Mechatronics Research Laboratory
Projects Overview

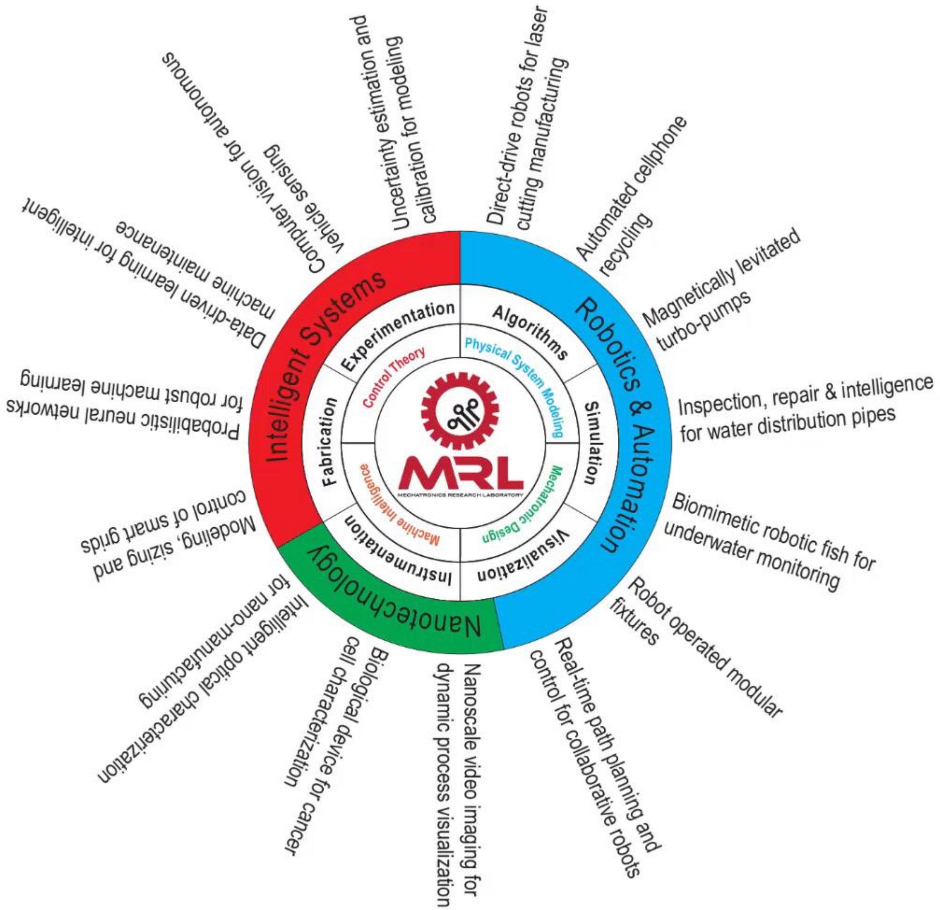
Director: Prof. Kamal Youcef-Toumi

Mar. 10th, 2022

Massachusetts Institute of Technology

MRL Research Overview

- Multidisciplinary projects with practical applications
- Fundamental Principles:
  - Control Theory, Physical System Modeling, Mechatronic Design, Computational Intelligence
- Methods: Algorithms, Simulation, Visualization, Instrumentation, Fabrication, Experimentation
- Three main Application fields:
  - Nanotechnology
  - Intelligent Systems
  - Robotics & Automation



MRL Project Outline

- Nanotechnology
  - Video-rate Imaging: Versatile Atomic Force Microscopy Designs
  - Nanoscale Inspection: High-precision & High-speed Optical Metrology
- Intelligent Systems
  - Intelligent System for Health Monitoring of Physical Machines
  - Machine Learning-based Control for Electrical Motors
  - Autonomous Agents in Context
  - Generalized Bayesian Regression
- Robotics & Automation
  - Technologies for Cell Phone Recycling
  - Technologies for In-pipe Inspection, Rehabilitation and Energy Harvesting
- Selected Previous Projects

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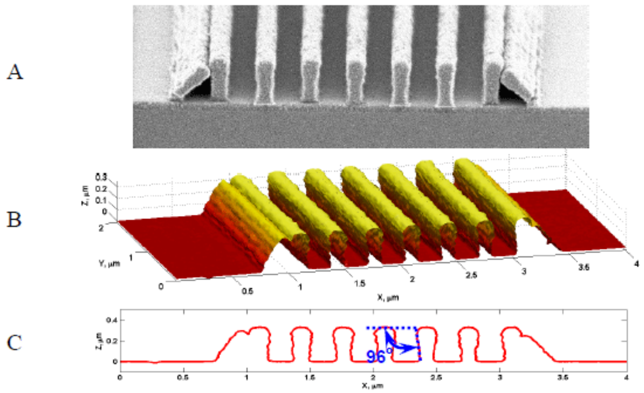
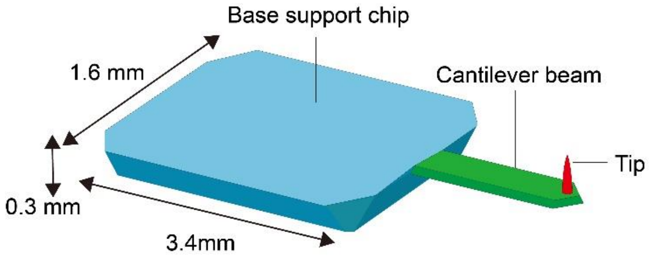
Atomic Force Microscope

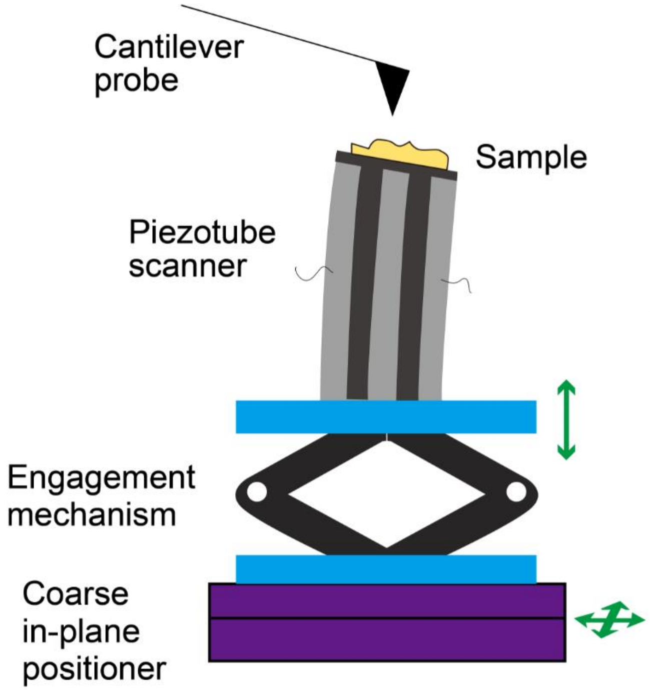
- Atomic Force Microscope (AFM): nanoscale imaging tool for surface characterization
- Key components: cantilever probe, positioner, controller



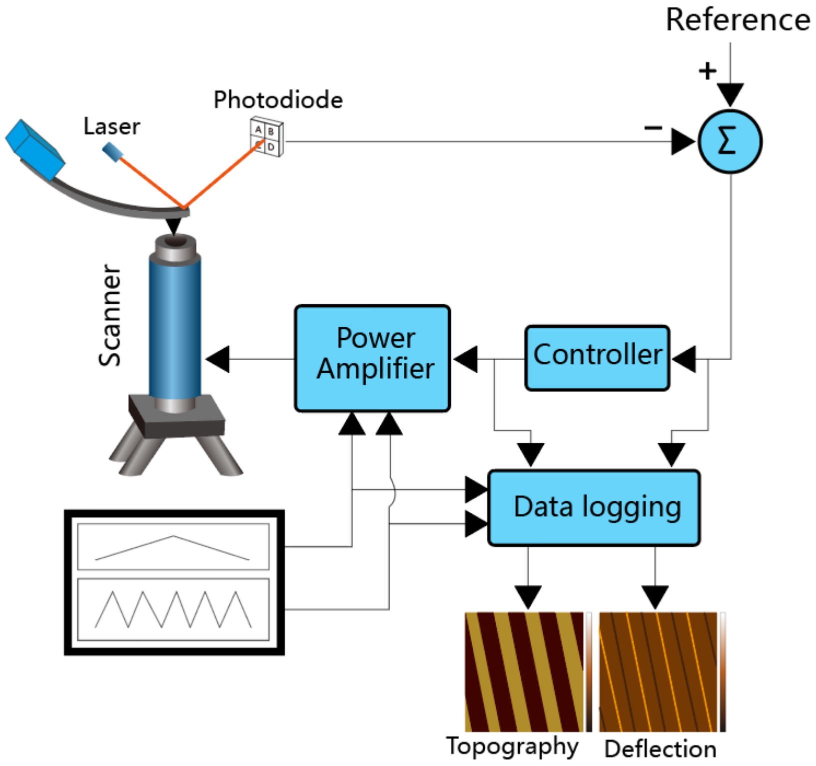
Topography image taken by AFM [ref]



Conventional AFM passive cantilever probe



AFM positioning system



AFM imaging control system

Research Objectives

Aspects for Improvement	1. High-speed Imaging	2. Native Environment	3. System Automation	4. Low-cost Education
Development in this work for new capabilities	High-speed and large-range AFM imaging for dynamic process visualization	AFM imaging in opaque liquid for observation in native environments	Automated experiment setup and batch processing of multiple AFM images	Low-cost modular AFM design with experiments as an educational platform

Primary Subsystmes

1. High-speed, large range or low-cost AFM nano-positioner design
2. Coated active cantilever probes for harsh opaque liquid operation
3. Algorithms for scanner control, automatic tuning and AFM imaging
4. High-bandwidth driver and signal processing electronics
5. Optical system for small probes with vision-based automation
6. Software implementation for high-speed big data processing
7. AFM system integration for visualization

Positioner
Cantilever
Controller
Driver
Optics & Vision
Software
Integration

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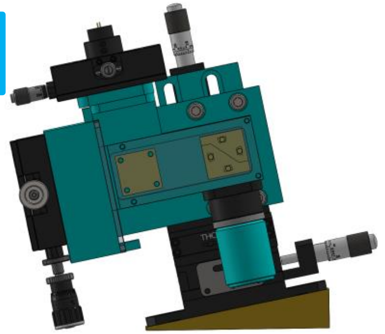

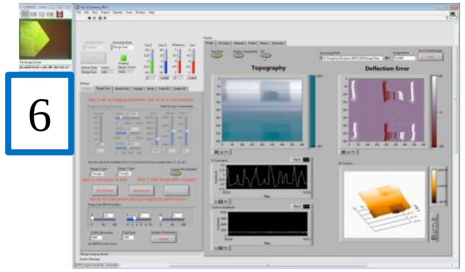
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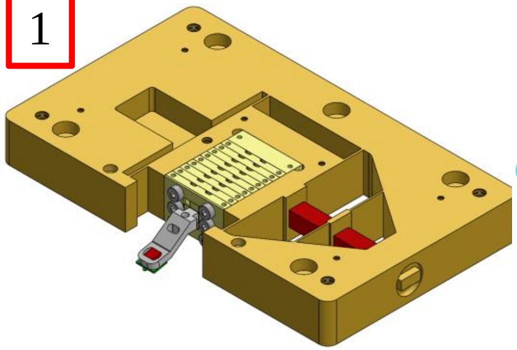

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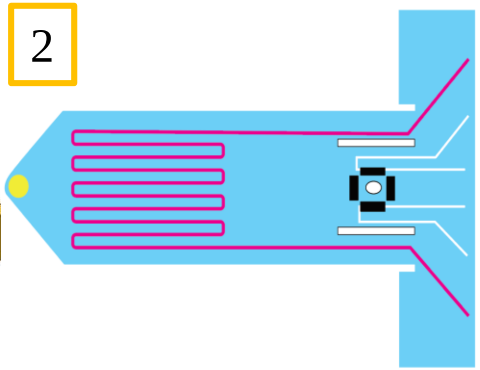

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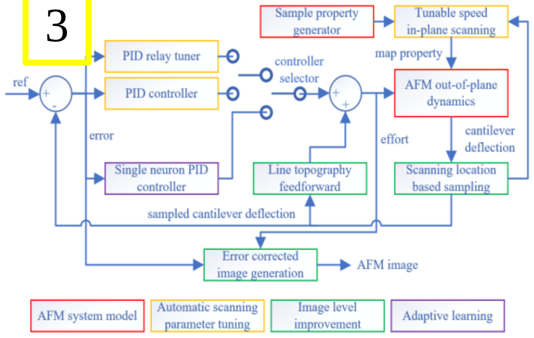

