

Constrained Learning for Assured Autonomy

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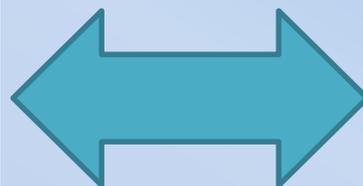
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- Perspective and Motivation
- Establishing a Context for Autonomy
 - Constraints and Objectives
- Contextual Reasoning
- Assured Decision Making – MILA
- Constrained Learning

We must choose between:

Sufficiently restricted
use cases s.t. sufficient
T&E certification is
affordable



Constrained use cases
s.t. hybrid T&E
certification and
performance-based
qualification is
acceptable

- Automatic vs. autonomous systems.
- To allow for more complexity in autonomy, must trade off ability to statically verify properties of the system.
 - Objective then becomes to bound system behavior, work to ensure system degrades/fails gracefully.

Waypoint Following Function

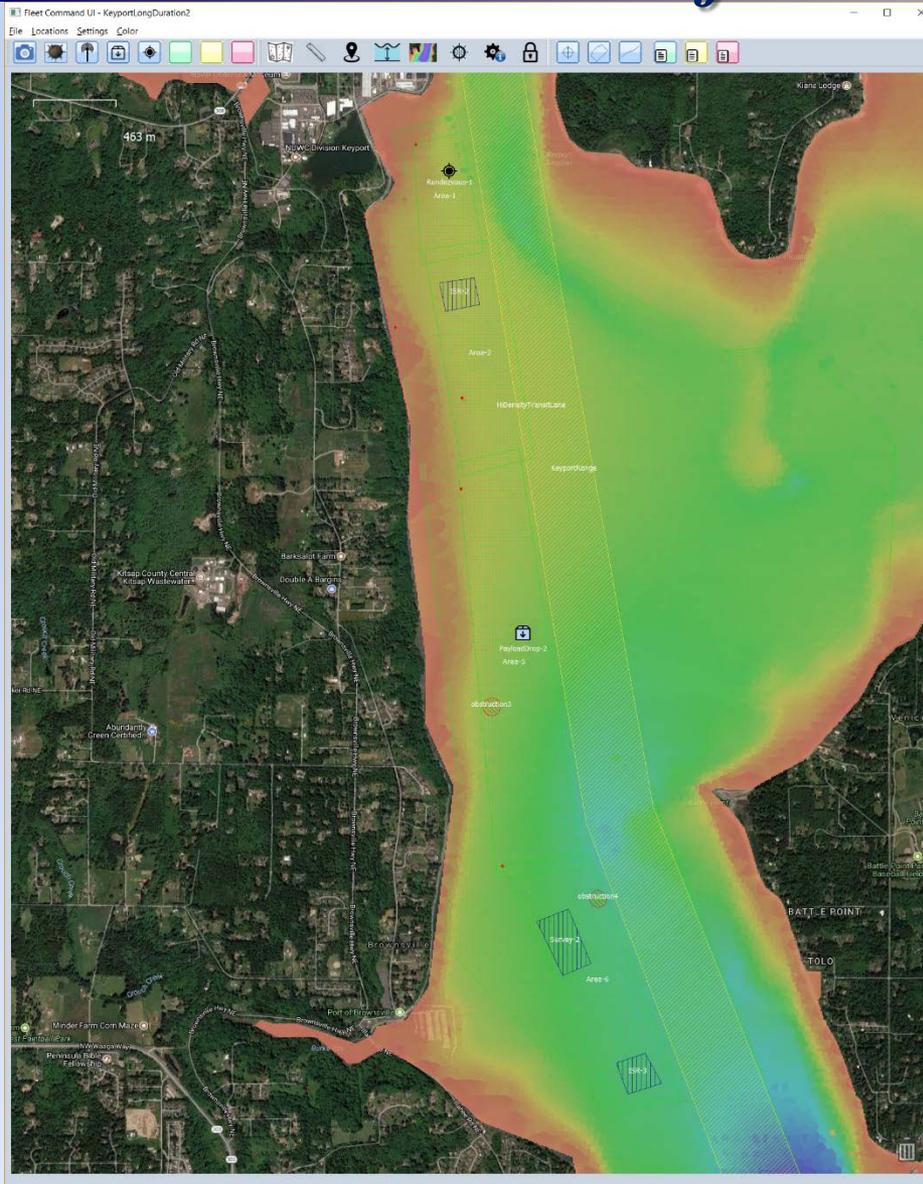


Notional Code Function

```
try {  
    // do something  
    // e.g. open a file  
}  
catch (...) {  
    throw (...)  
}
```

