



Autonomy and AI

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Introduction



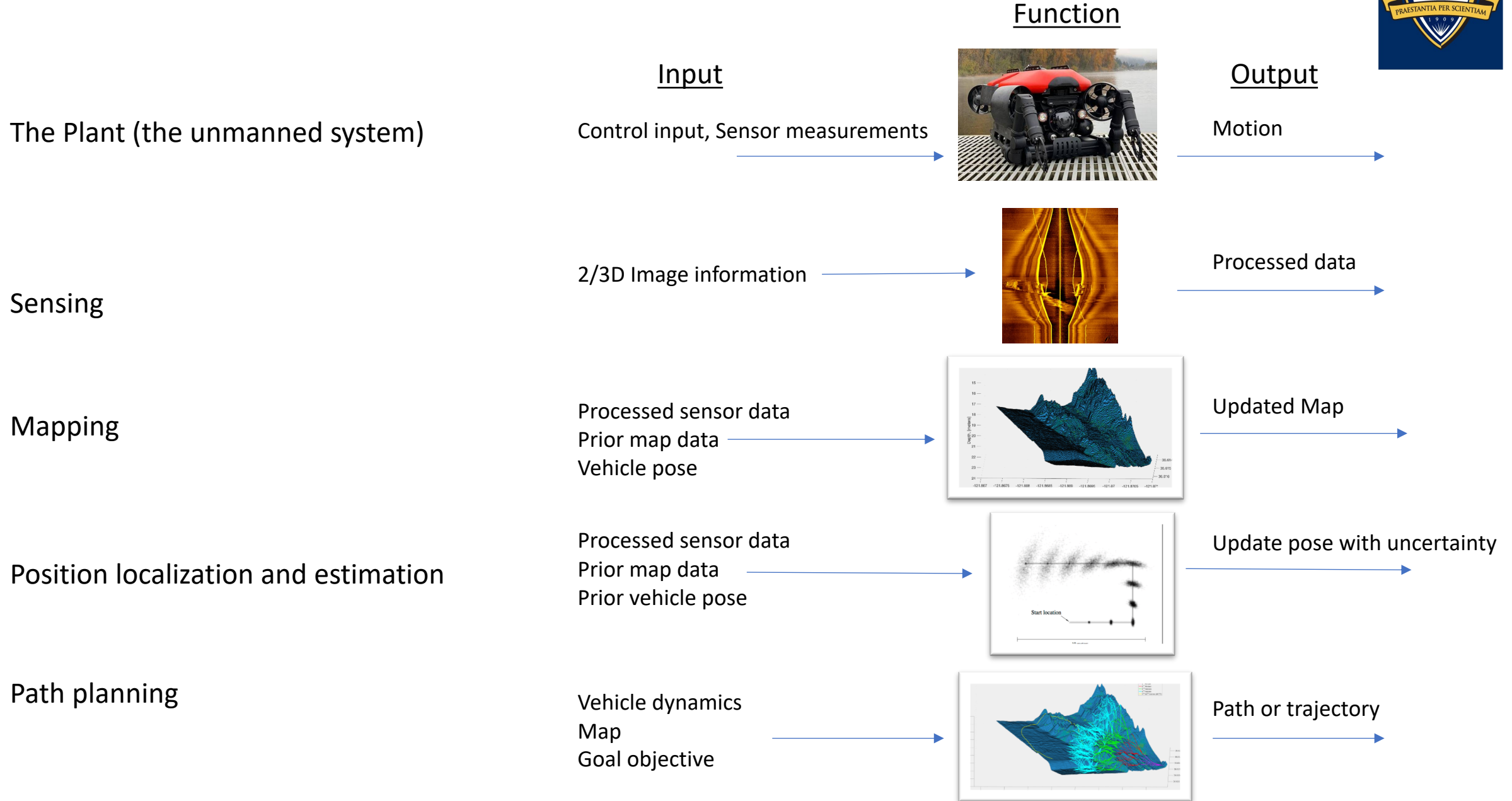
What I'm really going to talk about today is the ability of an unmanned mobile system to operate independently in a potentially unknown, dynamic environment.

