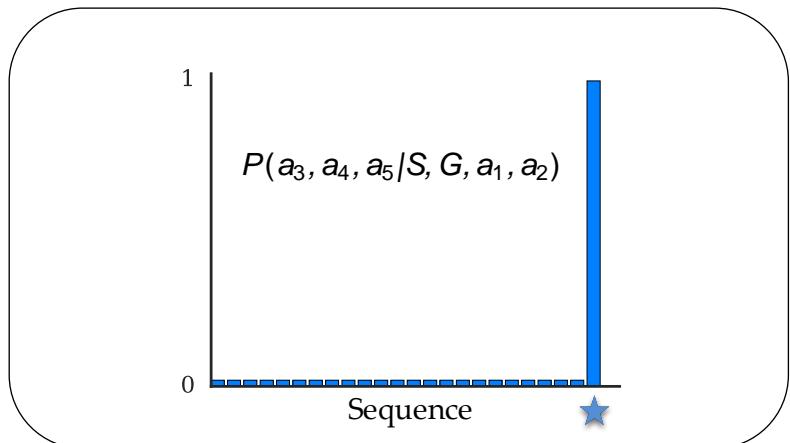
user's avatar



Efficient can be ambiguous



t-Predictable planning



Tractable t -Predictable algorithm

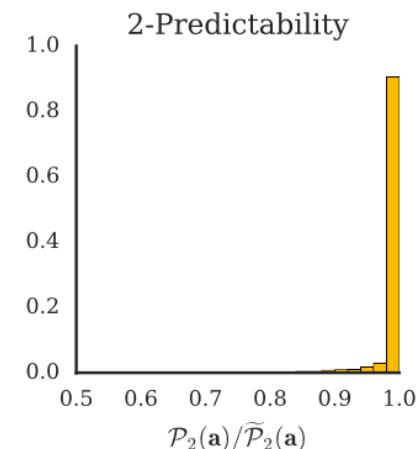
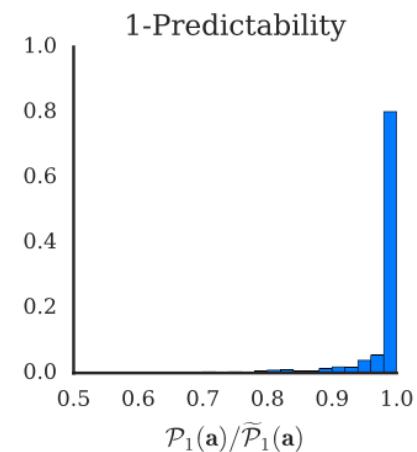
Challenge: evaluating t -predictability of a plan requires comparing it to all others sharing the same first t steps.

Insight: compare each plan only the best alternative.

Results: speed-up from factorial to exponential time

- returns the *exact* solution 90% of the time
- 1% average loss in t -predictability *when suboptimal*

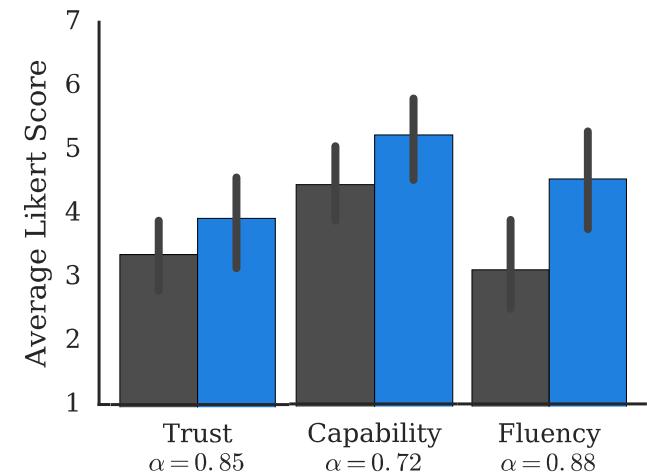
Ratio between exact and approximate t -predictability