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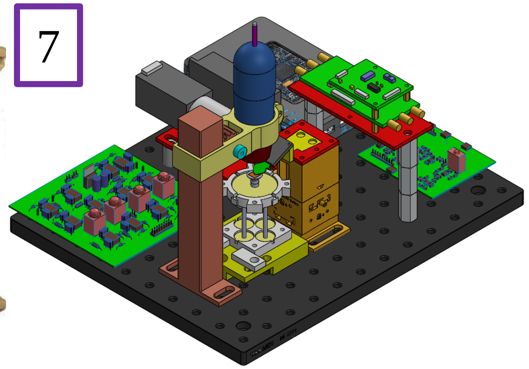
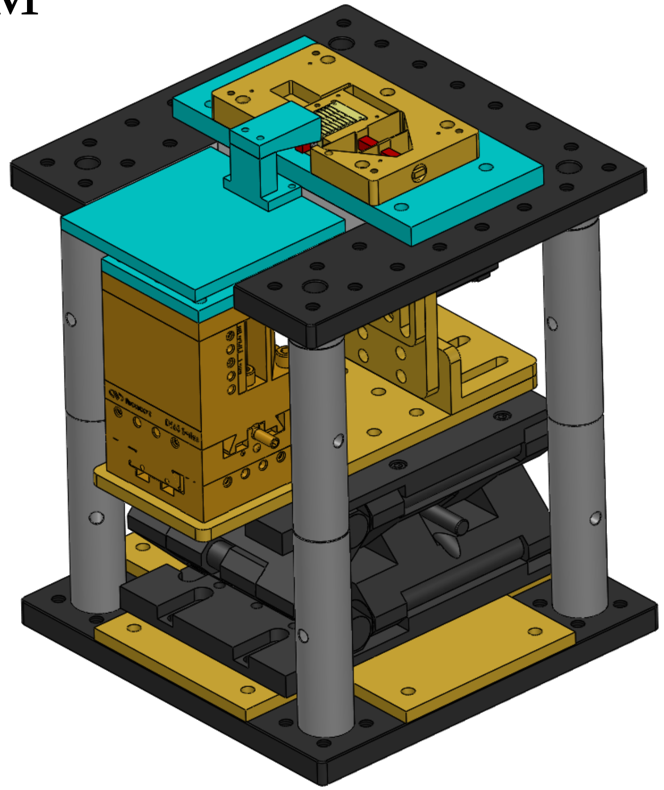


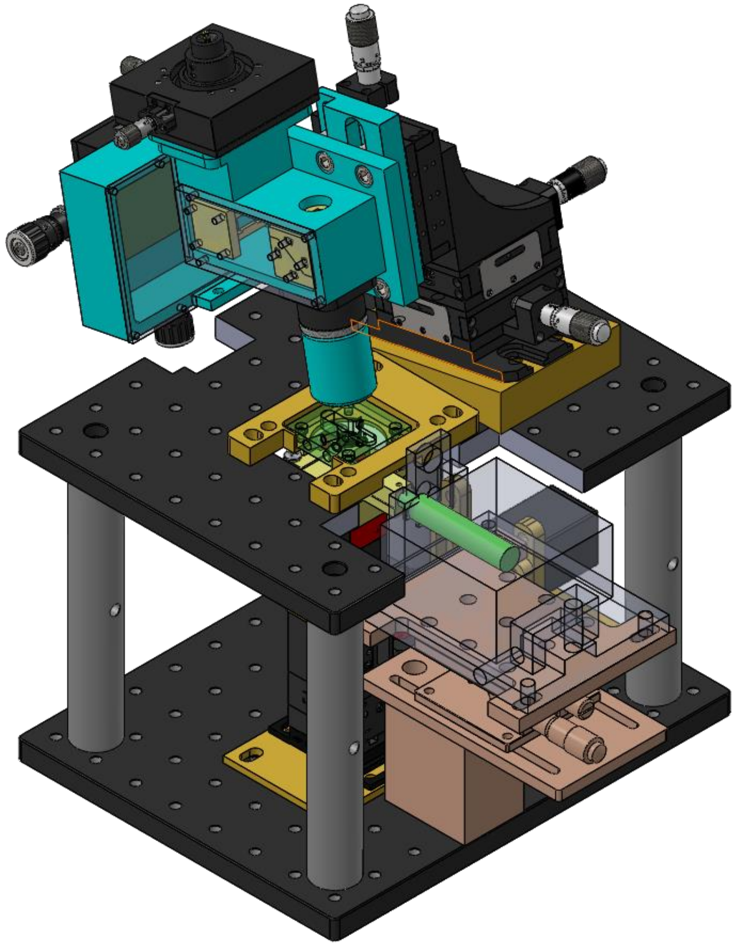
Custom AFM Systems at MRL

- Low-cost educational AFM
- Multi-layer stacked scanner AFM
- Versatile sample-scan AFM

Low-cost educational AFM



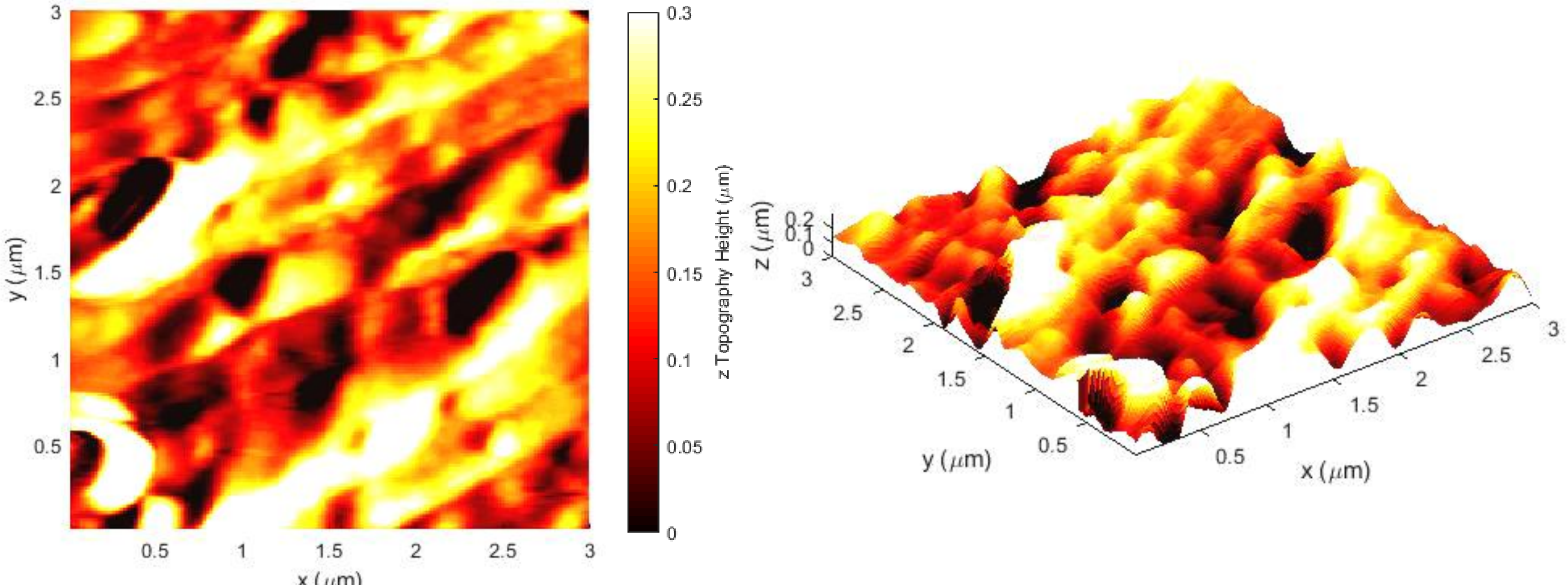
Multi-layer stacked scanner AFM



Versatile sample-scan AFM

Nanoscale Visualization

- Dynamic reaction process visualization in real-time
- Chemically harsh opaque liquid environment imaging
- Various applications in physics, chemistry, material science, biology



Imaging of calcite etching process at 20 FPS with top view and isometric view (4X)

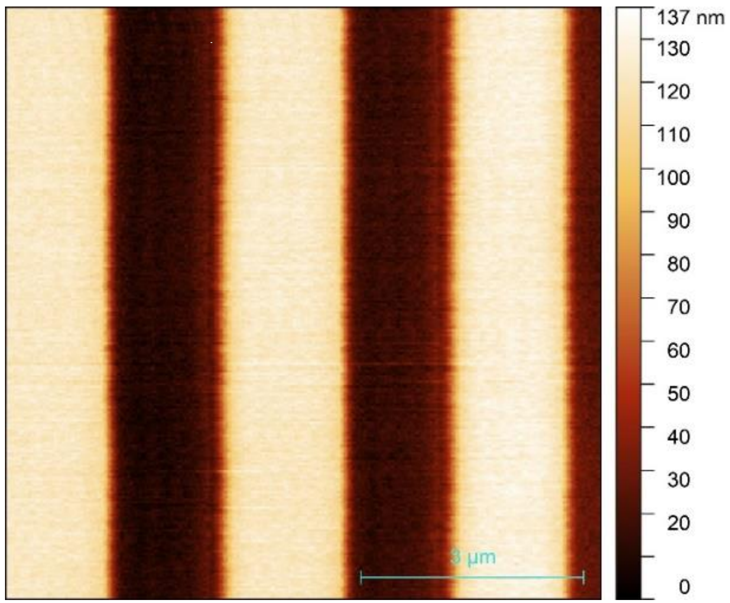
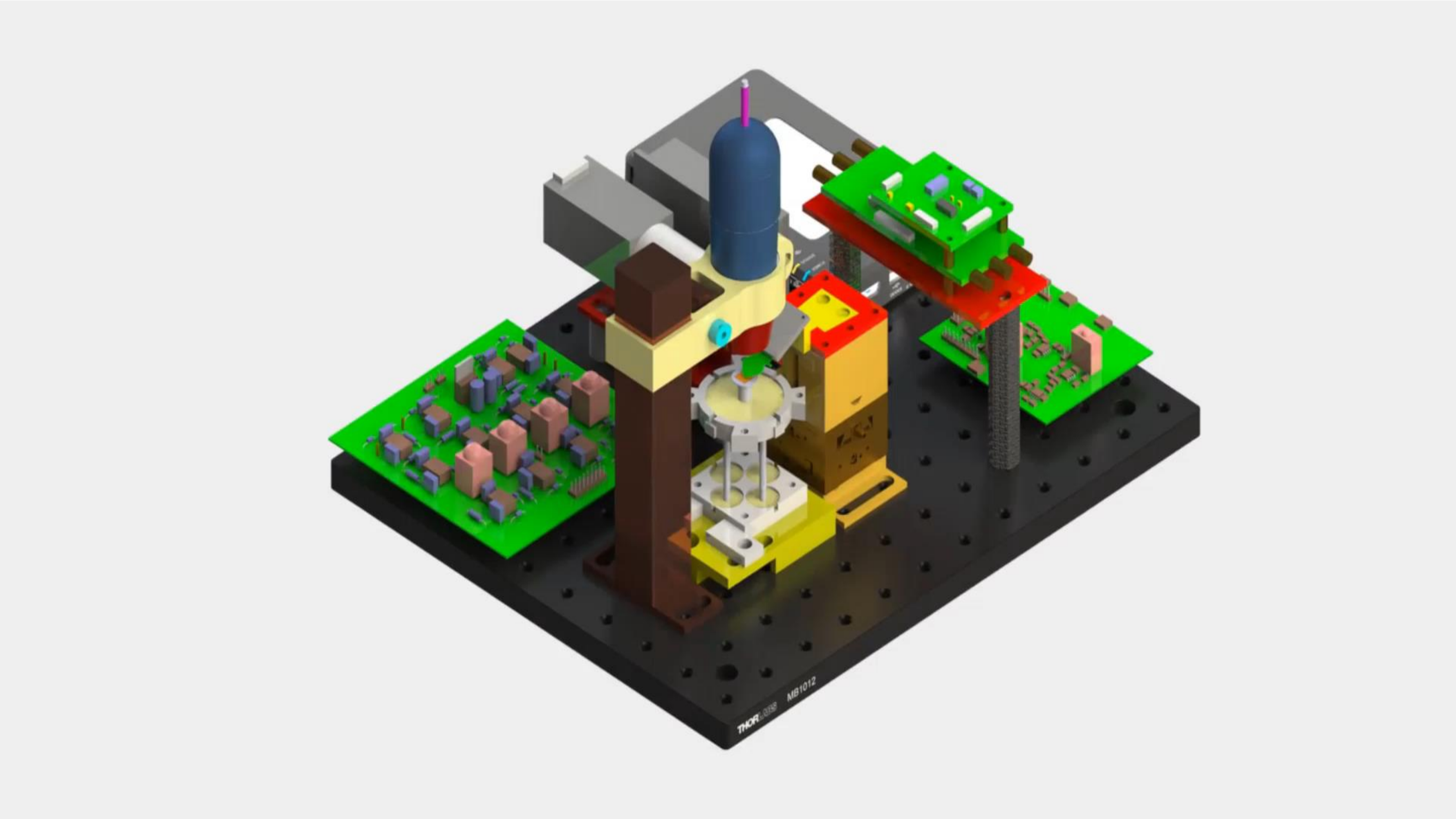