The talk reflects the impact that AI/ML has had on robotics from the [NPS CAVR](#) lab historical perspective

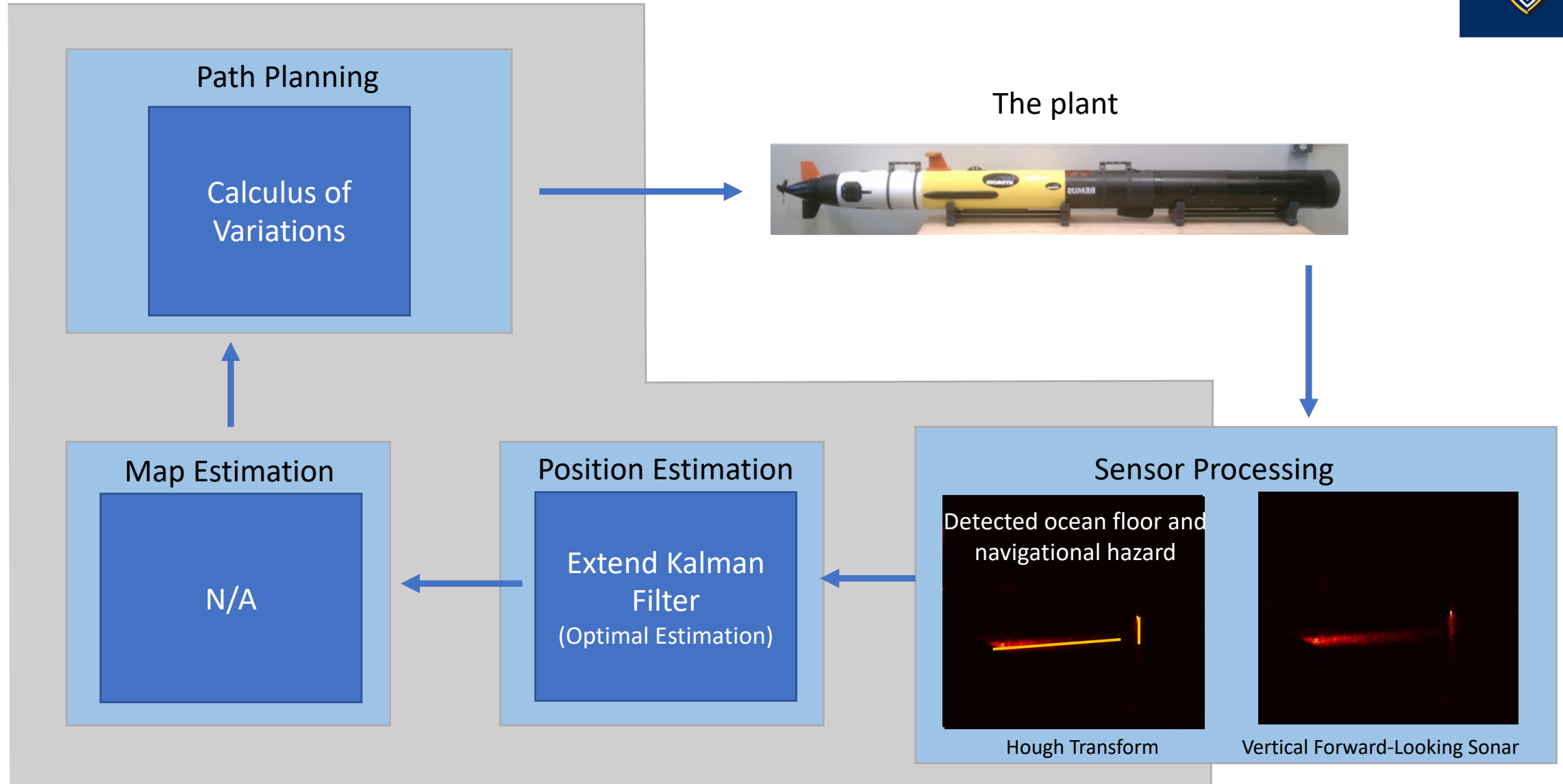
I'll provide overviews of what I believe are the AI/ML mathematical constructs that are currently the basis for achieving greater autonomy for these robotic systems.