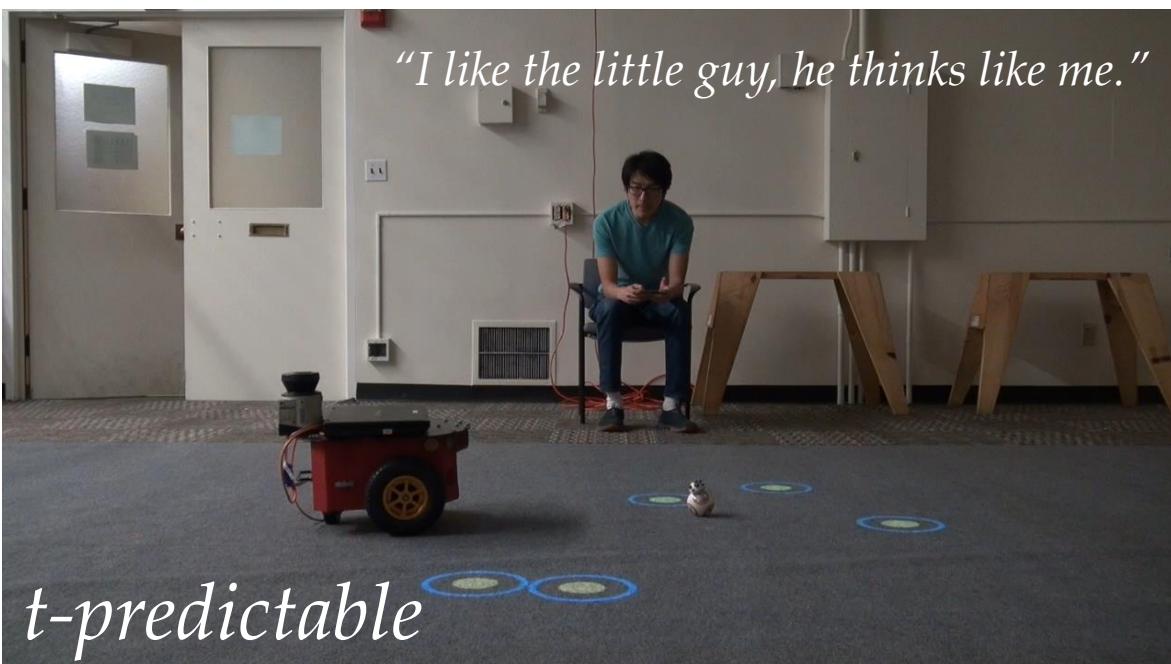
J. Fisac*, C. Liu*, J. Hamrick*,
K. Hedrick, S. Sastry, T. Griffiths, A. Dragan

"Generating plans that predict themselves", WAFR 2016

"Maybe I'm a dumb human [...]. It frustrated me."



