Module 1: Welcome and Motivation

ABE 598

Autonomous Decision Making in the Real-World

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Director: Distributed Autonomous Systems laboratory (www.daslab.illinois.edu)

Hello

- Girish Chowdhary, PhD 2010 Georgia Tech (Aerospace)
- Postdoc, MIT LIDS
- Asst Prof OSU 2013-2016
- Asst Prof UIUC 2016…
- 3 Years at DLR before Georgia Tech
- Google Scholar: https://scholar.google.com/citations?user=pf2zAXkAAAAJ&hl=en (Citations 1681, i10 40+, h-20+)
- Director of Distributed Autonomous Systems Lab
- IEEE senior member, AIAA Associate Fellow
- Winner: AFOSR Young Investigator Award: Robust Adaptive Autonomy in Contested Environments
- NSF NRI: Collaborative goal and policy learning with construction co-robots
- NSF CPS: Robust deep learning for Autonomous Agbots
- Associate editor: IEEE Transactions on Neural Networks and Learning Systems

Some logistics

- We will use Piazza
- Compass for homework etc
- Office hours, every T-TR 10:00-11:00, and 12:20 to 13:00, or by appointment
- Office:
  - M-T: AESB 128
  - W-F: CSL 150

What is this class

- Autonomy: Machines that accomplish difficult tasks in uncertain, time-varying, stochastic environments

1,000+ Google Self Driving Jobs | LinkedIn
https://www.linkedin.com/jobs/google-self-driving-jobs
Today's top 1493 **Google Self Driving jobs** in United States. Leverage your professional network, and get hired. New **Google Self Driving jobs** added daily.

5 trends for the future of manufacturing

https://www.weforum.org/agenda/2017/06/what-s-going-on-with-manufacturing-b013f435-1746-4bce-ac75-05c642652d42/

Autonomy

- Autonomy, AI, and Machine learning are the most rapidly growing areas in the applied sciences
- Classical AI has led to many advances in social media and computer science
- This course: The focus is on AI in the real world: Autonomy: AI for robotics?

What’s a robot?

- What’s a robot?
- Robot is embodied artificial intelligence
- An autonomous robot can adapt to its surroundings

Autonomous System Design

How do we adapt to uncertainties???

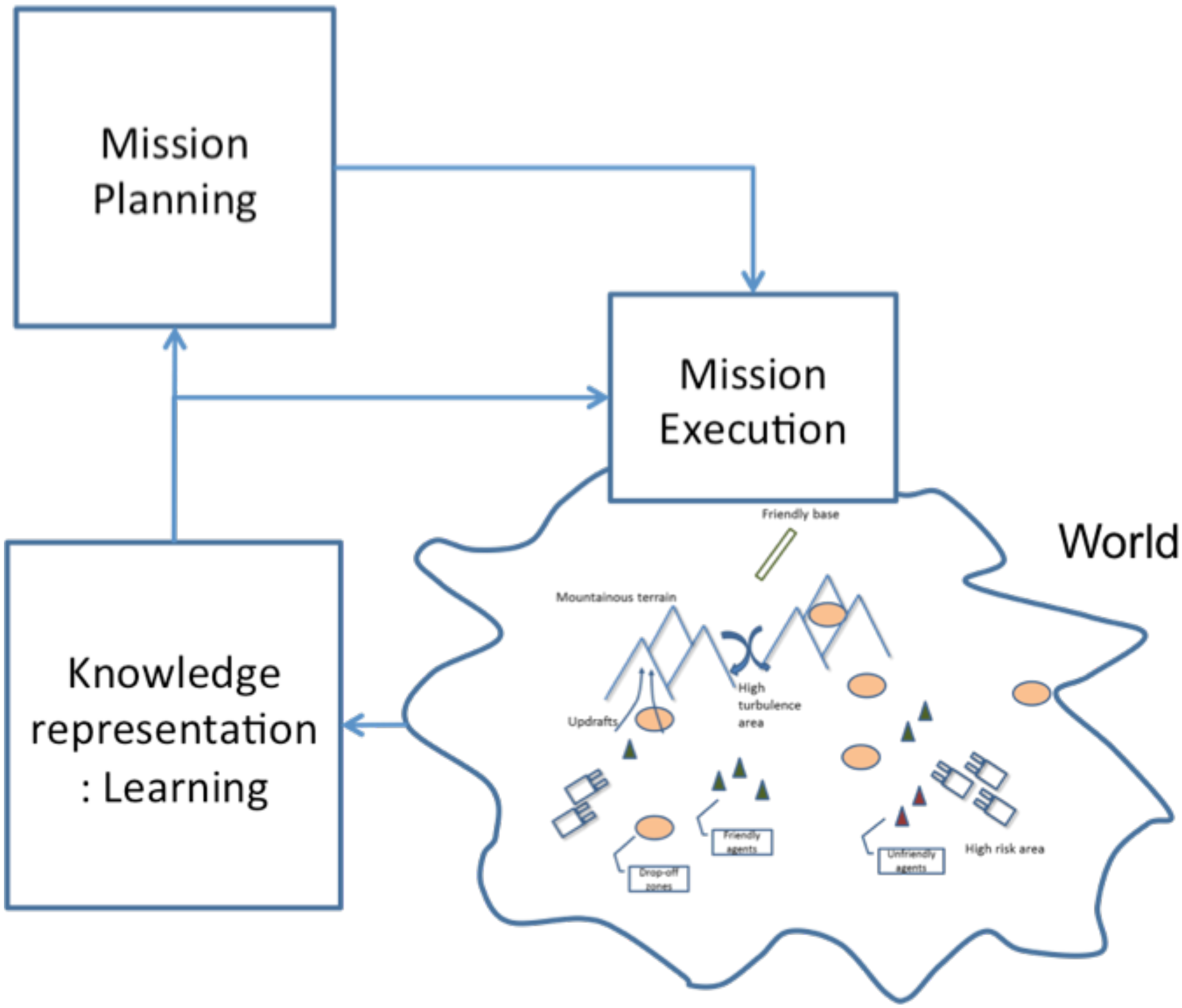
Syst

ematical
deling

Execution
environment
uncertain

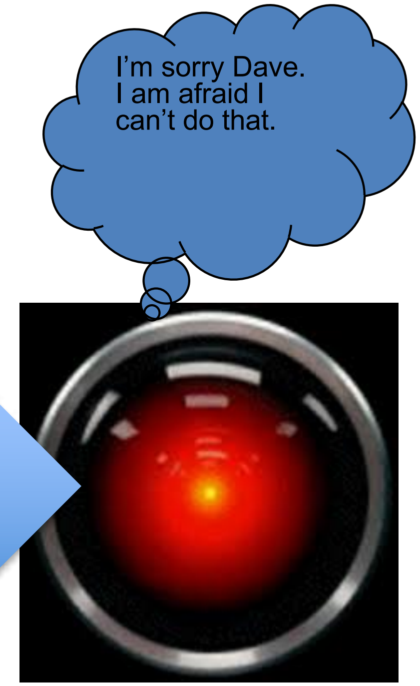
roximate models
to conservative
rollers

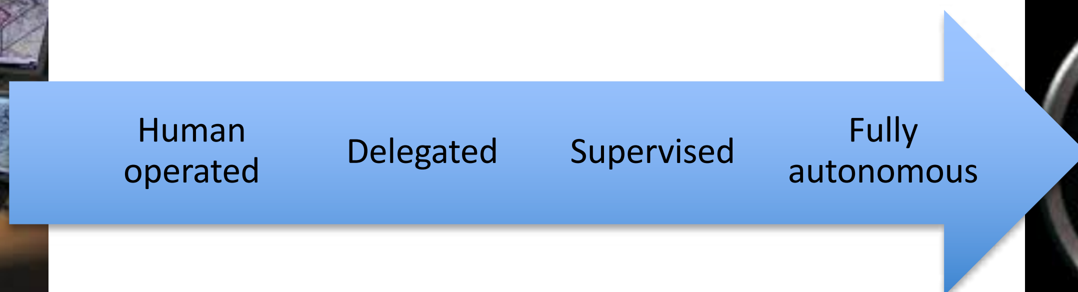
Higher level autonomy



UAS Autonomy

- Past: What are the *levels* of human and AI autonomy?

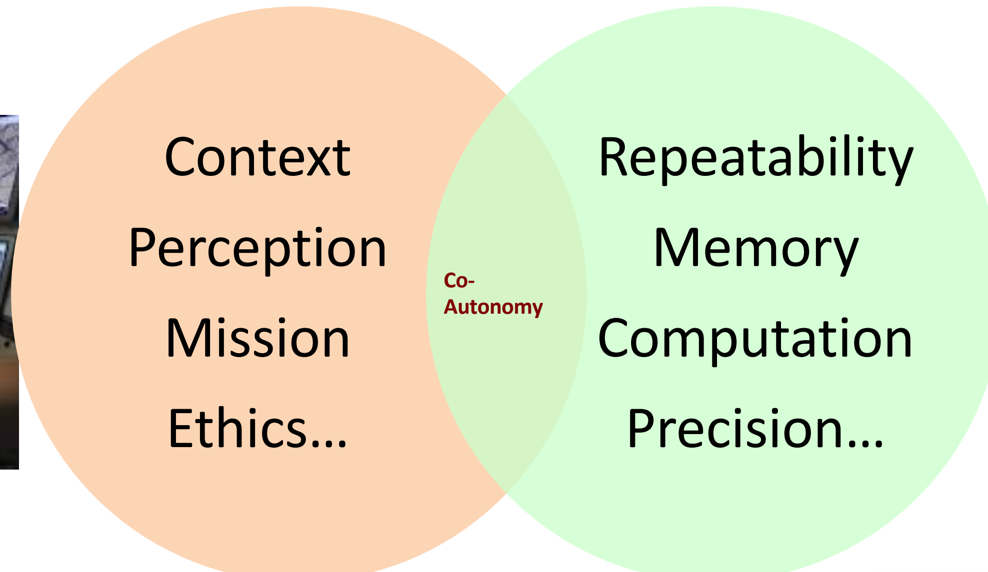


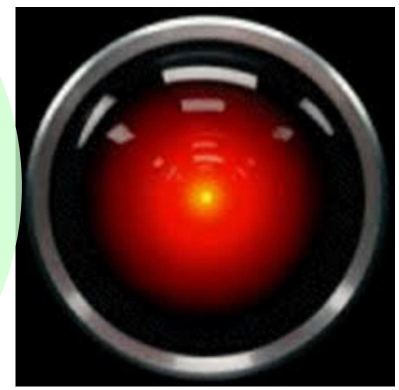


- Do hierarchic levels of autonomy really reflect reality?
- Environment Perception still remains a challenge
- Robots do not yet understand context or ethics
- Robust AI/Full-Autonomy in real-world dynamic environments seems a long-way out

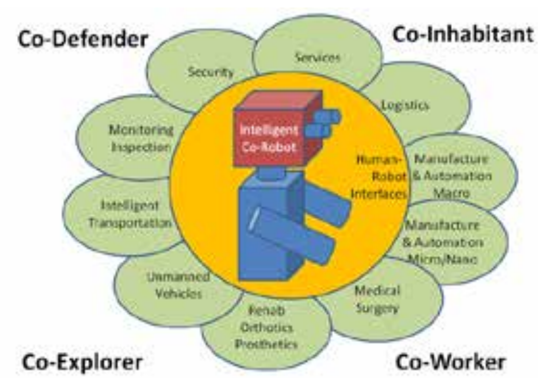
Autonomy

- What is the right *mixture* of human and AI autonomy?

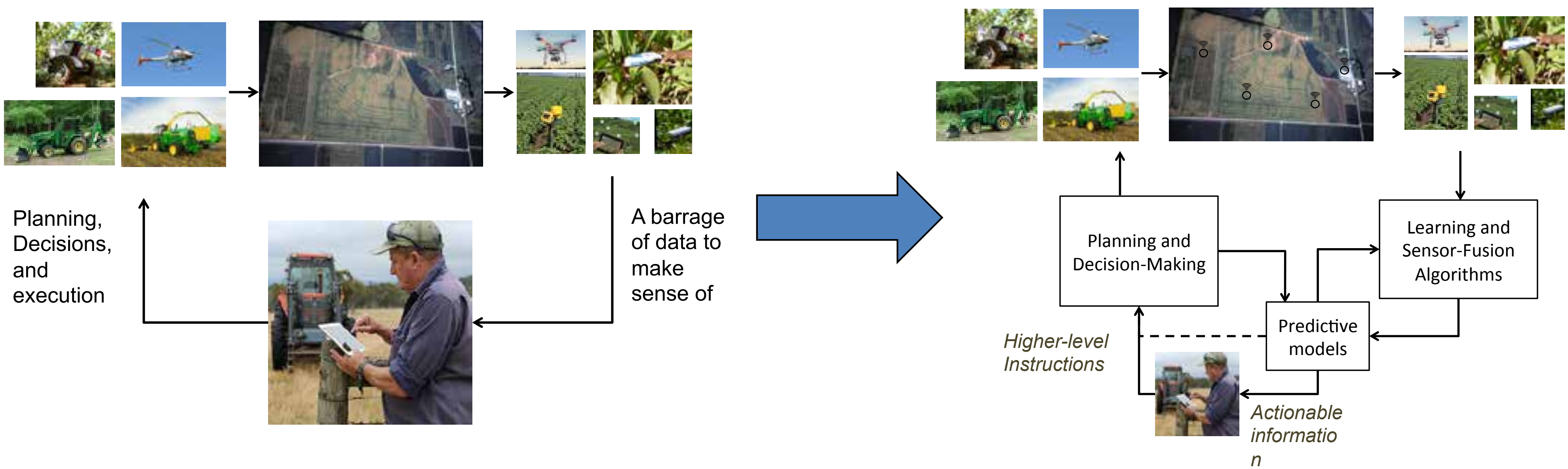




- Humans and robots work together
- NSF >> Co-robotics
- Practical immediately, but limited



Case study: Agricultural Autonomy



- Heterogeneous teams of humans, robots, and decision systems

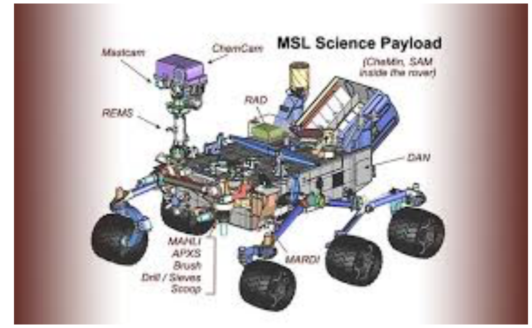
Autonomy in the real-world

- Self-Driving Cars
- UAS
- Smart-Grid
- Smart-Buildings
- Robotics
- So much more

Field robots

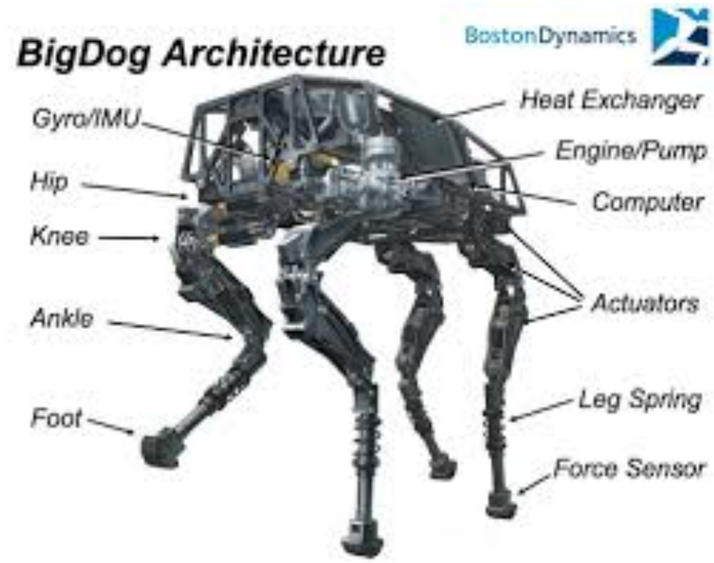
Reading: https://www.fginsight.com/vip/vip/robot-field-day-provides-glimpse-into-the-future-13419

Field Robots



Curiosity: https://mars.nasa.gov/msl/mission/mars-rover-curiosity-mission-updates/

Field Robots



Tracked Robots

Flying robots

Robots at home and with humans

Huge field robots

What's different about this course?