As you see the presentation, I'd encourage you to think critically – what are going to be the limitations of this approach?

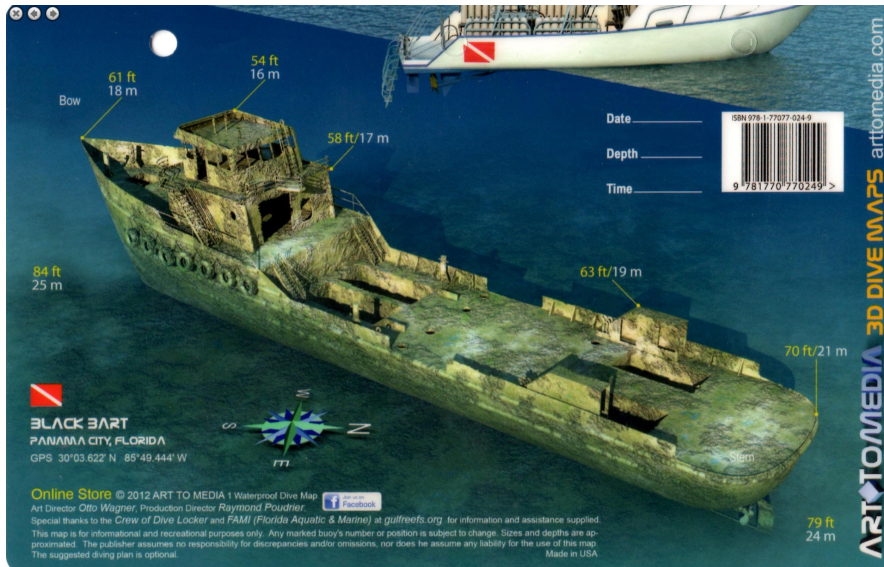
Components of Robotic Autonomy



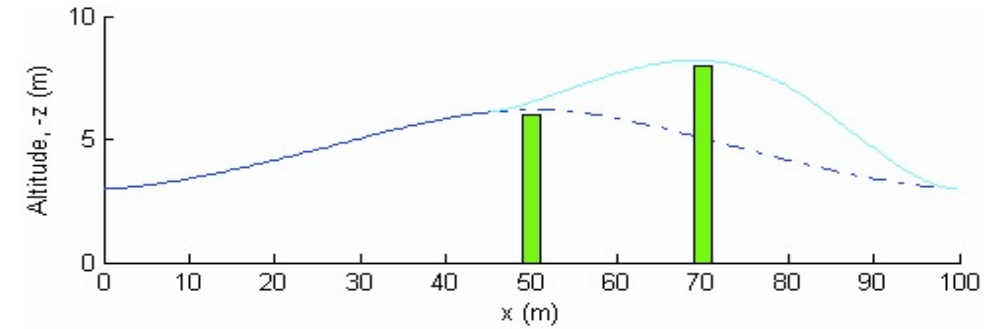
AUV Obstacle detection and avoidance (2005)