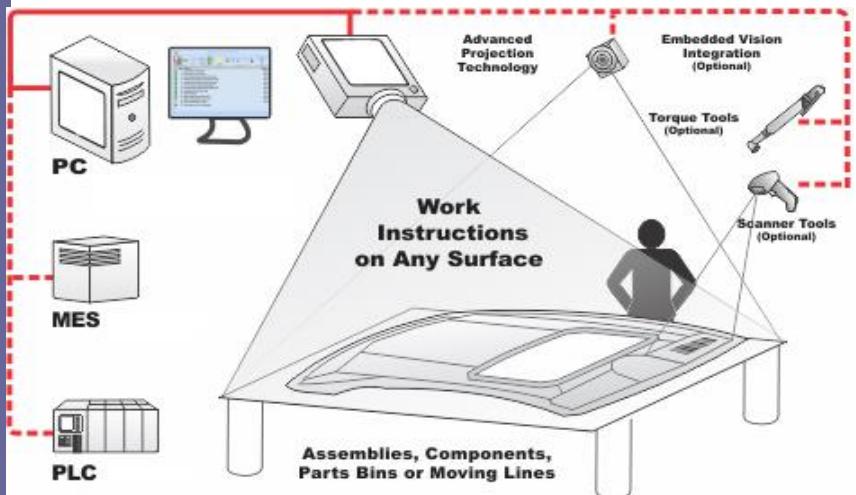
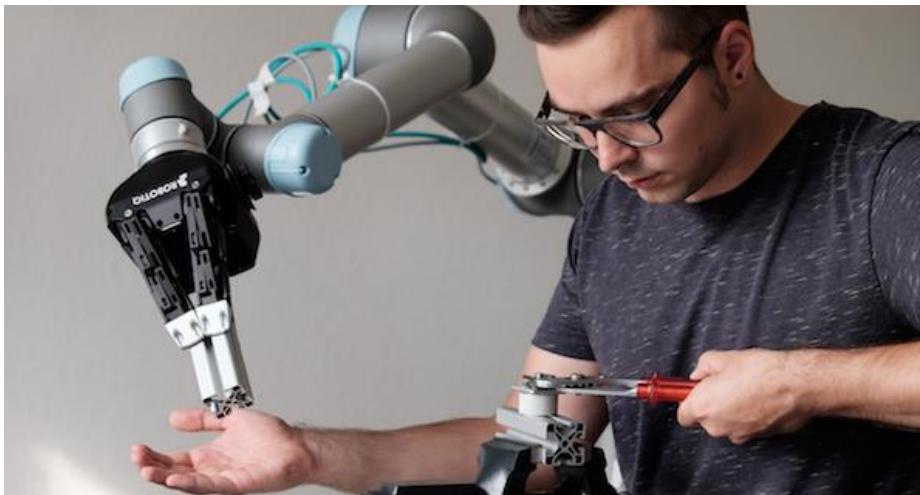
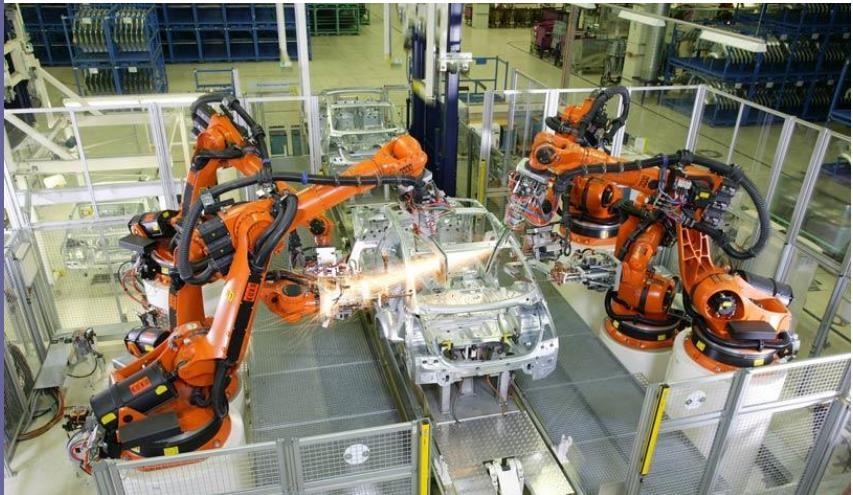
"I like the little guy, he thinks like me."



Completion rate is 2.8 times better

12 out of 14 participants prefer working with the t-predictable robot

Improving Human-Robot Collaboration with AR



SIEMENS

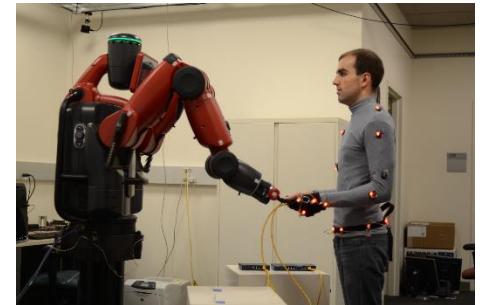
Next Big Thing: Integration with AR/VR



*Vehicle Control
(Tomlin, Borrelli)*



3D SLAM (Sastry)