- This is an integrative course
- Its at the bleeding edge of technology: We deal with subject matter that is rapidly evolving as we speak (as opposed to more traditional courses, such as linear control theory etc)
- Our hope is that by the end of this course, you can intelligently do research/work in autonomous decision making or its subfields
- Hence we will:
  - Cover material from several texts on elements of autonomous decision making, teaching you algorithms, and expecting you to generate software for those algorithms through 3 problem sets
  - Provide to you a sampling of the vast literature through a guided literature review (required reading, more on this later)
  - I will keep uploading interesting papers and tit-bits, not assessed, but should read
  - You will execute a project, since the best way to learn is by doing things

What is expected from you

- A genuine passion for learning about this rapidly evolving and very exciting field
- Proactive attitude towards learning and covering a wide range of topics in a semester
- You will be truly rewarded when you are on the job market or doing research
- Wider: The scope of the class
- Deeper: The contribution you should strive for in your project

Learning Outcomes

- Develop algorithms and architectures for autonomous decision making in the real world
- Understand fundamental principles of machine learning
  - Regression, classification, clustering
  - Deep learning
- Understand fundamental sequential decision making:
  - Markov Decision Process
- Understand fundamentals of reinforcement learning
  - Model based and model free
  - Deep Reinforcement learning
- Understand the interplay between machine learning, decision making, and control for real-world robots
- Survey a selection of papers in relevant areas of autonomous decision making
- Demonstrate the ability to develop software to achieve machine learning, reinforcement learning, and control tasks through a set of problem sets
- Demonstrate integrative knowledge of the topics covered in a final project relating to autonomous decision making for engineering applications

Keyword bingo

Regression

RRT

Breadth first

K-means

Recurrent neural networks

Deep learning

DP-means

MDPs

Reinforcement learning

Gaussian processes

DQN

Bayesian inference

DDPG

Dirichlet Processes

Latent Dirichlet allocations

Perception

Kalman filters

Grading

- This is a project based course
- You choose your project
- No team projects allowed
- 3 deliverables: IT 0 (50), 1 (100), and final report (300)
- Detailed in the syllabus
- 3 Psets involving coding (use any language, my code is in matlab)
- Required readings, detailed in syllabus

Point Breakout:

Problem Sets	= 450 points
Weekly readings	= 50 points
Project	= 500 points
Total	**= 1000 points**

Project

- IT 0: Come up with the problem formulation
- IT 1: Provide first solution
- IT 2: Final report
- Your goal is to contribute meaningfully above the state-of-the-art (depth)
- What gets a guaranteed A+: A project that can stand peer-review at RSS/ICML/NIPS/Top-tier conf. if converted to a paper (25% acceptance rate at these conferences)
- What gets a guaranteed B+: A project that is capable of getting into typical conferences with over 50% acceptance rate
- You have time for this: No Exams and only 3 psets (yay!)
- I recommend you try to synergize the project with your research

Syllabus

- **Module 1 Introduction to Autonomous Decision Making**
  - What is autonomy
  - Autonomous Agents
- **Module 2 Some preliminaries**
    - Probability Theory, with an emphasis on Bayesian formulations
    - Information Theory
    - Bayesian information fusion: Kalman Filters
- **Module 3 Classical Artificial Intelligence**
  - Search:
    - Solving decision making problems through search
    - Search techniques
  - Motion planning
    - Configuration spaces, groups, and SO(3)
    - Sampling based motion planning
  - Logistic Planning (non-sequential decision making)
    - Linear Programming
    - Chance constrained optimization and the notion of Risk
-

Syllabus contd

- **Module 4 Machine Learning for autonomy**
  - Principles of machine learning for knowledge representation: regression, clustering, classification, and association
  - Regression
    - Linear regression
    - Kernel models
    - Gaussian Process Regression
  - Classification (Supervised learning)
    - Logistic regression
    - Support vector machines
    - Neural Networks (Deep and non-deep)
  - Clustering (Unsupervised learning)
    - K-means clustering
    - Dirichlet process clustering and Bayesian nonparametrics
  - Deep Neural Networks
  - Spatiotemporal modeling
    - Modeling of spatiotemporal systems, Evolving Gaussian Processes
  - Hidden Markov Models

Syllabus contd

- **Module 5 Sequential decision making under Uncertainty**
  - Markov decision processes
    - The Markovian assumption in sequential decision making problem formulation
    - State, Action, and Transition spaces
    - Dynamic programming, value iteration, policy iteration, Trajectory-based algorithms
    - POMDPs (with SARSOP), DEC-POMDPs
  - Approximate Dynamic Programming
    - State-Action space parameterization and approximate representations
    - Linearly parameterized representations: kernel models, mixed-resolution tables, iFDD
    - Convergence results
  - Reinforcement learning
    - The MDP formulation for RL
    - The Exploration vs Exploitation tradeoff
    - Temporal difference methods
      - On-Policy: SARSA, LSPI and variants
      - Off-Policy: Q-learning, Q-iteration and variants
    - Approximate Reinforcement Learning
      - Linearly parameterized representations: kernel models, mixed-resolution tables, iFDD
      - Neural Network approximations
      - Convergence results, performance results
    - Model based RL
      - GP based RL
      - The POMDP formulation of Model Based RL
    - Deep Reinforcement learning
      - Deep Q (Google Deepmind's version)
      - Value iteration networks

Syllabus contd

- **Module 6: Where to from here? (If time permits)**
  - Integrating RL, ML, and control for robotics
  - Games, simulations, and virtual worlds
  - The future of machine learning in a connected world
- Autonomous decision making and internet of things

Books (none required to purchase)

- Classical AI (Module 1)
  - Russel and Norvig, Artificial Intelligence, a Modern Approach (http://aima.cs.berkeley.edu/)
  - Lavalle, Planning Algorithms, available online: http://planning.cs.uiuc.edu/
- Machine Learning and Deep Learning (Module 2)
  - Murphy, Machine Learning, A probabilistic Perspective
  - Goodfellow et al., Deep Learning
  - Bishop, Machine Learning and Pattern Recognition
- Sequential Decision Making and Reinforcement Learning (Module 3)
  - Kochendefer et al., Decision Making Under Uncertainty: Theory and Application
  - Busoniou, Reinforcement Learning and Markov Decision Processes
  - Bertsakes, Neurodynamic Programming

Readings

- I have uploaded all of the readings on Piazza
- The dates corresponding to the readings are in the Syllabus
- You need to submit a review of the paper (around half a page) before the date indicated on Piazza
- These represent work that I think is kind of important/interesting. You are expected to criticize the content as a peer-reviewer. I am not expecting a superficial review, but a deep peer review of merits and weaknesses
- R1 is special, it is a presentation from DoD, in your review focus on what you think are emerging areas in autonomy research at DoD
- In week 2 we will decide a strategy on presentation

TA

- We have a TA: Karan Chawala
- What does the TA do: Help grade homeworks, help answer questions, help grade projects, answer questions on Piazza about papers
- What does the TA not do: Write your code, coach you on a personal basis, do you project

So what is ADM?

- Autonomous Decision Making in the real world
  - What is autonomy?
  - What's a robot?
  - What's an autonomous robot?

Self Driving Cars

- https://youtu.be/aaOB-ErYq6Y
- https://www.youtube.com/watch?v=ftouPdU1-Bo

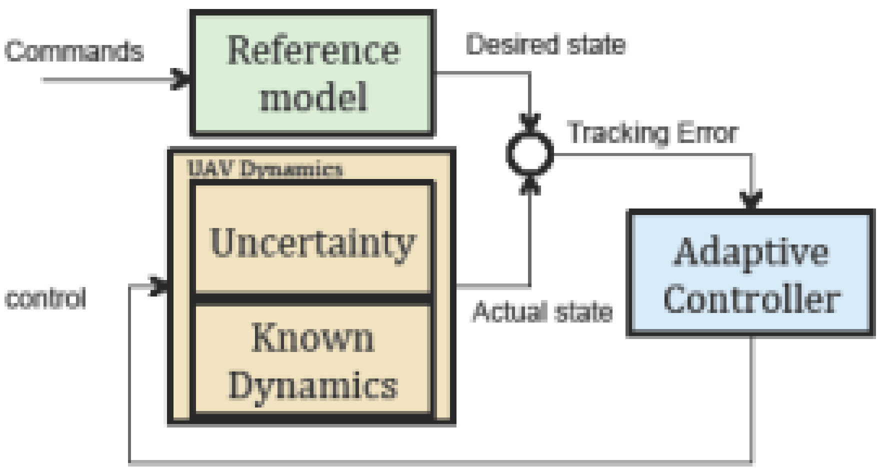
Factory automation

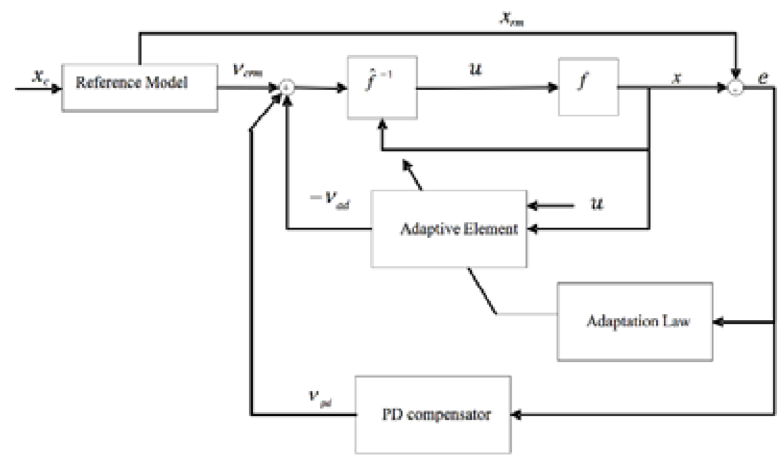
- https://www.youtube.com/watch?v=VpwkT2zV9H0 (BMW factory automation)
- https://www.youtube.com/watch?v=cLVCGEmkJs0 (Kiva robots)

Autonomy in structured environments

- GRASP Lab https://www.grasp.upenn.edu/success_story/aggressive_maneuvers_autonomous_quadrotor_flight
- ETH Zurich:http://robohub.org/three-new-quadrotor-videos-demonstrate-agile-control-and-the-power-of-machine-learning/

Model Reference Adaptive Control





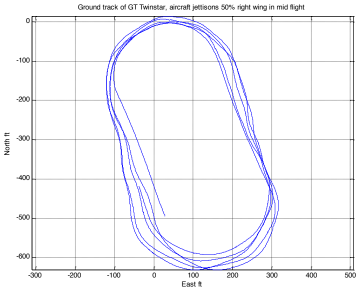
- *Model Reference Adaptive Control*: Make the uncertain system behave like the reference model
- Approach: Concurrent Learning Adaptive Control (Chowdhary PhD 2010)
  - Simultaneously track the reference model and learn the uncertainty
  - Strong theoretical (exponential stability) guarantees on convergence of weight and tracking error

Flight Test: GT Max UAV

See "Theory and flight Test validation of a concurrent learning adaptive controller", Chowdhary, Johnson, JGCD March-April 2011

- GT Max: Yamaha R-MAX
  - 66 kg
  - 3 m Rotor Diameter
- Flight with Single Hidden Layer Neural Network (Chowdhary and Johnson, JGCD 2010)

Fault-tolerant Adaptive Control



- Chowdhary et al. JGCD 2012, Autonomous Guidance and Control of Airplanes under Actuator Failures and Severe Structural Damage
- GT-Twinstar UAV: 3 lb, 4.7 ft wing span

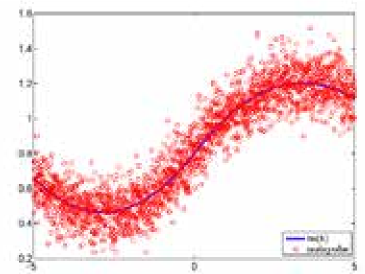
Fault Tolerant Control

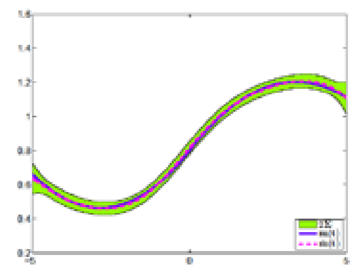
Plug-and-Adapt Autonomy

- Chowdhary G., Wu T., Cutler M., How J. P., "Rapid Transfer of Controllers Between UAVs using Learning Based Adaptive Control", IEEE International Conference on Robotics and Automation, 2013.

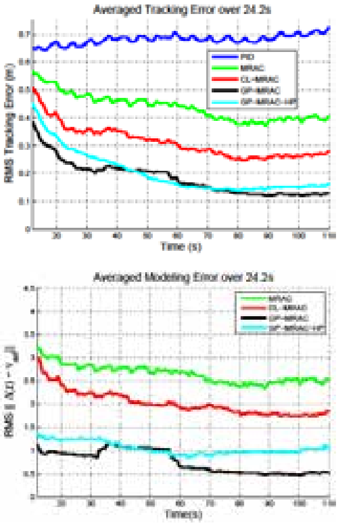
Gaussian Process MRAC: Bayesian Nonparametric Adaptive Control

- Challenges with Neural Networks:
  - How to select the structure of the model (number of basis functions)?
  - Can the model predict how good is its prediction?
  - Can it adapt its structure on-the-fly?
- Gaussian Processes: Distributions over functions
  - $\Delta(x) \sim GP(m(x), k(x, x'))$
    $m(x)$ is the mean function and $k(x, x')$ is the covariance function
- Bayesian Nonparametric approach:
  - Structure of the model and its parameters simultaneously inferred from data in real-time
- Budgeted real-time inference (Chowdhary et al. TNNLS 2013)



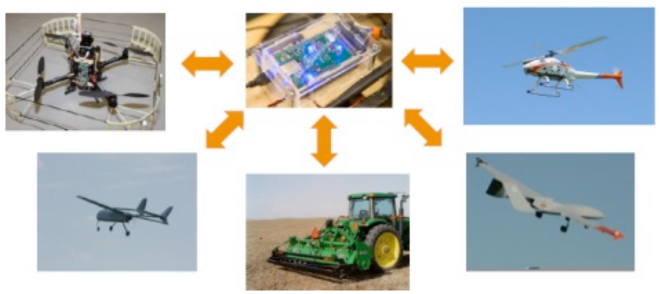


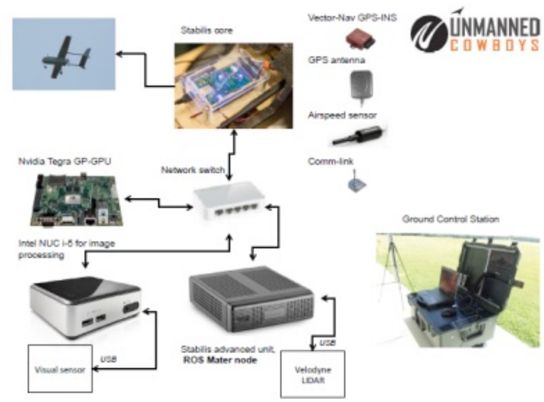
GP-MRAC: Disturbance Adaptation



- Grande, Chowdhary, How JAIS 2014 (Experimental Validation of Bayesian Nonparametric Adaptive Control using Gaussian Processes)
- GP-MRAC learns how the disturbance affect forces on the UAV

Plug and adapt autopilot: Stabilis

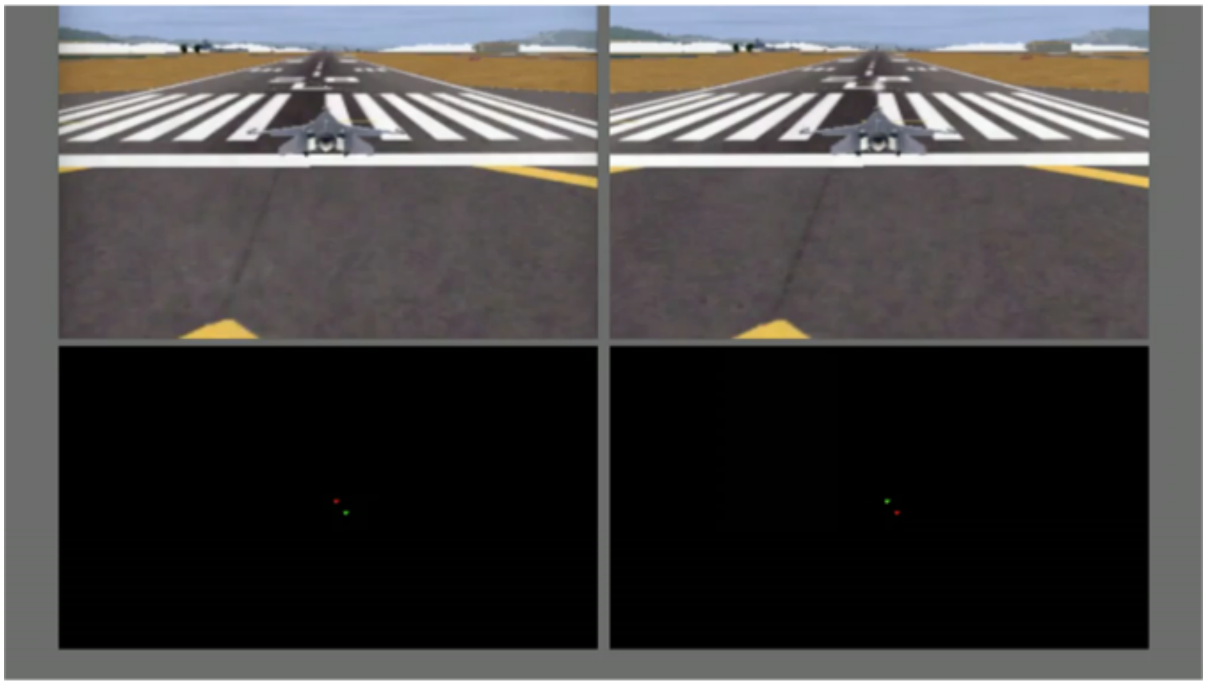




- STABILS: Plug-and-adapt autonomy module (much more than an autopilot)
- Works with ROS
- Designed to be customizable, hardware, sensors, platforms…
- Marketed by Unmanned Cowboys LLC (www.unmannedcowboys.com)