Image of a calibration grating in crude oil

MRL Educational AFM



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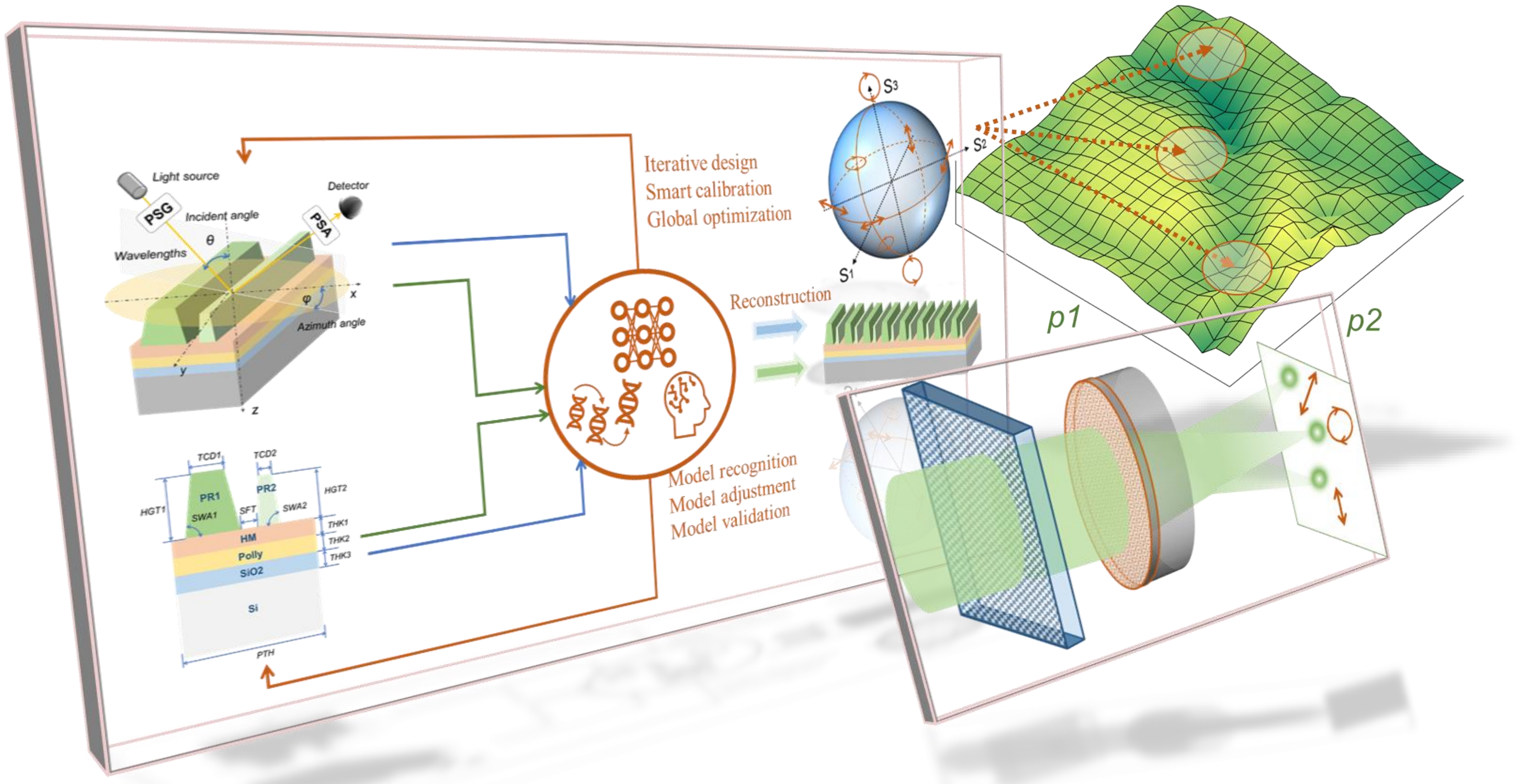
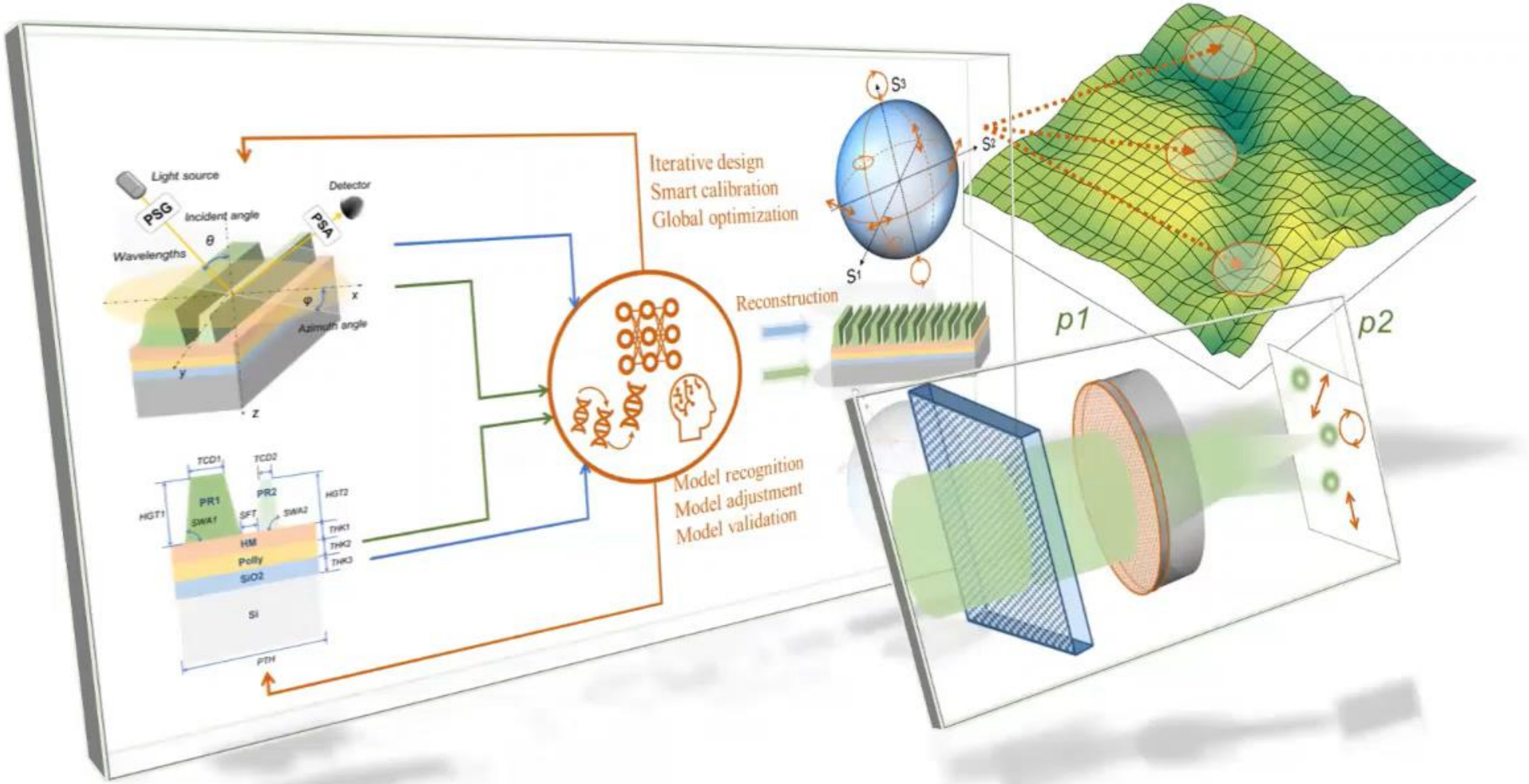
Nanoscale Inspection: High-precision & High-speed Optical Metrology



Nanoscale Inspection: High-precision & High-speed Optical Metrology

Open House 2021



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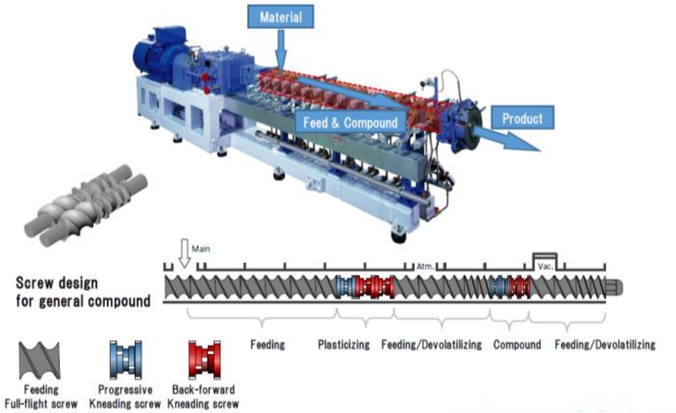
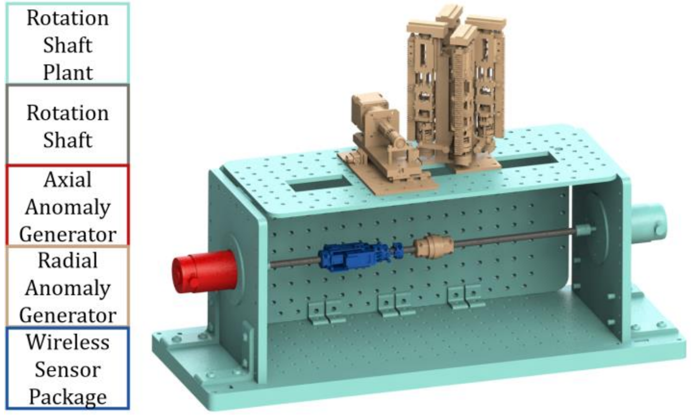
Multi-disciplinary Research Topics

- Mechatronics
  - Modeling, instrumentation, and smart utility
  - Real-time control system development deployment
  - Multi-modal sensor network design and interpretation
  - RL-based robotic predictive maintenance
- Machine Learning
  - Plant modeling and physics-informed learning
  - Transfer learning and zero-shot learning
  - Multi-modal sensor fusion and learning

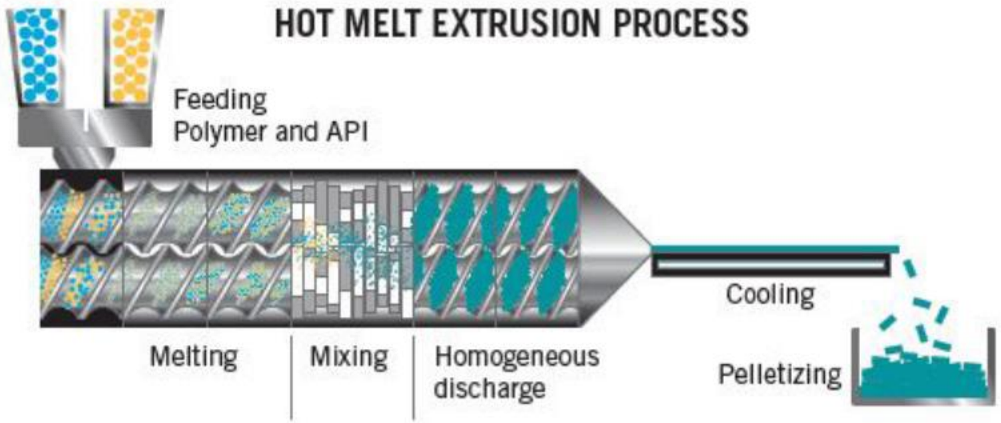




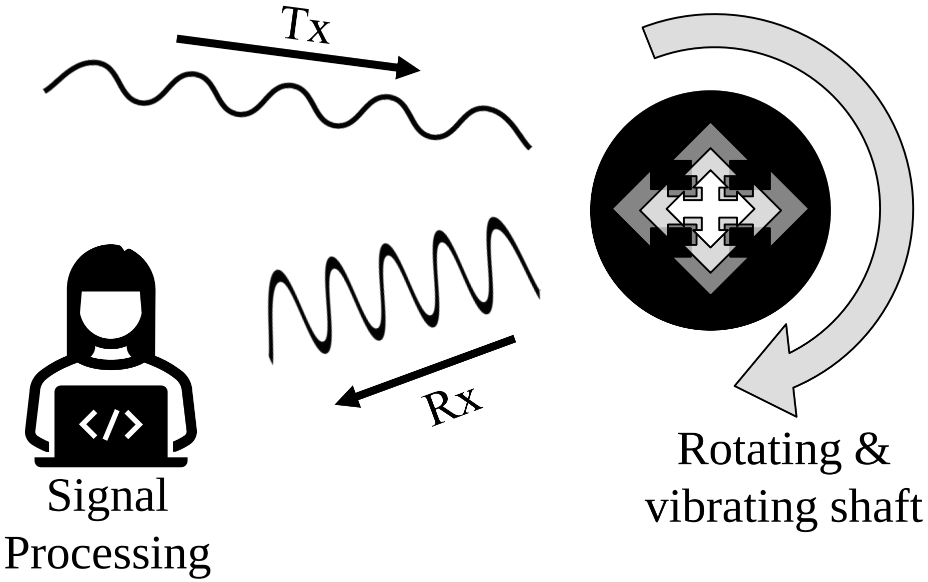
Radio-Frequency Sensing

Goal: Perform ongoing monitoring of machine health status through non-contact sensing of vibration and other anomalous behavior using radio-frequency instrumentation design.

