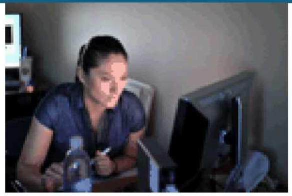
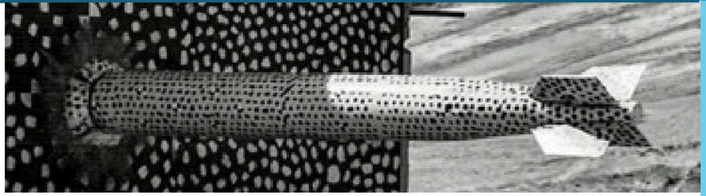
SAND2019-13842PE

Toward Dynamic, Tactical, Remote Robotic Ops: Active Perception and Other Key Technologies





PRESENTED BY

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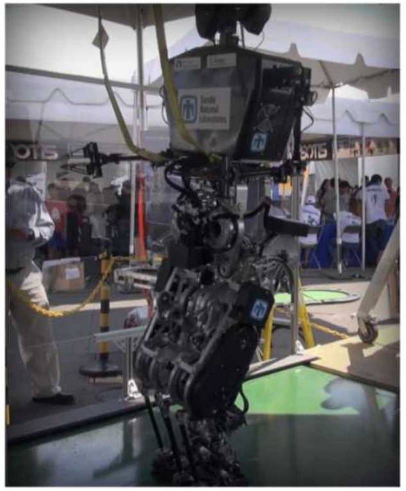
High Consequence Automation and Robotics

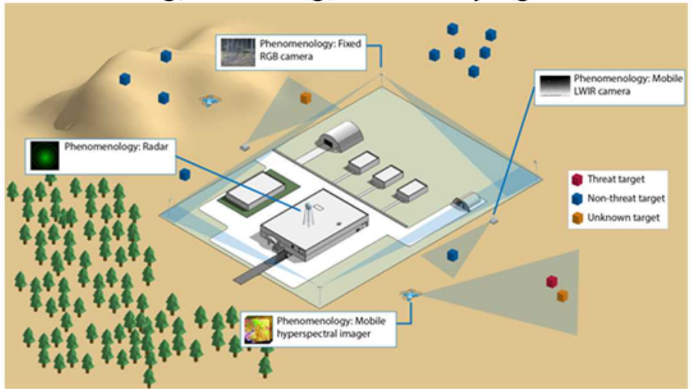
R → D → A

High Consequence Automation • Unique Mobility • Advanced Manipulation • Advanced Control Systems • Unmanned Systems Autonomy • Custom Mechatronics • Cybernetics • Simulation-Based Training, Response, & Operations

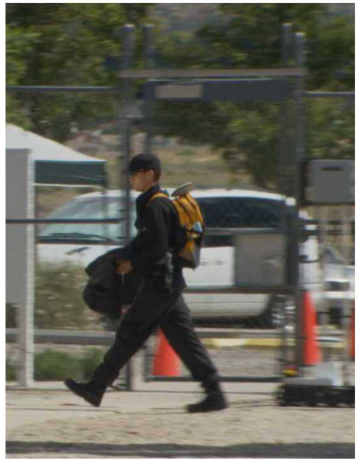


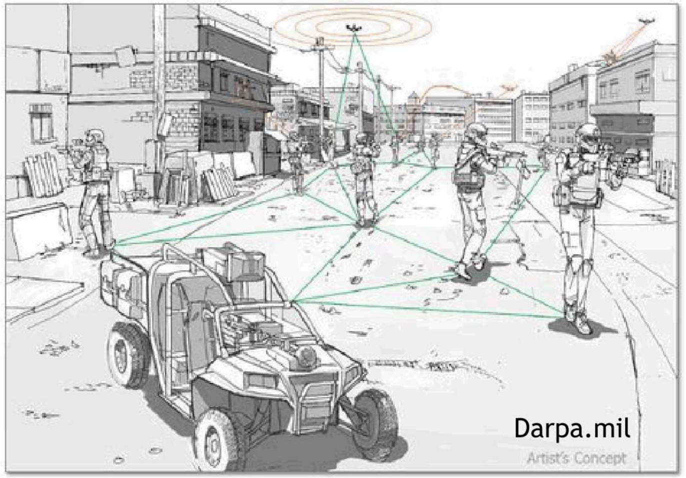
Tactical Operations with Unmanned Systems (UMS): Operate UMS teams toward goals at human (or faster) speeds, with human (or better) effectiveness, against dynamic environments & adversaries

Physical Security:
Detecting, Assessing, and Delaying Threats



Abandoned Facility Recon:
Unknown compound, potential adversaries





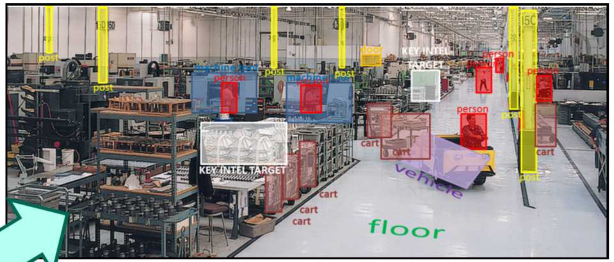
Future dismounted operations:
Migrating UMS from support to peers

Mine Rescue / Disaster Response:
Denied, uncertain, complex environments

Need: MOBILITY – EFFICIENCY – SPEED – COLLABORATION – PERCEPTION – TACTICS - ACTION

Moving up the Tactical UMS "Autonomy Ladder"

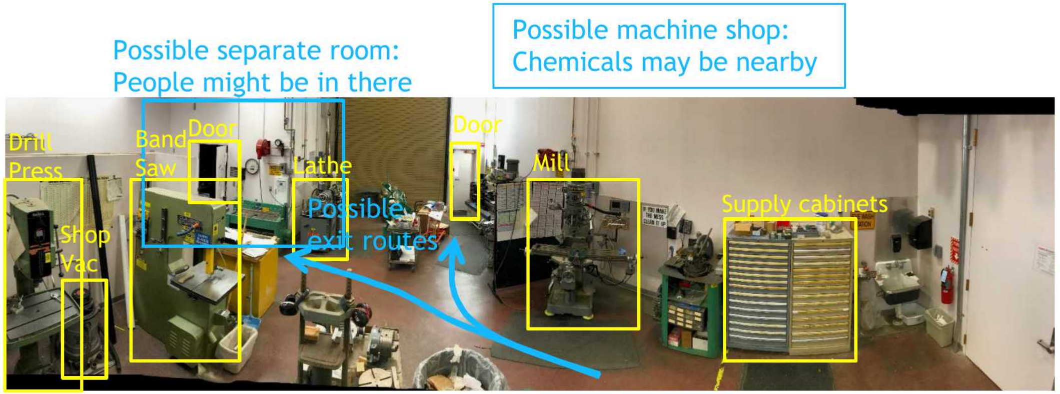
Level of Instruction	*Capabilities*	*Technologies*
"Go win the battle / war"		
	Strategic planning	AI / Strategic Reasoning / ???
"Secure the squad while it moves around"		
	Dynamic tactical engagements	Tactical Reasoning
"Find all the (tanks) in there and (swab) them."		
	Take *action* in unknown env.	Rapid Abstract Perception
"Go through that facility, bring back a map and pictures"		
	Navigate unknown / denied env.	✓ SLAM (Simult. Local. & Map.)
	Navigate known environments	✓ GPS, path planning
Drive / fly with joystick		

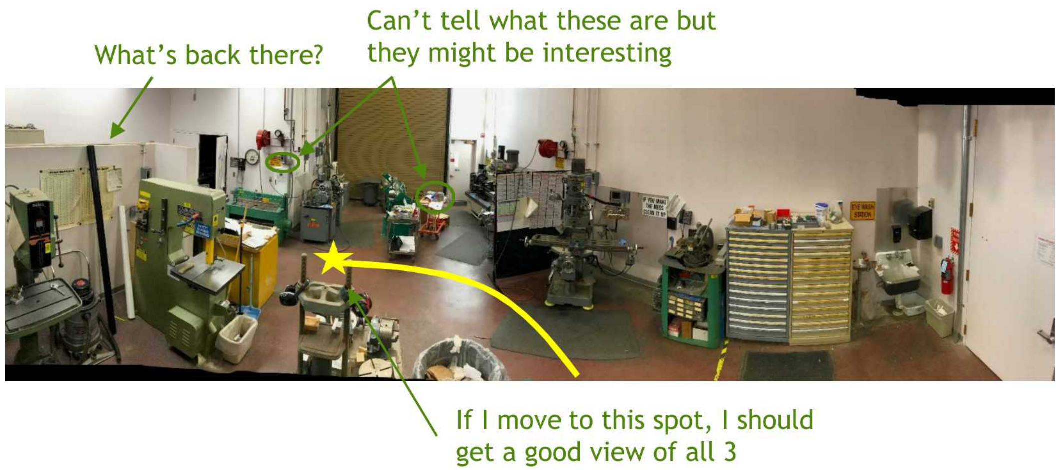


IROS 2014 Kinect Challenge
Github – RTAB-map

What do we mean by intelligent perception?

Elements:





Intelligently drawing higher-level conclusions (e.g. semantic classification) from sensor data

Controlling a sensor to autonomously drive down uncertainty by getting the <u>best data in real-time</u>

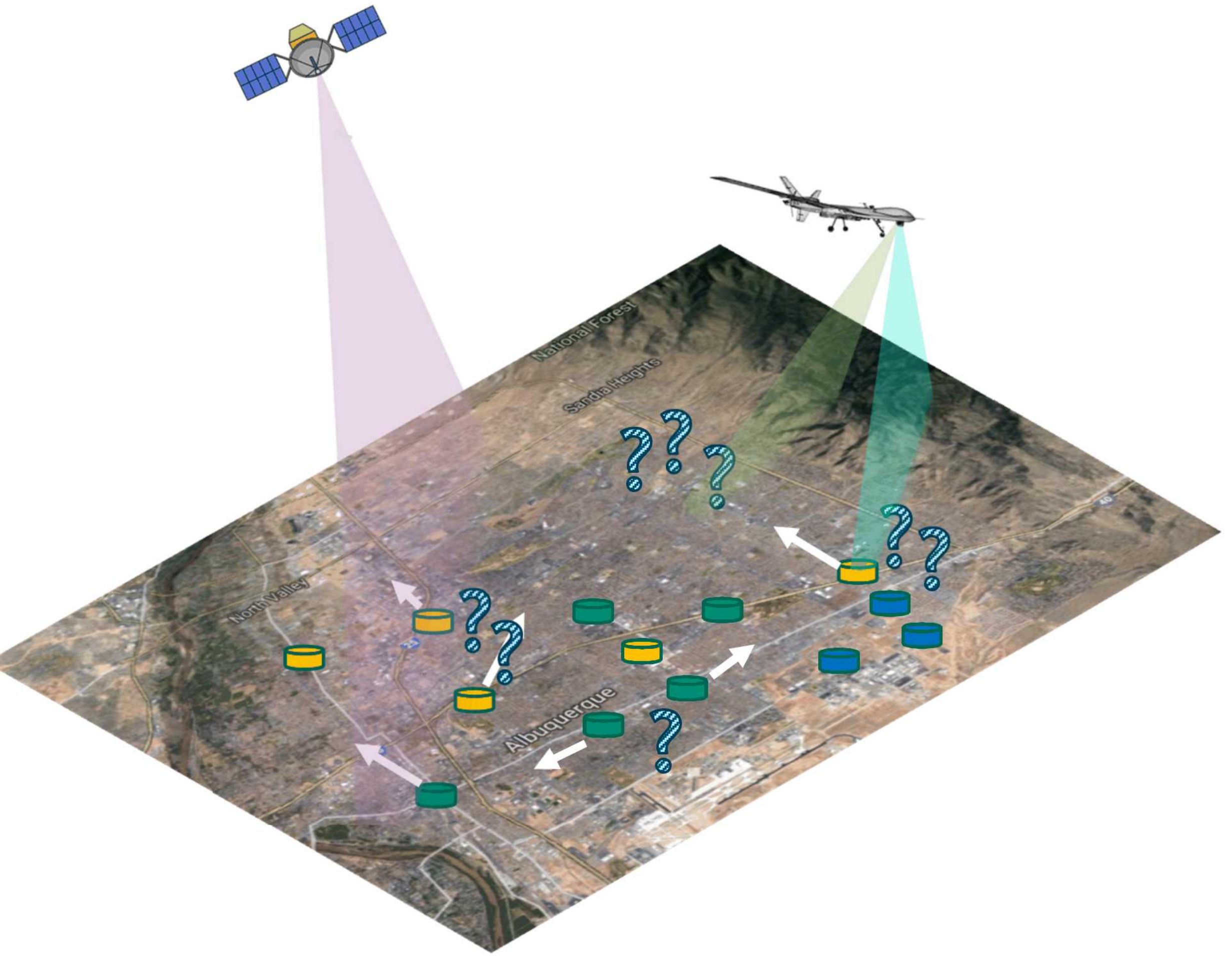
- Not just tip-and-cue; continuous (or large-space discrete) problem in space and time

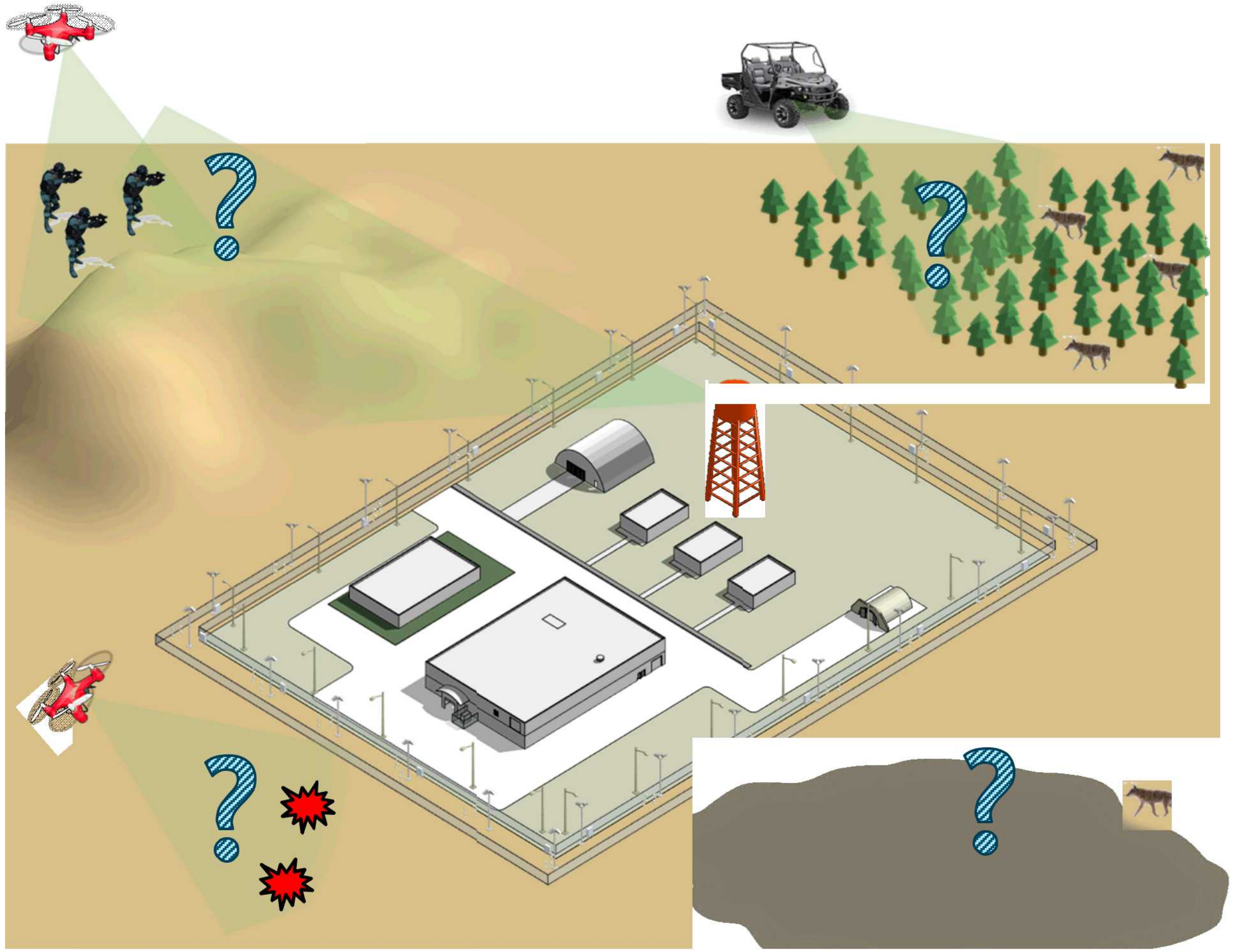
To autonomously drive down *semantic* uncertainty:

- Effectively requires placing a classifier, or an approximation of one, <u>inside</u> a control loop