Automatic stall recovery

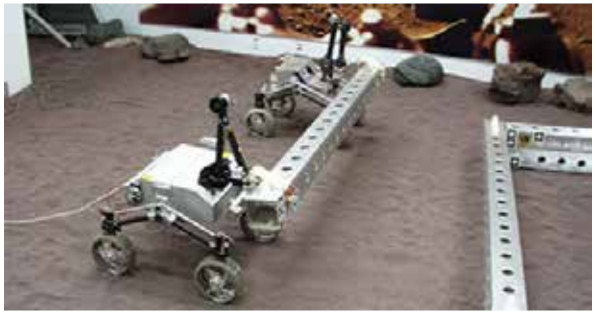
Multi-Agent Autonomy

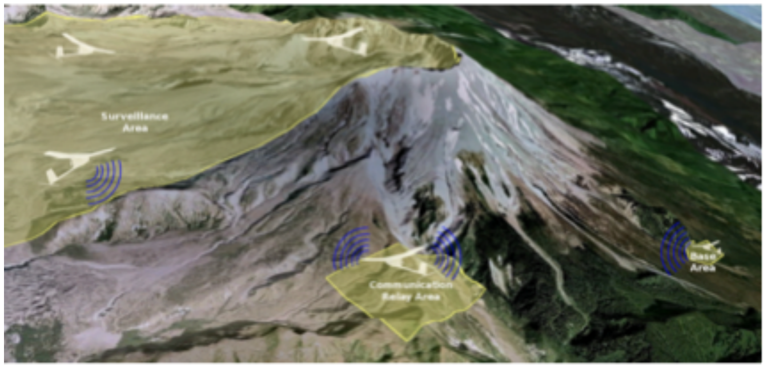


- Multiple UAS collaboratively explore simulated CO2 distributions over San Francisco Bay area

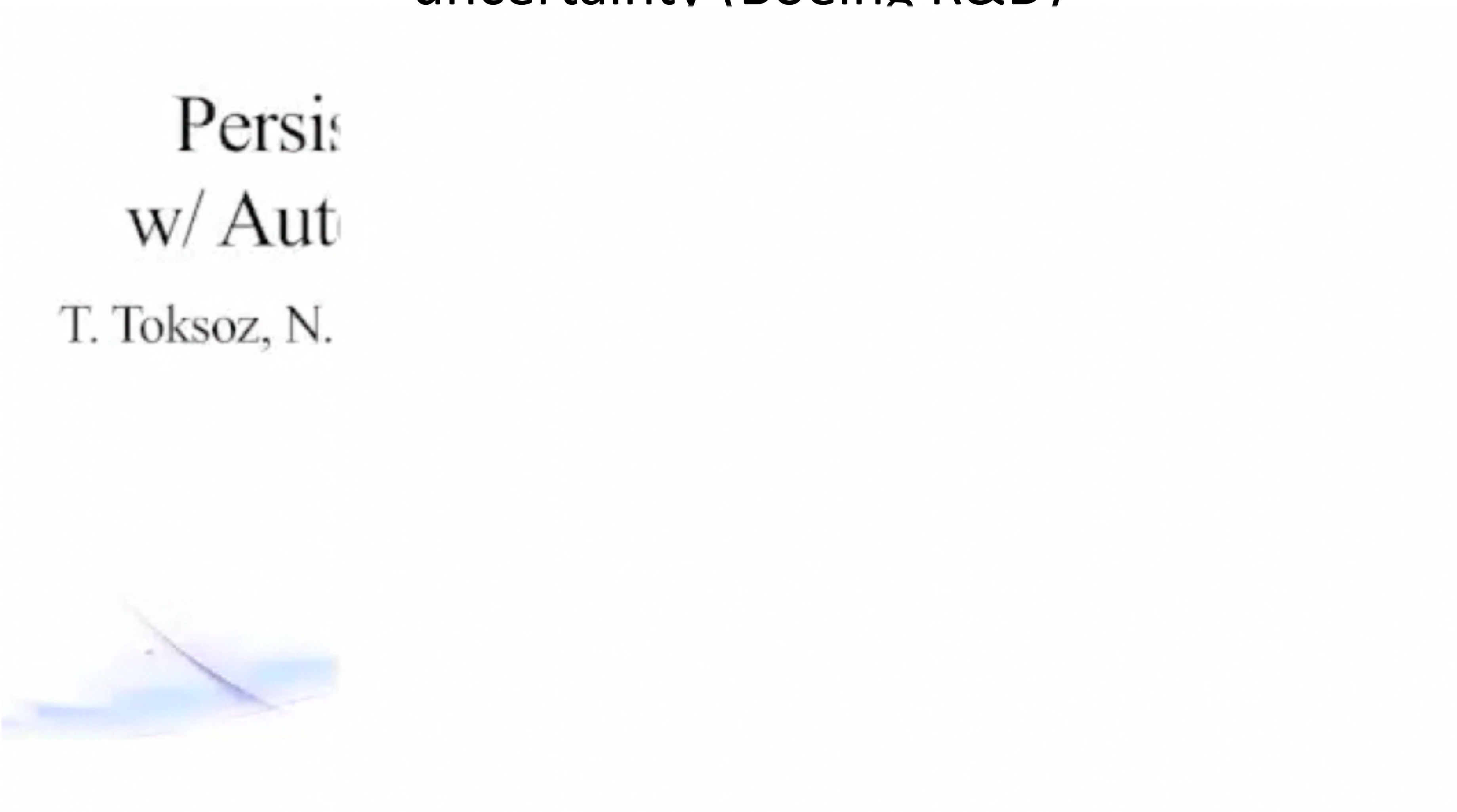
Long-Duration Large-Scale UAS Missions

- Aerospace planning problems Mission planning, Manufacturing, Air-traffic control
- Current UAS mission planning: simple heavily supervised missions
- Vision: UAS help with complex missions
  - Forward base resupply, persistent Search and Track
  - Cattle herding, crop-dusting,
  - First Response: storm watch, ISR
- Need long-duration (days, months) large-scale operation: beyond endurance of single UAS
- New challenges: Dynamically changing capabilities
  - Agent health may deteriorate, agents may fail
  - Agents may learn to execute missions better
  - Agent health and capabilities depend on the environmental states
    - GPS function of surroundings
    - vision/endurance function of weather)





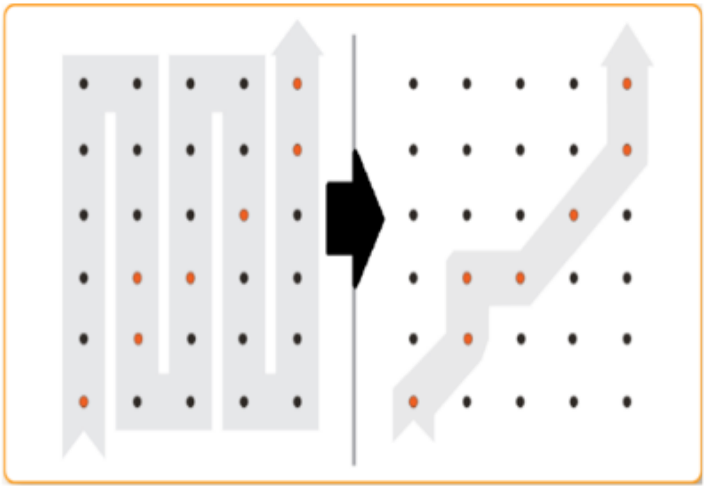
Collaborative mission planning and execution under uncertainty (Boeing R&D)



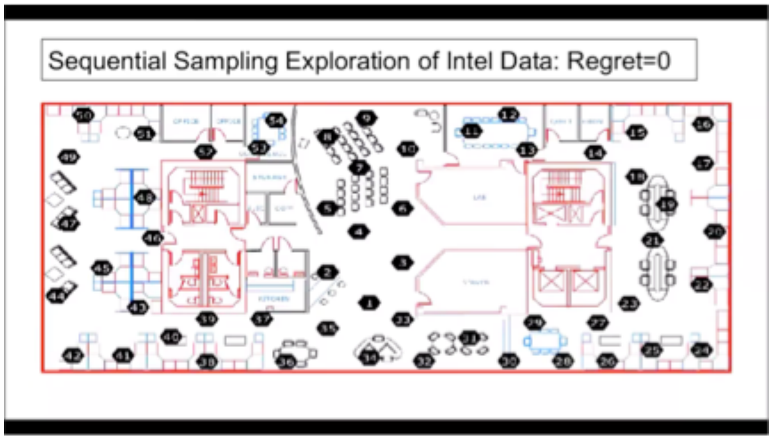
See e.g. "Health Aware Decentralized Planning and Learning for Large-Scale Multiagent Missions ", Ure, Chowdhary, Chen, How, Vian, AIAA Guidance, Navigation, and Control conference, 2013

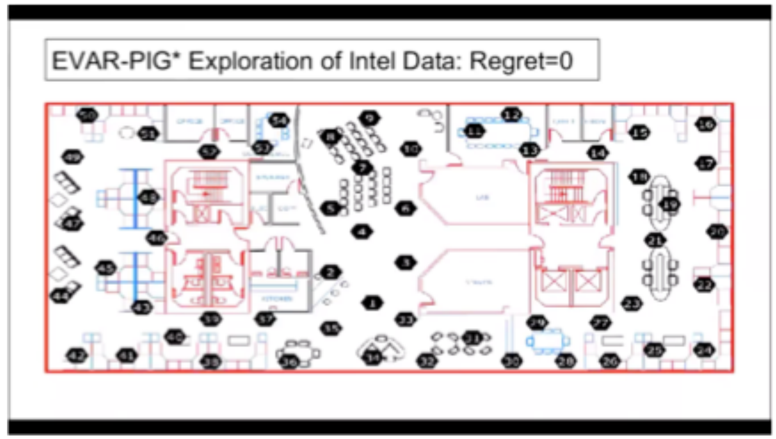
Adaptive UAS Mission Planning

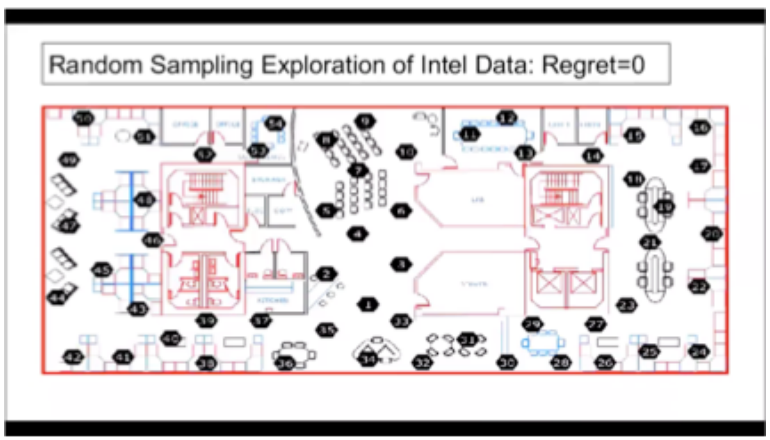
- UAS have limited capabilities:
  - Limited Range
  - Limited Endurance
  - Limited sensor resolution
- Grid based patterns are not sustainable: high labor and equipment cost
- Adaptive plan can get the most informative information for the least flight time

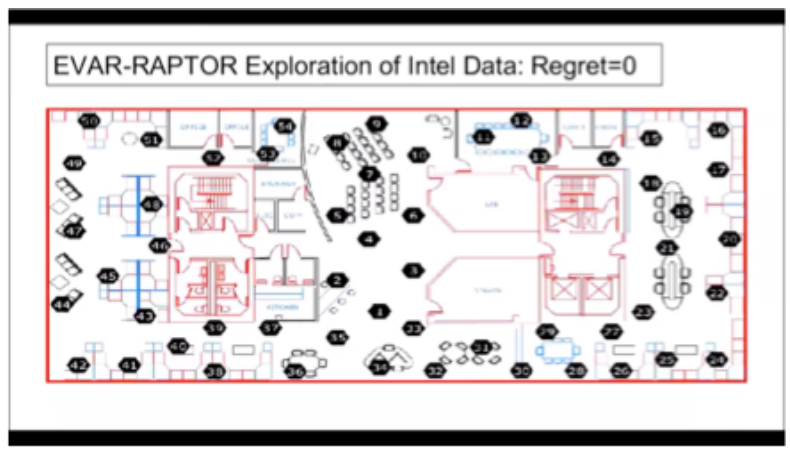


Informed Sampling Outperforms









Green Circle: Sensor being currently sampled
Red Circle: Accumulated information
Blue Circle: Predicted VoI

Axelrod A., Chowdhary G., Karaman S., Exploitation by informed exploration between isolated operatives for information theoretic data harvesting, IEEE Conference on Decision and Control, Osaka, Japan, Dec 2015

Mu B., Chowdhary G., How J. P., Efficient Distributed Sensing using Adaptive Censoring Based Inference, *Automatica*, Vol 50, No 6, pp 1590-1602, June 2014

Human Collaborative Robots

Can Co-robots Learn to Teach?

Brought to you by

Distributed Autonomous Systems (DAS) LAB at UIUC

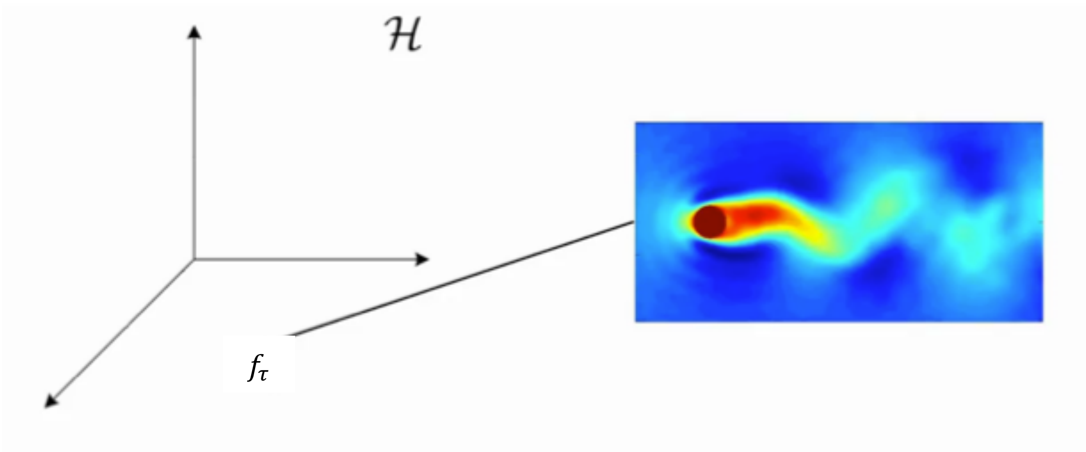
in collaboration with

Comparative Psychology Laboratory at Oklahoma State University.