In both cases, exceptional conditions cannot be handled beyond alerting a higher-level context of the exception.

Context of Mission-Level Constraints and Objectives for 'True' Autonomy

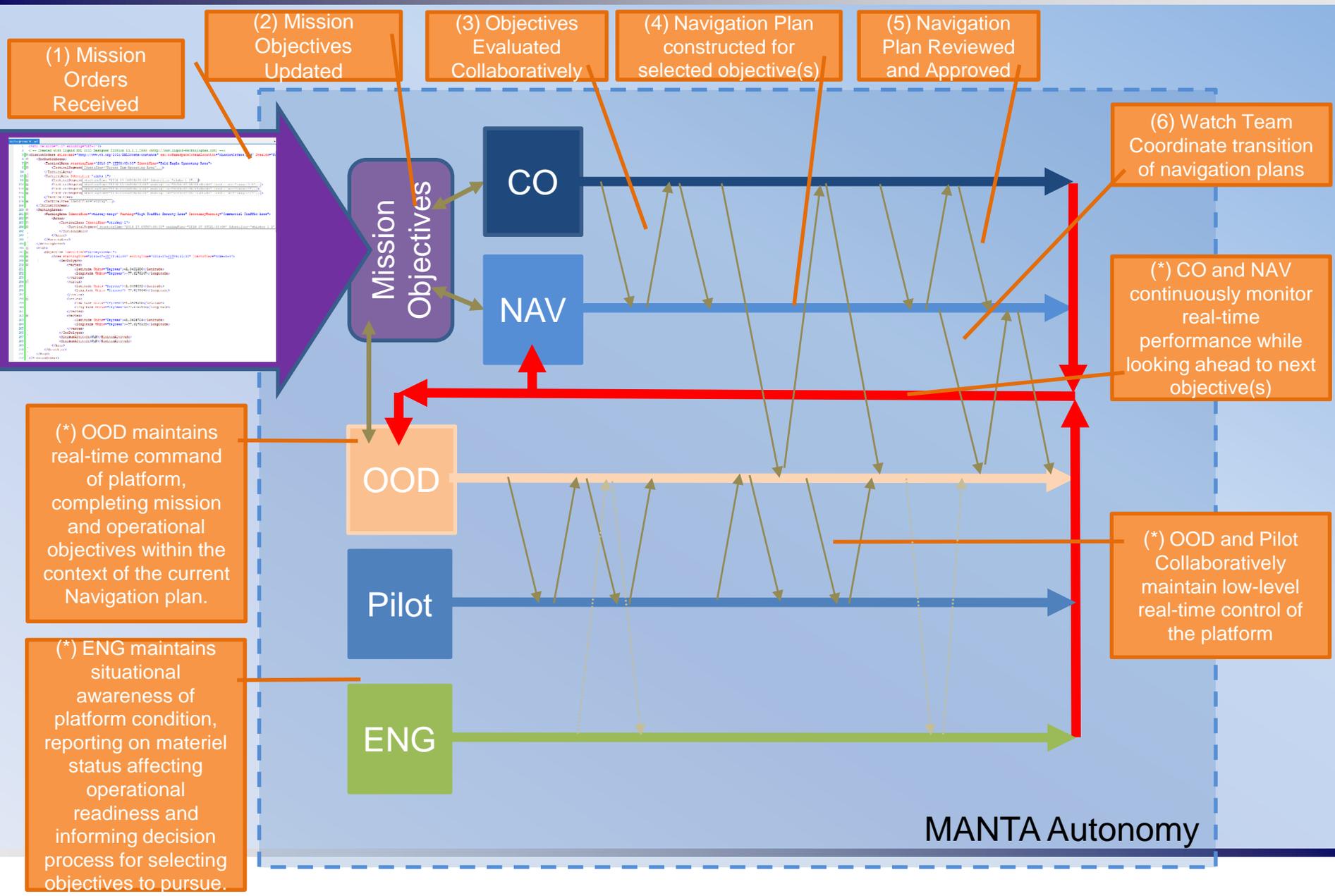


- Mission Orders consist of
- Spatial-temporal constraints defining where and when the AxS may be.
 - Informational Areas that may be operationally relevant (affect decisions)
 - Mission Objectives

This Context is used to

1. derive a course of action
2. Adapt course of action in presence of exceptional conditions.