Big challenge: putting pieces together into something that works in real world

Autonomous Threat Awareness



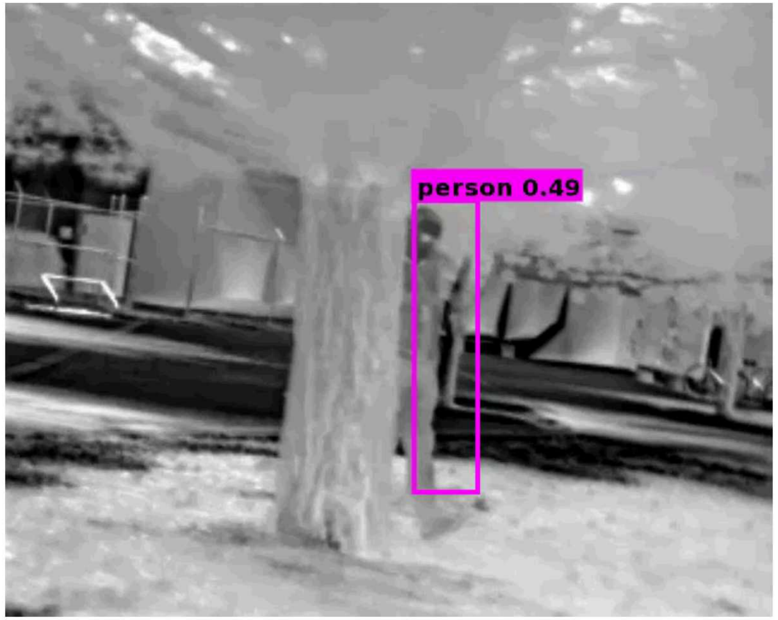


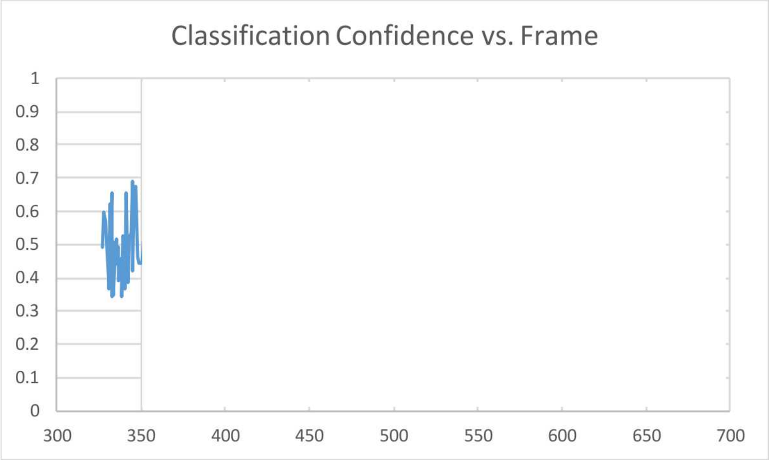
Place sensors to "minimize uncertainty in the threat environment"

- Presence, location (geometry) & identity (semantics) of objects of interest (or non-interest)
- Balance search (new detections) vs. characterization (prior detections

Solve this problem continuously & indefinitely

Why Moving Sensors?: The Benefits of Perspective Change

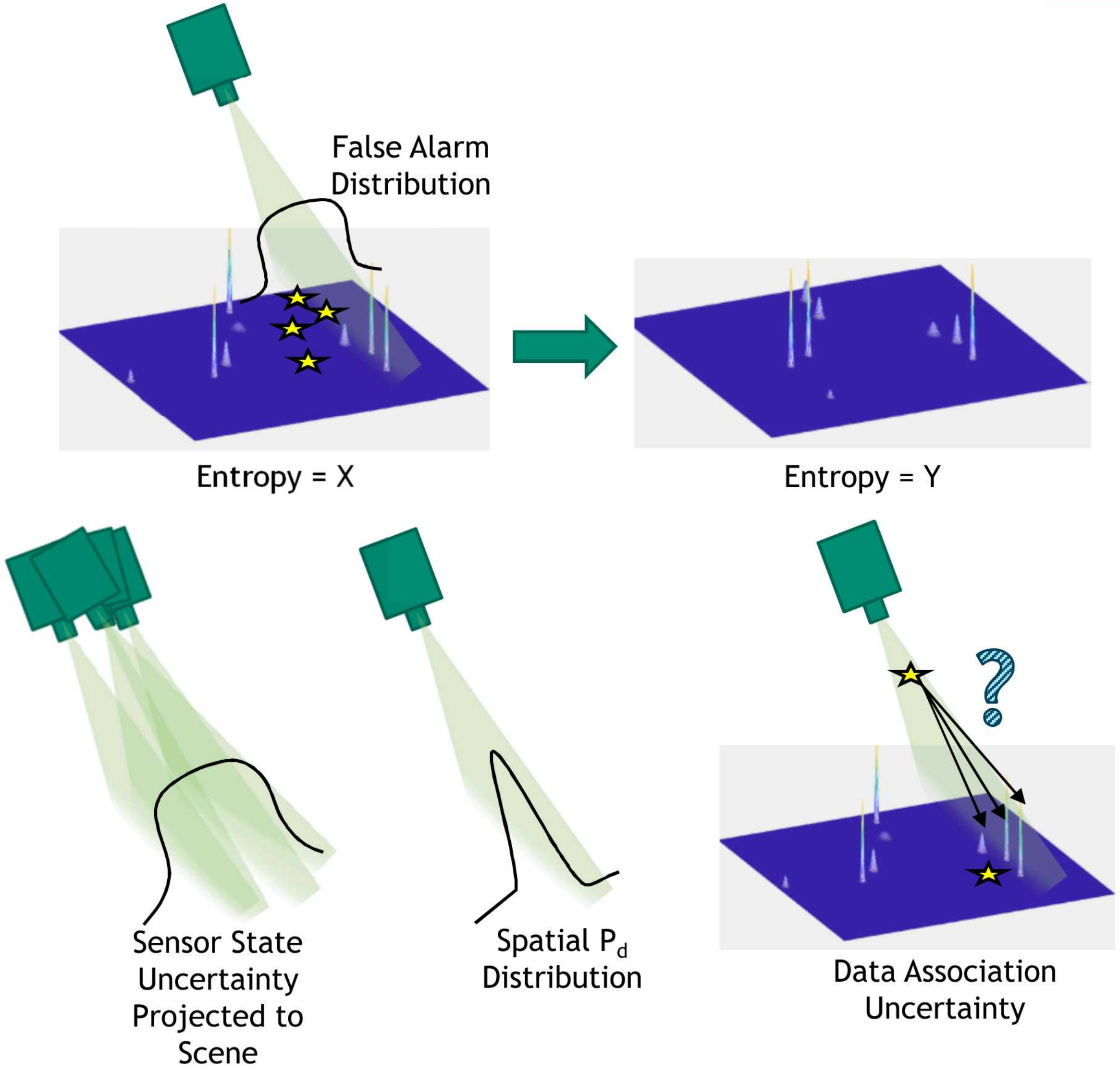




Info-Driven Control to Minimize Uncertainty: Challenges of Doing it "The Right Way"

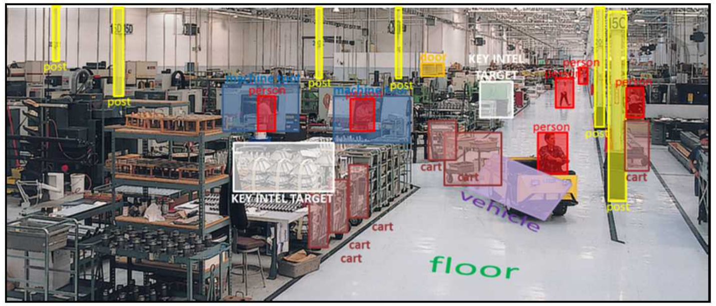
An ideal approach: treat everything probabilistically

- Compare current distribution (prior) to expected posterior based on predicted measurements
  - Select measurement that maximizes info gain via, e.g. direct optimal control
- (Some of the) sources of uncertainty:
  - Sensor state uncertainty
  - Probability of detection (with variations: spatial, geographic, target type, state, etc.)
  - False alarm rate (with variations as above…)
  - Multi-target data association uncertainty
  - Cardinality uncertainty (number of targets)
  - …..
- Frameworks exist to handle this (e.g. FISST tracking), but there are challenges
  - Real-world classifier output form (not pdf / pmf)
  - Scaling & computational challenges (real models are nonlinear)
  - Challenges particular to distributed systems (double counting, etc.)
  - ….



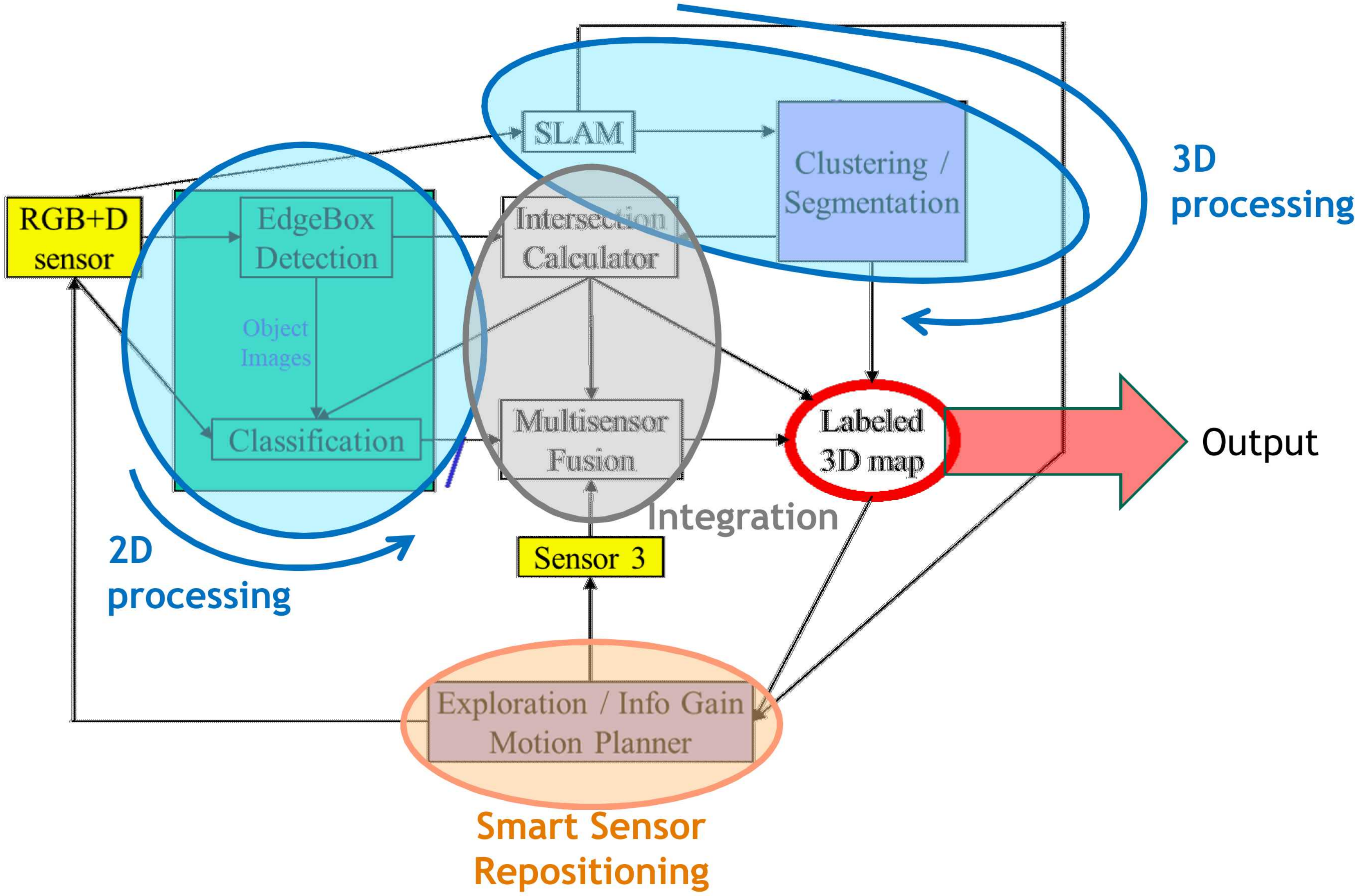
What can we implement now?

Rapid Abstraction in Confined Environments (RACE)



Autonomously: Swab all gas cylinders in chemistry labs or welding facilities. Map the whole space and locate any of the new MQ-3000 sensors.

- Semantic & geometric mapping
- Find rare objects
- Explore intelligently



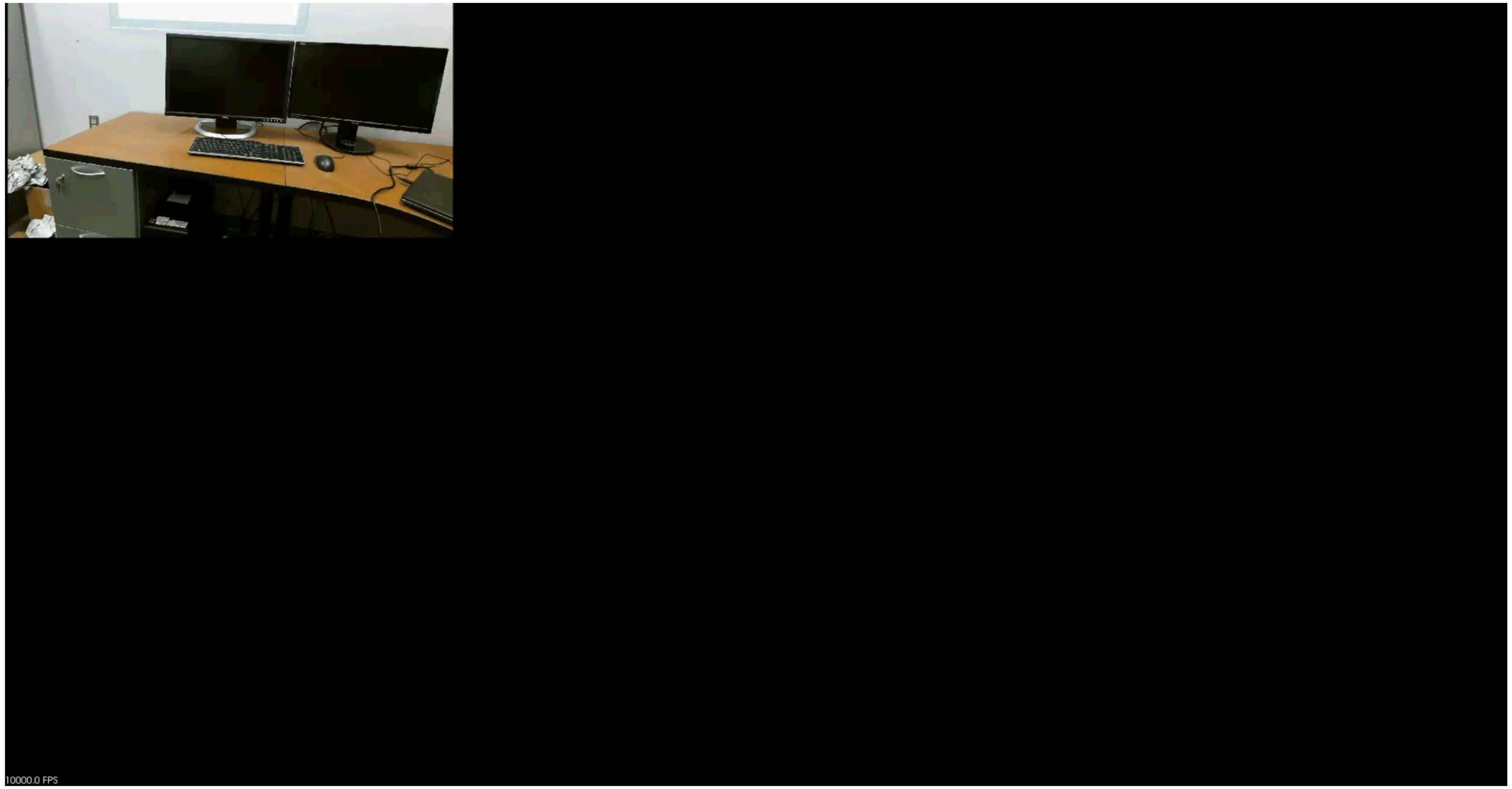
SLAM with segmentation

Surfel-based SLAM approach

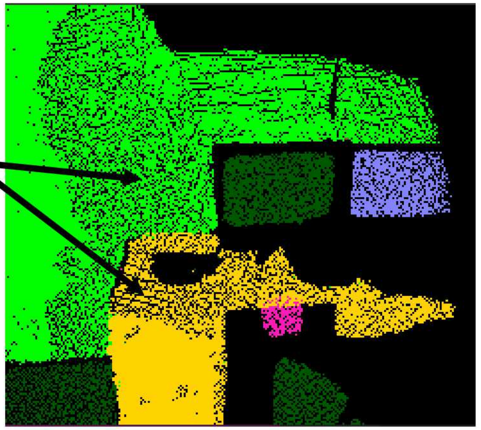
- Adaptation of [1, 2]

Real-time surface-normal based segmentation

- GPU adaptation of [3] for full resolution segmentation in real-time (~20Hz)



Distinct objects



1. Keller, et. al., “Real-Time 3D Reconstruction in Dynamic Scenes Using Point-Based Fusion”, *Int. Conf. 3D Vis.*, 2013
2. Whelan, et. al., “ElasticFusion: Real-Time Dense SLAM and Light Source Estimation”, *Int. J. Robot. Research*, 2016
3. Tateno, et. al., "Large scale and long standing simultaneous reconstruction and segmentation." Computer Vision and Image Understanding 157 (2017): 138-150.