Target Machinery: injection molding



Method: radio frequency sensing



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Sponsor Background

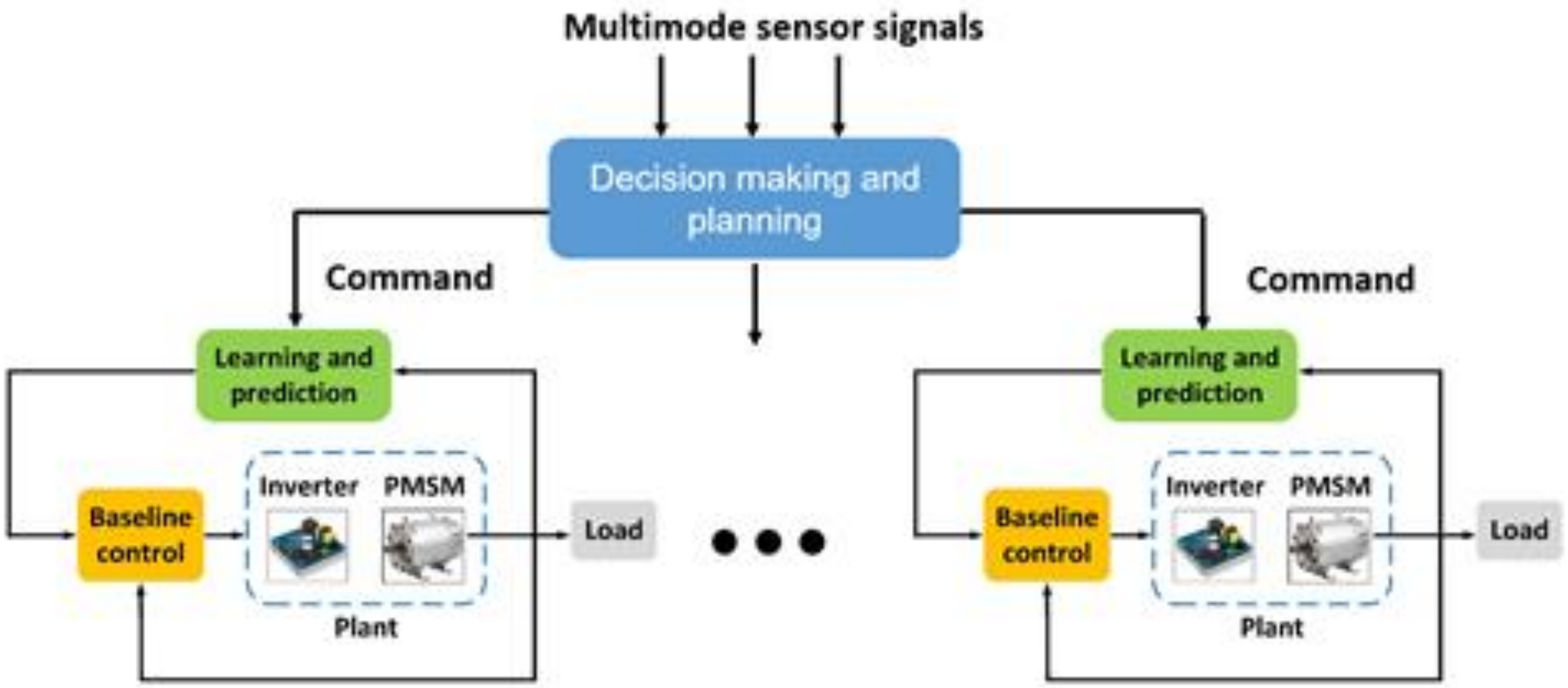
- **Weichai Group –** industry leader in engines, heavy machinery, bus and truck manufacturing
- **Industry 4.0 -** Increasing need for intelligent systems
- **Electrical Motors –** Useful in electrical buses, trucks and industrial robots

Why Machine Learning ?

- **Existing control strategies:** Vector Control (VC), Direct Torque Control (DTC)
- **Issues:**
  - Quality of calibrations of controller parameters depends on operator experience
  - Motor parameter accuracy affects robustness of control system
  - Response speed and accuracy unsatisfactory in certain applications

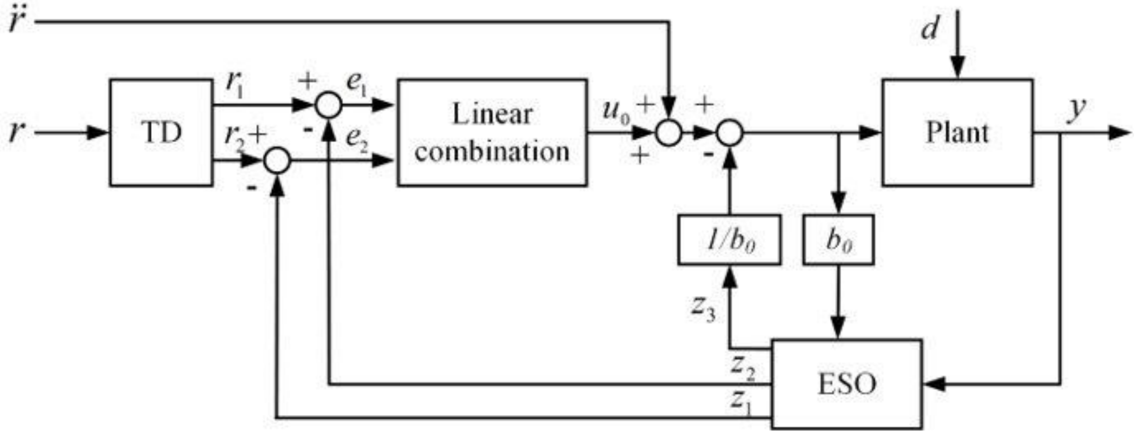
Proposed Control Architecture

Machine Learning based Multi-Level Control

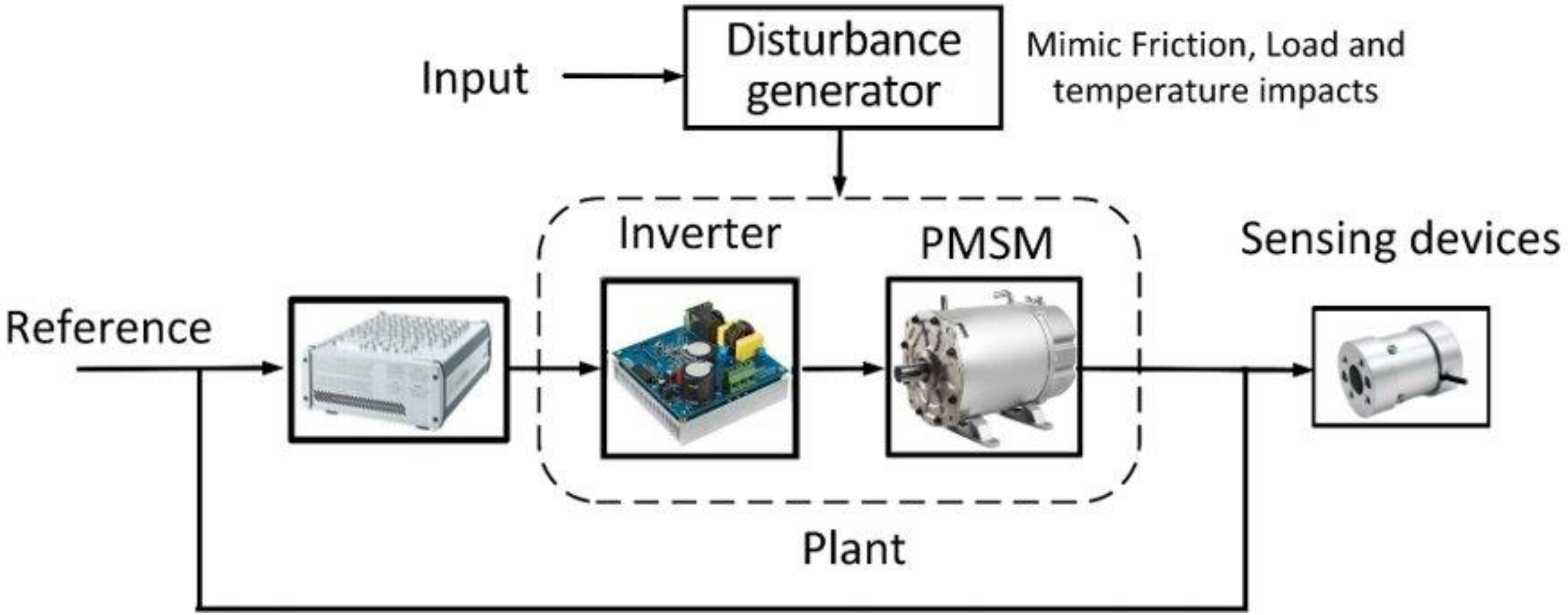


Control Strategies

- **Baseline Control:**
  - Active Disturbance Rejection Based Control: estimate disturbances as an augmented state
  - Time-Delay Control: estimate disturbances at *t* as the disturbances at *t-a*
- **Learning and Prediction:**
  - Feedforward Neural Networks
  - Reinforcement Learning



Experimental Setup Schematic



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Autonomous agents

Sensing:
Sensor selection;
Sensor placement;
Sensor fusion.

→ Clear view →

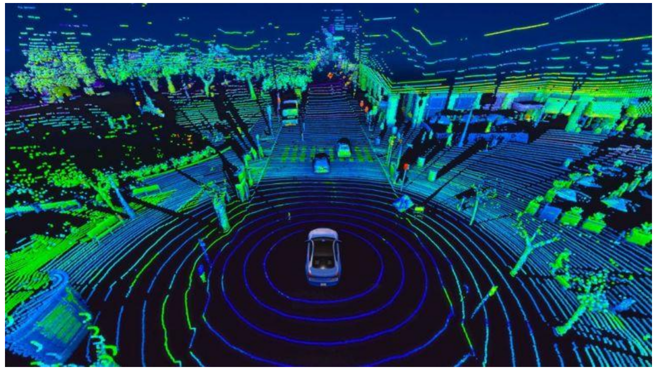
Scene Understanding:
3D reconstruction
Semantic segmentation
Identification and tracking