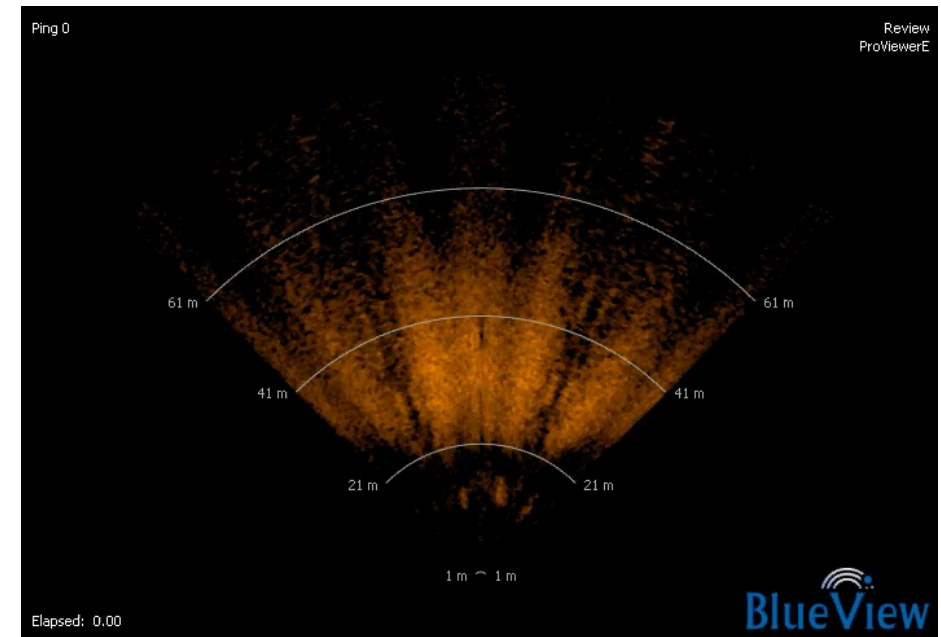
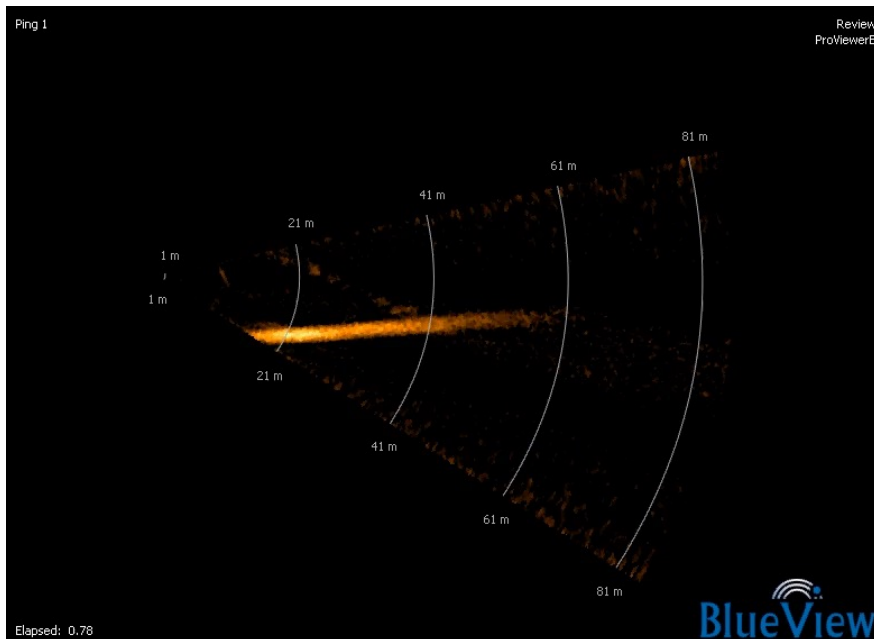
AUV Obstacle detection and avoidance (2005)



Trajectory Planning: Calculus of Variations



Importance of simulation: What is an obstacle



New autonomy example – Undersea Active Terrain Aided Nav (2020)

Description:

- GPS degraded or denied navigation solutions are required for current operational environments.
- Traditional Terrain Aided Navigation (TAN) is limited due to a requirement for a prior bathymetric map.
- This is limiting since frequently there is no prior map.