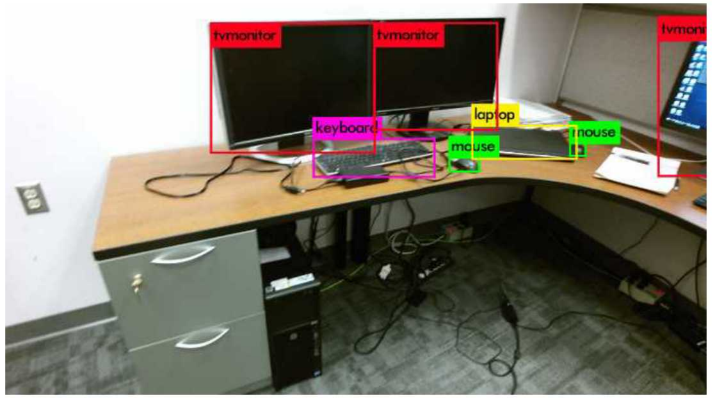
Object Detection and Classification

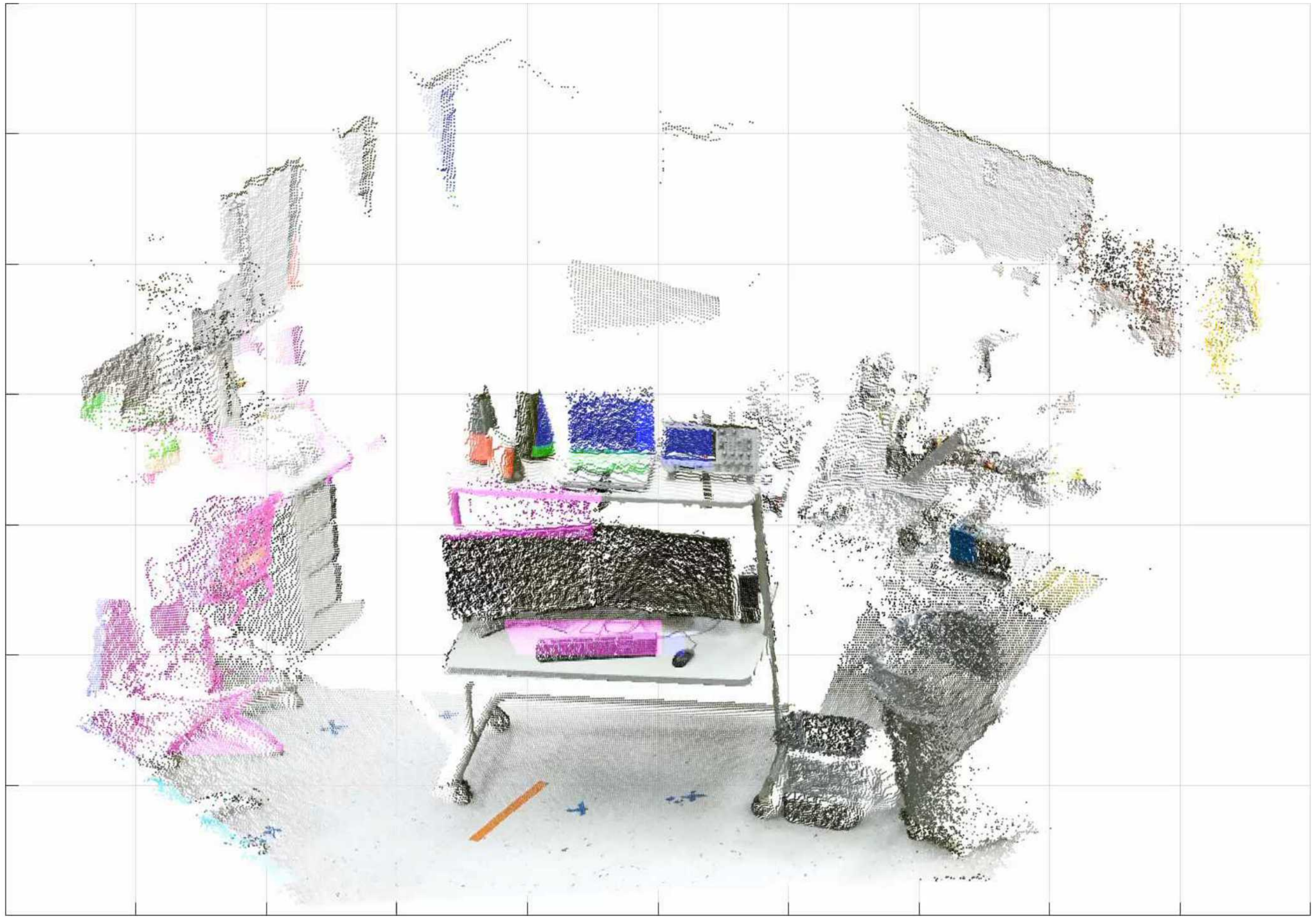
Apply YoloV3 [1] frame-by-frame

- RGB image CNN-based detector
- Provides bounding box and classification at ~20Hz
- Pretrained on common objects: computing (keyboard, mouse, laptop, display, etc), furniture (chair, table, etc.), household (refrigerator).
- Retrained with doors, cabinets, and other items of interest

Bayes update classification for every point

- Fuse information from multiple views, multiple sensors
- Compensate for false positives/negatives





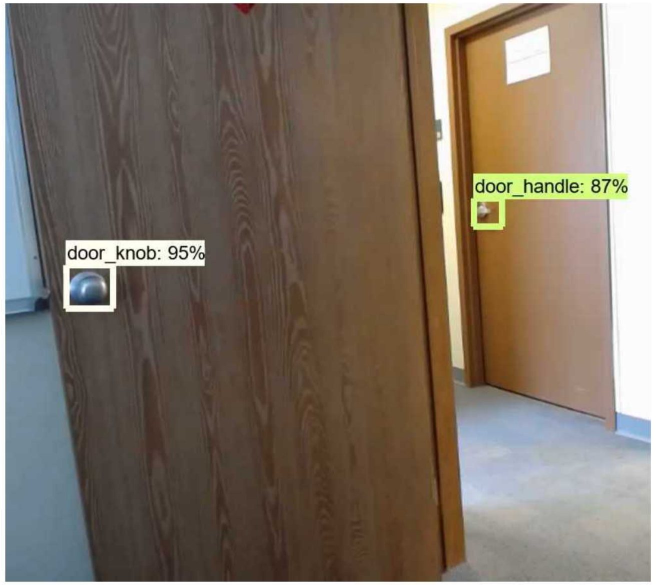
Colors indicate class labels (frame by frame)

1. J. Redmon and A. Farhadi. Yolov3: An incremental improvement. arXiv:1804.02767, 2018.

Uncommon Object Detection and Classification (1)

Retraining Deep Net Classifiers

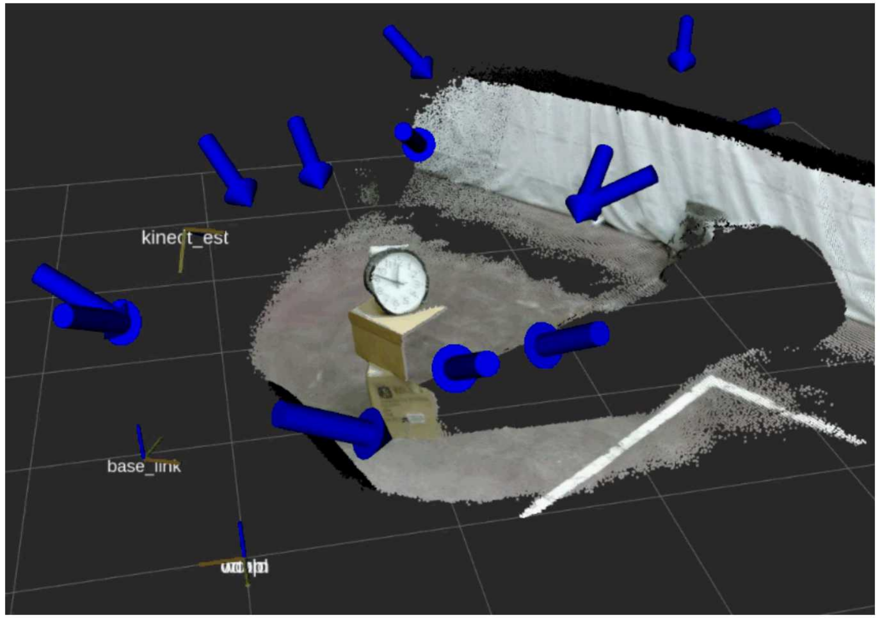
- For objects that are common but not in standard training sets



Low-Shot Methods

Text & Logos

Exploration & Information Gain

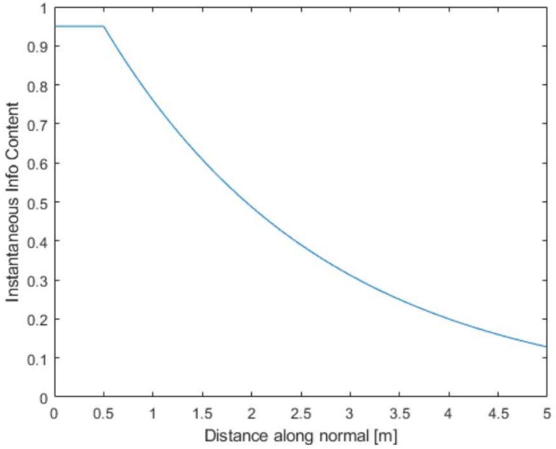


- Estimate the information gain of a new view by:
  1. Getting better views of objects
     - Instantaneous info content estimated by a heuristic considering distance and relative face normal
  2. Decreasing uncertainty in map occupancy [1]
     - Probabilistic occupancy grid (octree representation for efficient storage in 3D [2])

$$I\left(a\right)=w_1\Delta_a H+w_2\Delta_a IC$$

$$H\left(m\right)=-\sum_{c\in m}p\left(c\right)\log p\left(c\right)+\left(1-p\left(c\right)\right)\log\left(1-p\left(c\right)\right)$$

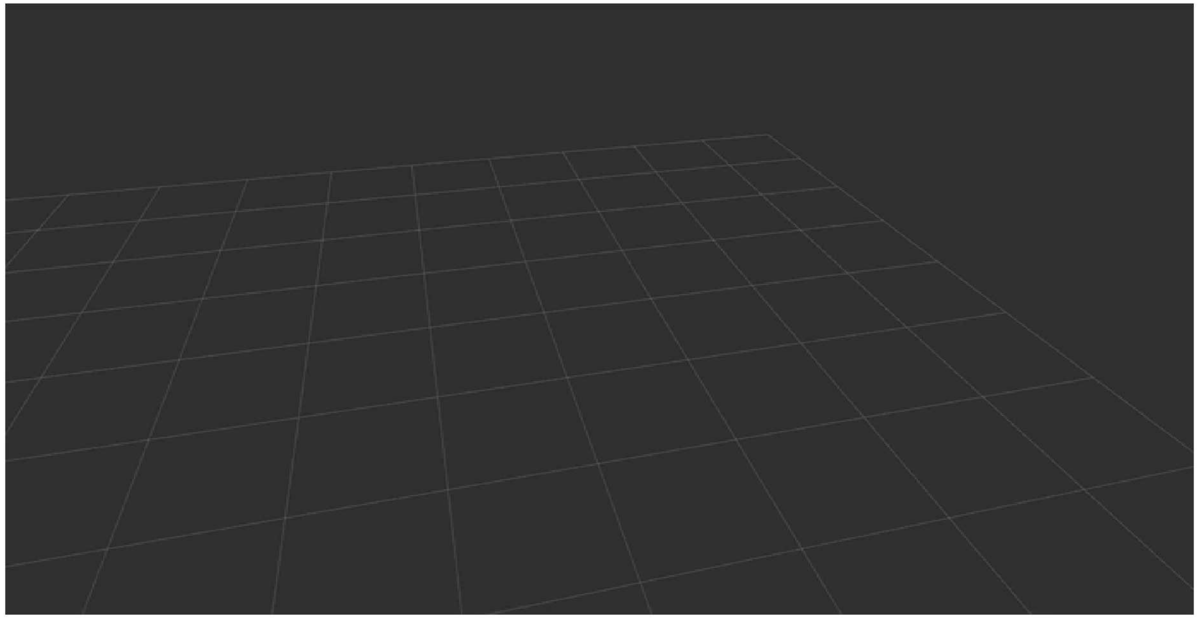
$$I.C._{ij}\left(\phi\right)=\underbrace{\mathbf{1}_{V_{F,i}}\left(\mathbf{x}_{t,j}+\mathbf{v}_{t,j}\left(\phi\right)\right)}_{\text{Point in view}}\underbrace{\max\left\{-\hat{\mathbf{v}}_{t,j}\left(\phi\right)\cdot\hat{\mathbf{x}}_{ij}\left(\phi\right),\ 0\right\}}_{\text{Surface facing camera}}\underbrace{\exp\left(-\lambda_1\left(\max\left\{\|\mathbf{x}_{t,j}-\mathbf{x}_{s,i}\|,\ d_{\min}\right\}-d_{\min}\right)\right)}_{\text{Distance to surfel}}$$

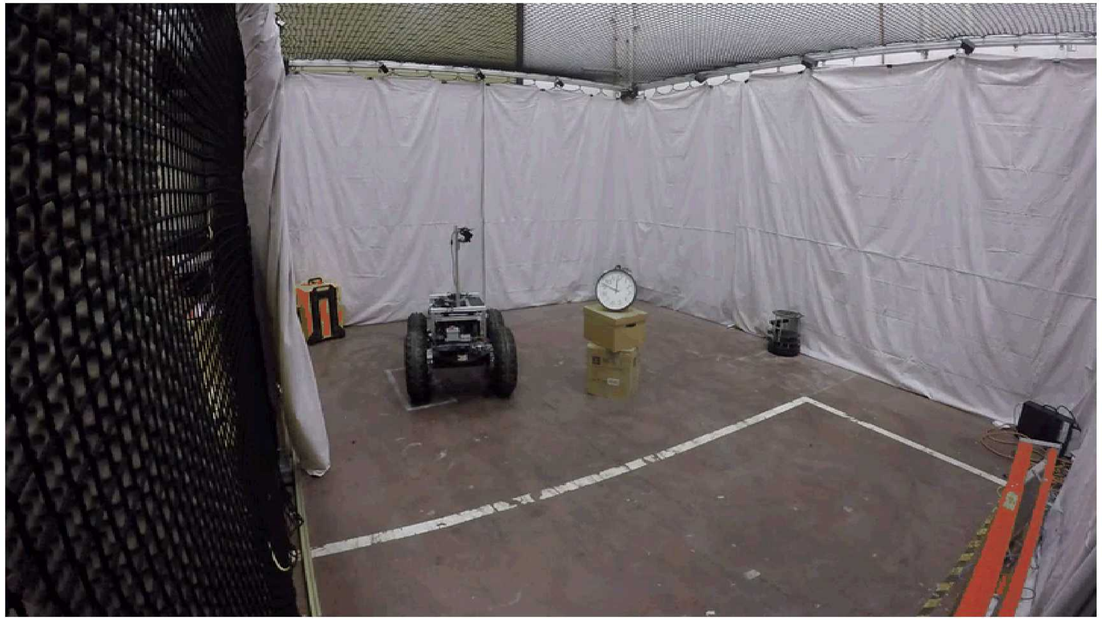


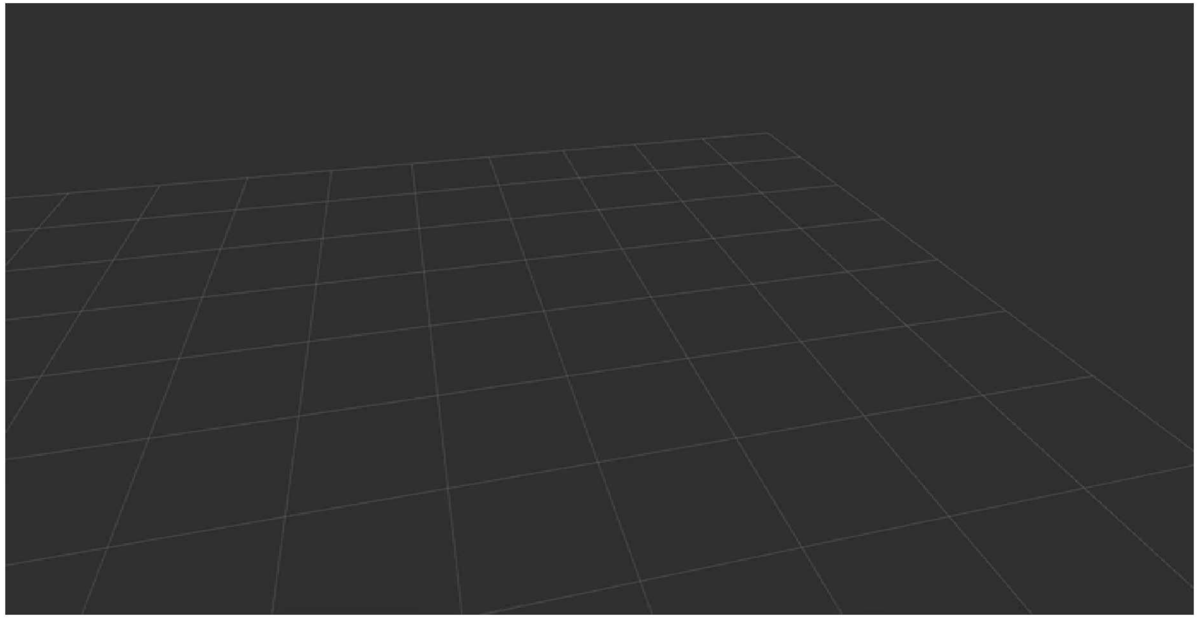
- But how to decide views to consider?
  1. Random sampling of space (for exploration)
  2. Disparate views of objects:
     1. PCA on object points provides rough size (filter out objects too small/large) and dominate object-relative directions.
     2. Pick feasible views along dominant directions.