Harshal Maske, Emily Kieson, Girish Chowdhary, and Charles Abramson

ILLINOIS
UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

Spatiotemporal modeling



$$f_{\tau+1} = \mathcal{A} f_\tau + \eta_\tau$$

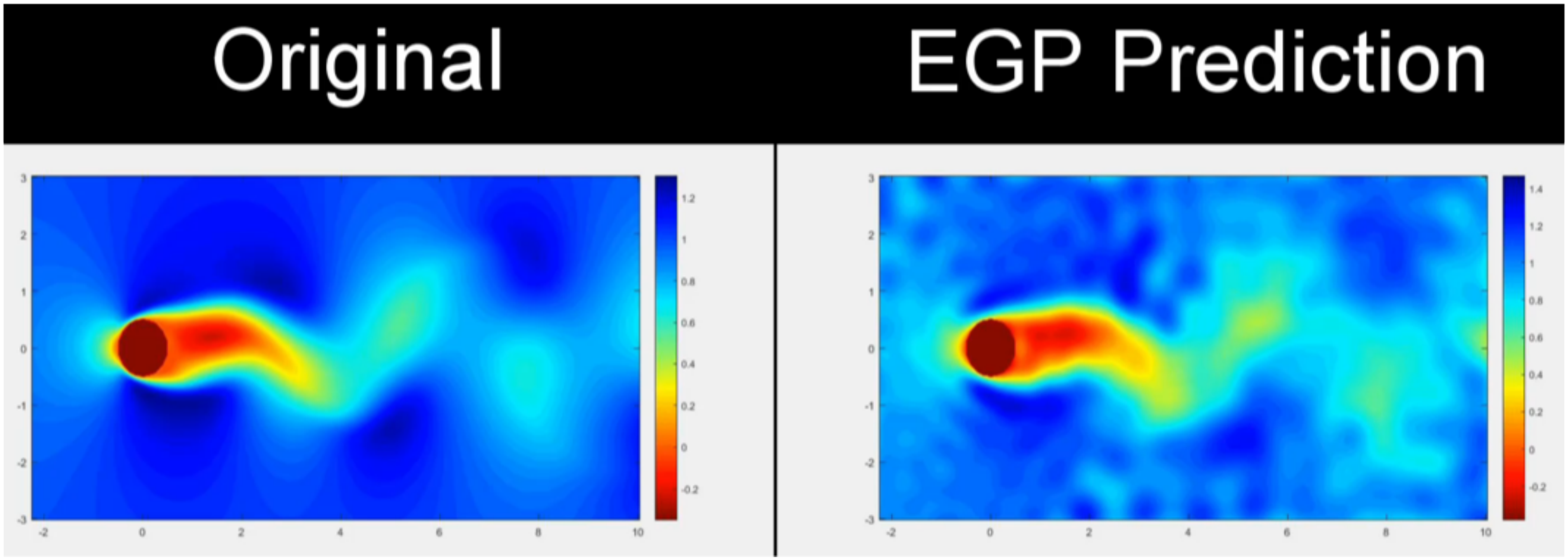
$$y_\tau = \mathcal{K} f_\tau + \zeta_\tau$$

- Each snapshot of the function
  = mean of a Gaussian Process
  = point in an RKHS $\mathcal{H}$

- Learn dynamics of f in $\mathcal{H}$ $\Rightarrow$ spatiotemporal evolution
  - Assume linear $\mathcal{A}: \mathcal{H} \to \mathcal{H}$
- Predict data: $\mathcal{K}: \mathcal{H} \to \mathbb{R}^N$

Modeling Nonlinear Dynamical Fluid Flows with Evolving Gaussian Processes

- 300 Kernels placed using Csato algorithm
- Kernel bandwidth of 0.4
- Reynolds Number = 100



Modeling Nonlinear Dynamical Fluid Flows with Evolving Gaussian Processes

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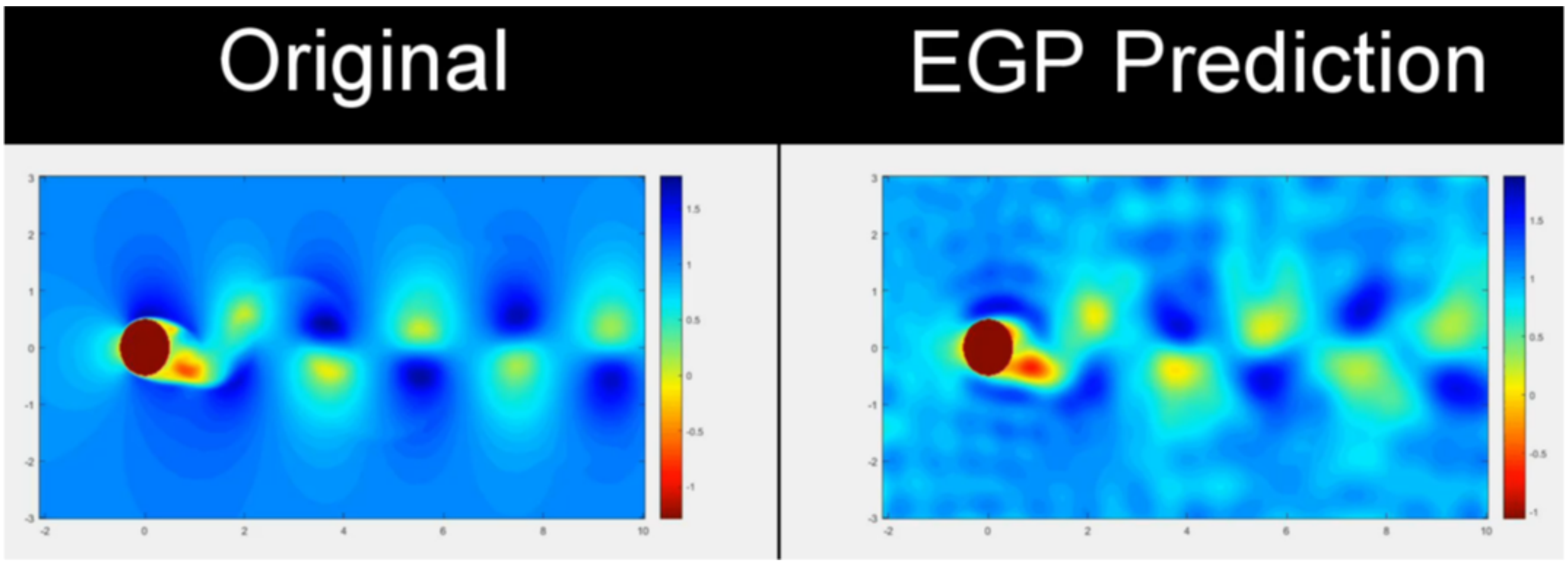
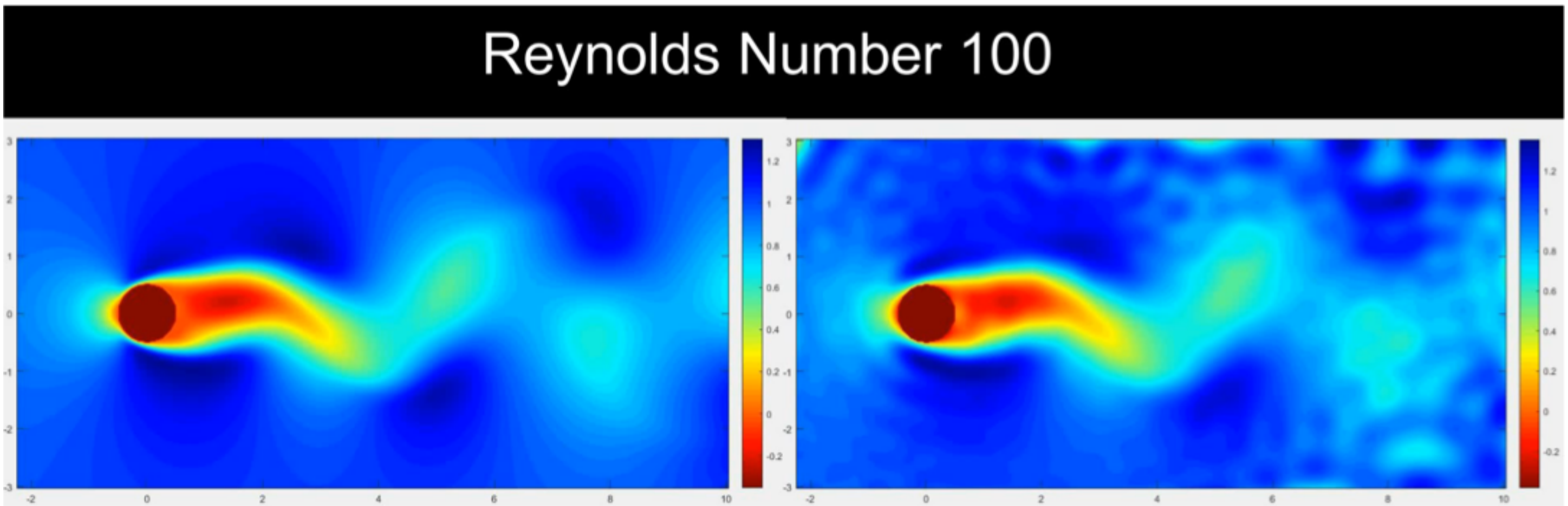


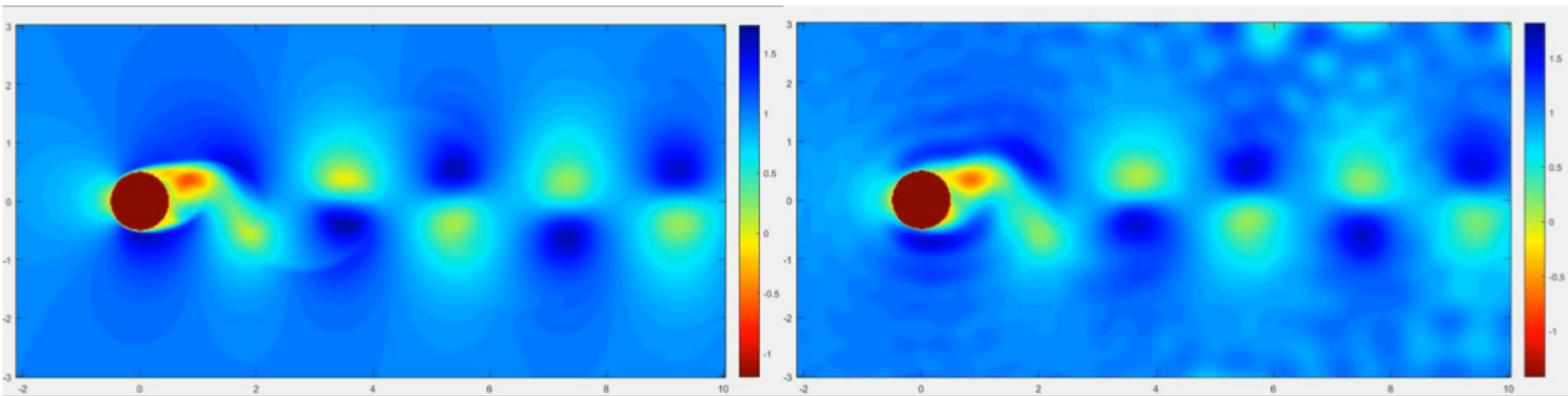
Learning Dynamics Across Similar Spatiotemporally Evolving Systems

- Single transition matrix A captures dynamics of 5 similar dynamical systems

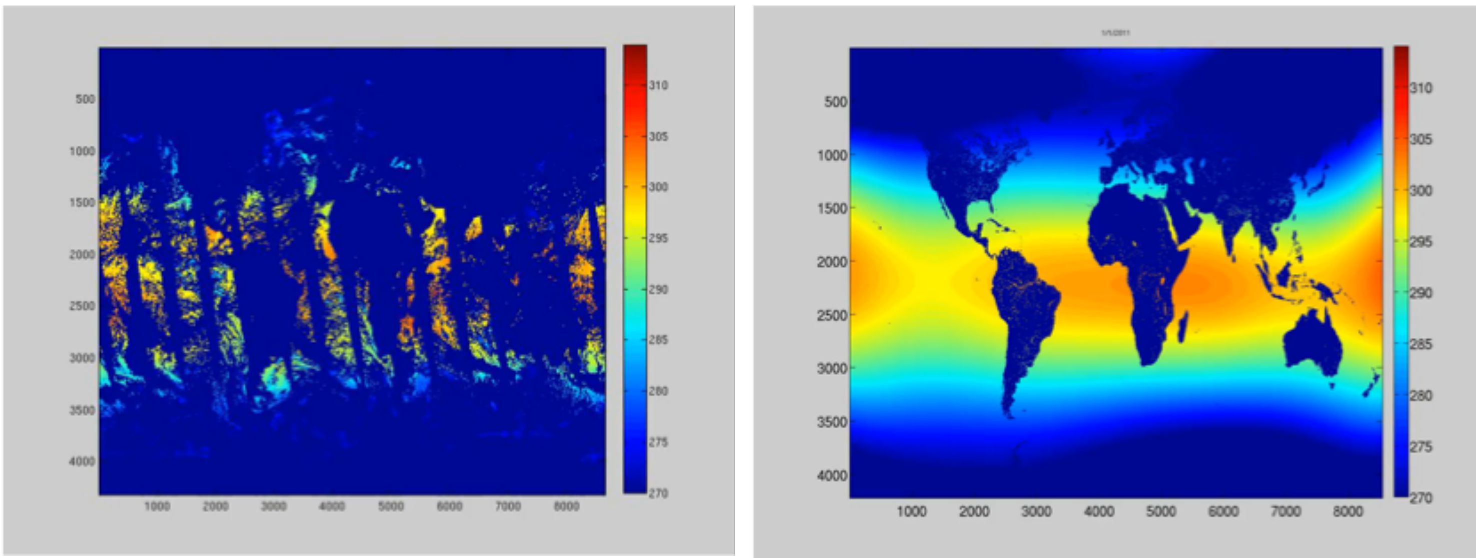


Learning Dynamics Across Similar Spatiotemporally Evolving Systems

- Model trained on 4 similar dynamical systems (Re=100, 300, 600, 1000) is able to predict on a fifth system, Re=800

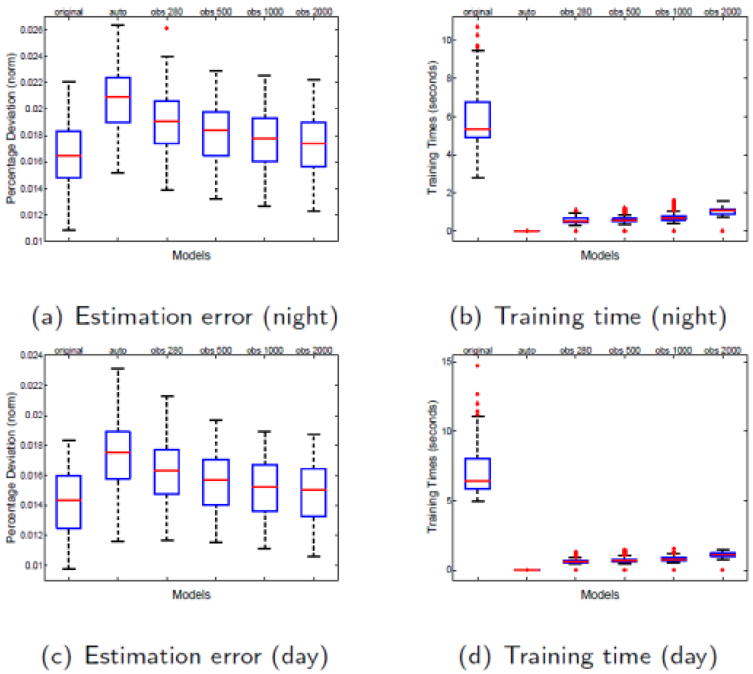


E-GP Results on AVHRR Satellite



AVHRR Pathfinder satellite global temperature data: Large (37 million sampling locations); challenging (lots of missing data); 2 million data-points a day, we analyze entire 2012

AVHRR results



(a) Estimation error (night) (b) Training time (night)

(c) Estimation error (day) (d) Training time (day)

Figure : Monitoring performance with different observers

- E-GP enables accurate prediction with very little measurements: 2000 a day
- Theoretical results: The number of sampling locations required is equal to the cyclic-index of A
- Insight: Estimating complex coupled phenomena needs fewer sensing locations

How many sensors are enough?

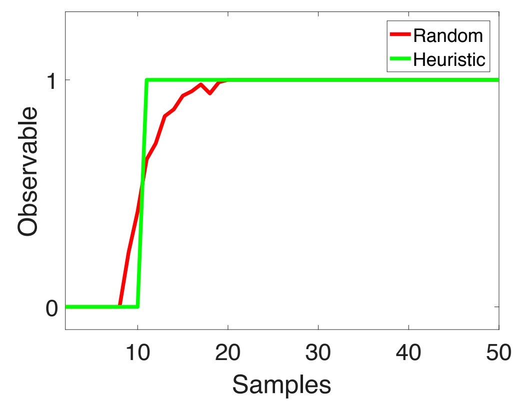
- How complex is the evolution?
  - How many distinct Eigenspaces are needed to describe the evolution
- A measure of complexity: How many sensors

Proposition: Lower bound on the number of sampling locations

Let $A \in \mathbb{R}^{m \times m}$ have a Jordan decomposition of the form $A = P \Lambda P^{-1}$, where Jordan blocks $\begin{bmatrix} \Lambda_1 & \Lambda_2 & \cdots & \Lambda_O \end{bmatrix}$ may have repeated eigenvalues. Then the lower bound ℓ on the number of sampling locations n is given by the cyclic index of A, given as

$$\ell = \max_{\lambda} \{ d[\mathrm{Ker}(A - \lambda_i I)] \}, \quad (8)$$

Furthermore if $n \geq \ell$, then the system is observable.