*Human Collaboration
(Bajcsy)*



Berkeley AR Headset

Robot OS



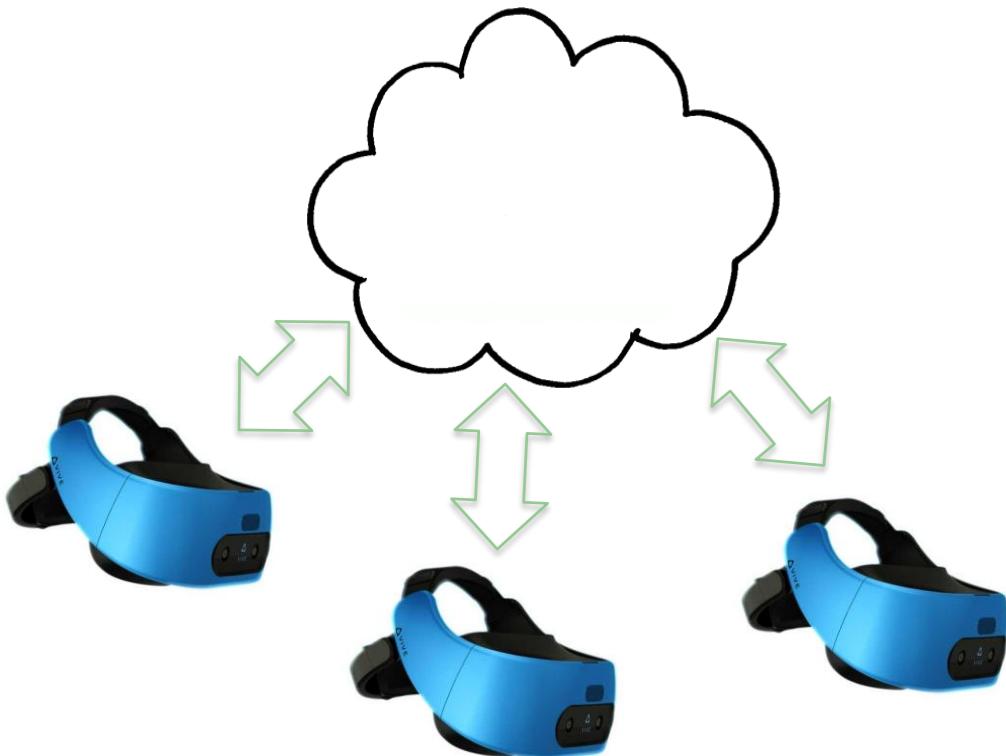
OpenARK: Open AR toolKit

- **Sensor fusion and calibration**
 - RGB camera
 - Depth camera
 - IMU
 - Stereo display
- **3D gesture detection and modeling**
 - 98.6% accuracy on CVRR hand database
- **Room-size SLAM and 3D Reconstruction**
 - Extension from ETH OKVIS package
 - One or two cameras with synced IMU
- **Nonrigid human avatar tracking**



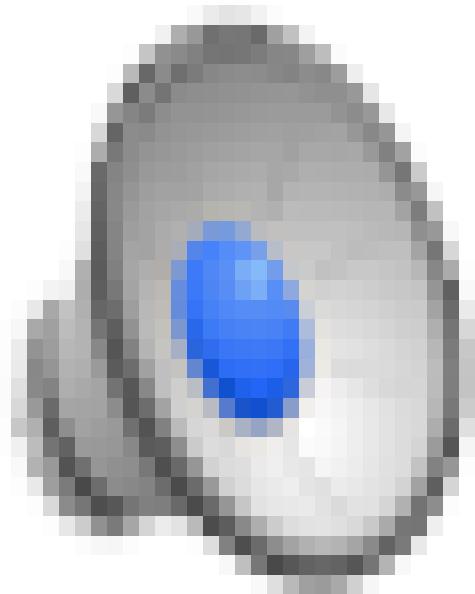
SIEMENS
Ingenuity for life

OpenARK Cloud in 5G Era

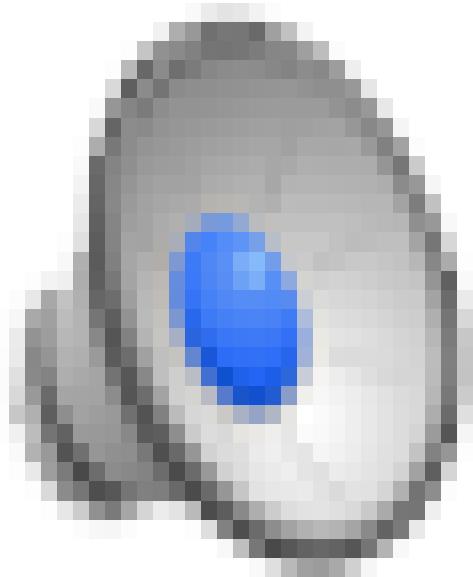


- Cloud based processing enables support for a wide variety of low power devices
- 5G Reduces latency and allows for seamless performance
- A single instance can support multiple devices
- Docker Support for easy deployment