Multiple Contextual Layers in MANTA

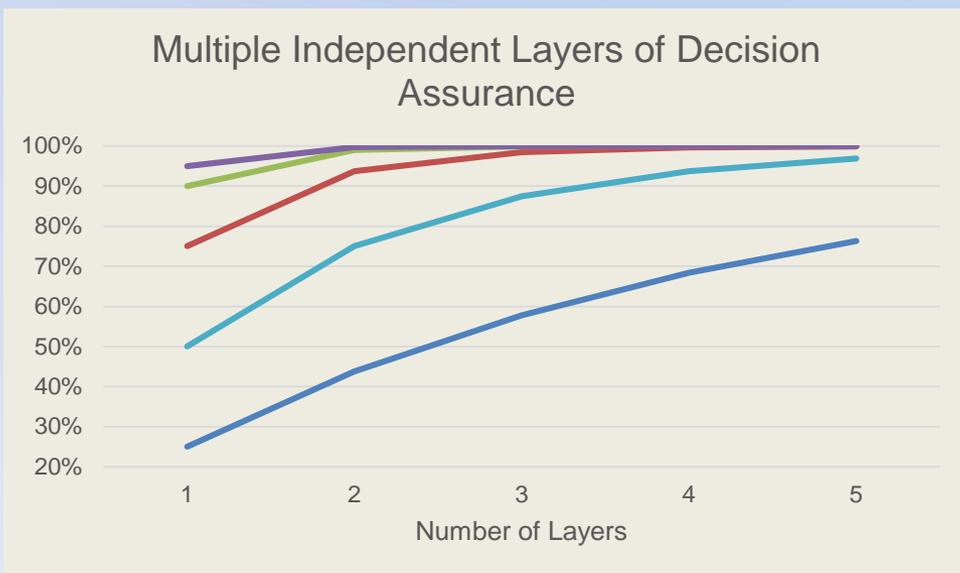


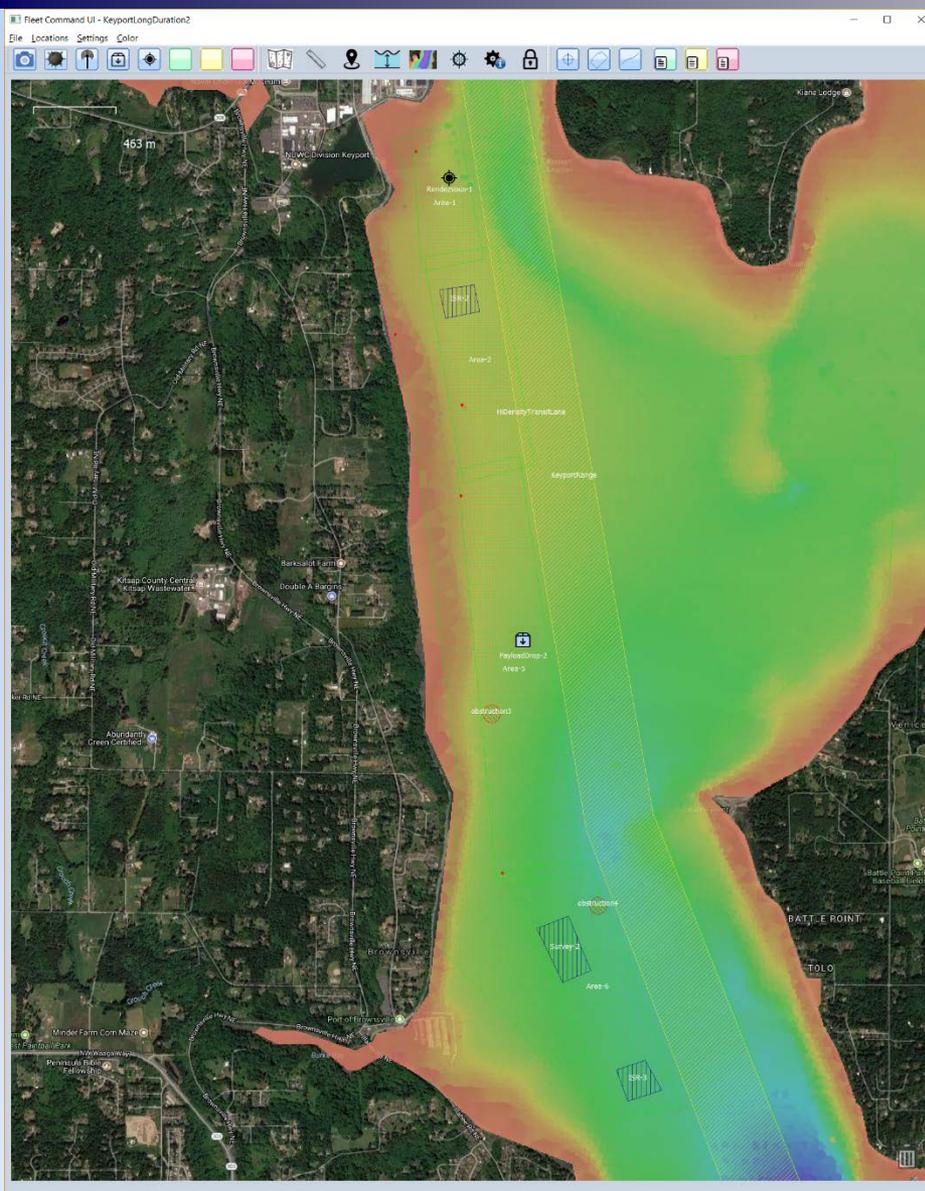
How can complex manned autonomous systems robustly and reliably perform in dynamic, unconstrained environments despite:

- Imperfect decisions
- Uncertain, incomplete, imprecise and contradictory data
 - Equipment and decision failures?

- Multiple, Independent Layers of Assurance enables:
 - Mission-level constrained, bounded learning.
 - Intrinsic error and fault tolerance.
 - Rapid deployment of capabilities.
 - Less time wasted trying for incremental improvements at high costs in time and money.
 - High-reliable, robust autonomy.
 - Supports handling need-to-know and software assurances best practices.
- MILA requires *non-bypassability, statistically independent* layers

- Focus not on exhaustive testing, but on maintaining **statistical independence** of failure modes.
 - May be augmented by varying scope.





Within these constraints, hard problems now handled by human operators may begin to be addressed:

1. The order in which mission objectives are pursued.
2. Adaptation to unexpected circumstances/patterns of life/environmental conditions.
3. Changes in objectives or constraints in long-duration autonomy.
4. Materiel failures on vehicle.

Provides a foundation within which better decisions may be made.

Learning for Optimality

Learning systems are generally only as good as the data on which they are trained and how well that training matches the in situ reality. Good training data is expensive, almost always insufficient for high assurance applications.

Re-casting learning in this constraint satisfaction approach, on-the-job learning in real world situations can be used to improve system performance over time.

Satisficing is a theoretical necessity in practical learning.

Teaching is needed, allowing for the transfer of knowledge that was gained at significant expense in money, time, blood, etc.

- Constrained learning as a T&E solution, not headache.
- MILA approach likely most cost effective, agile enough to keep pace with technological advances.
- Certification + qualification for complex autonomy VV&A / T&E.



Questions?

- Thank you!



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