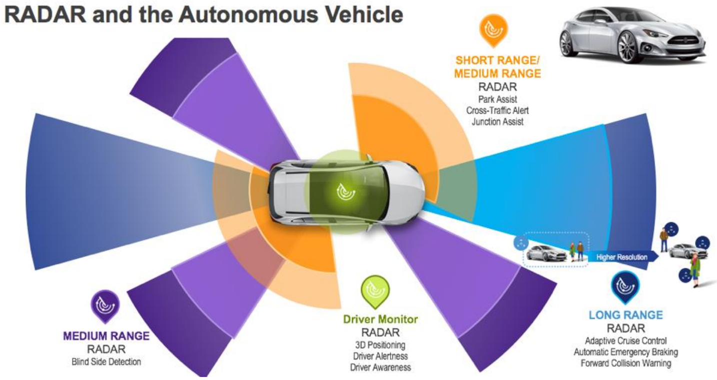
→ Understanding and prediction →

Navigation:
Safe, efficient, robust

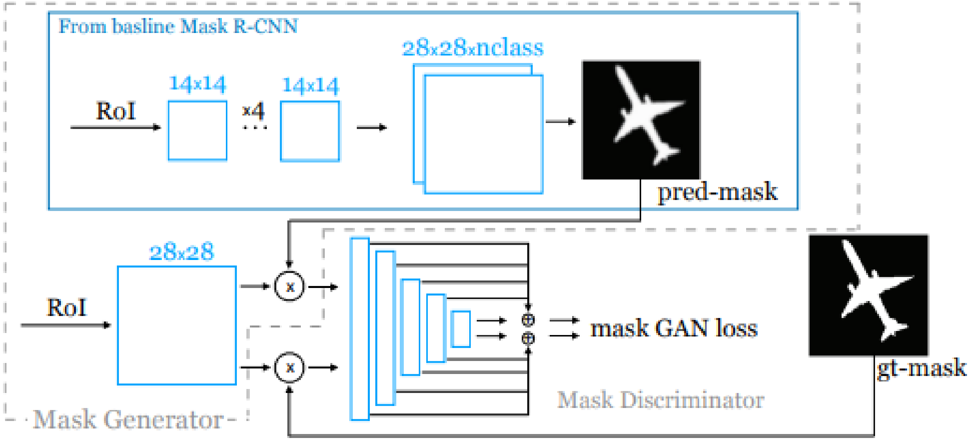
Sensing

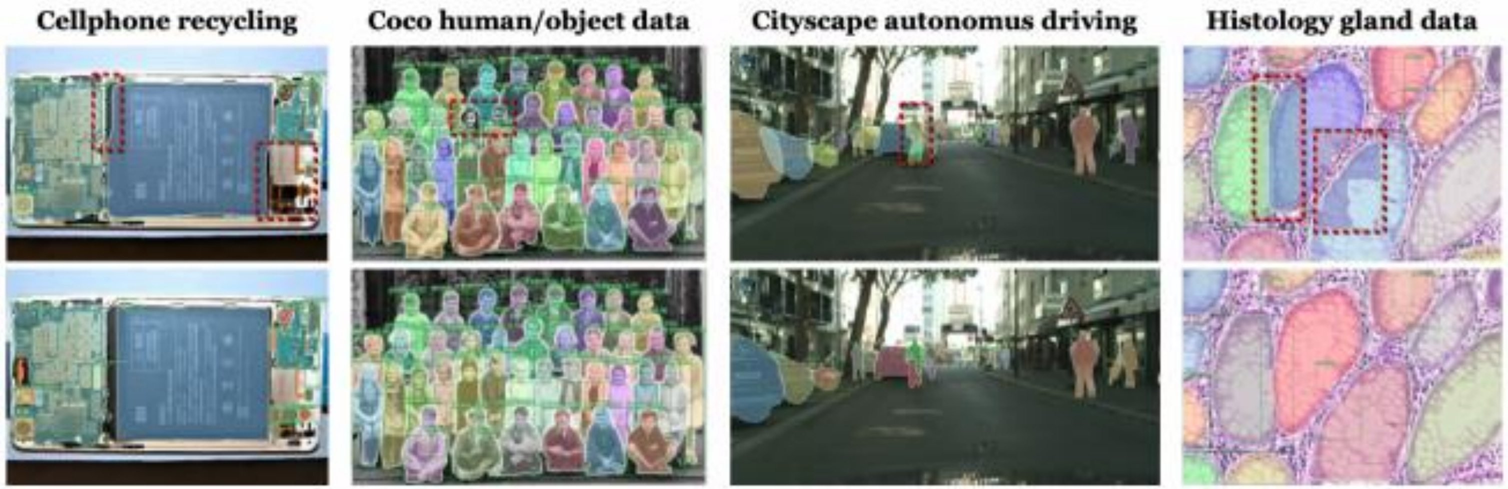
Sensing methods	Characteristics	Resolution	Cost	Other advantages	Other disadvantages
Camera	Passive, 2D imaging RGB	High	Low	High sampling rate	Light and weather sensitive
Stereo Camera	Passive, 3D imaging RGB-D	High	Low	High sampling rate	Light and weather sensitive
Radar	Active	Low	High	High sampling rate, light and weather insensitive, high penetration	Low accuracy, lacking of semantic information
LiDAR	Active, 3D scan	High	High	High sampling rate, light insensitive	Weather sensitive
Ultrasonic	Active, 1D scan	Low	Low	light and weather insensitive	Low range, low sampling rate





Scene understanding





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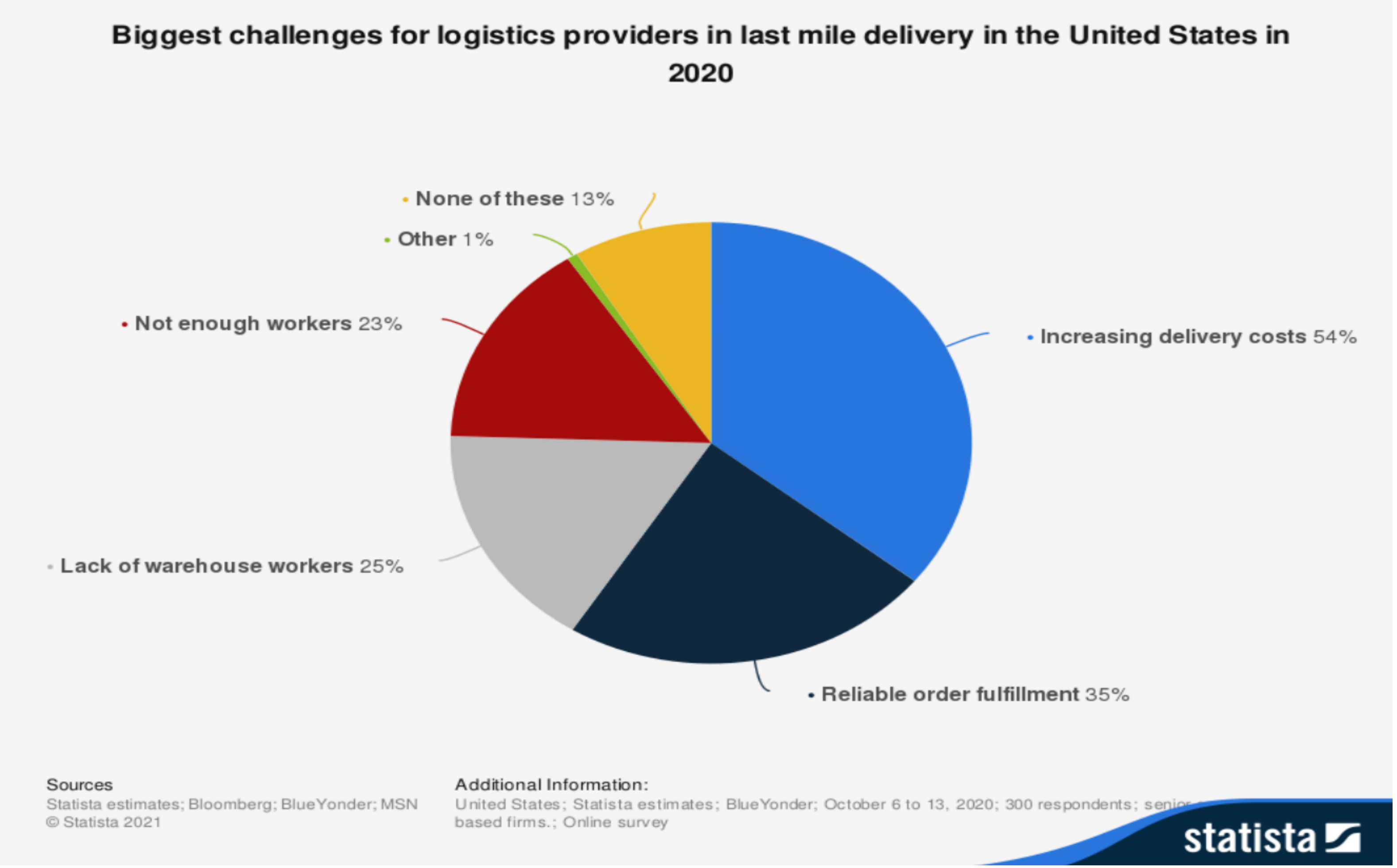
Le, Quang H., Kamal Youcef-Toumi, Dzmitry Tsetserukou, and Ali Jahanian. "Instance Semantic Segmentation Benefits from Generative Adversarial Networks." In *NeurIPS 2021 Workshop on Deep Generative Models and Downstream Applications*. 2021.

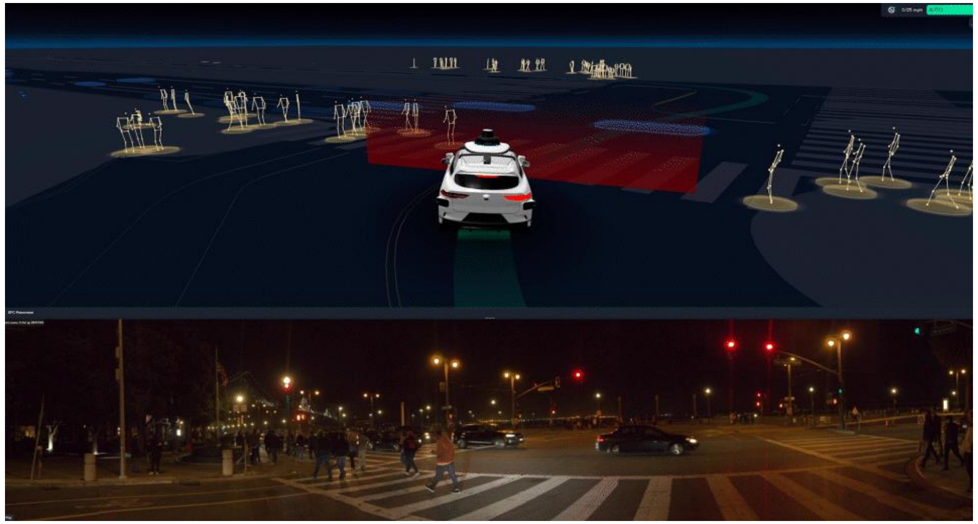
Last mile delivery and logistics

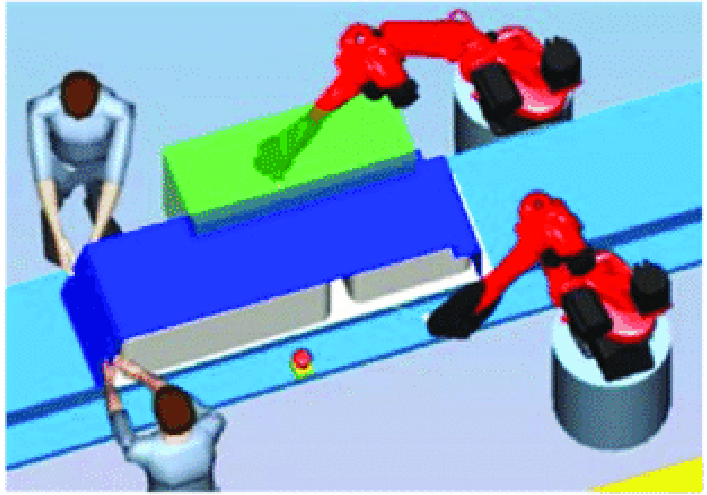


Autonomous mobile robots

Research focus:

- Motion planning in pedestrian rich environments
- Human intent prediction





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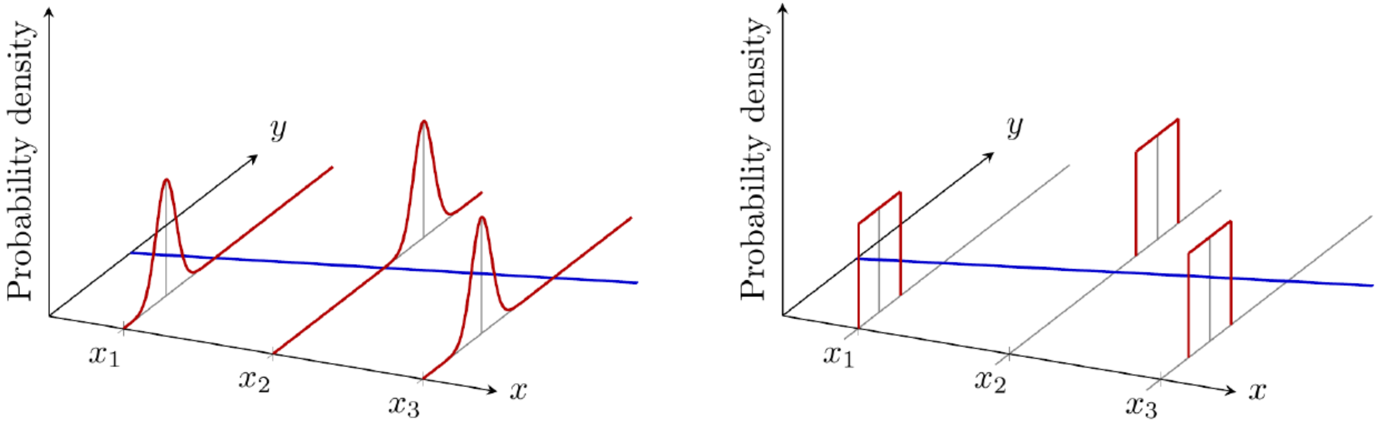
Generalized Bayesian Regression

- Standard Bayesian regression methods assume that the target variables (in fact, the residuals of the model) are normally distributed.
- That is, they assume a Gaussian uncertainty on the y-values (infinite tail distribution).
- However, this may not be the type of uncertainty that we have.
- For example, assume that the output values are bounded between two values (truncated tail distribution).