Random sensing can ensure observability (Internet of Things)

ILLINOIS

UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

The Robots are Coming– for your Food!

AKA: Collaborative Teams of Heterogeneous Robots for Agricultural Applications

Asst. Prof. Girish Chowdhary

Director of Distributed Autonomous Systems lab

Agricultural and Biological Engineering,

Coordinated Sciences Lab,

Institute for Genomic Biology,

Aerospace Engineering, Beckman Institute

www.daslab.illinois.edu

EARTHSENSE

Agricultural Intelligence

Advancing the Science of Autonomy

- Robotics
  - Small agricultural robots
  - Unmanned Aerial Systems
- Collaborative – Robotics
  - Learning from Human demonstrations
- Field Intelligence:
  - Machine learning
  - Neural Networks
- Adaptive Autonomy
  - Adaptive control
  - Reinforcement Learning

Group: 1 Research Faculty, 1 Postdocs, 2 Research Engineers, 6 PhD students, 3 MS, 4 research assistants

High Throughput Phenotyping

- Phenotyping: Relating genetics to plant traits
- Critical to efficient and productive breeding
- Currently labor intensive




DOE ARPA-E TERRA-MEPP

Energy Department Bets $30 Million On More & Better Biofuel, With Robots (& Drones)

June 19th, 2015 by Tina Casey

The Energy Department has just announced a whopping $30 million round of projects for biofuel research, aimed at the transportation sector. We've been on a biofuel binge all week but this really tops them all in terms of cutting-edge technology and, yes, robots are involved.

PUBLIC RELEASE: 24-JUN-2015

University of Illinois awarded $3.1 million to develop all-terrain rovers for high-throughput field phenotyping

Research to accelerate crop breeding for increased yields

CARL R. WOESE INSTITUTE FOR GENOMIC BIOLOGY, UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

SECTIONS Chicago Tribune START TRIAL 12 weeks FREE LOG IN

THURSDAY JUL. 20, 2017 SPORTS BREAKING HOY MOST POPULAR OPINION SUBURBS 78°

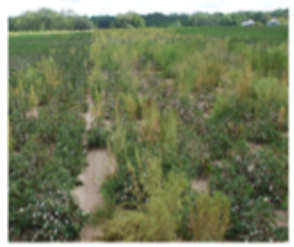
Blue Sky Innovation / Blue Sky Originals

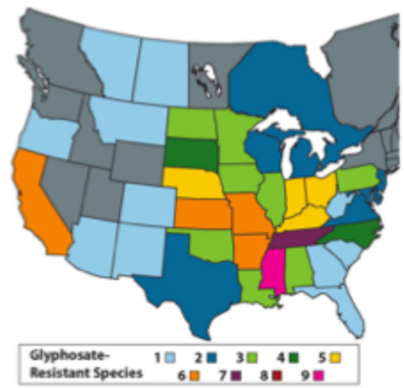
This self-driving robot from U. of I. could shape the future of farming

tools to find important patterns."

Girish Chowdhary, an assistant professor of agricultural and biological engineering, is pictured with TERRA-MEPP. (Carl R. Woese Institute for Genomic Biology photo)

Herbicide Resistant Weeds!

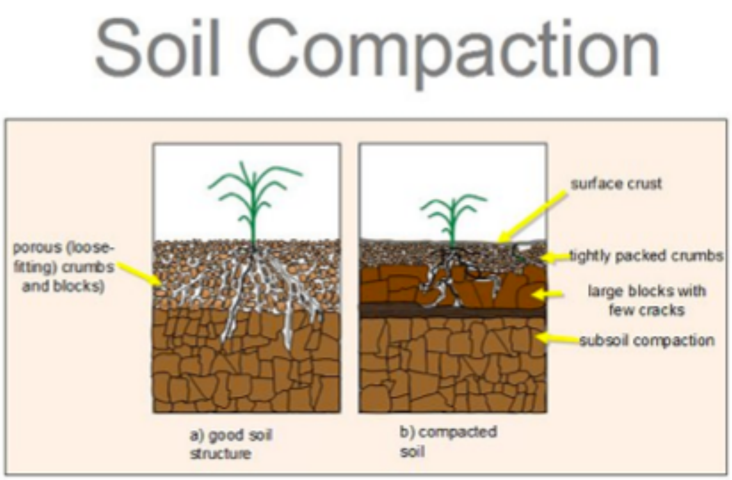




Confirmed Glyphosate resistant weeds in US

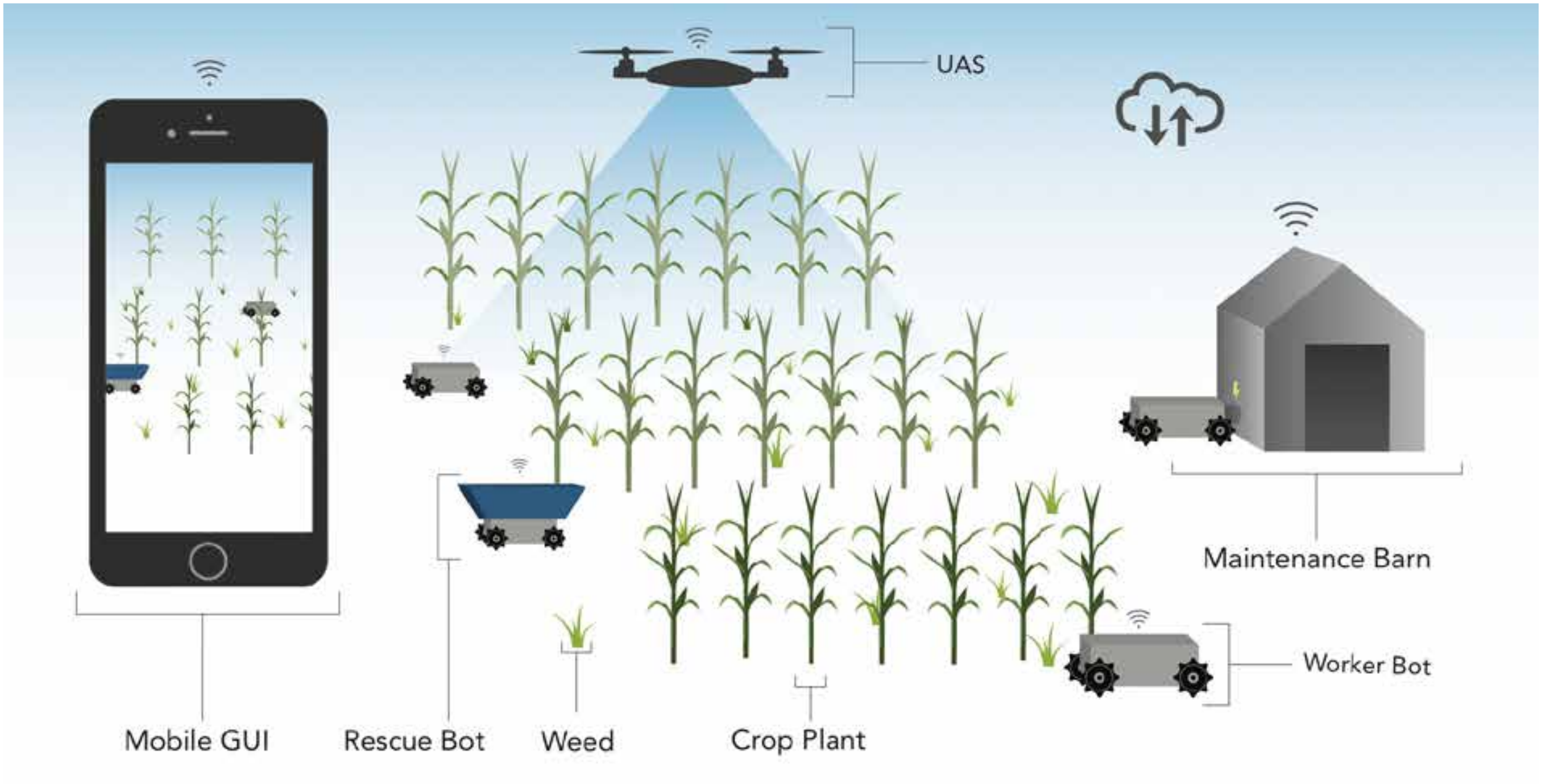
- Examples: 5-way multiple resistant Waterhemp and Palmer Amaranth
- Current cost 5-6 Billion, and on the rise!
- Mechanical control is the only evolutionarily sustainable way

Soil Compaction yield loss 5-50%



- Good farming requires light equipment

Smart Robotic Teams for Agriculture



Integrative Research Goals:

- Autonomy
- Multi-robot collaboration
- Cost
- Seamless Human-Machine interaction

Where are the ag robots?

Main challenges:
- Autonomy
- Cost
- Ease of use

Ag-Robotics is Hard!

- Field scales are large
- Economics are tough to beat (Pederson 2003)
- Environment is unstructured

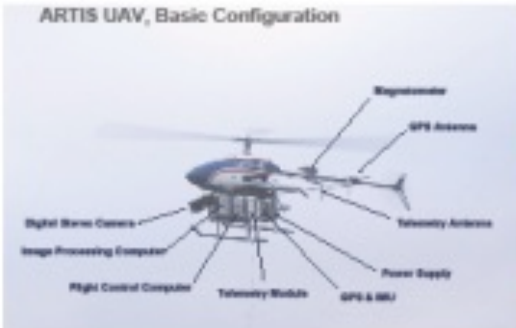
Small Agricultural Robots








Compact Low-Cost UAS are Practical



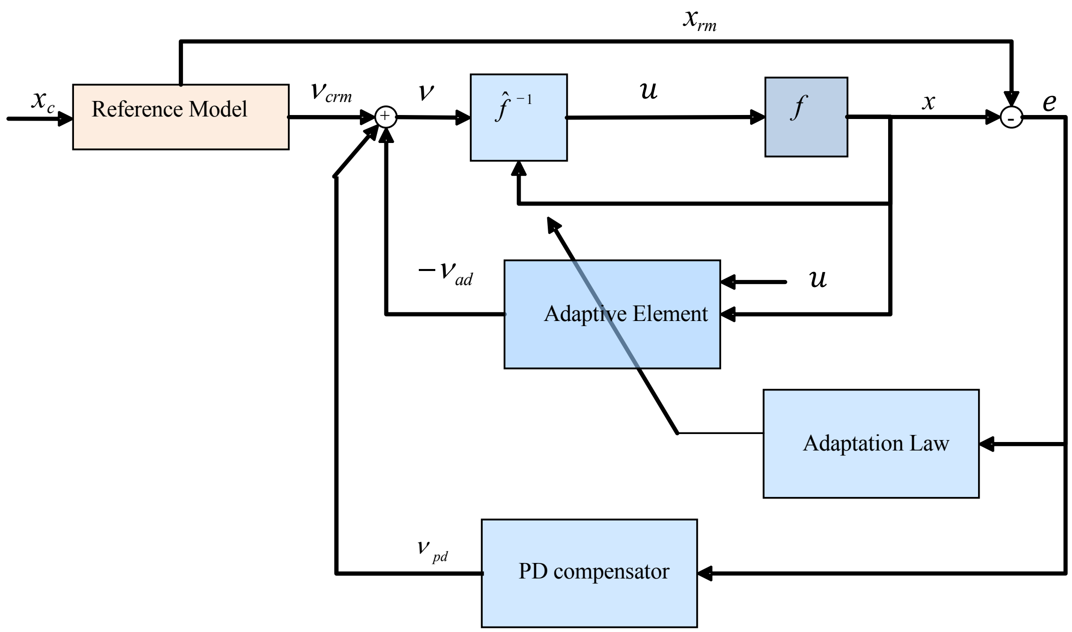
2003, DLR ARTIS UAV testbed, two Intel flight computers

2015, Stabilis plug-and-adapt autopilot, credit card sized!

A plug-and-play autopilot designed to work across several aerospace vehicles.

- Widely adopted consumer systems are low-cost, simple, and multi-purpose

Overview of Inversion Based MRAC



- Approximate inversion model $\hat{f}$
- Design a pseudocontrol ν to minimize the tracking error: $e = x - x_{rm}$

Modeling error $\Delta \in \Re^n$

$$\dot{x} = \hat{f}(x,u) + \boxed{\left[f(x,u) - \hat{f}(x,u)\right]}$$

- Combined pseudo-control action:

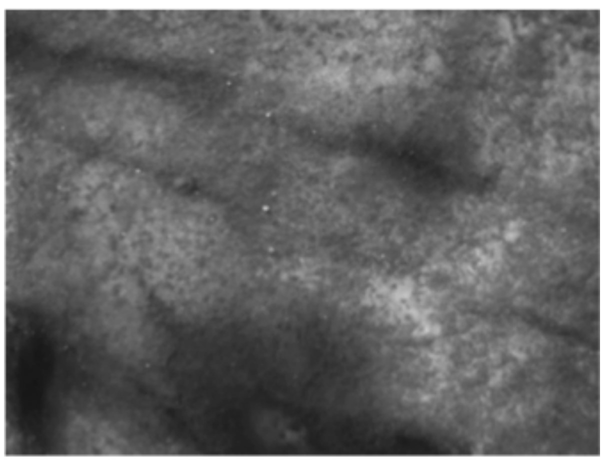
$$\nu = -Ke + \dot{x}_{rm} - \nu_{ad}$$

- Tracking error dynamics

$$\dot{e} = Ae + B(\nu_{ad} - \Delta)$$

Adaptive Systems

Vision based control



Chowdhary et al. GPS-denied Indoor and Outdoor Monocular Vision Aided Navigation and Control of Unmanned Aircraft, **Journal of Field Robotics, 2013**

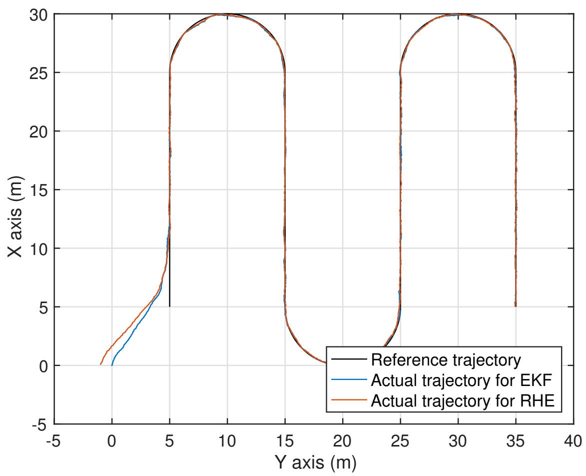
Collaborative Robotic Teams

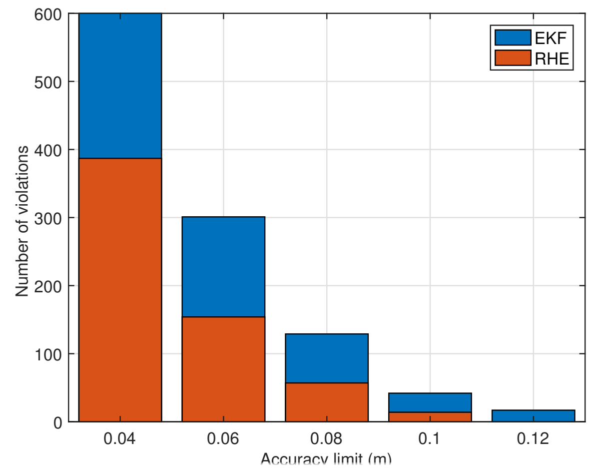
TERRA Robots

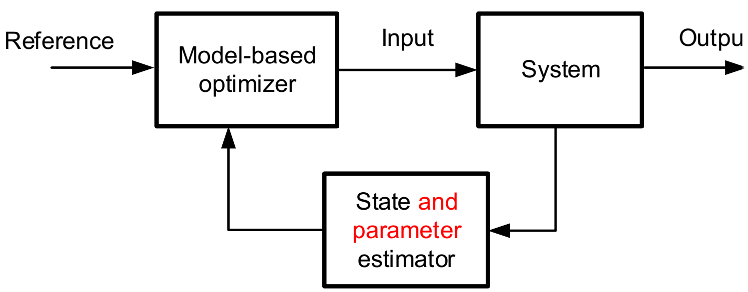
Terra Family of robots

Precision Autonomous Navigation

High-Precision GPS auto-steer







$$\min_{\xi(t),p,u(t)} \quad \frac{1}{2}\left\{ \left\| \begin{array}{c} \hat{\xi} - \xi(t_{k-N+1}) \\ \hat{p} - p \end{array} \right\|^2_{H_N} + \sum_{i=k-N+1}^{k} \| z_m(t_i) - z(t_i) \|^2_{H_k} \right\}$$

$$\begin{aligned} \text{s. t.} \quad & \dot{\xi}(t) = f(\xi(t), u(t), p) \\ & z(t) = h(\xi(t), u(t), p) \\ & \xi_{min} \leq \xi(t) \leq \xi_{max} \\ & p_{min} \leq p \leq p_{max} \qquad \forall t \in [t_{k-N}, t_k] \end{aligned}$$

$$\begin{aligned} 0 \leq \; & \mu \leq 1 \\ 0 \leq \; & \kappa \leq 1 \end{aligned}$$