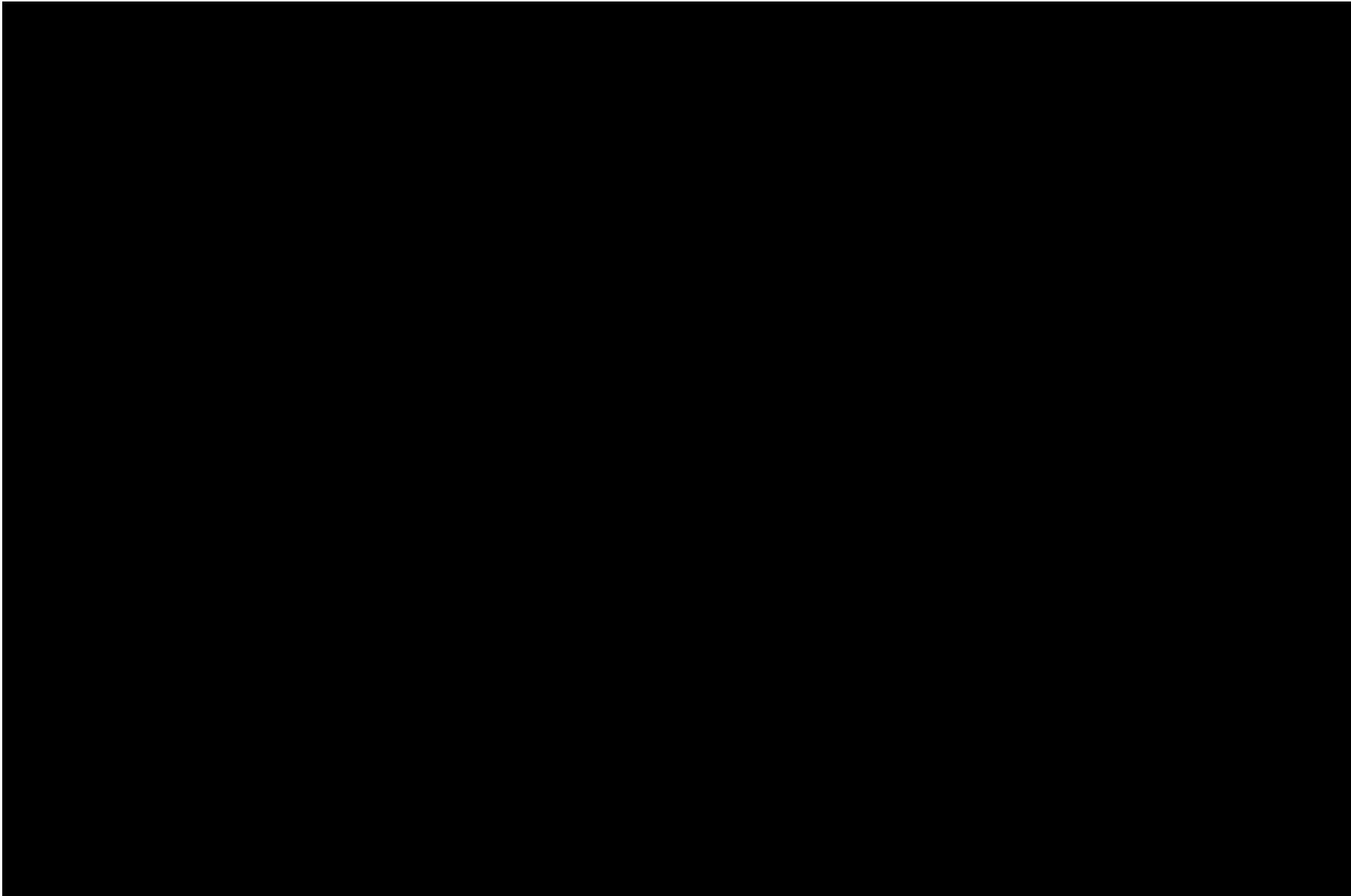
Cloud based Gesture Demo



Human Avatar Tracking Demo



Room-Scale 3D Reconstruction Demo



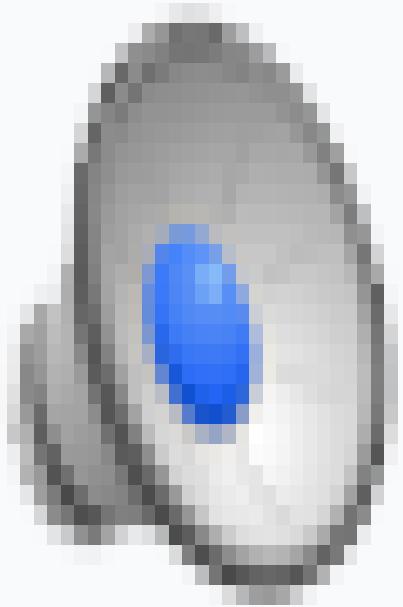
Project Highlight: ISAACS



Full System Working Demo



Pengram Remote Expert AR Demo





Health @ Home

Objective

Create and integrate novel medical technologies, delivery systems, diagnostic devices, and analysis methods that will define high-quality and cost-effective healthcare of the future.

Strategy

1. Health technology development,
2. Health system design, and
3. Academic-industry integration.



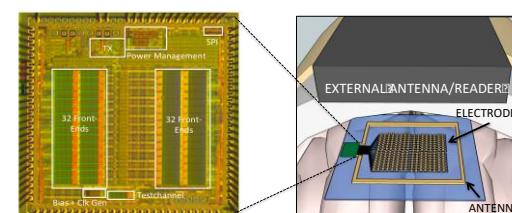
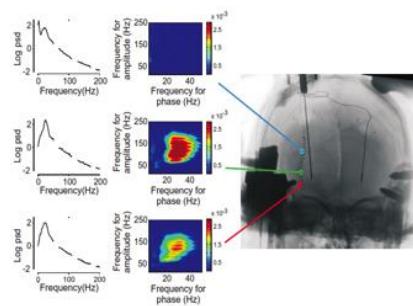
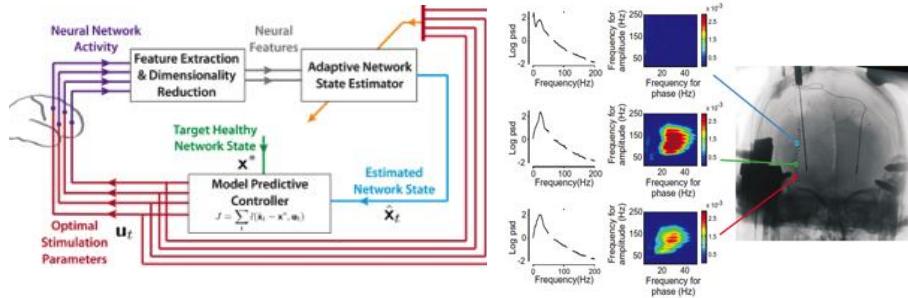


Center for Neural Engineering & Prostheses (CNEP)

Integrates cutting-edge engineering with world-class neuroscience to **develop technology to restore sensory, motor, and cognitive function** in patients with disabling neurological conditions.

Mission is to create a multi-disciplinary environment for

- **Educate** future neural engineers, neuroscientists and clinicians