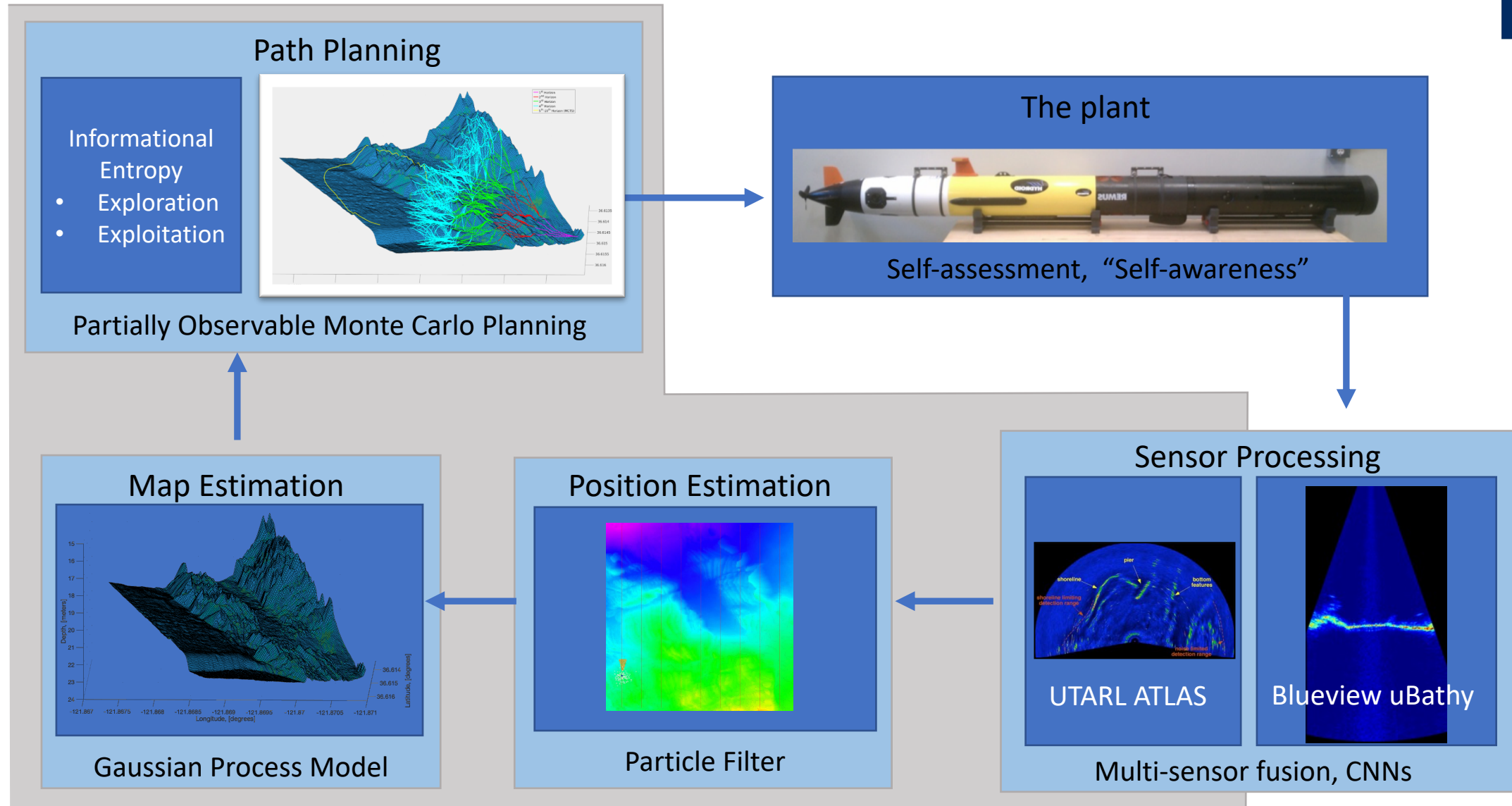
Solution:

- Active TAN - Dynamically build a map simultaneous with a bathymetric coverage mission.
- Balance exploration/exploitation using an information theoretic framework
- Exploration – emphasize search when confident about vehicle position.
- Exploit – emphasize localization on features when AUV position is poor

Application:

- Under ice – Use the ice topology as a map that can be used for position estimation.
- ICEX – Navy exercise run by the Arctic Submarine Lab once every two years
- 200 miles North of Prudhoe Bay, AK Northern most point of Alaska.
- Moving ice flow – 1 m/s, 24NM per day, non-linear motion

Evaluating the impact of AI/ML on robotic autonomy



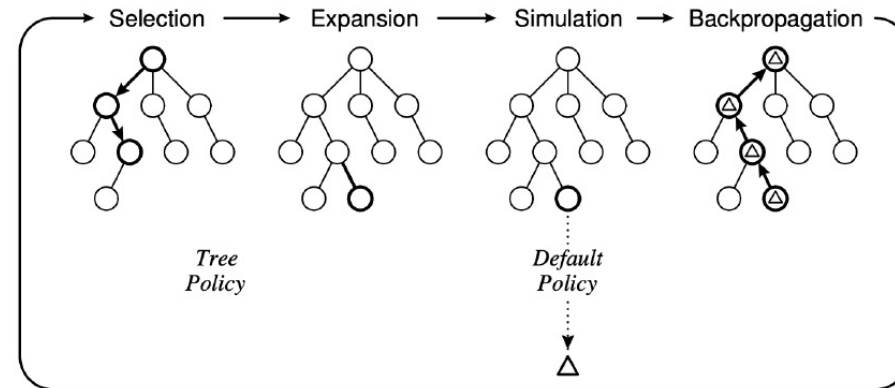
Partially Observable Monte Carlo Planning (POMCP) = POMDP + MCTS



$$Q_t(\mathbf{b}, \mathbf{a}) = \rho(\mathbf{b}, \mathbf{a}) + \gamma \int_{\mathbf{z}' \in \mathcal{Z}} \eta(\mathbf{z}' | \mathbf{b}, \mathbf{a}) V_{t-1}^* \tau(\mathbf{b}, \mathbf{a}, \mathbf{z}') d\mathbf{z}'$$

$$V_t^*(\mathbf{b}) = \sup_{\mathbf{a} \in \mathcal{A}} Q_t(\mathbf{b}, \mathbf{a})$$