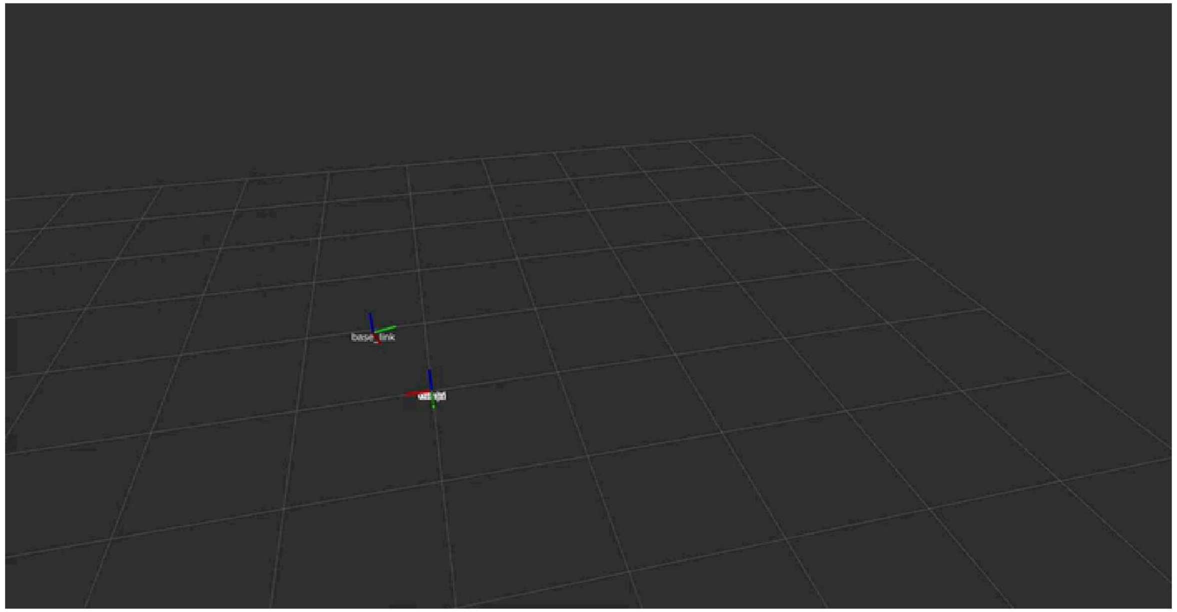
1. Stachniss, et. al., “Information Gain-based Exploration Using Rao-Blackwellized Particle Filters”, *Robotics: Science and Systems*. Vol. 2. 2005
2. Hornung, Armin, et al. "OctoMap: An efficient probabilistic 3D mapping framework based on octrees." *Autonomous Robots* 34.3 (2013): 189-206.

Perceiving a single object

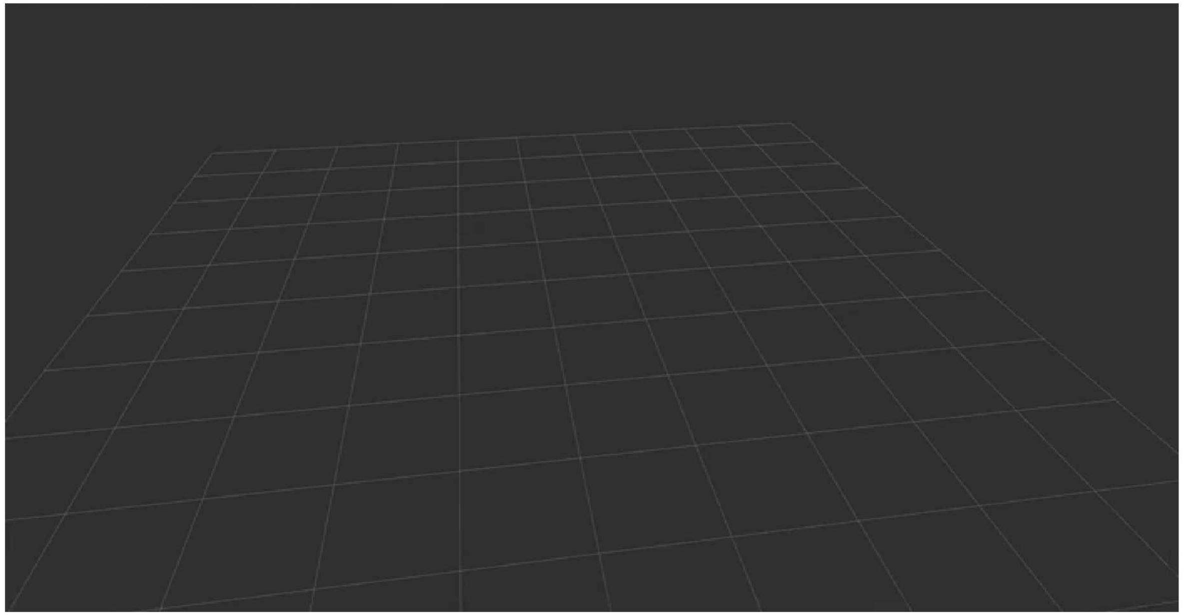


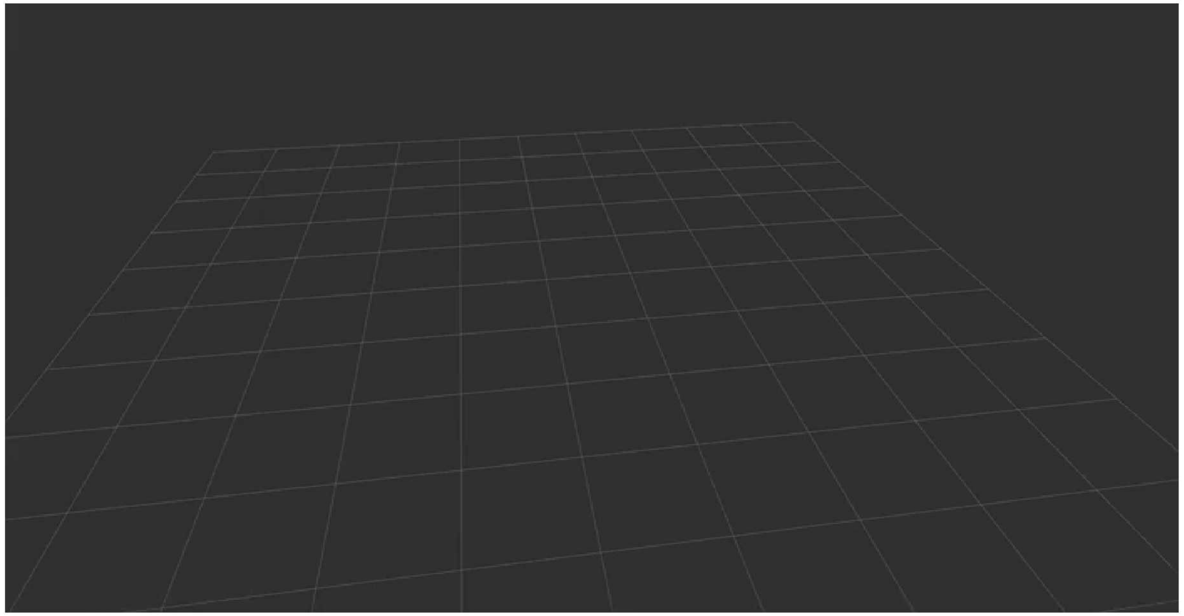


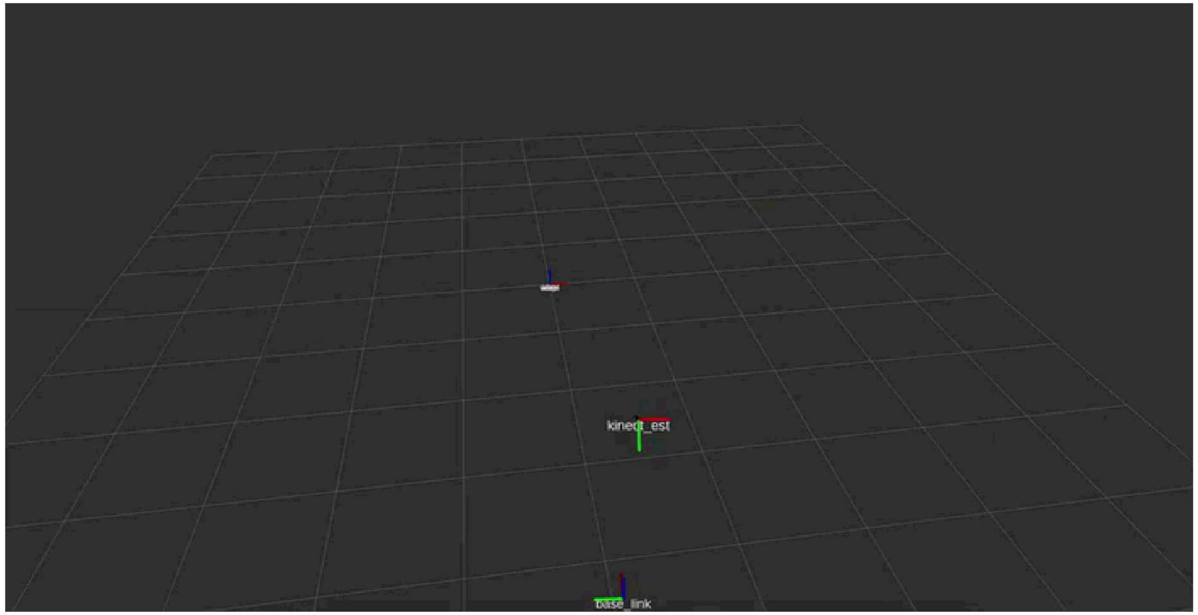




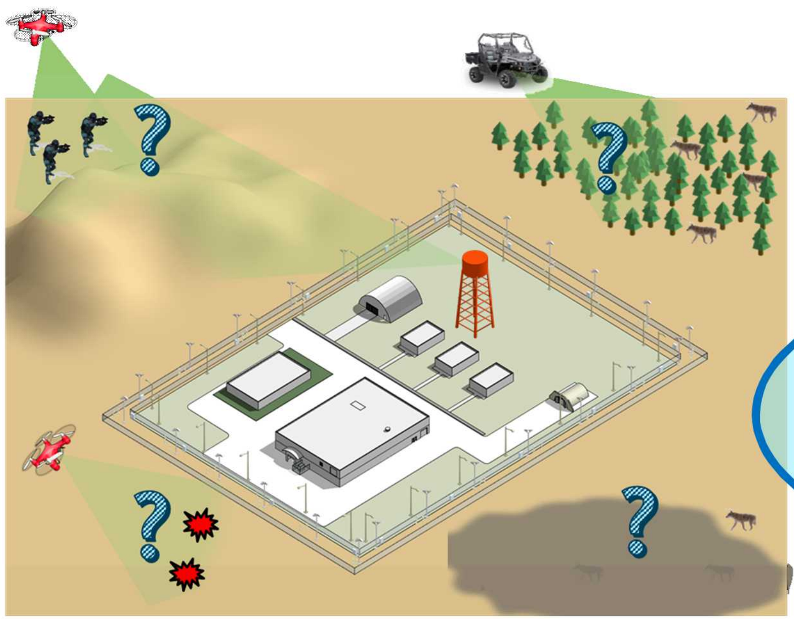
Perception Toolchain in Rich Environment



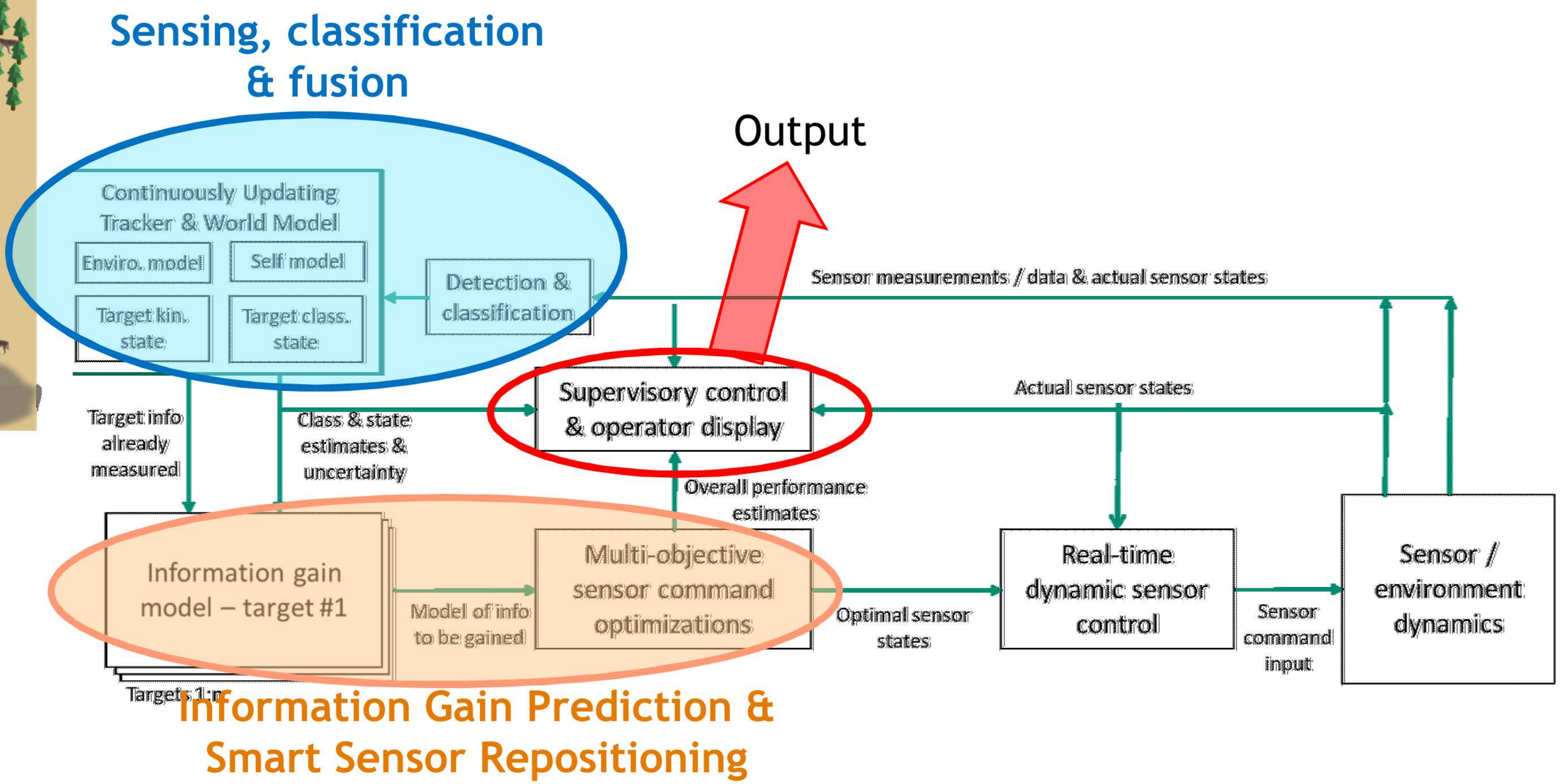




Autonomous Detection & Assessment with Moving Sensors (ADAMS)



Goal: Find & identify potential threats *before* they reach secure perimeter, without human intervention



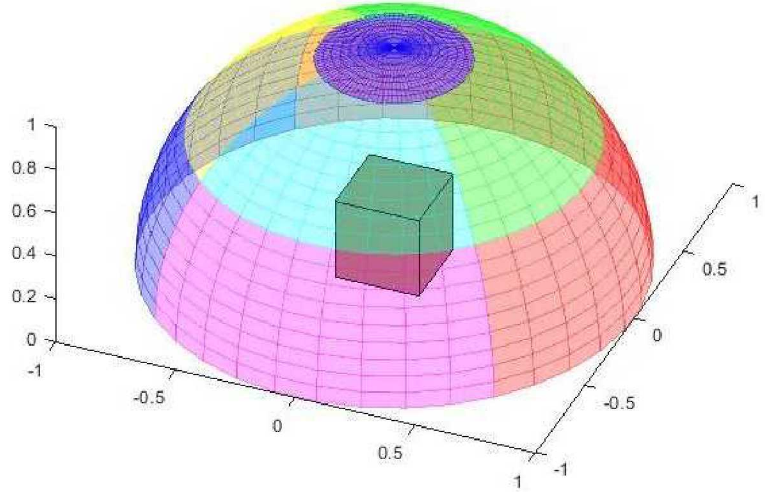
- Multi-sensor fusion and integration in tracker
- Multi-objective optimization of sensor actions
- Ground & airborne sensors

Information State & Gain Models (IGMs)