Generalized Bayesian Regression

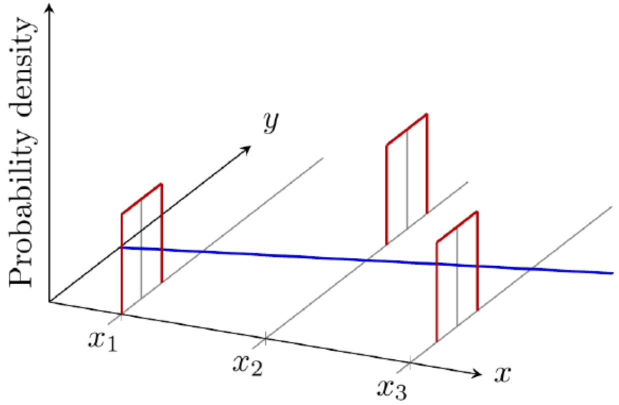


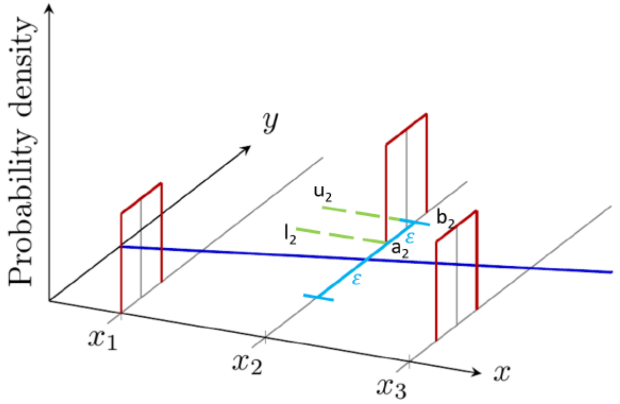
- **Left)** Gaussian targets assumption: Bayesian regression finds a linear model that sits in low probability regions of the data.

- **Right)** Uniform targets assumption: Bayesian regression cannot find a linear model since no linear model can pass through each data distribution (i.e. interval) simultaneously.

Can we devise a generalized Bayesian regression approach that is able to find a model under any target distribution assumption?

Generalized Bayesian Regression





Standard Bayesian Regression

$$\mathcal{Z} = \int_{\vec{\alpha}} \mathcal{L}(\vec{\alpha}) \cdot \pi(\vec{\alpha})\, d\vec{\alpha}$$

$$\mathcal{L}(\vec{\alpha}) = \prod_{j=1}^{n} \frac{\Theta\left(a_j \leq M(x_j; \vec{\alpha}) \leq b_j\right)}{b_j - a_j}$$

$$\mathcal{Z} = 0 \rightarrow \text{Fails! :(}$$

Generalized Bayesian Regression

$$\mathcal{Z}(B) = \int_{\vec{\alpha}} \mathcal{L}(\vec{\alpha}, B) \cdot \pi(\vec{\alpha})\, d\vec{\alpha}$$

$$\mathcal{L}(\vec{\alpha}, B) = \prod_{j=1}^{n} \frac{u_j - l_j}{b_j - a_j}$$

$$\mathcal{Z}(B) \neq 0 \rightarrow \text{Works! :)}$$

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Synopsis

- Motivation
- Objective
- Problem
- Our Solution
  - Method
  - Implementation
- Results
- Generalization
- Conclusion


See the E-Waste! Training Visual Intelligence to See Dense Circuit Boards for Recycling

Ali Jahanian[1], Quang H. Le[1], Kamal Youcef-Toumi[1], and Dzmitry Tsetserukou[2]

GAN Mask R-CNN: Instance semantic segmentation benefits from generative adversarial networks

Quang Le, Kamal Youcef-Toumi, Dzmitry Tsetserukou, Ali Jahanian

MIT, Skoltech

Abstract. In designing instance segmentation ConvNets that reconstruct masks, segmentation is often taken as its literal definition – assigning label to every pixel – for defining the loss functions. That is, using losses that compute the difference between pixels in the predicted (reconstructed) mask and the ground truth mask –a template matching mechanism. However, any such instance segmentation ConvNet is a generator, so we can lay the problem of predicting masks as a GANs game framework: We can think the ground truth mask is drawn from the true distribution, and a ConvNet like Mask R-CNN is an implicit model that infers the true distribution. Then, designing a discriminator in front of this generator will close the loop of GANs concept and more importantly obtains a loss that is trained not hand-designed. We show this design outperforms the baseline when trying on, without extra settings, several different domains: cellphone recycling, autonomous driving, large-scale object detection, and medical glands. Further, we observe in general GANs yield masks that account for better boundaries, clutter, and small details.

Fig. 1. Instance semantic segmentation has applications in many domains, and each domain may have a specific goal and challenges, e.g., cellphone recycling objects need clear boundaries and seeing small details for disassembling, COCO and Cityscape are large-scale, and glands are heterogeneous with coalescing pixels. Learning a generic loss in only one generic architecture, and regardless of the kind of underlying domain, we show a GAN loss generally improves the accuracy and quality of the task. Top row: results of the baseline Mask R-CNN. Bottom row: results of incorporating the baseline's loss with a GAN loss. For ease of comparison, we highlight (with the red dotted-boxes) some failures in the baseline results.

Andrew Rae

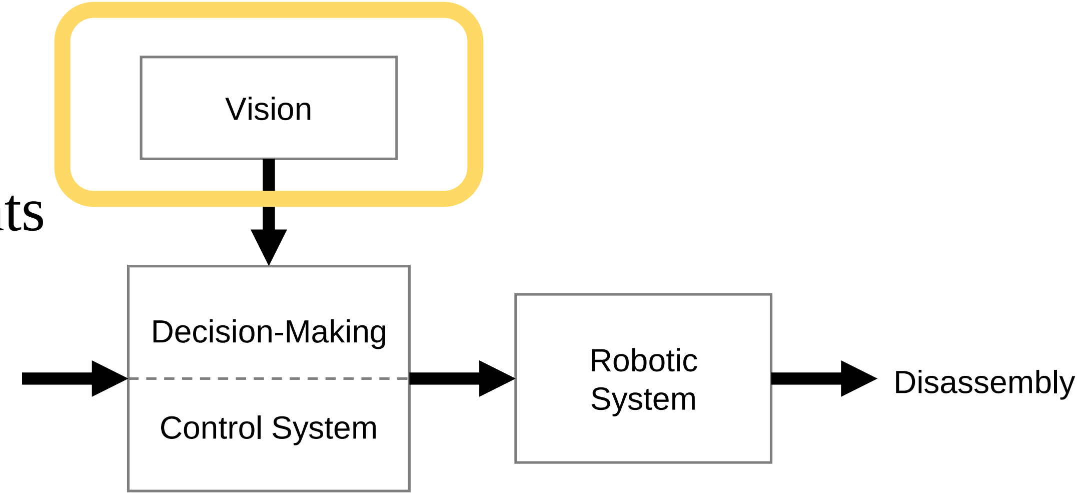
Some Numbers on E-Waste

- Globally, we produce millions of metric tons per year
- Current solution: melt it!
  - Out of 1 million cellphones
    - 16,000kg of copper
    - 350kg of silver
    - 34kg of gold
    - 15kg of Palladium
  - After all, only 20% recycled

https://collections.unu.edu/eserv/UNU:6341/Global-E-waste_Monitor_2017__electronic_single_pages_.pdf

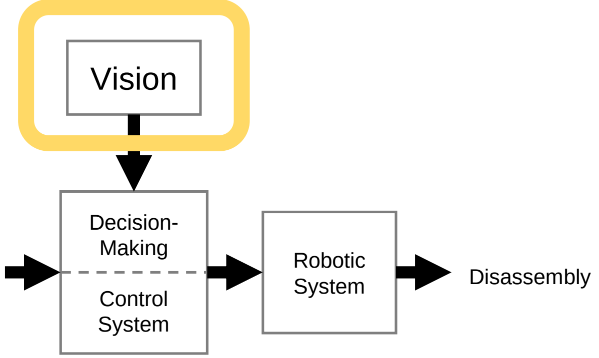
Objectives

- Augment the robotic system with vision for making the system autonomous
- See cellphone components
- Learn how to see and parse cellphone components
  - generalize seeing for parsing
- Serve as both input and feedback for decision-making system
  - Measure components and their clearances
  - Did the robotic system accomplish the task successfully?



Schematic view of the robotic system when vision and decision-making subsystems are incorporated.

Demo of Robotic Disassembly



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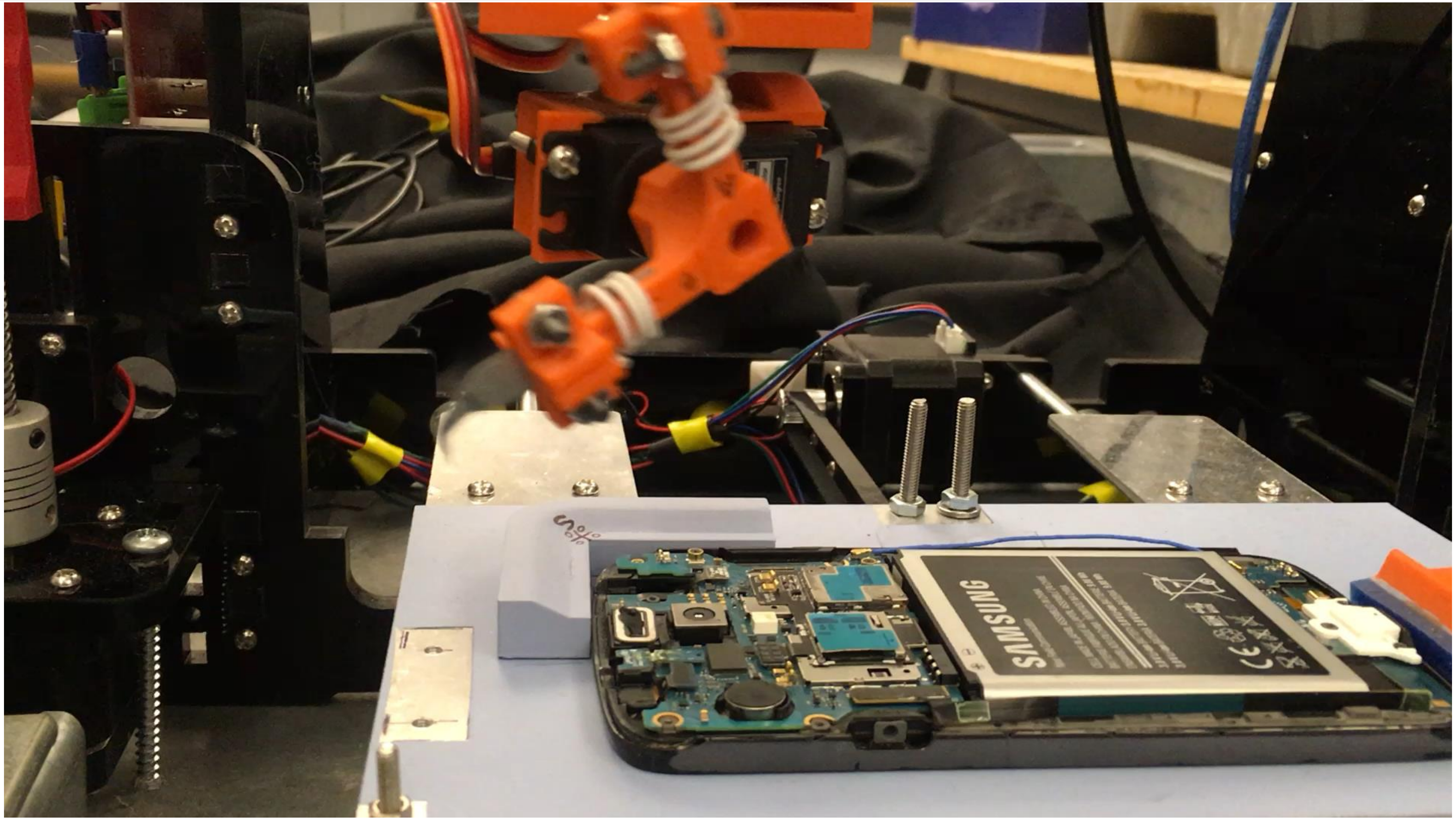