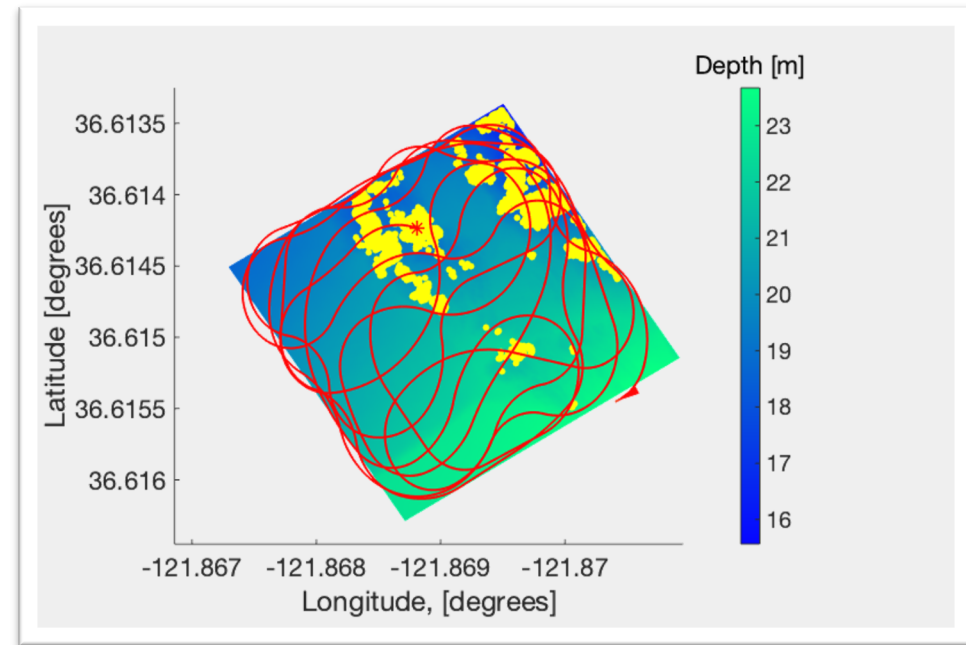
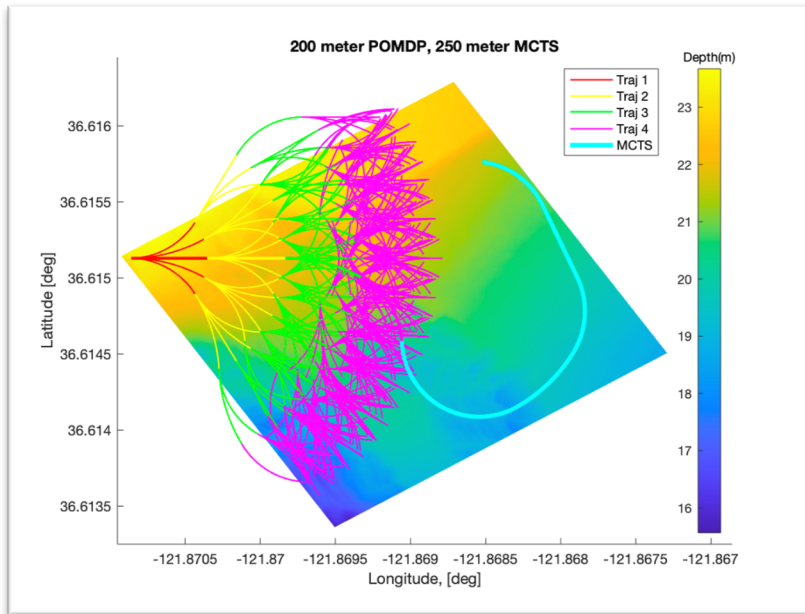
$$\pi_t^*(\mathbf{b}) = \arg \sup_{\mathbf{a} \in \mathcal{A}} Q_t(\mathbf{b}, \mathbf{a})$$



UCB1

Partially Observable Markov Decision Process (POMDP)

Monte Carlo Tree Search (MCTS)



Planning Example

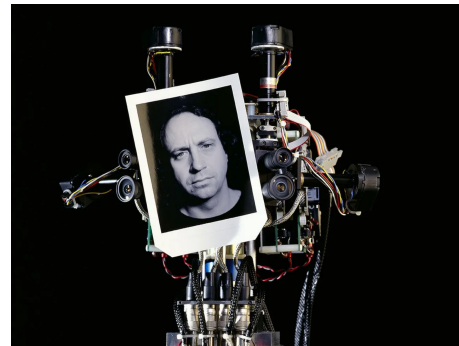
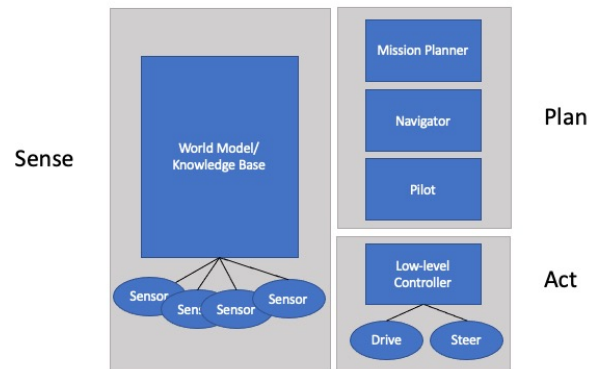
Back to the future – integration of multiple behaviors



So far, I've shown 2 examples of autonomy. Each could be considered a behavior – one for obstacle detection and avoidance and a second for area coverage.