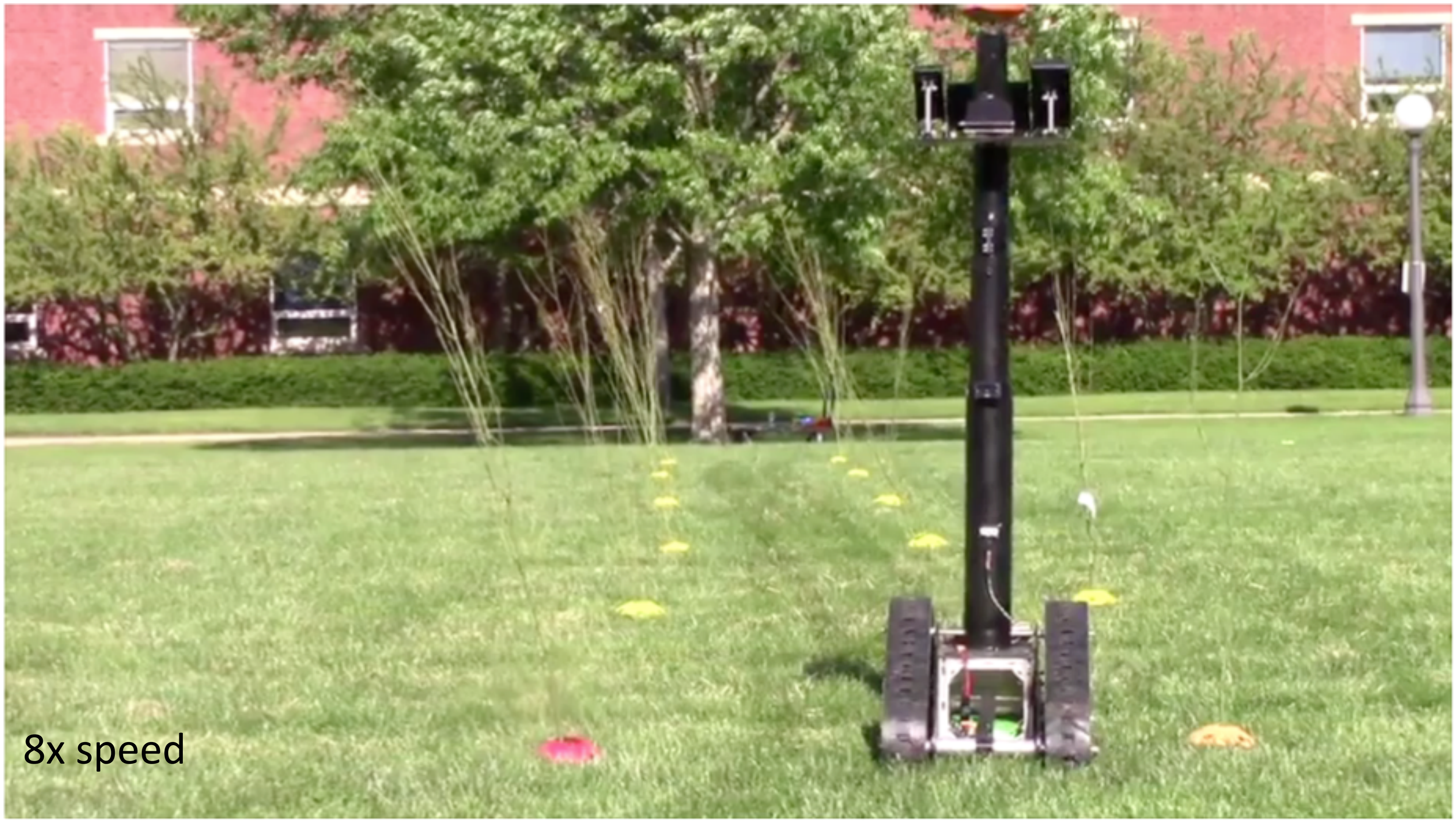
$$\begin{aligned} \dot{x} &= \mu v \cos\theta \\ \dot{y} &= \mu v \sin\theta \\ \dot{\theta} &= \kappa\omega \end{aligned}$$

$$\begin{aligned} \xi &= \left[\begin{array}{ccc} x & y & \theta \end{array}\right]^T \\ p &= \left[\begin{array}{ccc} v & \mu & \kappa \end{array}\right]^T \\ u &= \omega \\ z &= \left[\begin{array}{cccc} x & y & v & \omega \end{array}\right]^T \end{aligned}$$

Erkan Kayacan , Sierra N. Young, Joshua Peschel and Girish Chowdhary, "High Precision Control of Tracked Field Robots in the Presence of Unknown Traction Coefficients", Journal of Field Robotics , Under Review

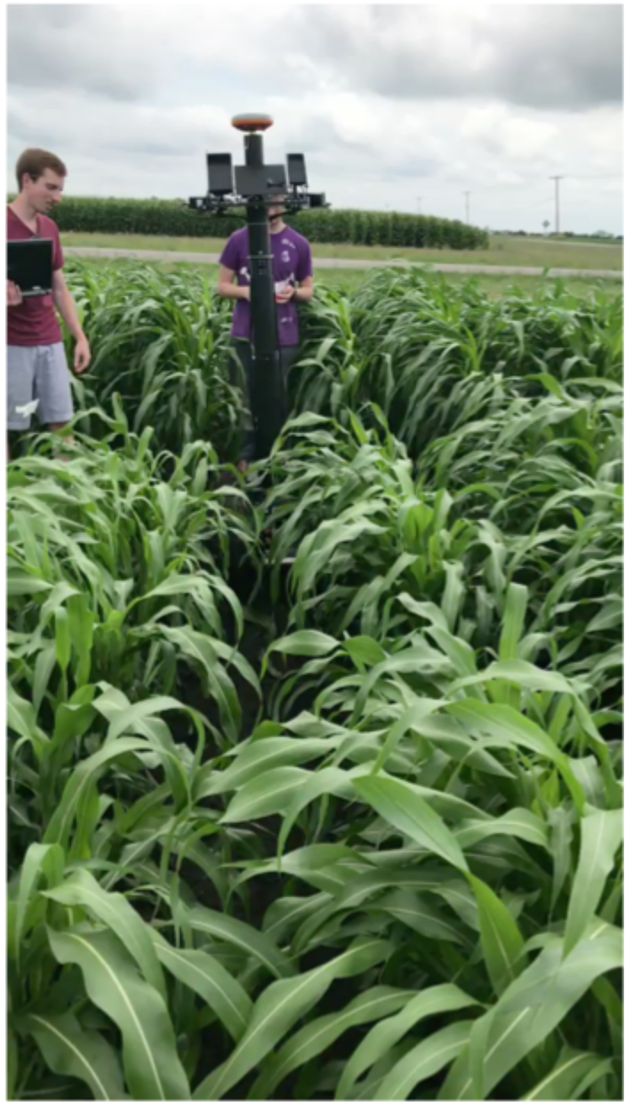
Erkan Kayacan and Girish Chowdhary, ”Guidance and Control of 3D-Printed Robots", The 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2017)

autonomous Path Following and obstacle avoidance



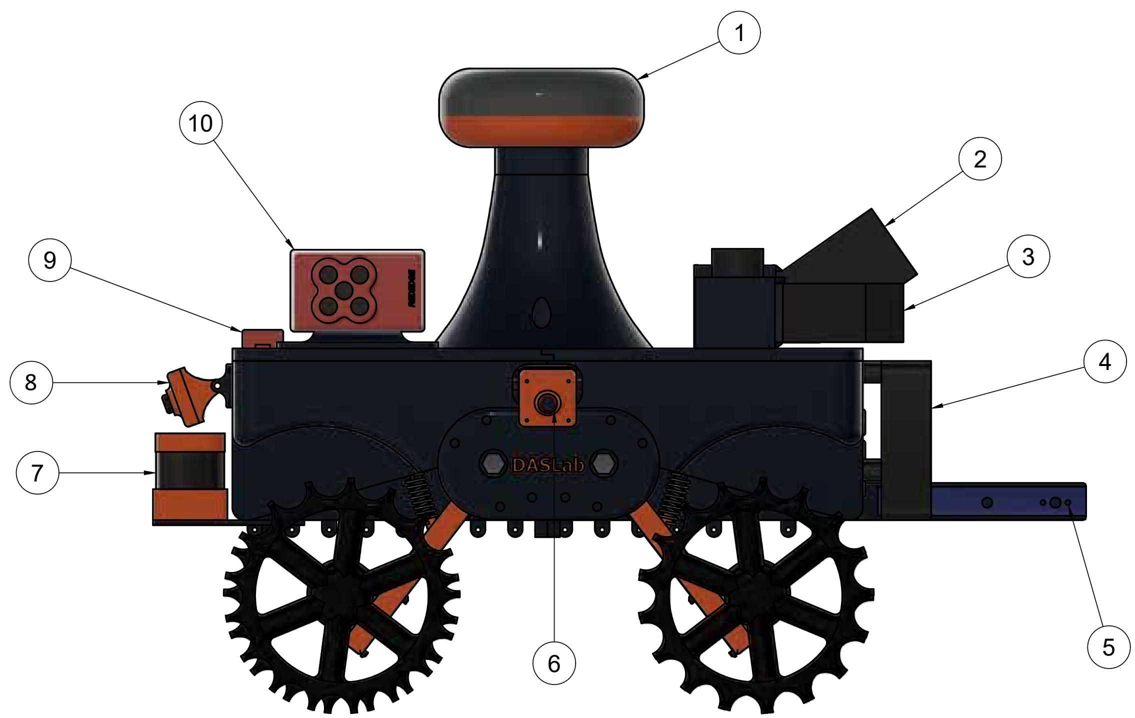
Sensors

Autonomous Testing in Sorghum plots 2017



TerraSentia 1

14.5 lbs., 11 inches wide, 8.5 hrs. endurance in field



1. GPS Antenna
2. Bayspec sensor (optional)
3. Bayspec sensor (optional)
4. Cooling system
5. Intel RealSense sensor (optional) and mount
6. Embedded visual sensors
7. Lidar Sensor (optional) and mount
8. Embedded visual sensor
9. RedEedge GPS (optional)
10. RedEdge multispectral camera (optional) and mount

Computing features:
- NVDIA Tegra GPU OR Intel NUC computer
- Autonomous navigation system
- SD Card for data recording
- Li-PO 12 V Batteries (3)

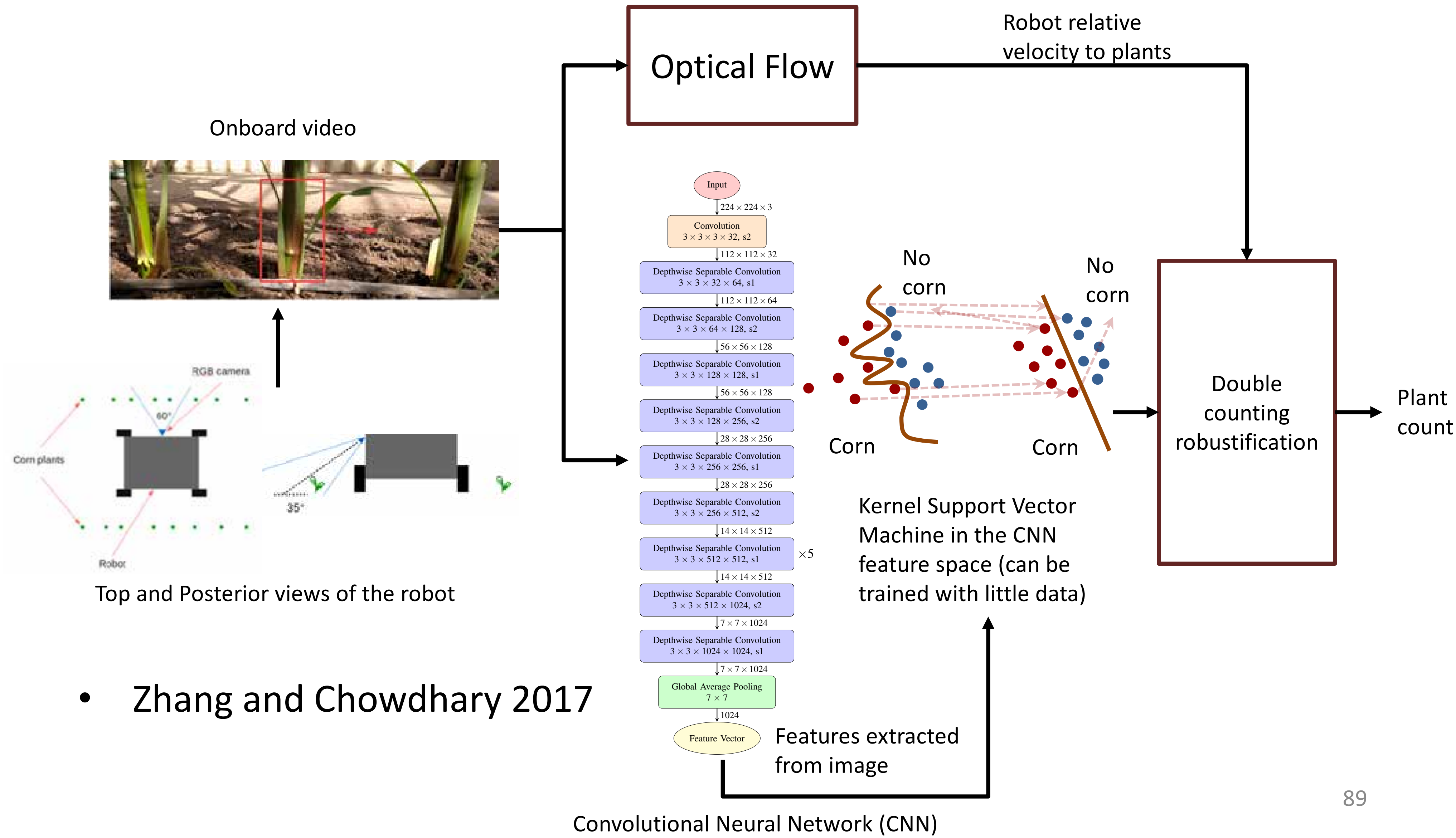
Motion features
- Battery operated (3 Li Po batteries)
- Independent suspension
- 4 wheel drive
- 1 mile/Hr speed