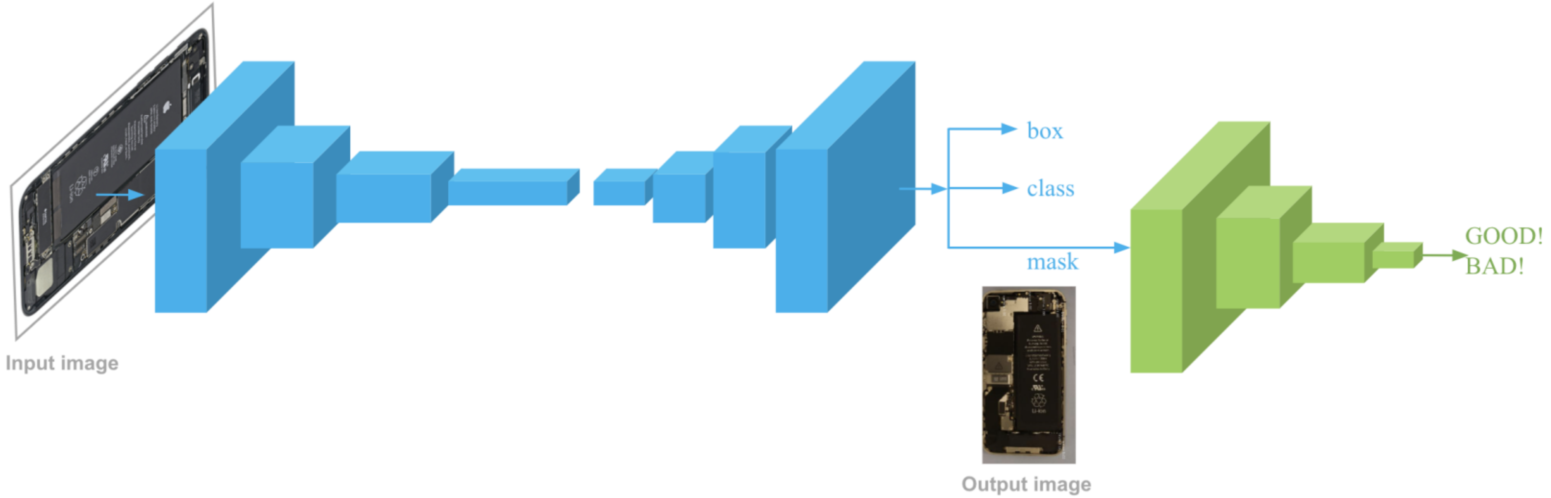
Problem/Challenges

- Small components and micron-scale gaps between them
- Limited pose (and thus limited viewpoints), difficult to capture
  - RGB-D or point clouds with an effective precision
  - Unless using several-thousand-dollar high-end 3D scanner
- The amount of data is limited due to the specificity
  - Design from each manufacturer
  - Occlusion
- How to do it for automation and robotics usage in manufacturing?

Computer Vision Method

- We designed a deep learning neural network with a "learnable" objective

GANs (Generative Adversarial Network) Loss



$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\log D(G(\mathbf{x}))+\log(1-D(\mathbf{y}))]$$

Cellphone Object Recognition

Cellphone recycling

baseline Mask R-CNN

Our method

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  - Technologies for In-pipe Inspection, Rehabilitation and Energy Harvesting
- Selected Previous Projects

A Severe Problem – Water Leakage

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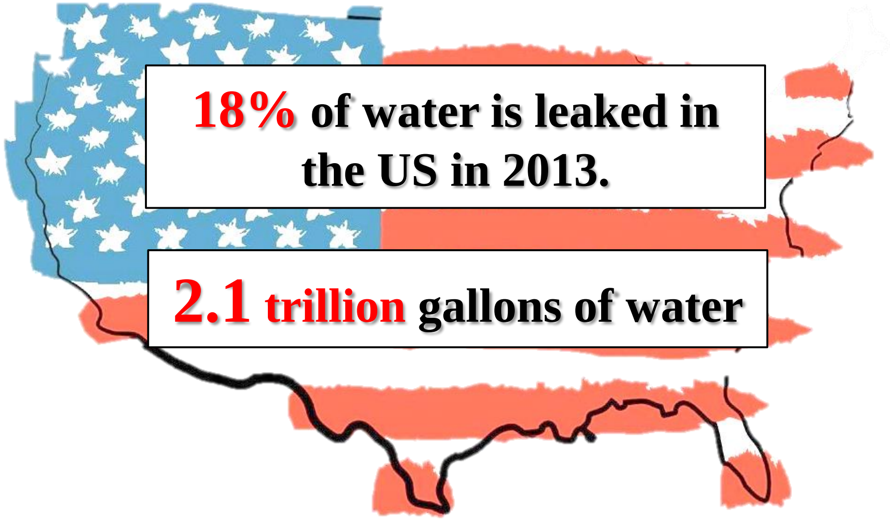
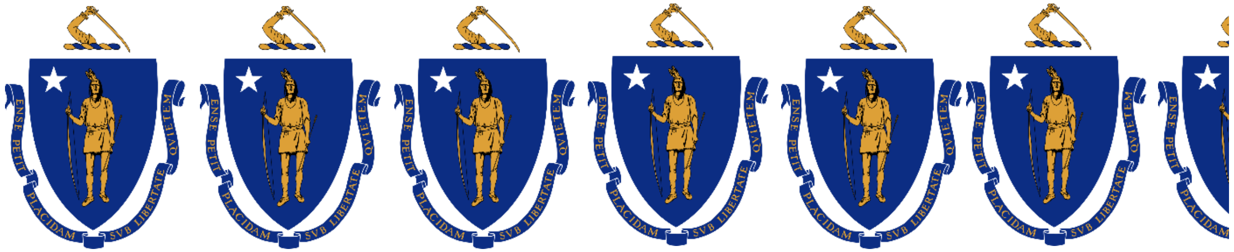


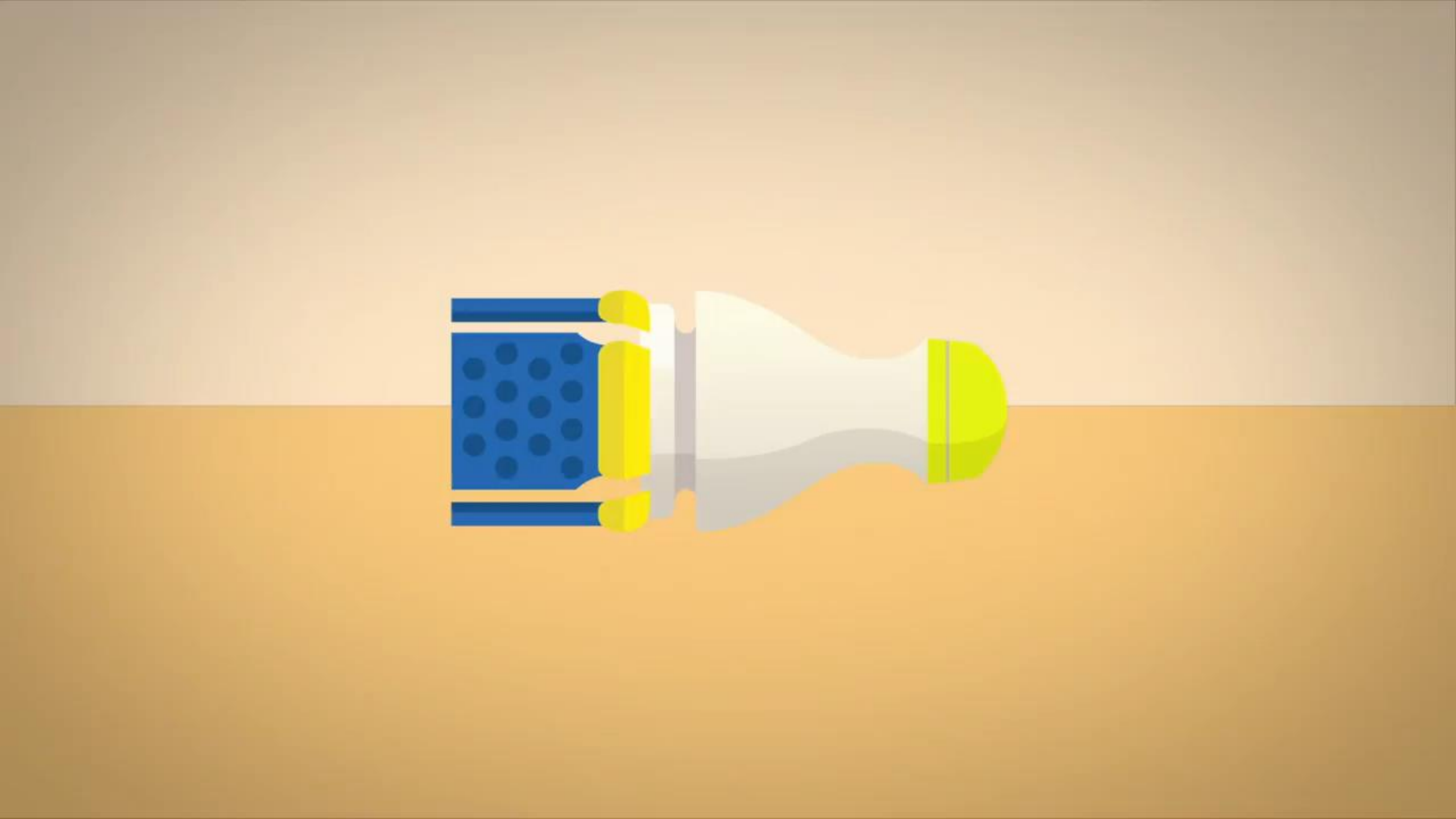
18% of water is leaked in the US in 2013.

2.1 trillion gallons of water



6.3 times of annual Massachusetts water consumption

The Case for Fixing the Leaks: Protecting people and saving water while supporting economic growth in the Great Lakes region. CNT, 2013



Magnetohydrodynamics Energy Harvester

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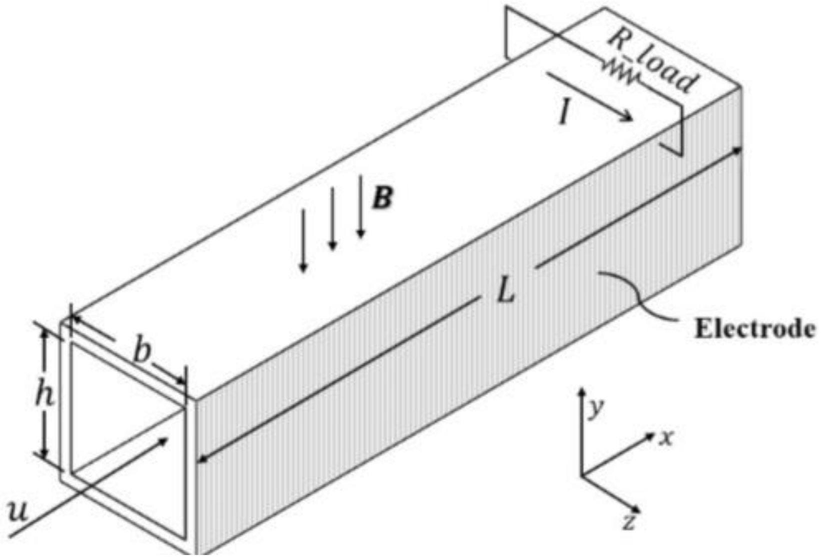
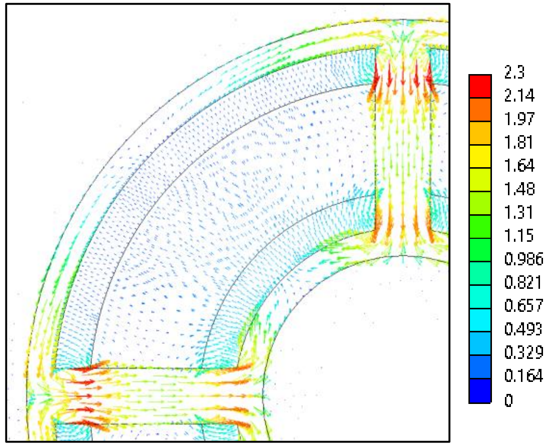
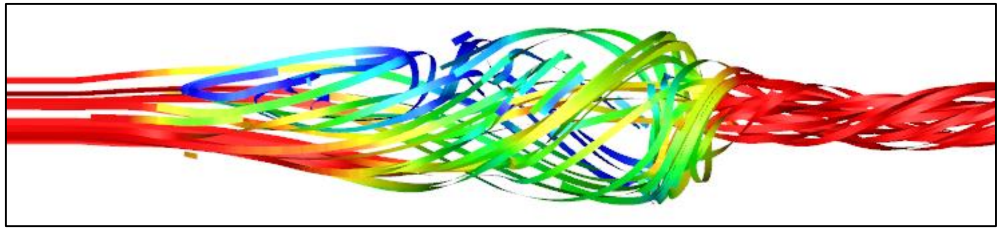
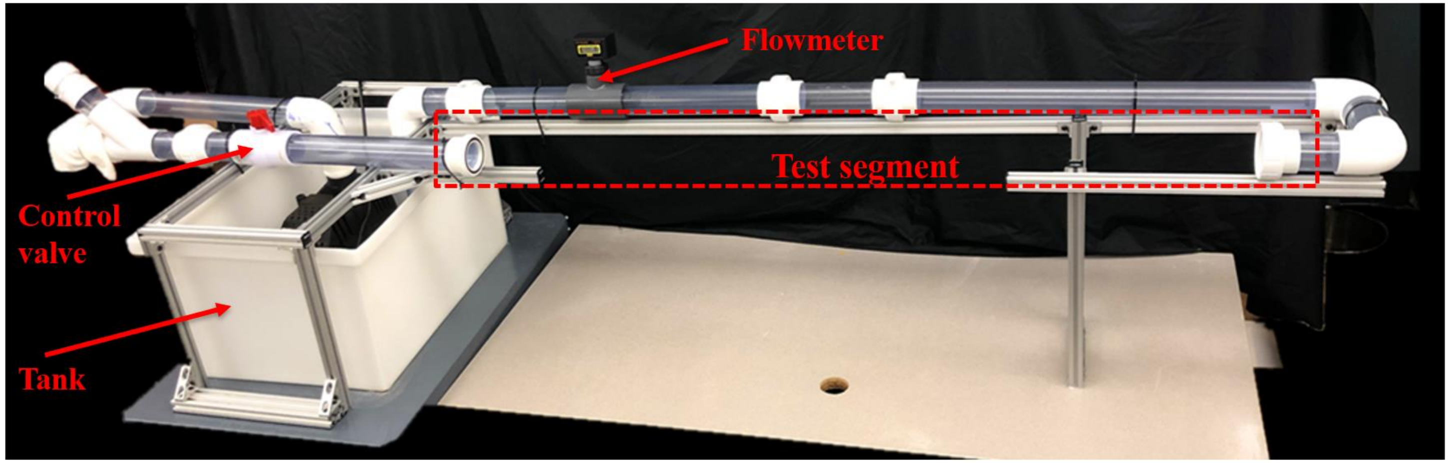