Goal: Predict information gain (or uncertainty reduction) from new sensor views

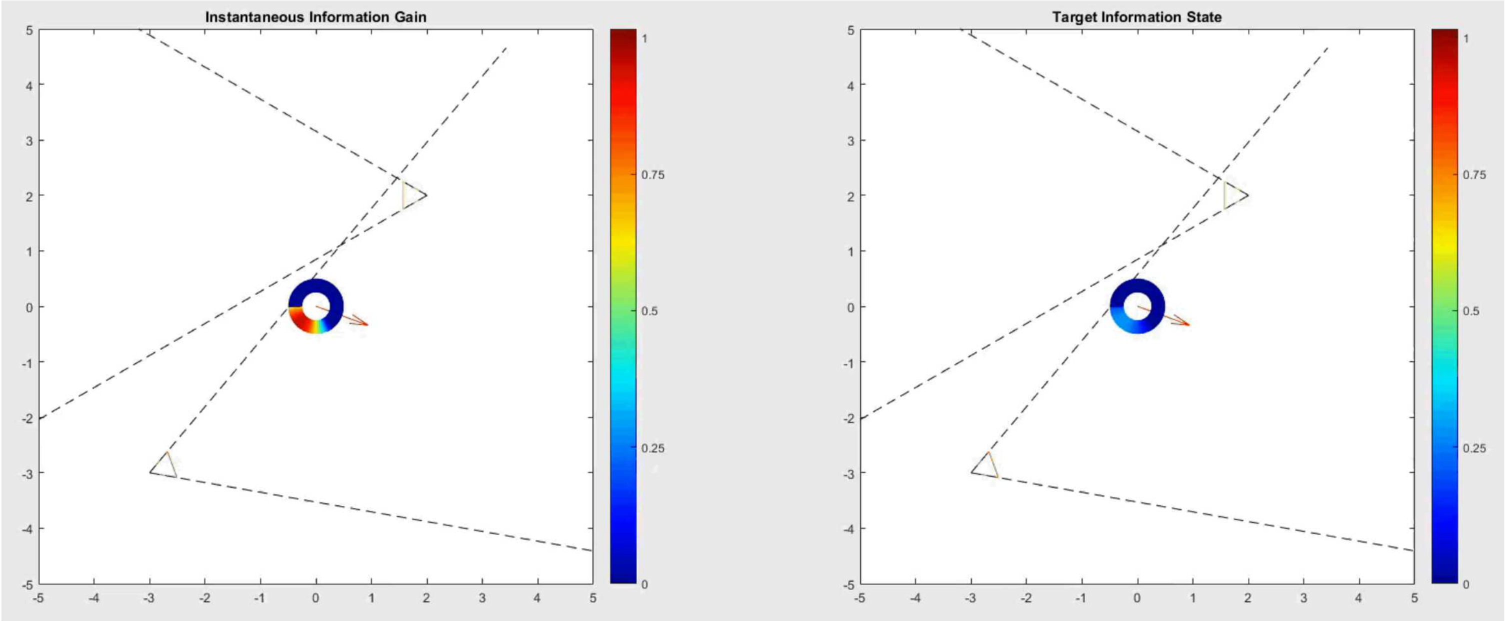
Challenge:

- Rigorous methods for predicting info gain in kinematic measurements do not directly extend to classifiers
- In particular, behavior of data-driven (e.g. CNN) classifiers is notoriously hard to model



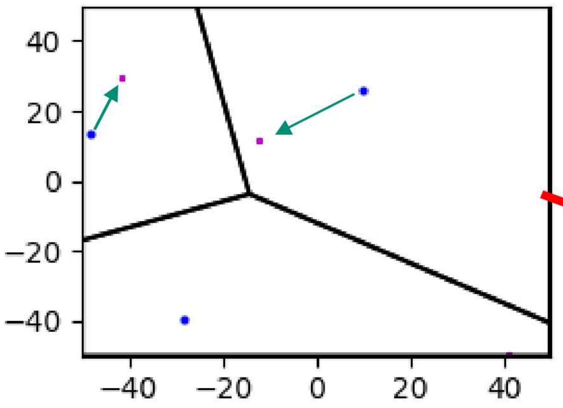
Near-term approach

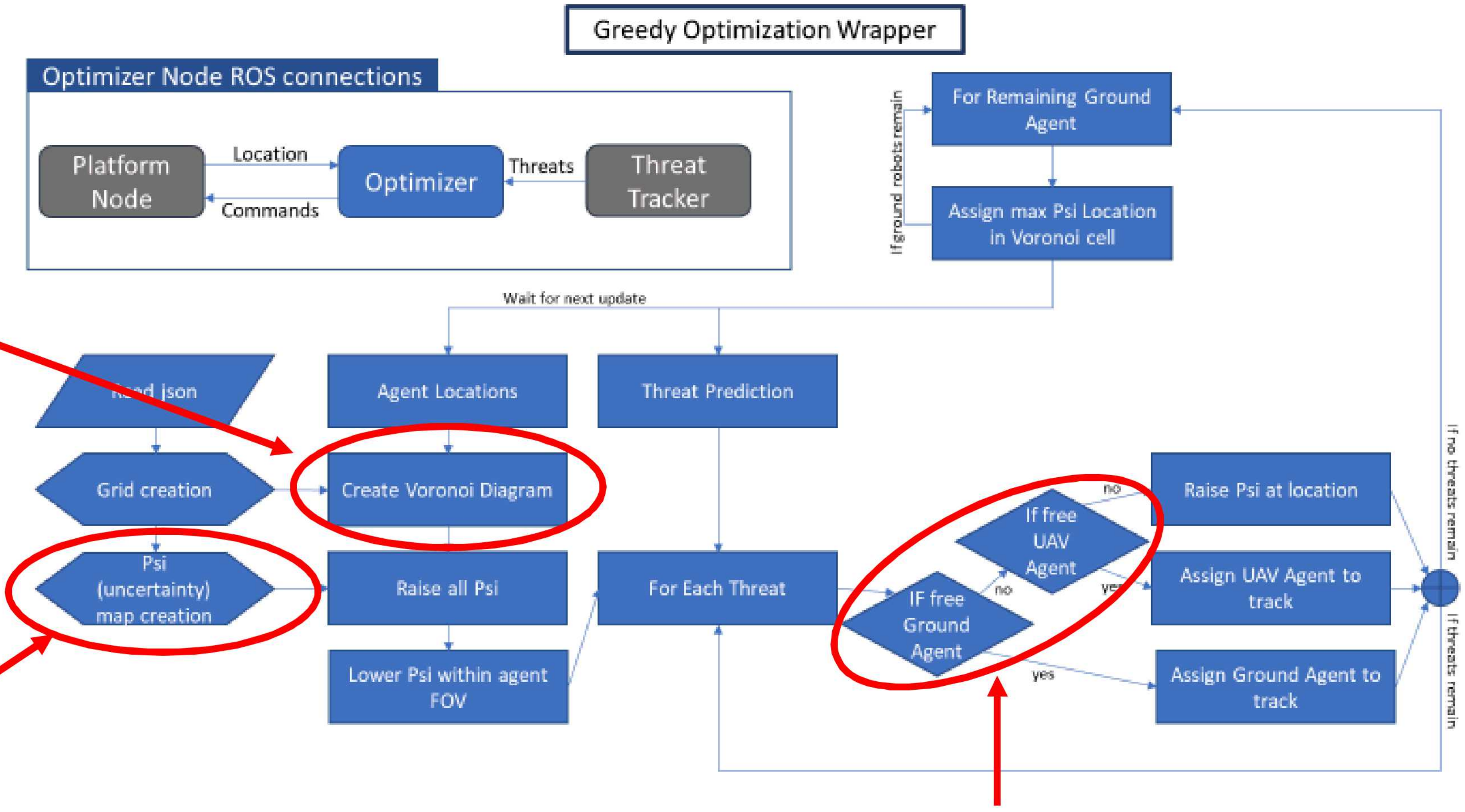
- Heuristic models based on past data
- E.g. "Novel pixels on target"
  - Novel sensor <u>type</u> or <u>perspective</u>
- (*Approximation* of classifier in loop)

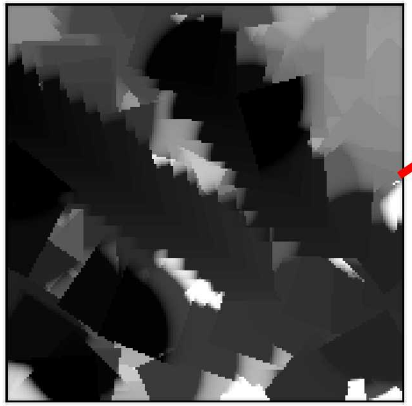


Sensor Placement Optimizer

Voronoi diagram: defines instantaneous regions of patrol responsibility



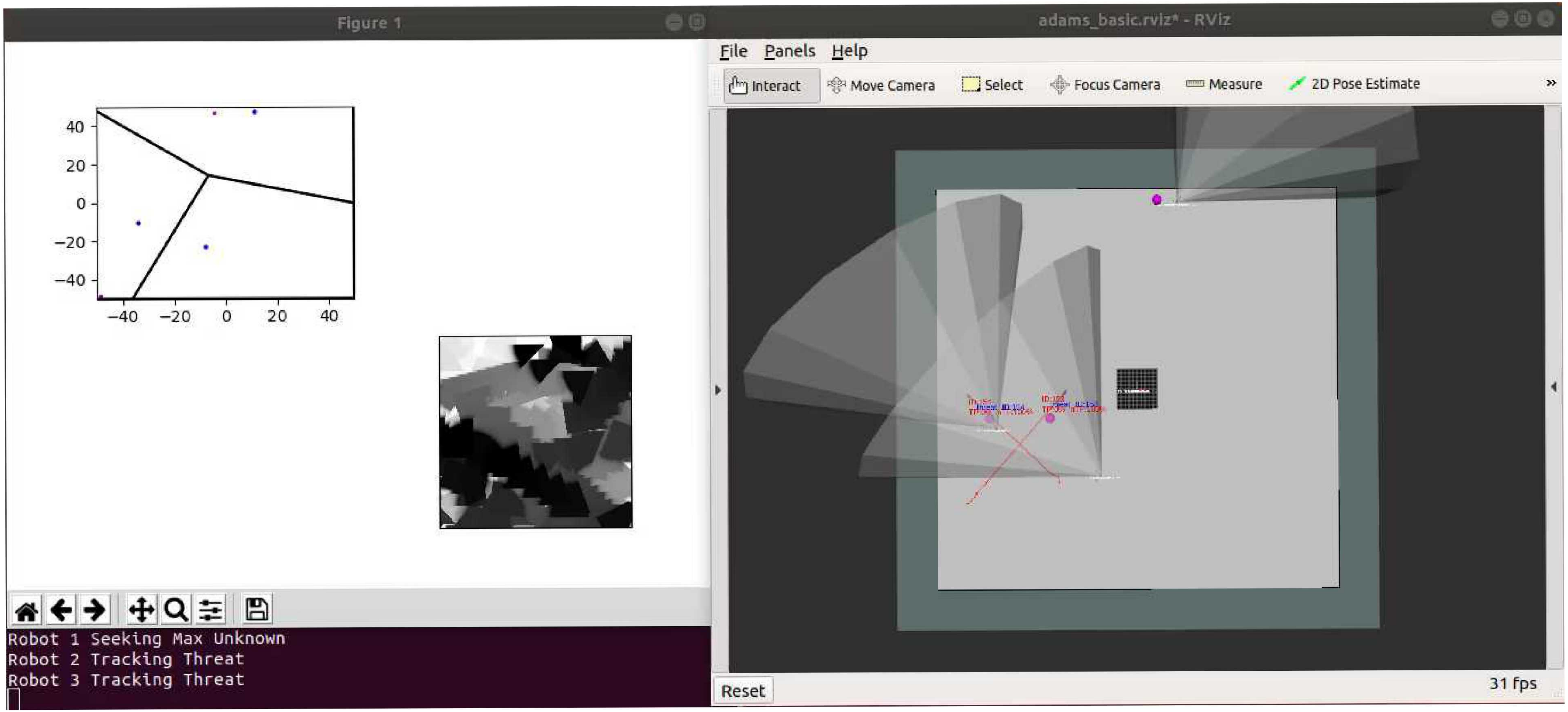




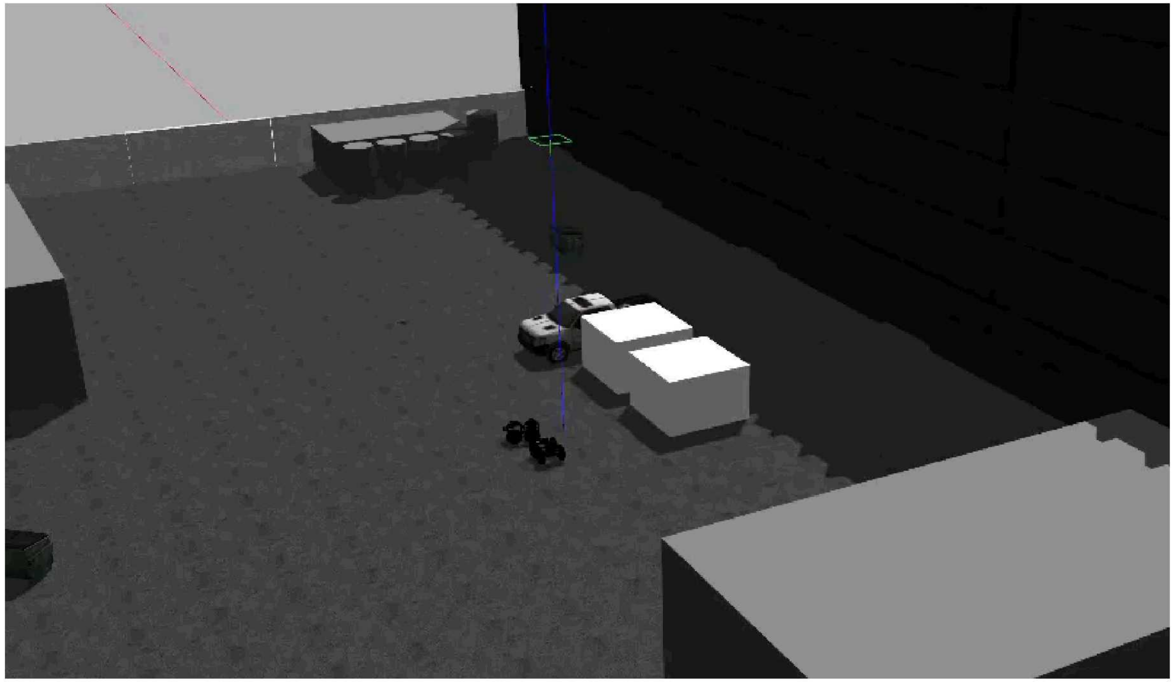
Psi map: uncertainty vs. position
Black is low uncertainty
White is high uncertainty

UGVs & UAVs treated differently due to energy properties (much more to do here)

Sensor Placement Optimizer



Simulated Scenarios in Gazebo and Umbra



Sim environments

- Gazebo, for vehicle physics & ROS integration
- Umbra, for multi-agent Monte Carlo scenario sims in realistic sites

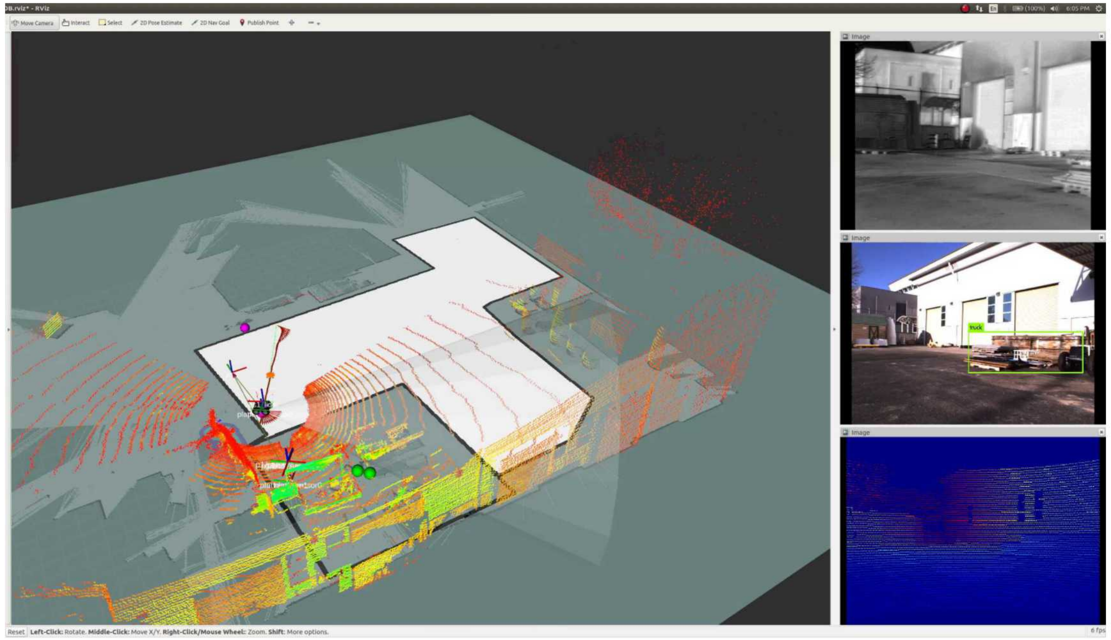
Uncertainty metrics (for sims & experiments)