- **Lead** scientific research and neural prosthetic technology development
- **Ensure** efficient translation of research into human





Wearable Electronics Lab

Innovative Electronics Materials and Devices at
the convergence of Nanofabrication and Printing



Roll-to-Roll
Processing

- Leveraging our strengths in novel materials, devices, and process technologies for future ultra-low-power, smart wearables
- Developing a new manufacturing platform for ubiquitous electronics



Energy



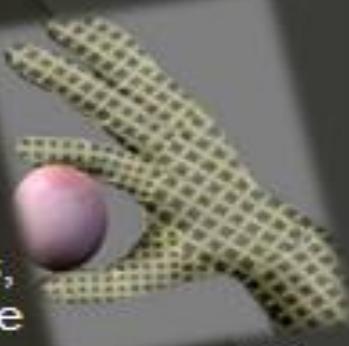
Flexible electronics



New User Interfaces



Healthcare / Bio



Robotics

Interfacing EE and chemistry through materials innovation.



The Human Intranet

An open scalable platform

- Seamlessly integrating ever-increasing number of sensor, actuation, computation, storage, communication and energy nodes located around, on, or in human body
- Acting in symbiosis with functions provided by the body itself,
- Fundamentally altering ways humans operate, and interact with physical and cyberworld
- Grand Fusion of Robotics + AR/VR + Neurotechnology