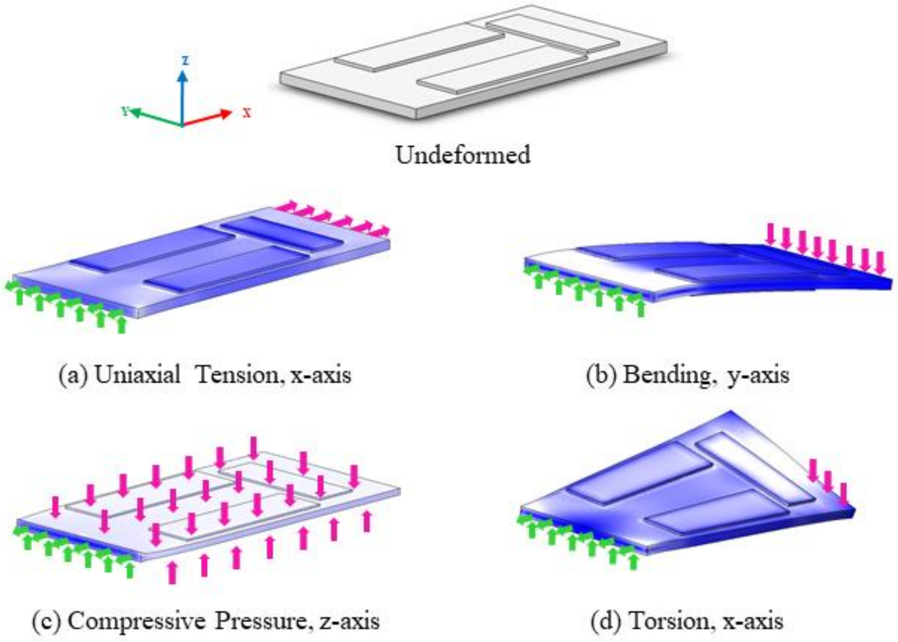




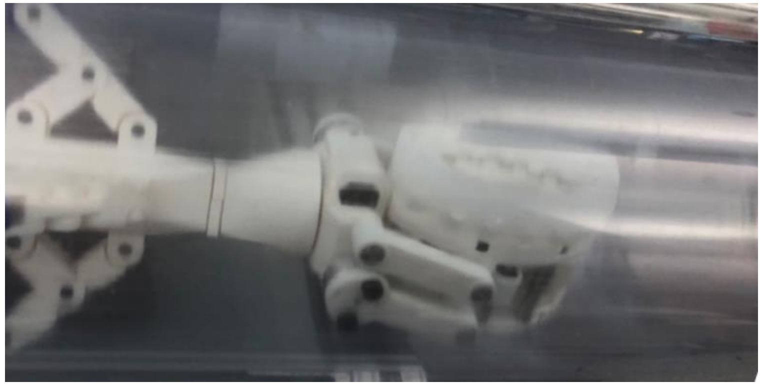


Sensors to Identify Leaks and Map Pipes

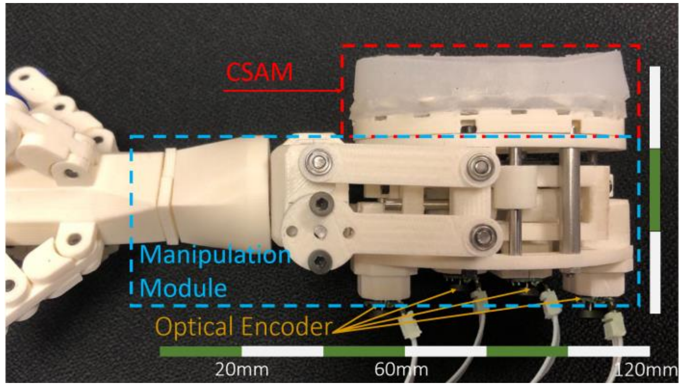
- Design a soft sensor that can measure and decouple all four deformation modes
- Determine how leaks and obstacles affect the sensor readings
- Validate the sensor in a water pipe
- Use sensor data to improve in-pipe localization



In-Pipe Contamination-Less Rehabilitation Robot

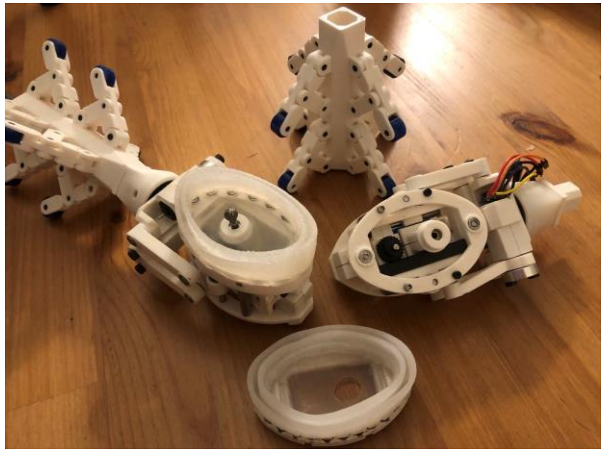


In-Pipe Deployment. (4in-diameter Pipe)

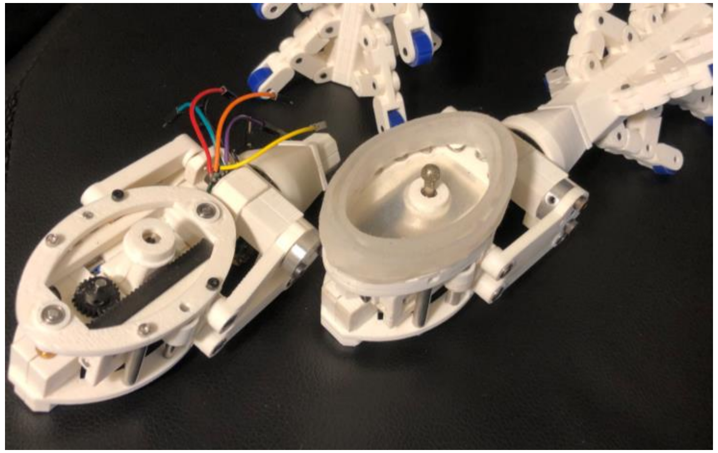


Modular Architecture.

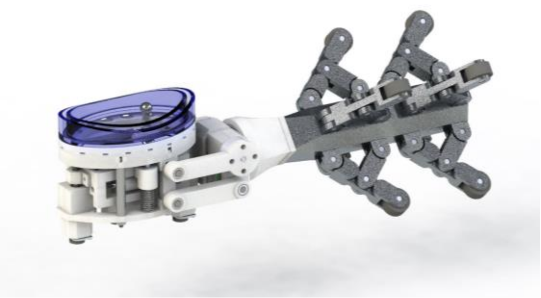
Design for Assembly.



Multiple Robots.



Multiple Robots.

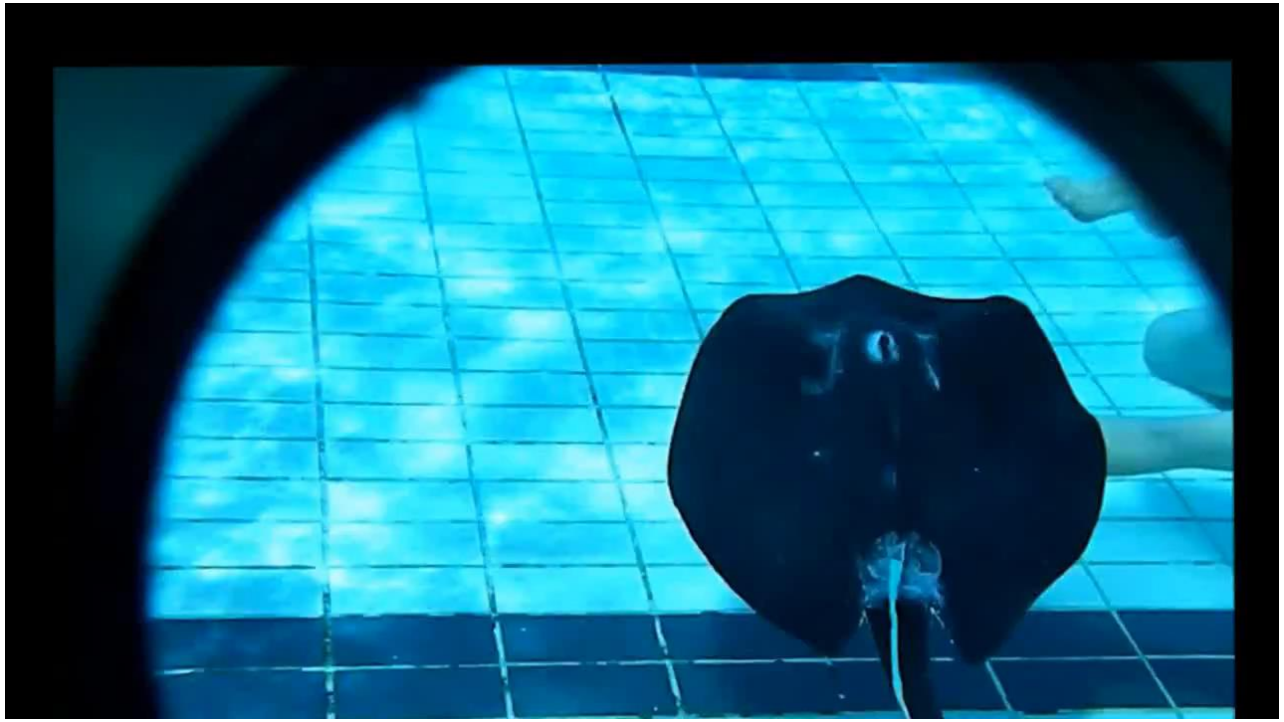


MRL Project Outline

- Nanotechnology
  - Video-rate Imaging: Versatile Atomic Force Microscopy Designs
  - Nanoscale Inspection: High-precision & High-speed Optical Metrology
- Intelligent Systems
  - Intelligent System for Health Monitoring of Physical Machines
  - Machine Learning-based Control for Electrical Motors
  - Autonomous Agents in Context
  - Generalized Bayesian Regression
- Robotics & Automation
  - Technologies for Cell Phone Recycling
  - Technologies for In-pipe Inspection, Rehabilitation and Energy Harvesting
- Selected Previous Projects

Project Videos

- Mechanical design and manufacturing
- Robot Collision Avoidance



Potential Openings

MECHATRONICS RESEARCH LABORATORY

- Contact for potential openings
  - Point of contact: Steven Yip Fun Yeung yyeung@mit.edu
  - Lab assistant: Barbra Williams barbraw@mit.edu
  - Prof. Kamal Youcef-Toumi youcef@mit.edu

Thank you!

Q&A