- Patrol
  - Revisit time
  - Percent time observed
  - Diversity of sensor phenomenologies
  - Etc.
- Targets
  - Time to detect
  - Time to classify

Variables

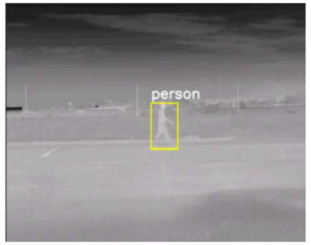
- Number & types of sensors
  - Mobile
    - Vehicle type
  - Stationary

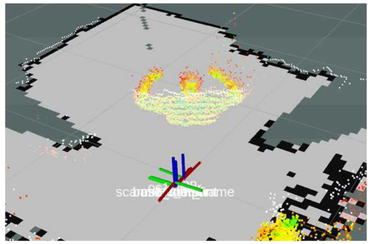
Experiments (Ramping Up)



Multi-sensor fusion
- Visible & thermal detection & classification
- LIDAR detection

Multi-objective (patrol & ID) optimization





Vehicles
- Segway RMP 440
- Semi-custom multirotor

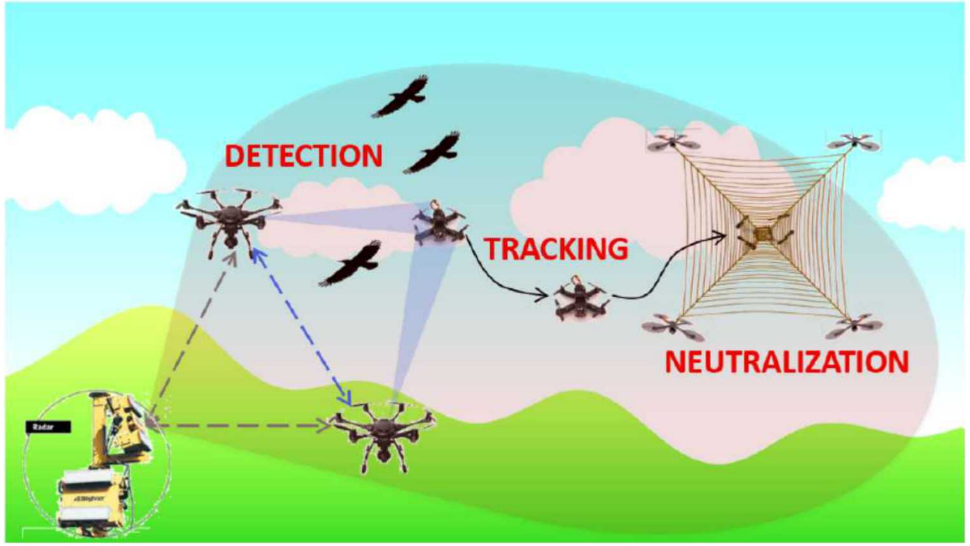
Aerial Suppression of Airborne Threats (ASAP)

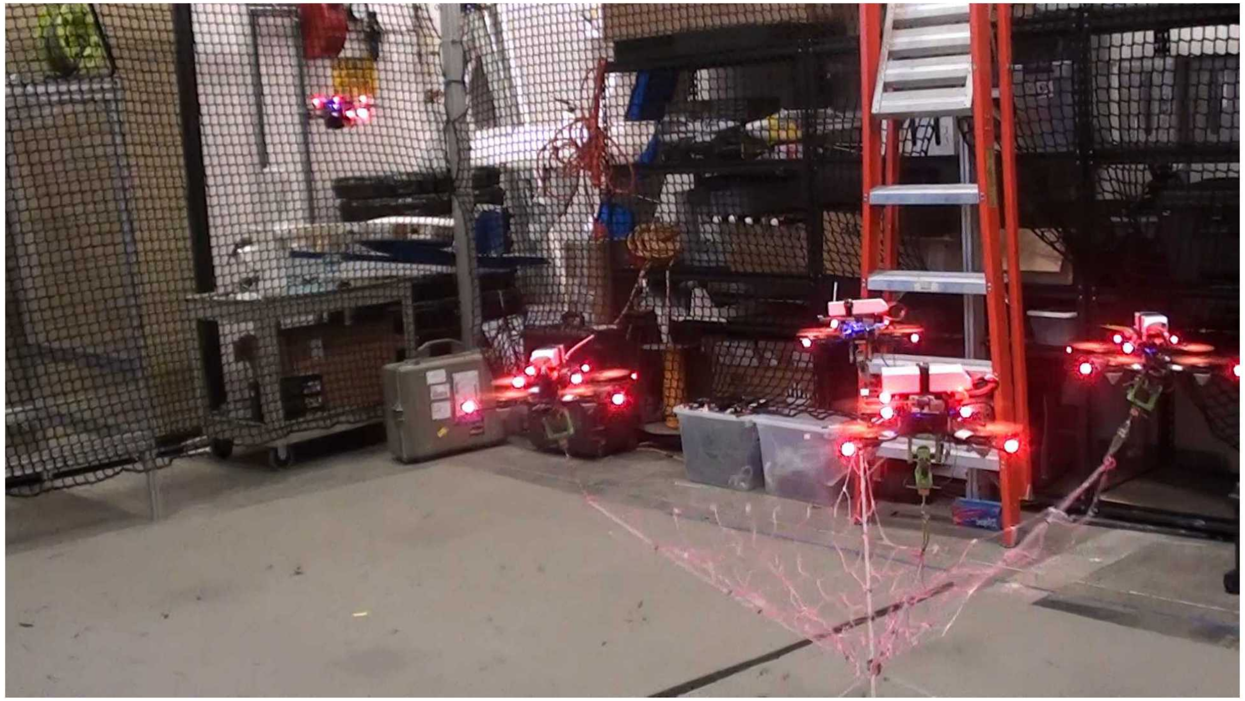
What do we do if we find threats?

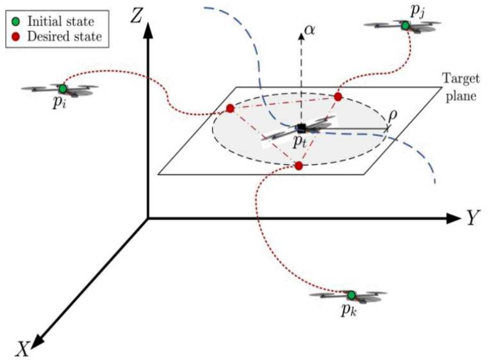
Example of an end-to-end unmanned security solution

Ground-air multisensory fusion

Neutralization with a “SmartNet”



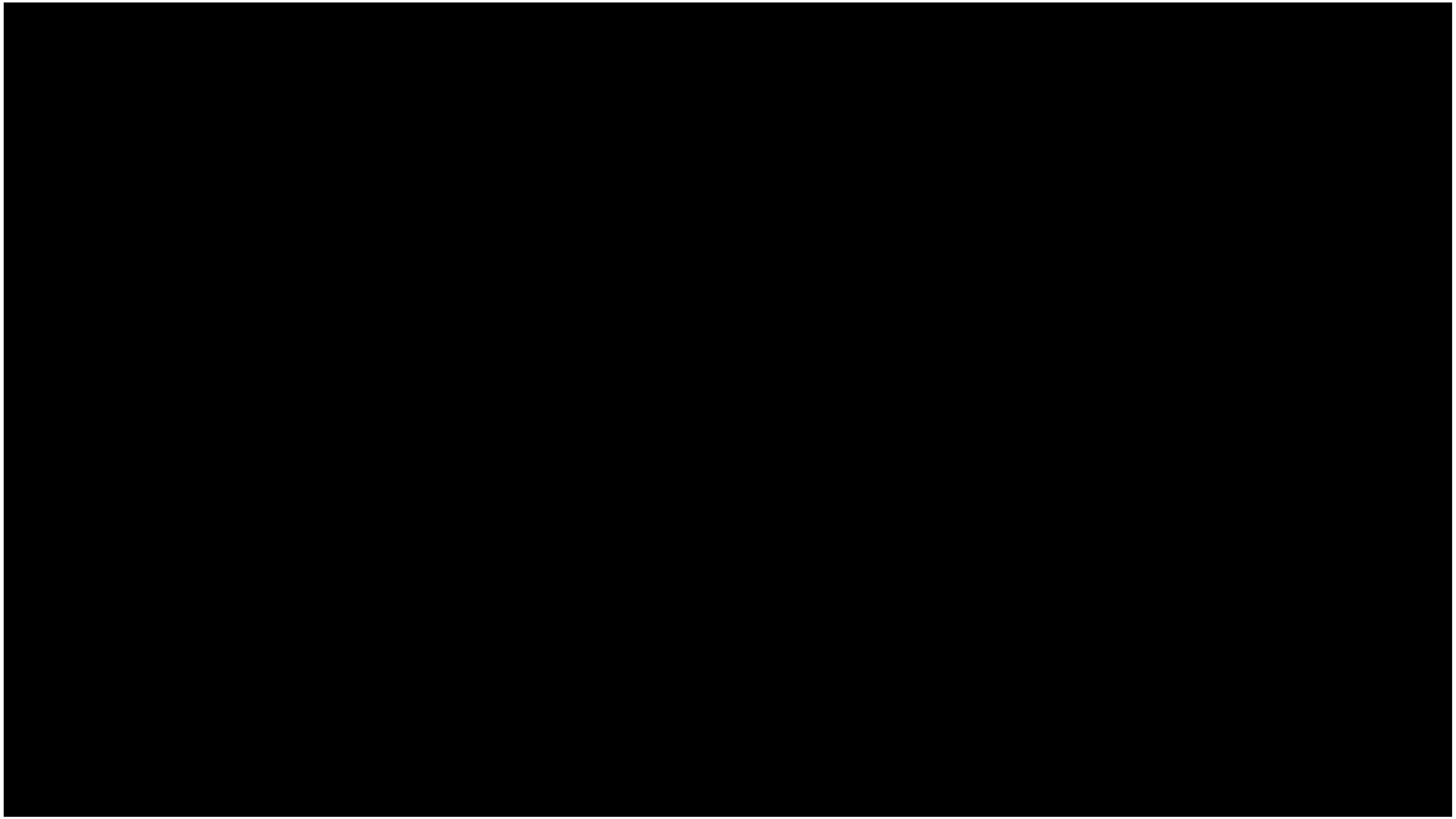




Intercept trajectories via cyclic pursuit & stochastic reachability capture planning
(Fierro, Oishi & co. @ UNM)

Robotic Mobility – Gemini Scout Mine Rescue

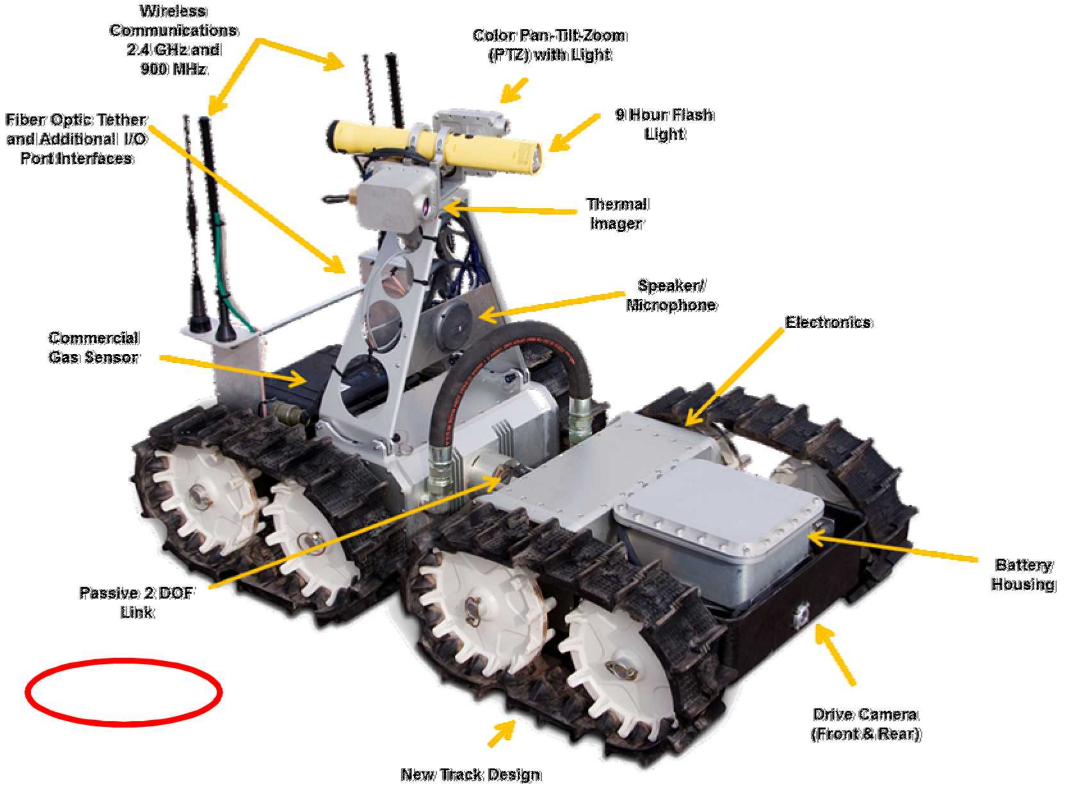
Tactical Autonomy Needs: MOBILITY – EFFICIENCY – SPEED – COLLABORATION – PERCEPTION – TACTICS

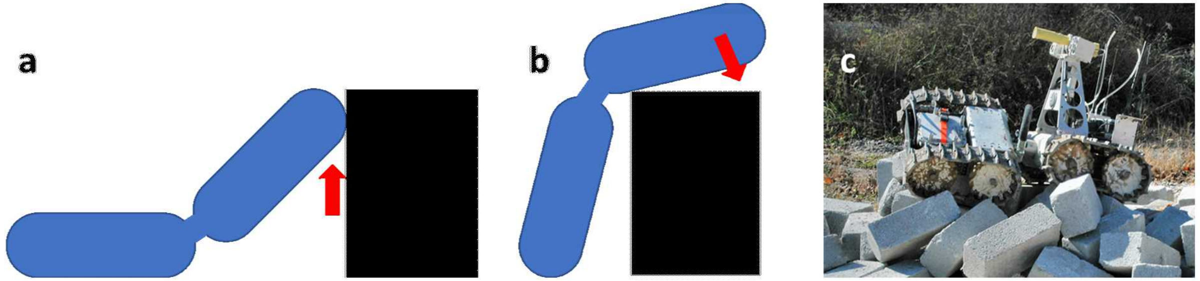


Pushing the Limits of Tracked Mobility

Gemini: Design derived from mobility analysis for wheeled and tracked vehicles traversing obstacles

- Dual body ideal for larger obstacles, unstructured terrain
- Ground contact optimization for joint DOFs, track geometry, skid steer
- Passive joint mobility advantages
  - a – maintain traction while starting vertical climb
  - b – regain traction & shift CG over obstacle top
  - c – roll DOF keeps track in ground contact





Max obstacle size is limited to a fraction of body dimensions – unless…

Robotic Mobility – Urban Hopper

Tactical Autonomy Needs: MOBILITY – EFFICIENCY – SPEED – COLLABORATION – PERCEPTION – TACTICS - ACTION

Combustion-Powered Hopping

Tactical Autonomy Needs: MOBILITY – EFFICIENCY – SPEED – COLLABORATION – PERCEPTION – TACTICS - ACTION

Energy efficiency comparison

- Firm ground hop energy:

$$E_{hop} \approx \varepsilon_{piston} M \cdot g \cdot h$$

Piston efficiency

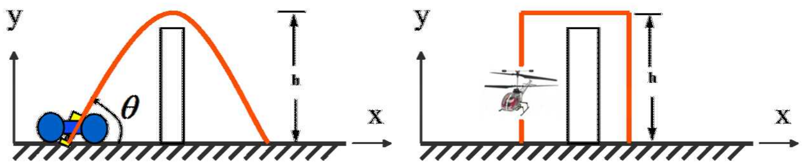
- Energy to hover:

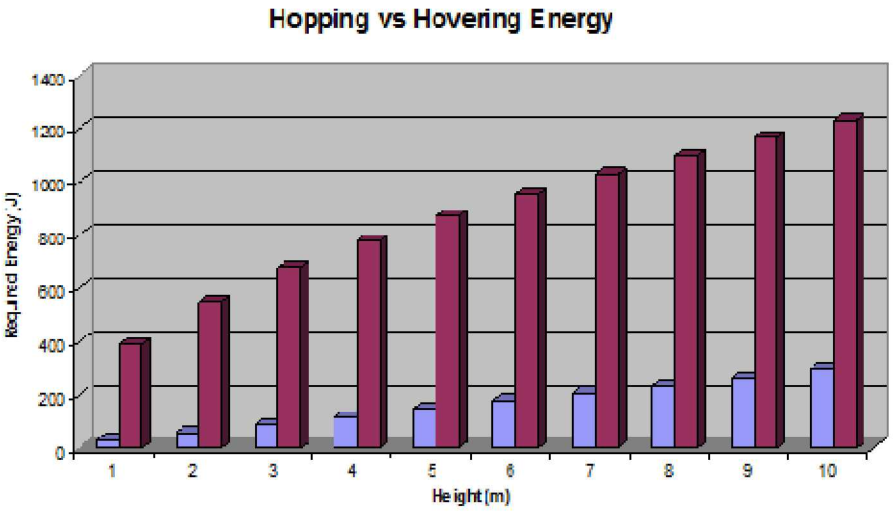
$$E_{hover} = \frac{(1+\varepsilon_{prop})}{2} \cdot \sqrt{\frac{F}{A \cdot \rho}} \cdot \sqrt{\frac{2 \cdot M \cdot h}{\frac{1}{M \cdot g} - \frac{1}{F}}}$$