Corn Counting

More Corn Counting

Assumption Illinois, NCGA fields, 1 month old corn, lots of water damage

Corn Counting algorithm



- Zhang and Chowdhary 2017

Corn Counting on older Corn

- We will train deep NNs across corn stages in winter

Stem Width Estimation

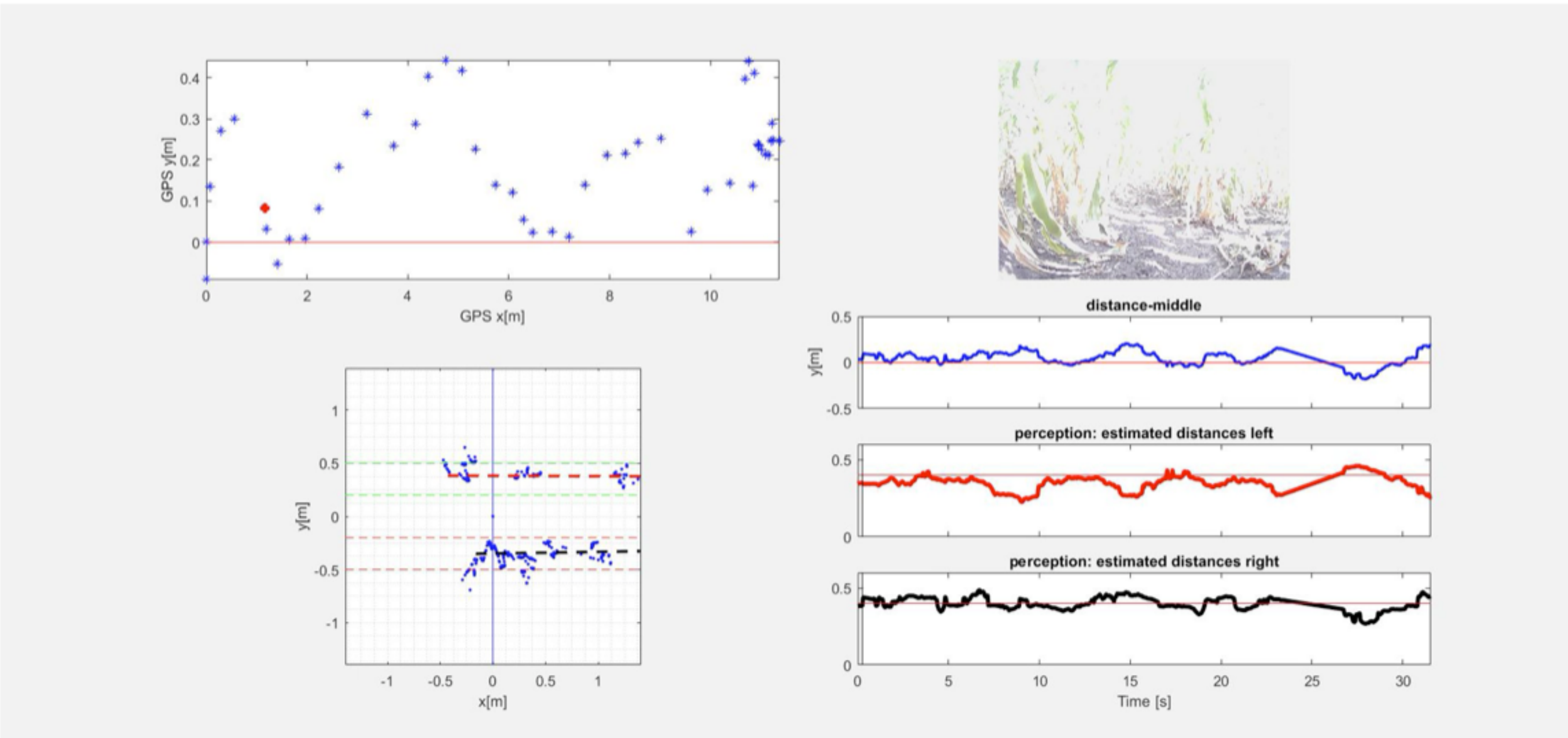
- Lidar data used to estimate depth to Sorghum stalk
- Achieved error: <5%

Lane keeping with LIDAR

[Video of what the LIDAR sees]

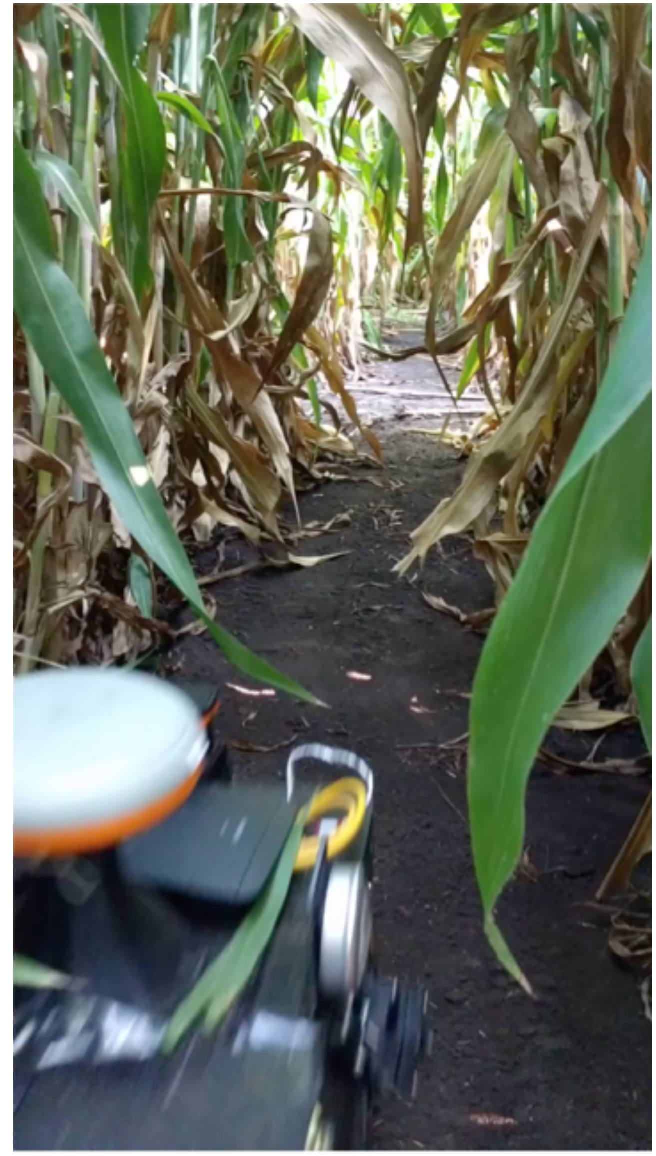
Moving horizon estimator detects middle of the lane using 2-D scanning laser LIDAR, output is integrated with onboard control. Notice the robustness even with thin corn stalks

Lane keeping with LIDAR



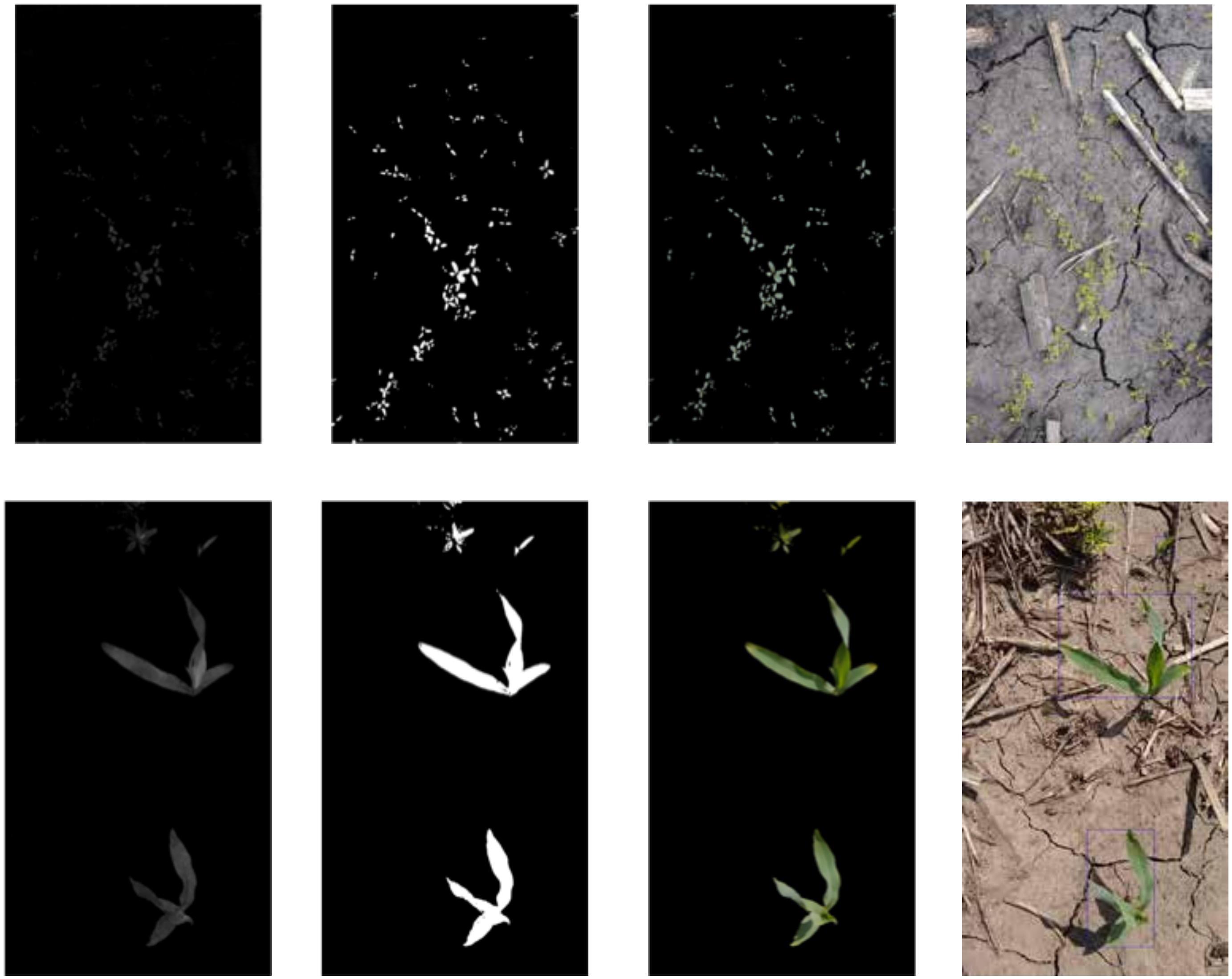
[Video of what the LIDAR sees]

LIDAR based navigation



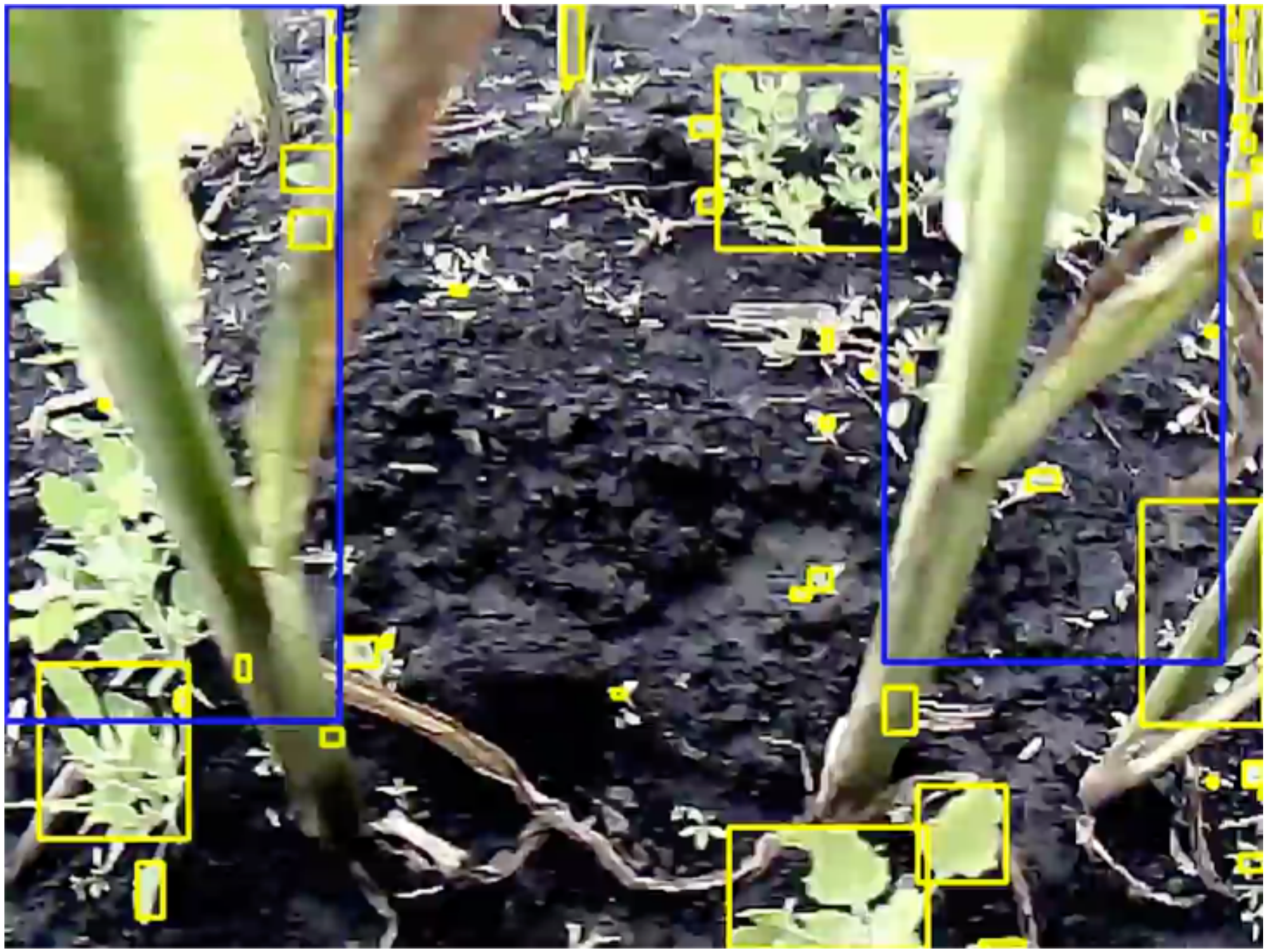
Lane keeping with Convolutional DNN

Broad Leaf Weed Detection



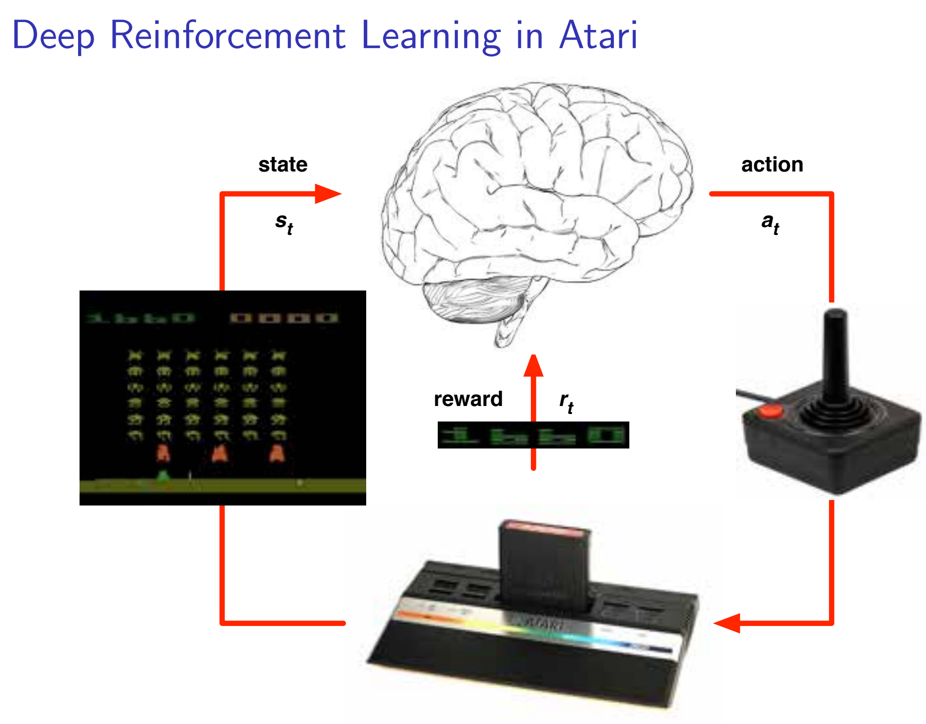
1 2 3 4

Weed detection



- Blue is Corn, yellow is “weed” (not corn)

In Atari



- David Silver: A Tutorial on Deep RL, in Piazza

Is Robustness a concern?