How does a control/software architecture handle prioritization of multiple (potentially competing) behaviors?

Historically



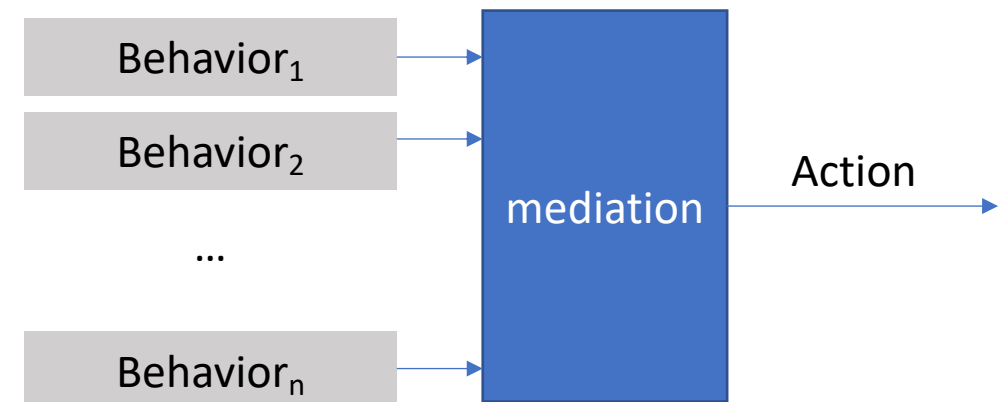
[Rodney Brooks MIT](#)

Behavior-based architectures

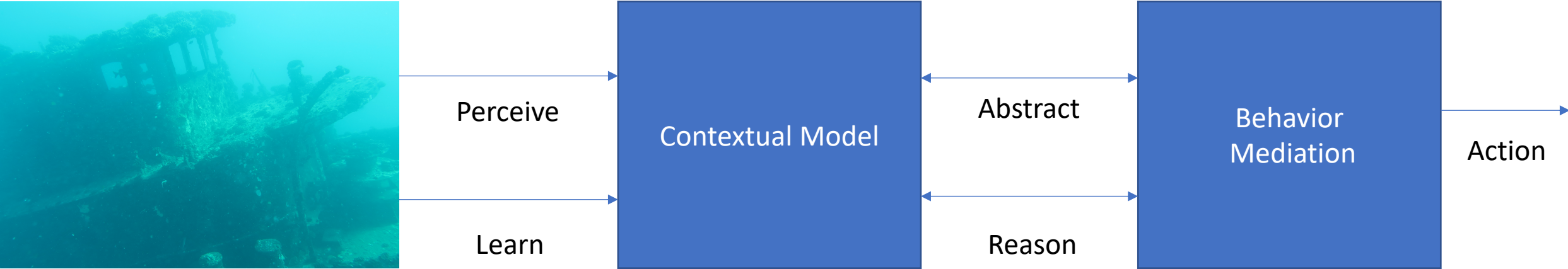
- Subsumption
- Action selection
- Motor schemas

Approaches with AI/ML

- Multi-objective Optimization
- Integration of ML techniques with Semantic Inference
 - Contextual Adaptation



Robotic Contextual Model



USS Nashua, Oahu, HI

As an alternative to sense-plan-act

Conclusions



- In the last 15 years AI/ML techniques have infiltrated the robot autonomy feedback
 - Sensor processing
 - Mapping
 - Position Estimation
 - Self-awareness
 - Path planning
- On the importance of data and simulation
- Limitations associated with current AI/ML techniques
- On the importance of operational context and data inference
- A final comment on networked systems