Reduce energy by increasing propeller area

- Scaling with obstacle height:
  - Piston & prop efficiencies are similar
  - Efficiencies cross as height increases
  - Hopping is preferred for small obstacles, when ground is hard
- Why?
  - Hovering uses (air) mass flow, which creates velocity dependence

To efficiently traverse small obstacles: “Drive when you can, hop when you have to”





Human-Like Mobility: Legged robots

Legs offer great appeal for mobility
- Step over & onto obstacles
- Mobility (somewhat) less dependent on terrain type
- Balancing bipeds: high reach with small footprint (world built for people)

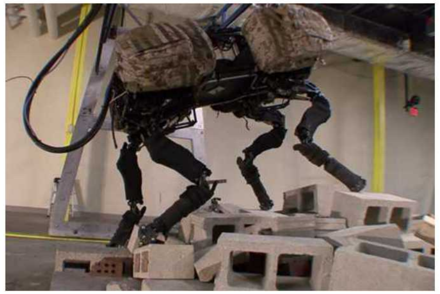
Major challenges
- Walking control is (still) hard
- Endurance
  - Cost of transport (dimensionless)
    - Bicyclist: >0.1; Production car: >0.3 (the wheel was a great idea!)
    - Horse: >0.2; Person: >0.3
    - Legged robots: ~5-30?

$$COT = \frac{E}{m \cdot g \cdot d}$$

Improving endurance
- Supply: better batteries, hydrocarbons, harvesting?
- Consumption: gait efficiency, drive efficiency

Goal: Improve endurance without compromising functional behavior (ideally)


BDI Atlas

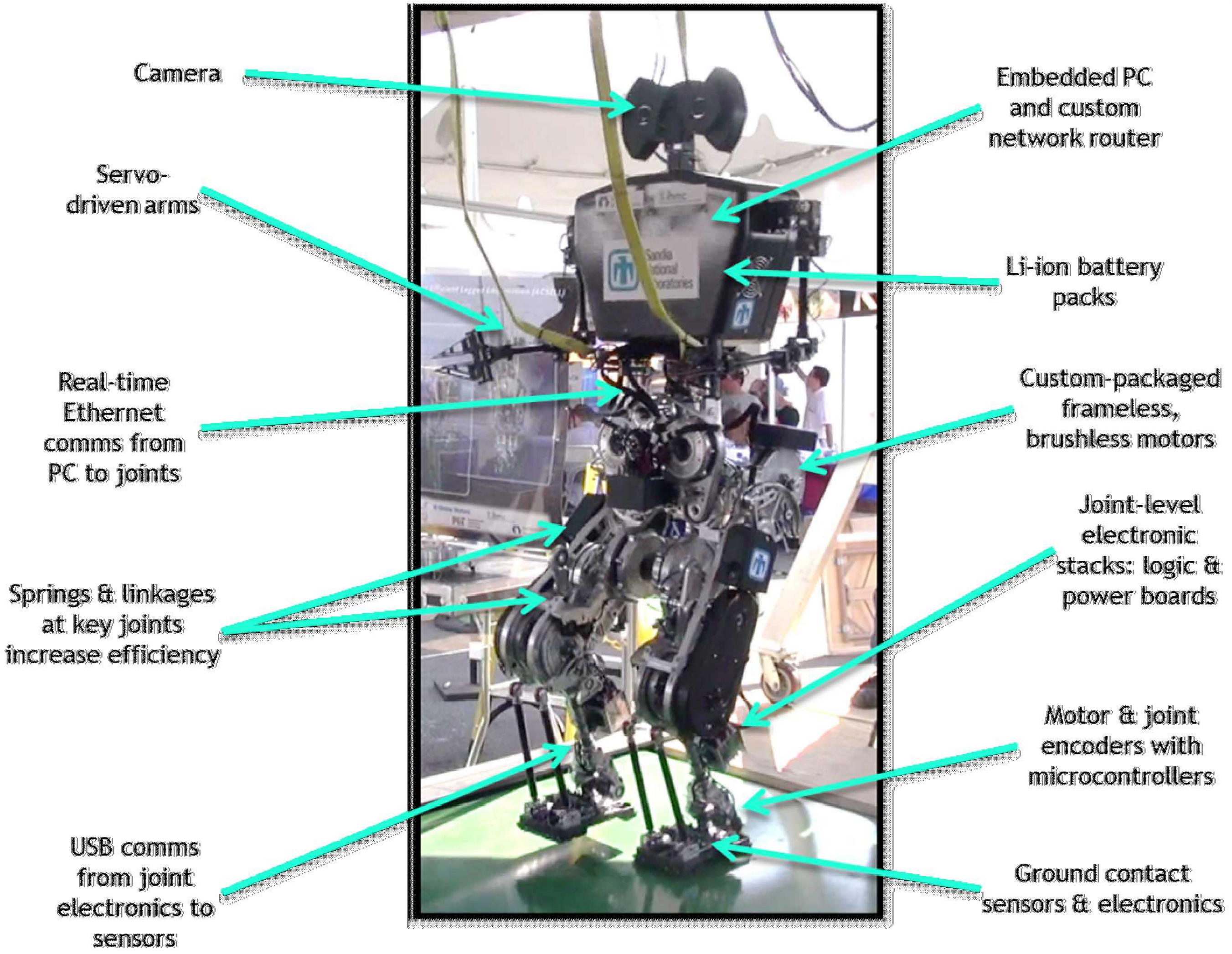

BDI Big Dog

LS3 – Boston Dynamics


Cornell Ranger

Robotic Mobility – Efficient Legged Locomotion

Tactical Autonomy Needs: MOBILITY – EFFICIENCY – SPEED – COLLABORATION – PERCEPTION – TACTICS - ACTION



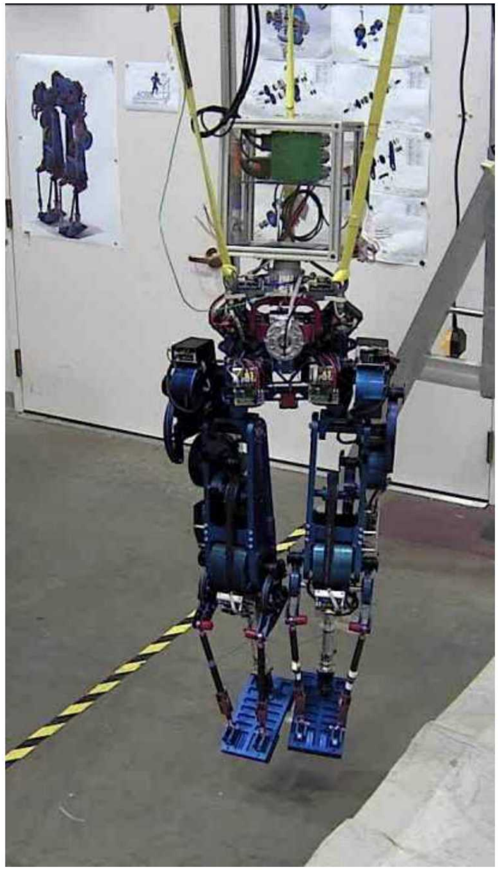
WANDERER

- Walks @ ~270 W locomotive power (420 W total)
- Walks 5+ hrs, 3-4 km per charge (further if not so slow!)
- Versatile mobility (15 locomotive DOF, 29 total)
- All electric, nearly silent

Efficient Mobility: Start With Efficient Drivetrain

Tactical Autonomy Needs: MOBILITY – EFFICIENCY – SPEED – COLLABORATION – PERCEPTION – TACTICS - ACTION

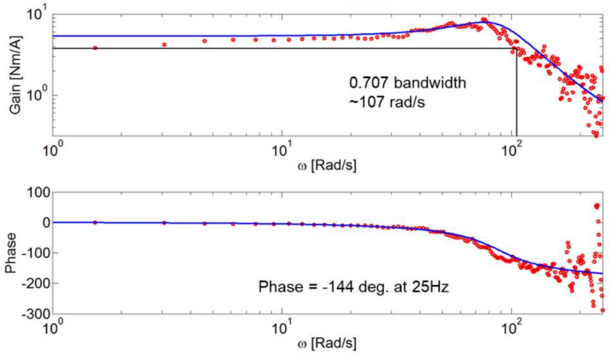
1) Minimal drivetrain & joint friction & inertia (more on inertia later)

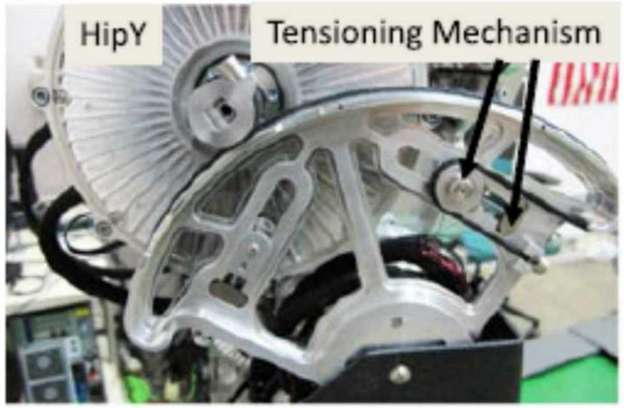


Highly backdrivable when unpowered, minimizing friction loss and enabling regeneration

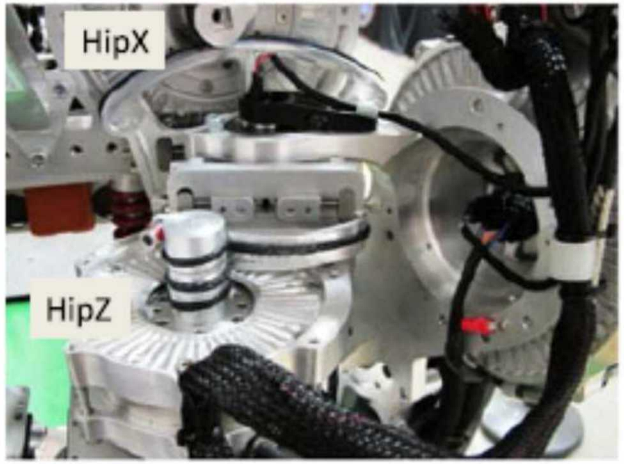
2) Compact, high-efficiency, low-ratio speed reducing transmissions

Rob. Aut. Let. 2017





(a)



(b)

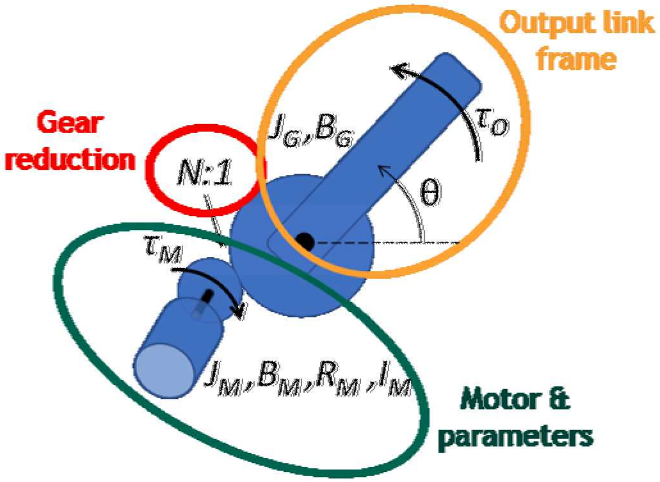
Synthetic Vectran cables provide tighter bend radius per tensile strength vs. steel

- 94% efficiency on walking trajectories, which include high & low torque & speed
- ~28 Hz bandwidth

Efficient Mobility: Motor & Geartrain Sizing

Tactical Autonomy Needs: MOBILITY – EFFICIENCY – SPEED – COLLABORATION – PERCEPTION – TACTICS - ACTION

3) Large motors with as low transmission ratio as possible



EOM in output frame:

$$J_T\ddot{\theta} + B_T\dot{\theta} = N\tau_M + \tau_O$$

Equivalent inertia & damping at output:

$$J_T = J_G + N^2 J_M \qquad B_T = B_G + N^2 B_M$$

$$P_M = \underbrace{I_M^2 R_M}_{\text{Electrical Loss}} + \underbrace{N\tau_M\dot{\theta}}_{\text{Mechanical Work}}$$

Using small motors and gearing, with torque feedback to achieve desired torque control (low mechanical impedance) behavior, can be inefficient

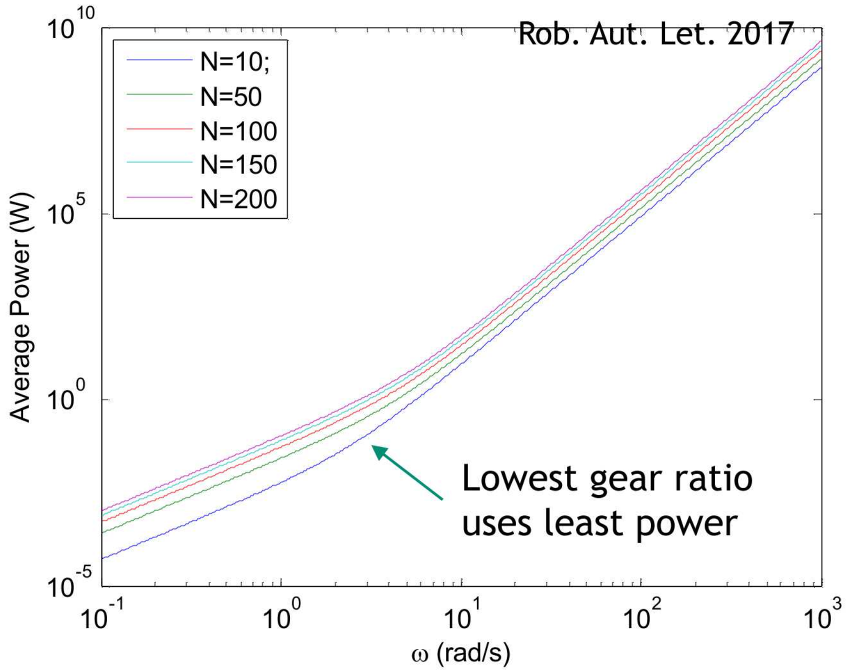
- As N increases, apparent inertia & damping increase by N^2
- Adding series elasticity does not necessarily reduce energy consumption (and can increase it)

Average power over cyclic trajectory:

$$P_{avg} = \frac{1}{2}\left(\frac{J_T}{K_m N}\right)^2 \omega^4$$

If increasing N and reducing motor size, $K_m N$ stays roughly constant, but J_T increases by ~N

Target output: zero torque (as exemplar)



There can be a *substantial energy penalty* to using small motors with large gearing and torque feedback for torque control

Efficient Mobility: Thermal Efficiency

Tactical Autonomy Needs: MOBILITY – EFFICIENCY – SPEED – COLLABORATION – PERCEPTION – TACTICS - ACTION

4) Actively cool motors to increase capacity – and gain net efficiency

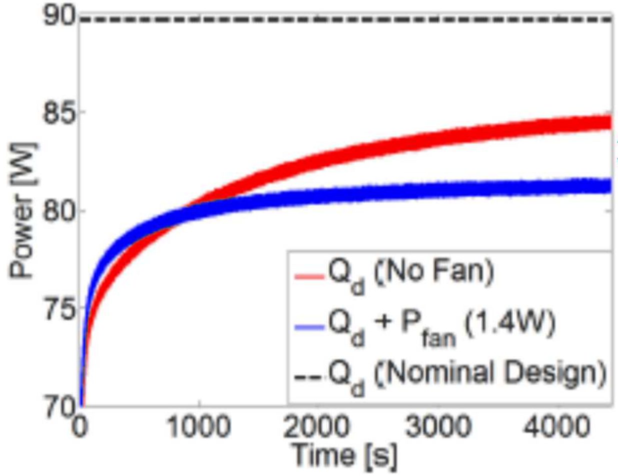
$I_M^2 R_M$

is the enemy!