Figure: Half Cheetah

- Slight variation in mass
- Slight variation in friction

Huge impact

Results

Figure: DDPG [6]

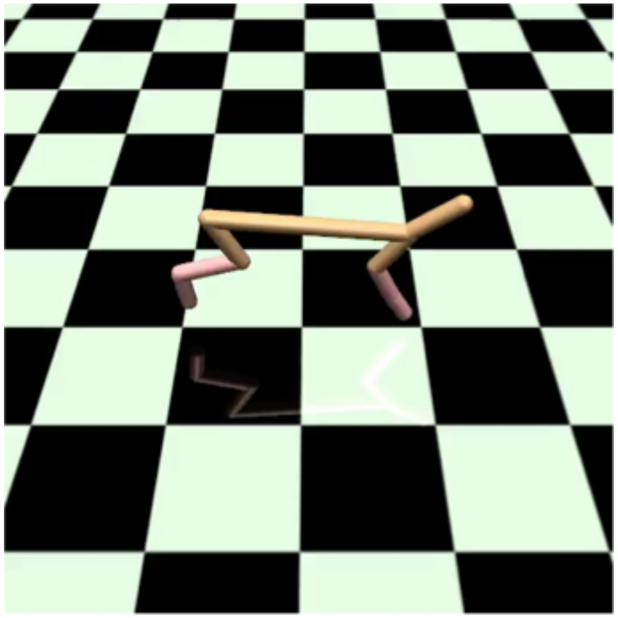
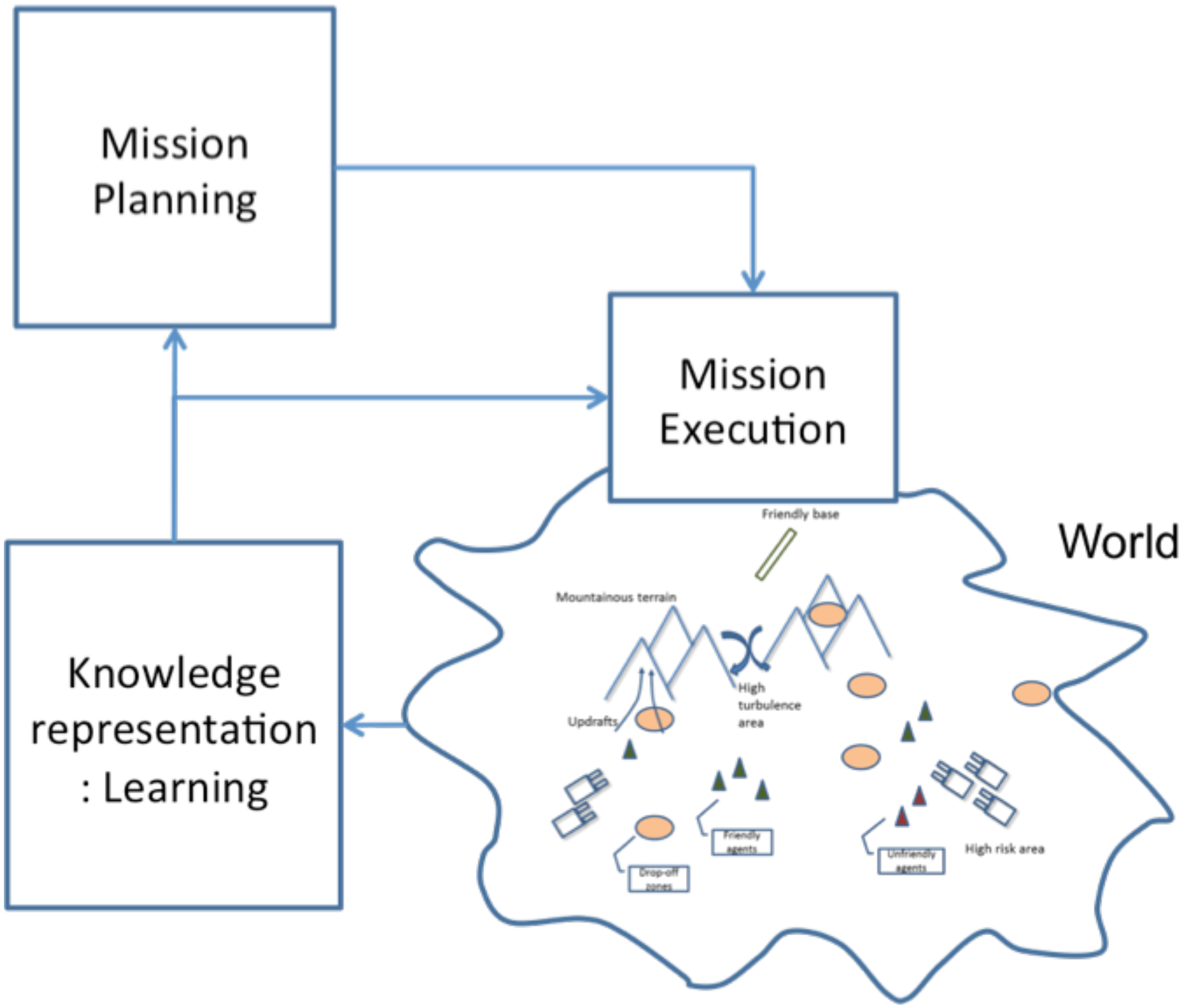


Figure: Robust DDPG

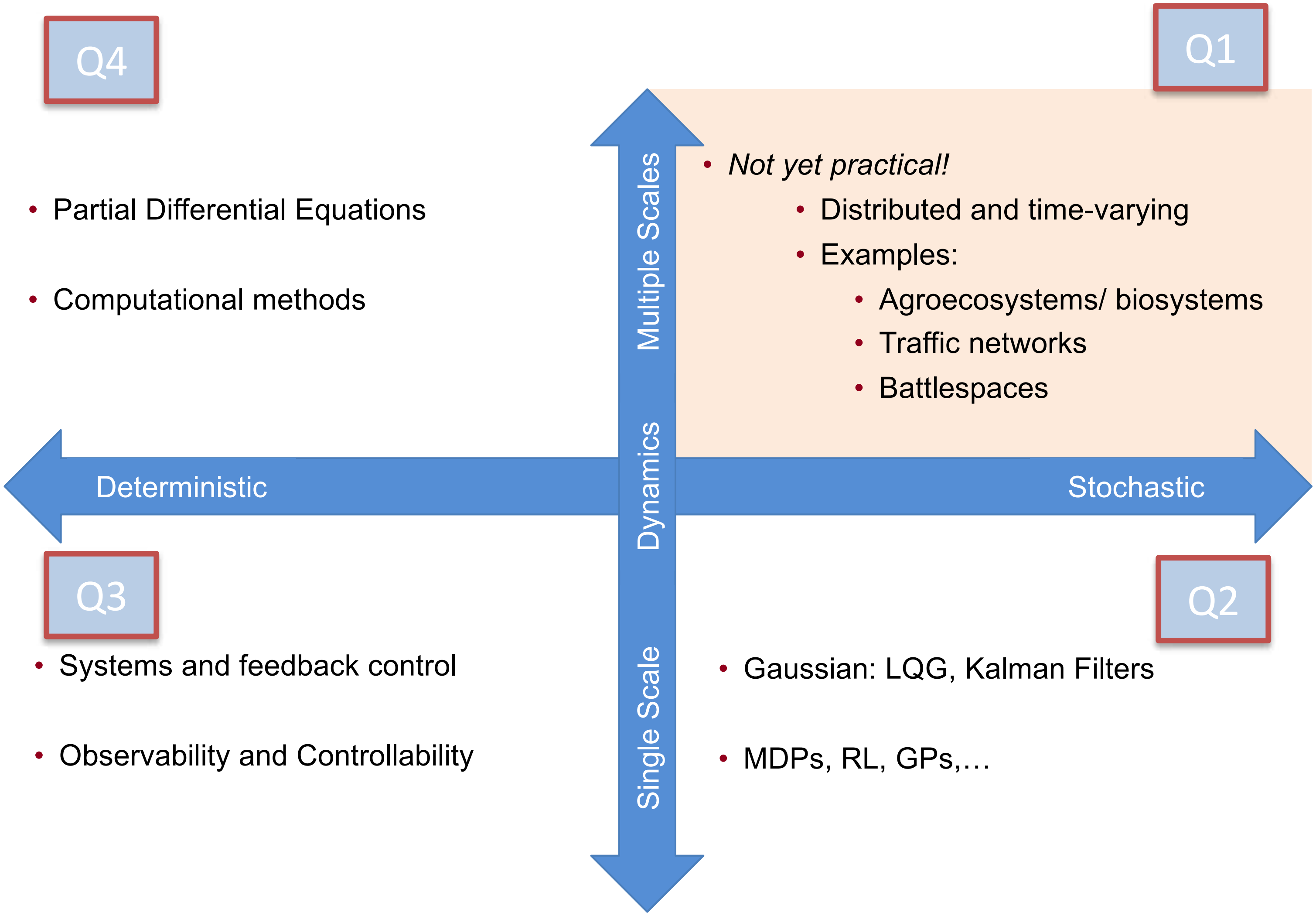
Many things

- We saw many things that make up an autonomous system

Higher level autonomy



Challenges in Autonomy



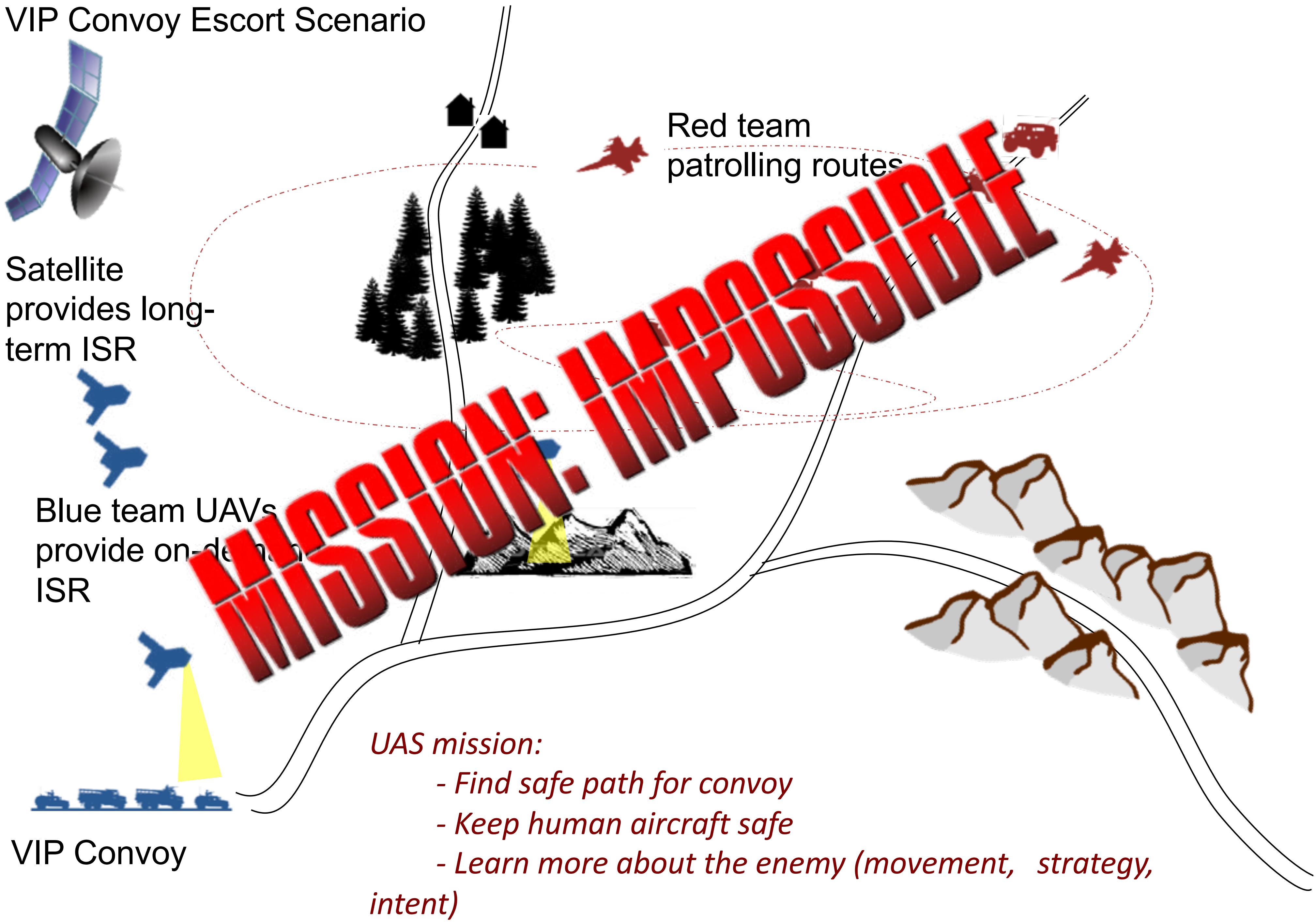
The quadrant game

- Learning objective: Separate types of autonomy problems
  - Complexity (dynamic scales)
  - Stochasticity
- Autonomous cars
- Farm bots
- Airplane autopilots
- Smart grids
- Human assisted surgery
- Home care robots

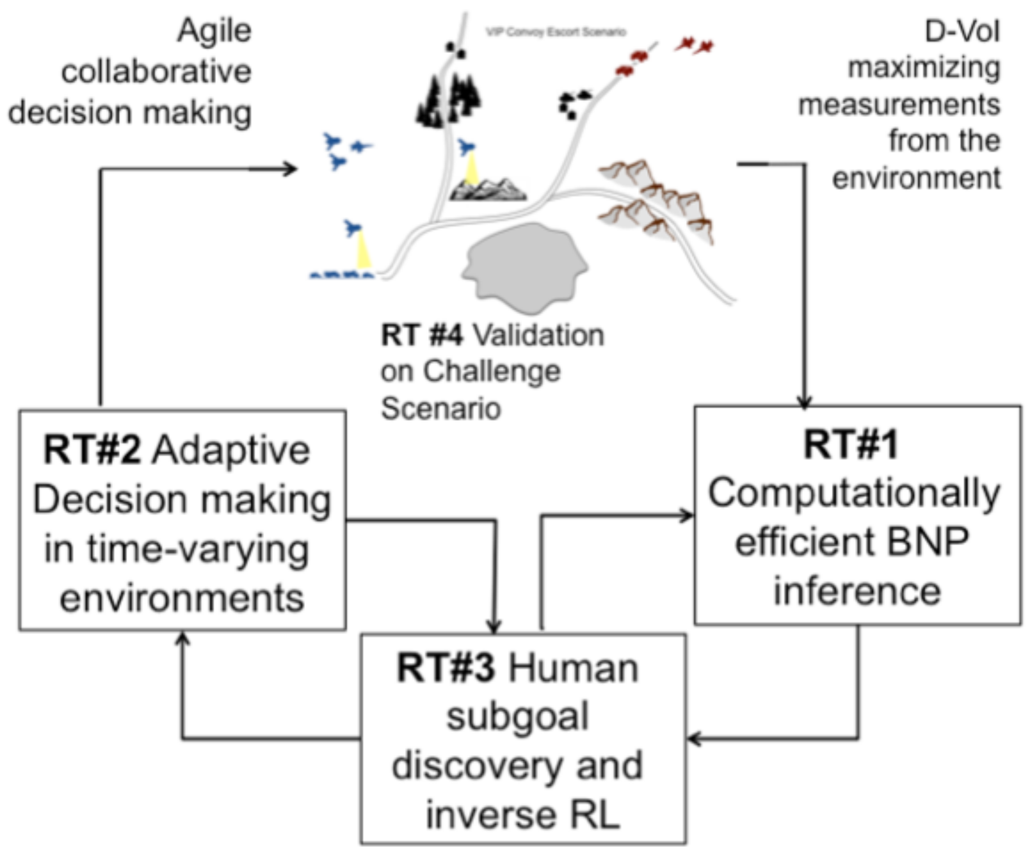
Let’s design an autonomous car?

What systems make an autonomous farm?

- Types of robots
- Subsystems of robot


VIP Convoy Escort Scenario
Satellite provides long-term ISR
Red team patrolling routes
Blue team UAVs
provide on-de
ISR
MISSION: IMPOSSIBLE
MISSION: IMPOSSIBLE
VIP Convoy
UAS mission:
- Find safe path for convoy
- Keep human aircraft safe
- Learn more about the enemy (movement, strategy, intent)

Robust Autonomy in Contested Environments



Major subsystems

- Perception
  - Localization and mapping
  - Object detection and classification
- Reasoning and environment modeling
- Decision making
- Path planning
- Control
- Supervisory systems

So how do we study autonomy?

- We separate the course in three core streams:
- Principles of autonomy: In-Class teaching
  - Principles for Higher level perception
  - Principles for decision making under uncertainty
- Architectures for autonomy: Problem formulations: Your project
- Mechanisms/methods for autonomy: Keeping up with the literature: Weekly Readings and updates

Paper reviews

- Summary: Summarize the paper, what are the main contributions? Where does the work fit in the literature? What advances does it make?
- Significance: What is the significance of those advances? Which communities/application areas would benefit from the contributions in the paper?
- Technical commentary: Are the methods correct? Do the derivations make sense? Are the assumptions employed reasonable? If there are experiments, are they described in sufficient detail?
- Speculative commentary: How could the work be improved? What are some glaring flaws? Are there any subtle flaws? What could be some extensions?
- Literature trail: Provide 3 papers that are cited in this paper. Provide 3 papers that cite this paper (if there are any)
- Other comments: Things that you want to say that are not covered by above
- Useful link: http://matt.might.net/articles/how-to-peer-review/

Projects

- BYO topic:
  - Machine learning
  - RL
  - Search/AI
- We give you topic:
  - Domain 1: Kill-web
  - Domain 2: Convoy escort
  - Domain 3: Mechanical weeding agbots (http://test.denisos.com/research/)
  - Domain 4: Robots (if we can get them on time)