$$\alpha_{Cu} = 0.4\ {}^{\%}/_{°C}$$

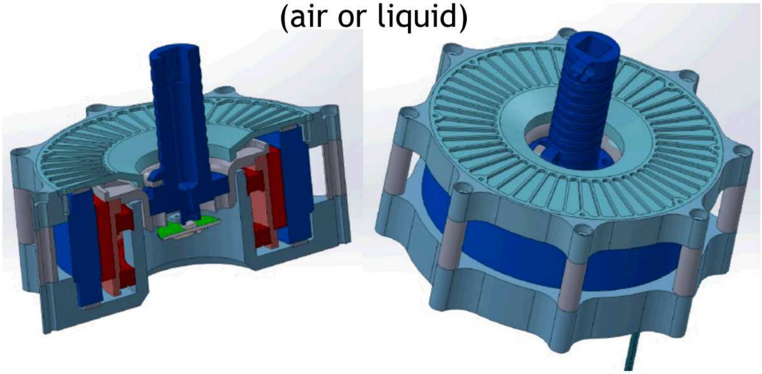
Package frameless motors minimally

1.4 W fan, at stall current

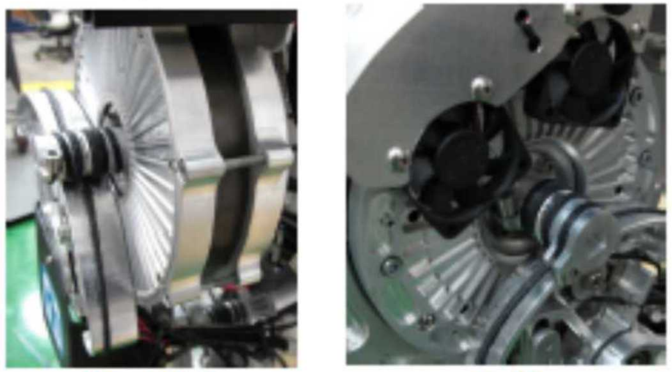


Net power savings: keeping coils cool saves more power than spent on fans

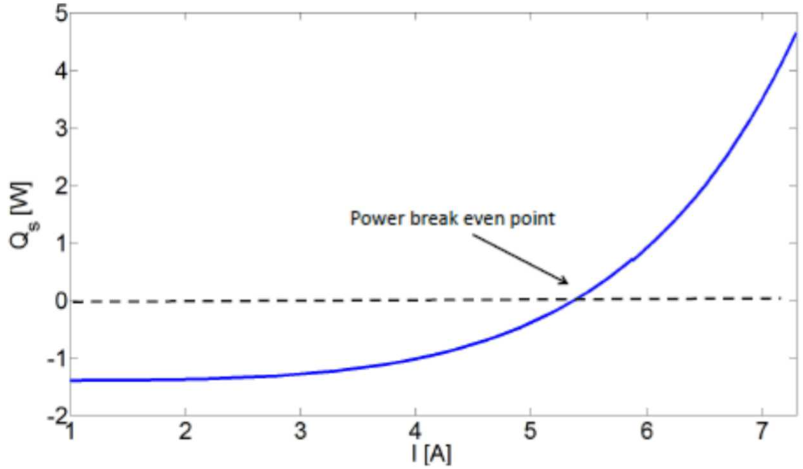
Expose stator outer circumference for cooling (air or liquid)



High heat transfer motor housings



Hip Pitch Ankle



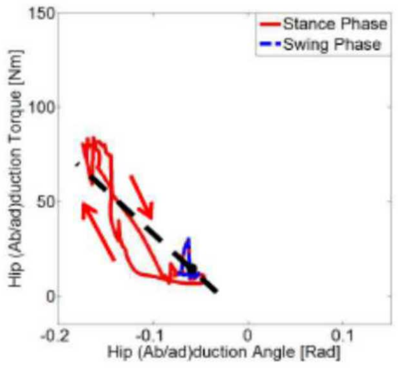
DSCC 2016

Efficient Mobility: Sculpt Loading for Behaviors

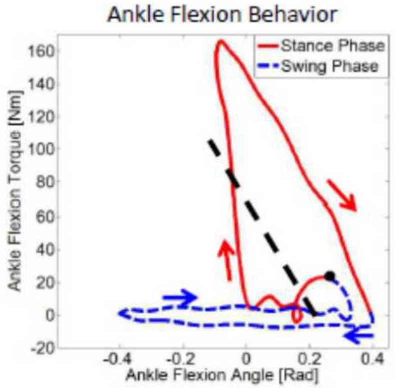
Tactical Autonomy Needs: MOBILITY – EFFICIENCY – SPEED – COLLABORATION – PERCEPTION – TACTICS - ACTION

5) Passive mechanisms (“support elements”) exploit common walking characteristics to optimize energy extraction from motors (& minimize $I_M^2 R_M$)

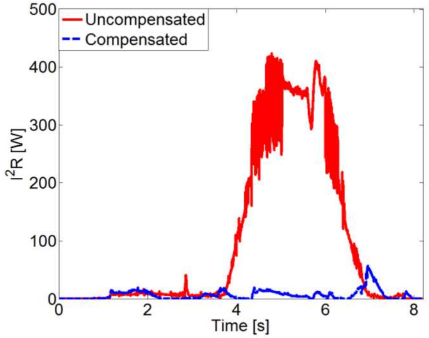
Parallel elasticity at hip & ankle

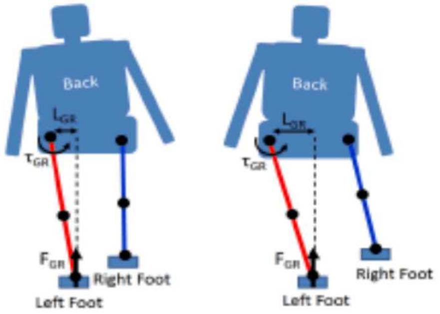


(f) Crouched Robot Data (69kg, 0.11m/s)

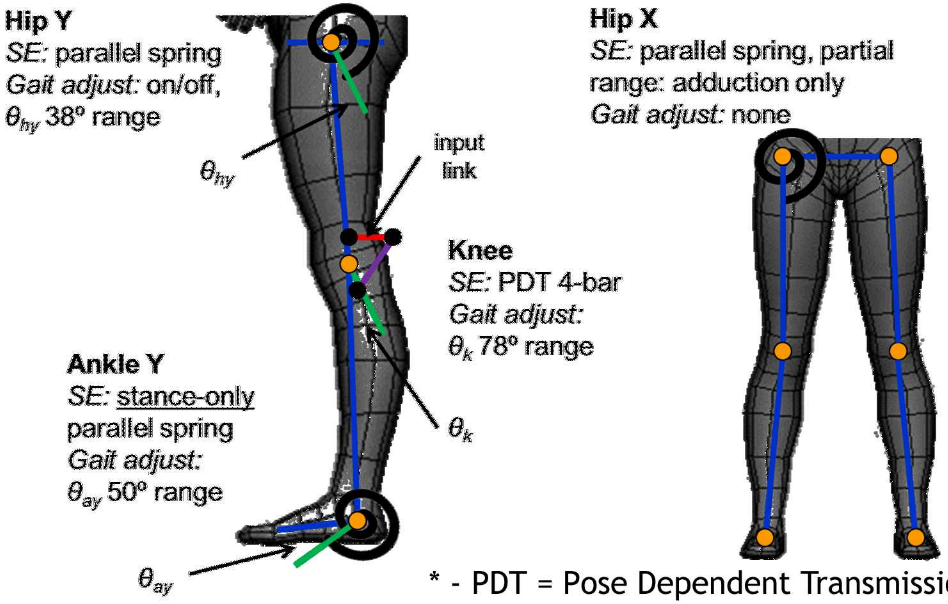


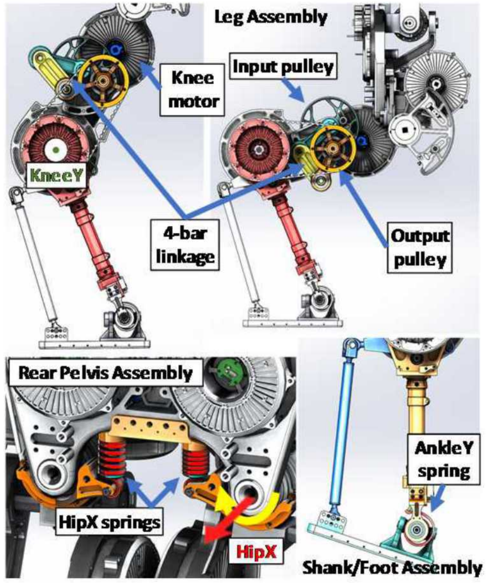
(b) Human-like Robot Data (89kg, 1.2m/s)



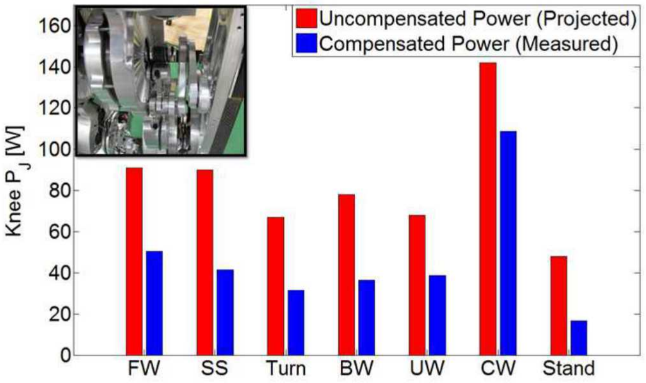


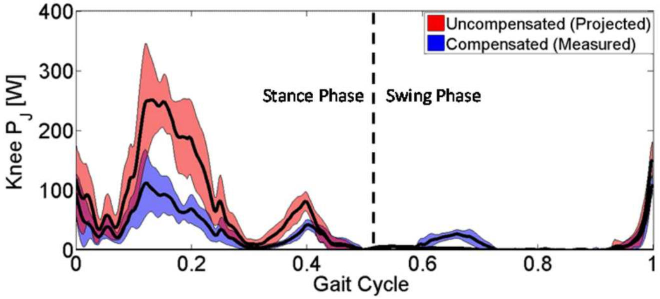
T. Mech. 2016





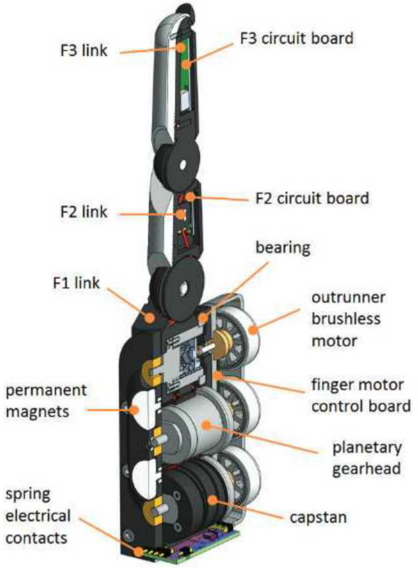
* - PDT = Pose Dependent Transmission

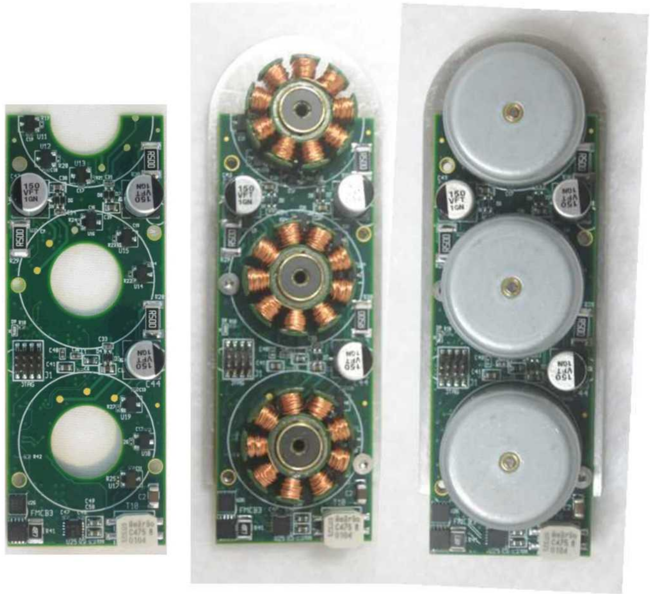




On WANDERER: SE’s reduce locomotive power by 43% (!)

Custom Mechatronics and Manipulation (Sandia Hand)





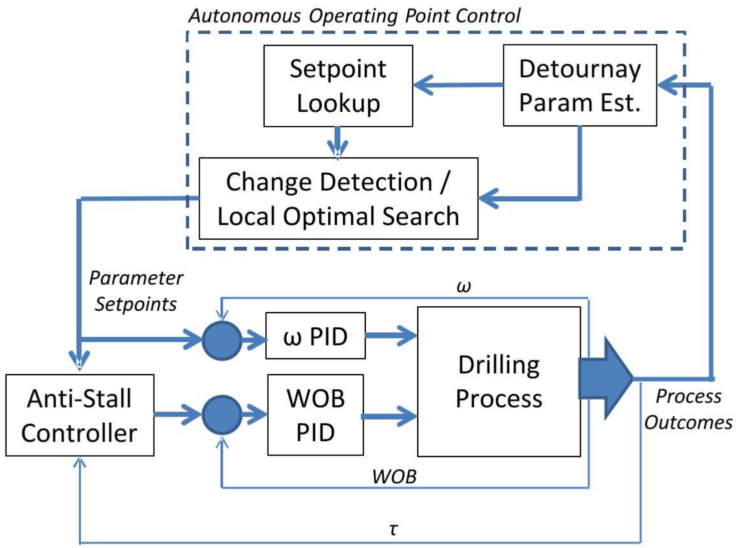
What's Coming? More Effective Interactions with Physical World

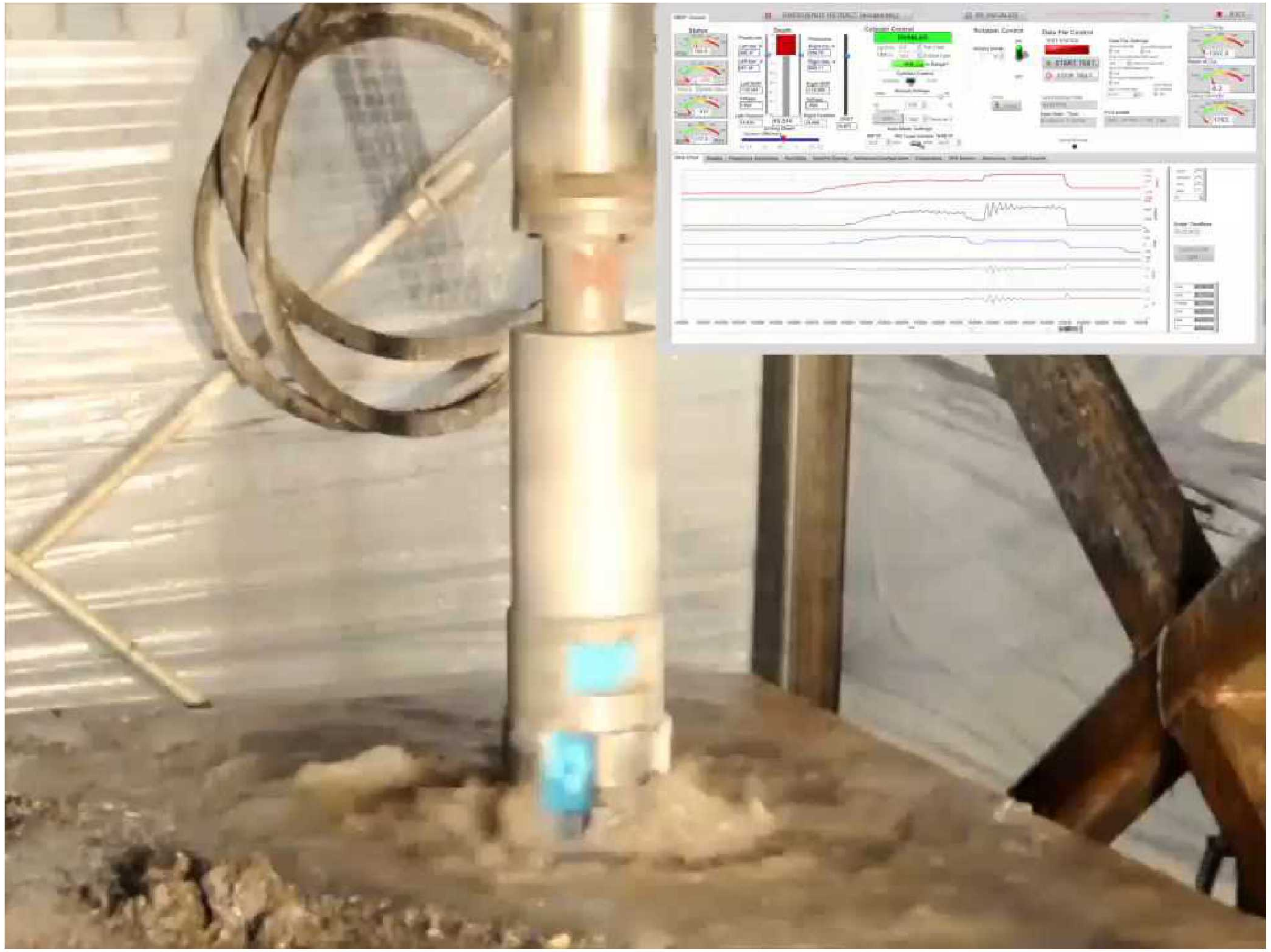
Semi-autonomous door opening (kind….of….slow…)

Novel Effectors for Toughest Applications: e.g. Autonomous Drilling

Hierarchical controller
- Classifies drilling medium via physics-based parameter estimation in real-time
- Local golden-section search for optimal
- Optimize speed or MSE (efficiency)

Working toward highly portable, non expert-operated, fast drilling systems, e.g. for mine rescue or rapid geothermal exploration





Thank You

<u>Core SNL team</u>
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Mike Kuehl
Keith LeGrand
Ani Mazumdar
Anup Parikh
Jon Salton
Steve Spencer

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Mark Koch (Image / Sig. Processing)
Jason Krein (Embedded Sensing)
Jiann Su (Geothermal Research)

<u>Major External Collaborators</u>
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Meeko Oishi (UNM)
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